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Automated Airborne EM and borehole data integration for depth to bedrock extraction

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SUMMARY

Airborne electromagnetic (AEM) was used to supplement a geotechnical investigation for a highway construction project in Norway. Variable bedrock threshold resistivity hindered efforts to track depth to bedrock, motivating us to develop an automated algorithm to extract depth to bedrock from both boreholes and AEM data. We developed two variations of this algorithm: one using simple Gaussian or inverse distance weighting interpolators, and another using ordinary kriging and combined parameter probability distribution functions.

Evaluation shows that for preliminary surveys, significant savings in boreholes required can be made without sacrificing bedrock model accuracy. However, issues with AEM noise and data quality likely reduced the comparative advantage that including AEM provided. Moreover, AEM cannot supersede direct sampling where the model accuracy required exceed the resolution possible with the geophysical method. Nevertheless, using AEM in the way can still reduce the number of required boreholes and hence reduce site investigation costs because we can identify high probability zones for shallow bedrock, identify steep or anomalous bedrock topography, and estimate the spatial variability of depth.

Key words: Airborne electromagnetic, Geotechnical investigation, Depth to bedrock, Interpolation, Geostatistical modelling

INTRODUCTION

Airborne electromagnetic (AEM) surveys have great potential to reduce the cost of geotechnical investigations, but are limited by the difficulty in interpreting indirect data. To illustrate, we present the case of a new, major highway linking East Norway with Sweden, the E16 from Kløfta to Kongsvinger some 50 km NE of Oslo, where 32 km of new motorway are planned from Nybakk to Slomarka (Figure 1). As part of the geotechnical design, we supplemented the geotechnical ground investigation - drilling programme with AEM measurements. The primary aim of the AEM survey was to obtain depth to bedrock and get further information about the extent of sensitive clay. However, lateral variations in bedrock threshold resistivity complicated interpretation, as a single, homogenous resistivity did not match borehole data. While semi-manually picking did provide an acceptable model, this process was time consuming and a more automated, repeatable, and objective approach is preferred.

This challenge of integrating direct data sets with geophysical measurements is commonplace with near-surface geophysical applications. Knowledge-based (cognitive) approaches have been the traditional approach. While recent examples such as Jørgensen et al. (2013) shown their utility, the methods can be difficult to document and not repeatable. Geostatistical approaches (for example, He et al. (2014) and Strebelle 2002) help overcome this, but selecting appropriate threshold values are still the largest challenge (Foged 2014). Constrained inversion can be used (Chouteau 2013), but is limited to cases with comparably simple geological configurations.

In order to achieve the cost savings potential that AEM presents, our aim was to develop an interpolating algorithm to automatically track depth to bedrock using both AEM and sparse borehole data. Our goal with this method was to (1) provide an exact match with ground truth data; (2) account for variable bedrock threshold resistivity; (3) quantify prediction uncertainty; and (4) limit manual input from user. Our later evaluation and cross-validation of the algorithm shows that substantial cost savings are indeed possible by integrating AEM data in this way.

METHOD

Project Setting

The survey was conducted with the SkyTEM 302 system using a 314 m^2 frame with two turns in the high moment and one turn in the low moment to obtain high near surface resolution. A general description of the system can be found in Sørensen and Auken (2004). A total of 178 line-km was flown in three consecutive days in January 2013. Three parallel lines with a spacing of 25 m where flown along the planned road corridor. Additional lines with nominal spacing 125 m covered two river crossings: 15 lines near Vorma/Vormsund, and 9 lines near Uåa. Raw data were processed using the Århus workbench (www.aarhusgeo.com) using a smooth, pseudo-3D spatially constrained inversion with twenty depth layers.

In addition, boreholes were dug at 1388 locations, 842 of which were less than 125 m from the AEM lines. Most soil investigations were rotary pressure soundings, but some were total soundings and cone penetration tests. While there is

some uncertainty with depth to bedrock measurements unless total soundings are used, the uncertainty is assumed negligible compared to the coarseness of the AEM data.

While overburden geology in this area is quite complex, bedrock characteristics are relatively simple. The survey area consists of various glaciomarine and glaciofluvial sediments over granitic to dioritic layered gneisses. Geological maps consulted did not show any sharp compositional boundaries in the bedrock, and no such boundaries were seen the AEM resistivity model either. Hence, a smoothly-varying model for threshold resistivity should be appropriate.

Bedrock Tracking Algorithm

Our algorithm involves four major computational steps (Figure 2). These are:

1. Find an appropriate bedrock threshold resistivity at the boreholes locations
2. Interpolate the bedrock threshold resistivity at AEM sounding locations
3. Find the depth to bedrock at AEM sounding locations based on the resistivity profile and the chosen threshold resistivity
4. Interpolate depth to bedrock everywhere

Two different variations of the method were tested. Variation 1 used only simple interpolator weight functions– Gaussian or Inverse Distance Weighting – for Steps 1, 2, and 4. Then, in step 3, the exact intersection between the threshold resistivity and resistivity profile becomes the depth selected. Variation 2 uses ordinary kriging instead of interpolation. Kriging is advantageous both because it is a data-derived rather than arbitrary interpolation function and because it provides an interpolator variance which can be carried forward through multiple interpolation steps. Bedrock depth is selected in Step 3 by combining probability distribution functions (PDFs) for threshold resistivity, AEM resistivity sounding, and initial depth estimate. A comparison of how each Variation selected depth in Step 3 is shown in Figure 3.

After computing depth to bedrock for the full data set, each variation was evaluated using a cross-validation procedure. Each interpolator was given a random combination and number of boreholes as input, and depth predictions at the remaining borehole locations was requested as output. This output was compared to actual measurements, and the cross-validation was repeated using only the input borehole data without AEM data. We conducted 1500 trails for Variation 1 and 500 trials for Variation 2.

RESULTS AND DISCUSSION

A comparison of the root mean square (RMS) prediction error from the cross-validation trials shows that with both Variation 1 and 2, using AEM data in this way results in considerable average gains in bedrock model accuracy (Figure 4). This comparative gain is lost when boreholes spacing is roughly half of the nominal AEM line spacing (~75 m). The comparative advantage is dependent on local topography as well. The AEM interpolator has a clear advantage on the fringes of the river valley and at the edges of borehole coverage, being between 5 and 15 m closer to the measured value on average. Meanwhile, there is little difference in modelled prediction in flat areas.

The gains in model accuracy are limited by some shortcomings of the data set. Approximately 35% of all depth picks at AEM soundings (Step 3 of the algorithm) are rejected due to poor data quality. The inversion algorithm was unable to resolve some model layers above the bedrock interface, hence there was no resolvable transition to bedrock resistivity in the sounding. An additional 2% of depth picks are rejected in Variation 1 because it deviates too far from the initial depth estimate, as in the case shown in Figure 3.

In general, Variation 2 produces the best results. As Figure 4 shows, it produces a more accurate model. Moreover, the prediction error estimates computed may be useful for further applications, such as mapping the probability of encountering bedrock at a certain depth. However, Variation 2 fails to provide an output when too few or too sparsely spaced boreholes are used because some observations are required before a semi-variogram model can be fitted. Moreover, on average, actual prediction errors are 1.6 greater than error estimates calculated. Finally, some adjustment on the automatic variogram modelling was required so that the algorithm did not select unreasonably large correlation distances (ranges) or used too few lag bins. While Variation 1 lacks the prediction error and accuracy, it is still usable in very sparsely sampled trails and required nearly no user adjustment.

CONCLUSION

We successfully created a depth to bedrock tracking algorithm which combines AEM and borehole data. We get an exact match with ground truth data and can account for variable bedrock threshold resistivity. We can estimate prediction error given sufficient borehole information, but for an unknown reason, these are underestimated. Finally, while some user input is required to find reasonable bounds on correlation distances, the algorithm is far more efficient than the previously used cognitive modelling approach.

Evaluation of the two method variations developed showed that at sparse borehole spacings, significant savings on boreholes can be made. However, AEM cannot supersede direct measurements in cases where the required resolution is beyond the precision limits of the geophysical method. Nevertheless, we show that there is still potential for cost reductions because early AEM surveys, even with a small sample of boreholes, can (a) identify early on zones where shallow bedrock is likely to be; (b) identify areas of steep or locally anomalous of bedrock topography; and (c) estimate the spatial variability of depth, giving a more informed choice of borehole spacing during later phases of investigation.

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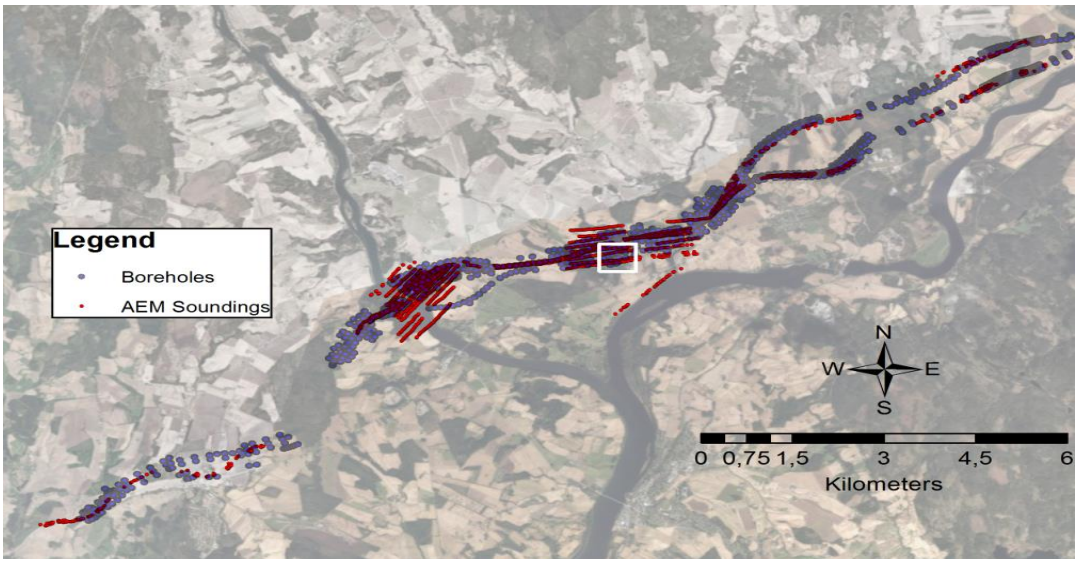

Figure 1. Location of the planned E16 highway upgrade construction northeast of Oslo, Norway, showing extent of the AEM and borehole soundings collected.

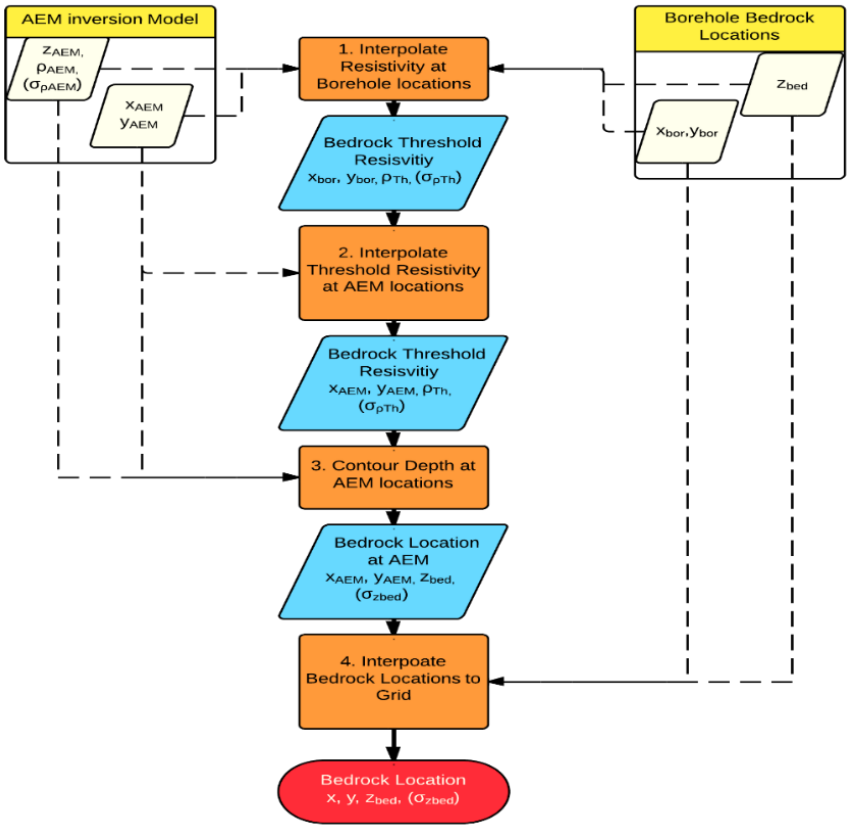

Figure 2. Overview of data flow and major computational steps of the bedrock tracking algorithm developed.

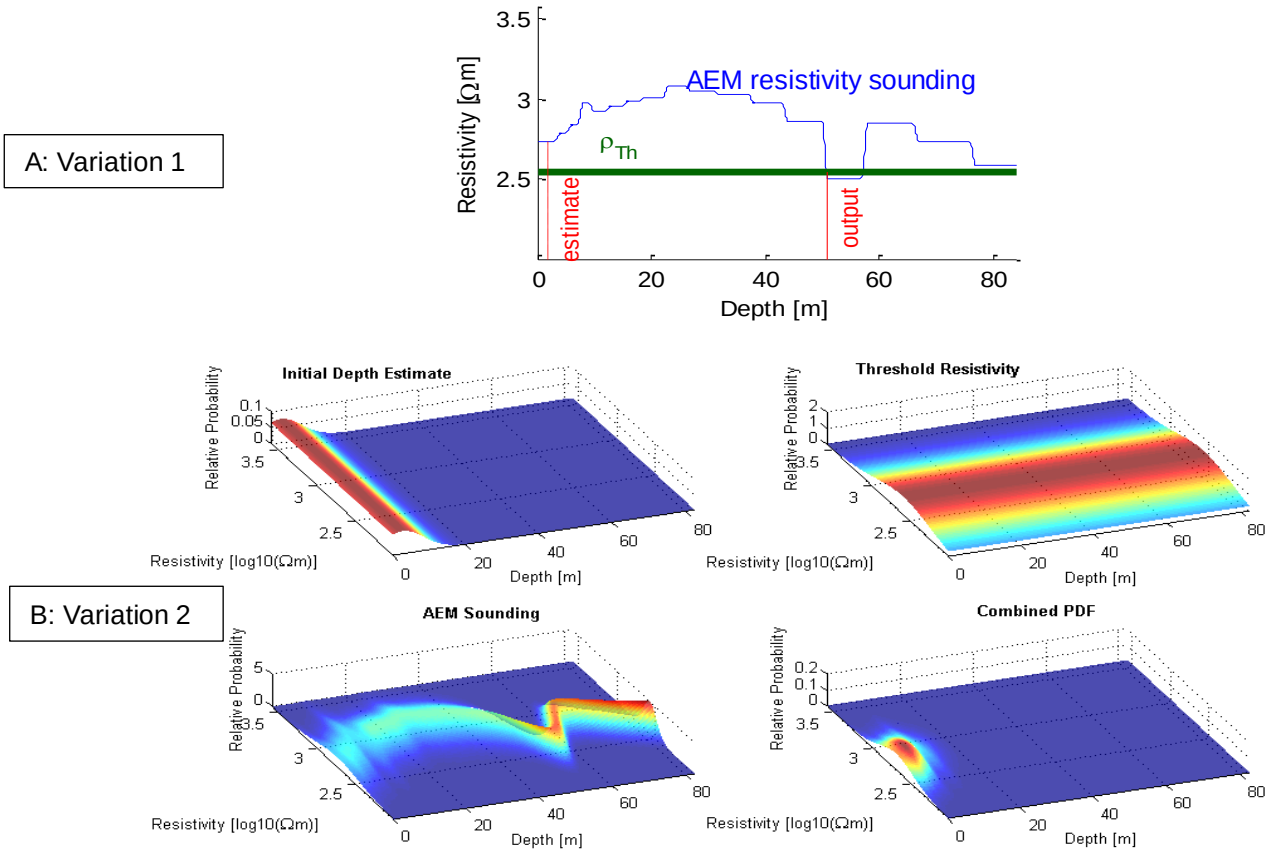

Figure 3. Illustration of the bedrock depth selection method used in Step 3 of the algorithm using either Variation. While in most cases, finding an exact match of threshold resistivity and AEM sounding curve using

Variation 1 (A) provides a valid depth selection, this example illustrates the advantage of using probability distribution functions in Variation 2 (B).

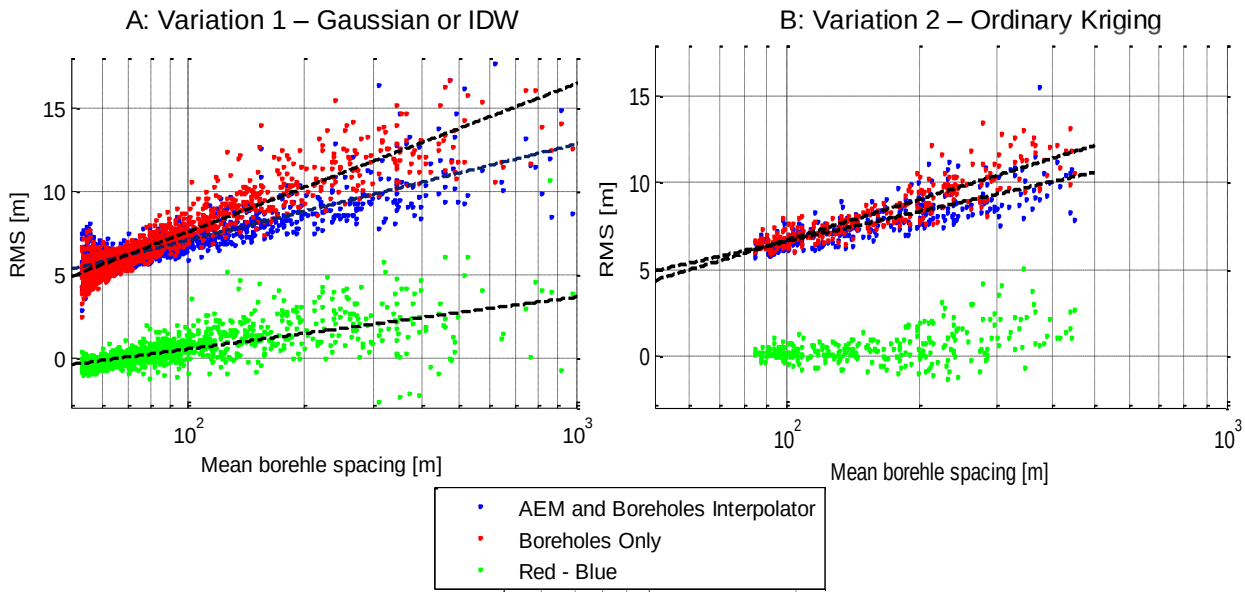

Figure 4. RMS prediction error for depth to bedrock versus mean borehole spacing. Each Variation is also compared to the average error of using only borehole data instead of combining both data sets.