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Large scale, efficient geotechnical soil investigations applying machine learning on airborne geophysical models

L'application des réseaux neuronaux artificiels et la géophysique aéroportée dans les études géotechniques à grande échelle

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ABSTRACT: Infrastructure cost overruns and delays are persistent challenges for engineers and project owners. Reported average cost overruns from 20 to 50 per cent for linear infrastructure are typical. Assessing geological risk is a significant part of planning; however, this risk is hard to control given the high cost of detailed ground investigation programs using traditional approaches (i.e. geotechnical drillings). Airborne geo-scanning is a technology that is increasingly being used to mitigate geological uncertainty. We have translated complicated geophysical models to parameters valuable for engineers using artificial neural networks. In this study we illustrate the applicability of airborne geo-scanning surveys to derive bedrock topography (i.e. depth of cover). Tight integration of accurate geophysical models and sparse geotechnical data is a key element leading to final bedrock topography uncertainty of a few meters or 20 % – 30 % of the sediment thickness.

RÉSUMÉ: Les surcoûts et les délais dans les projets d'infrastructures sont des défis constants pour les ingénieurs et maîtres d'ouvrage. Les surcoûts de 20 à 50 % sont communs dans la construction d'infrastructures linéaires (par ex. les autoroutes, les voie ferrées, les tunnels). L'évaluation du risque géologique a une grande part dans la planification de ces projets. Ce risque est difficile à contrôler à cause des coûts élevés des forages, la méthode traditionnelle pour les études géotechniques. Les systèmes géophysiques héliportés deviennent de plus en plus communs pour de telles études. Nous avons extrait des paramètres géotechniques de ces données géophysiques en nous servant de réseaux neuronaux artificiels. Dans cet article nous illustrons l'applicabilité des campagnes aéroportées dans la cartographie de la topographie du substrat rocheux. En intégrant nos modèles géophysiques avec des forages épars nous réussissons à déterminer l'épaisseur des sédiments avec une précision de 20-30%.

Keywords: Site Investigations; Linear Infrastructure; Geophysics; Machine Learning; Geology

1 INTRODUCTION

The geological risk in large scale infrastructure projects is frequently identified as the key factor leading to significant schedule delays and cost overruns (Beckers et al. 2013). In the early stages of planning, finding suitable areas for both tunnels and roads is critical. Large areas have to be covered to be able to see and compare the risk choosing between surface constructions on deep and soft sediments along one route or tunnels along another route. Conventional geotechnical ground investigation are too costly and time intensive to provide full coverage over an area of interest. Airborne geo-scanning is an emerging technology that can be able to mitigate the geological uncertainty of these areas and it can give geologists the tool needed to make the right choices at an early stage in big infrastructure projects. Choices that can reduce the mentioned overruns of 20-50 % of original budgeted project costs. Airborne geo-scanning makes use of a well-established near-surface geophysical technique (Airborne Electromagnetics) providing a rapid and seamless overview of the geophysical properties within an area (Pfaffhuber et al. 2016). In the past, significant labour had to be invested to manually or semi-automatically interpret geophysical models into usable geotechnical parameters (Christensen et al. 2015). Recently, we have developed machine-learning-based methods that integrate the acquired geophysical model with sparse geotechnical soil investigations into a unified ground model (Lysdahl et al. 2018). In this study we compare the performance of our artificial neural network (ANN) to earlier interpretation techniques used in two past projects: a road project from 2013 and a railway project from 2016. Bedrock topography is our primary target. In addition to bedrock topography, other studies have illustrated the applicability of the method for mapping of sensitive clay (Lysdahl et al. 2017), identifying major weakness zones in rock (Pfaffhuber et al. 2016) and de-risking contaminated mass management (Pfaffhuber et al. 2017).

1.1 Method background

We briefly outline the methodology and refer to articles for more detailed description.

The geophysical models that we interpret come from processed airborne electromagnetic survey data. In these surveys, a helicopter tows equipment 30 m above the ground. The SkyTEM 302 system was used in the road-building project, and the SkyTEM 304 system in the railway project (Sørensen and Auken 2004). These systems measure electromagnetic induction effects between itself and the ground, a response that is dependent on the electrical resistivity of the uppermost few hundred metres of the ground. Data was processed manually removing potential noise and coupling effects and inverted to a 3D resistivity model using spatially constrained inversion with Aarhus Workbench, a specialized piece of software. The resulting 3D resistivity model has a vertical resolution ranging from meters close to the surface to tens of meters at larger depths and a lateral resolution of roughly 50 to 150 meters (Christiansen et al. 2006).

These geophysical surveys were paired with ground investigations. At the time of the original projects, approximately 400 boreholes had been drilled in the road case and 17 in the railroad case. Some of these were dug prior to geophysical surveys, whereas others were completed after the survey but before an interpreted bedrock model was delivered. Additional holes have been drilled since then. The survey areas now contain 1107 and 41 holes, respectively. A mix of total soundings and rotary-pressure soundings were used in the road case, whereas only total soundings were used in the other. These new drillings help to evaluate the accuracy of earlier bedrock models. This involved both computing aggregate error statistics and inspecting the spatial distribution of errors with maps.

Our new artificial neural network (ANN) extracts bedrock topography from the geophysical model by using existing geotechnical soundings as training data. It is based on multi-layer perceptron regression and is implemented in the "scikit-learn" python package (Pedregosa et al. 2011). Resistivity and borehole data are not always co-located. We solve this issue by interpolating resistivity data at borehole locations and training the networks on these resistivity values.

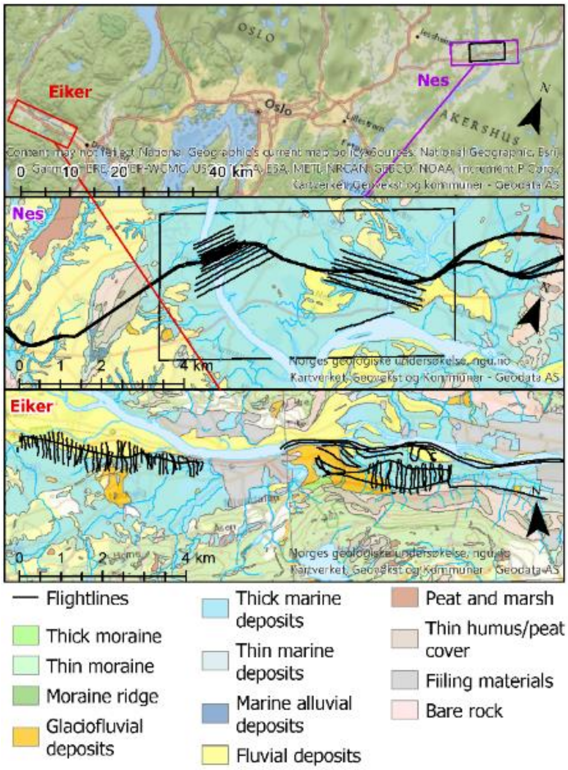

Figure 1 Top: Overview map indicating project areas, Middle: Surficial geology and survey lines in area 1, Bottom: Surficial geology and flight lines in area 2, stippled box indicates subset shown in results section.

We tested the performance of the ANN in several ways. In both field case studies, we compare the earlier bedrock models to new models created by ANNs trained on either the full set of boreholes or on a subset that was available at earlier time in the project. We also systematically tested the effect that the number of boreholes used as training data has on the accuracy of a bedrock model. For a given number of boreholes, we trained 50 neural networks on random subsets of boreholes and computed error statistics for all 50 bedrock models. With the same random subsets of boreholes, we also created bedrock models by simply triangulating the measured bedrock positions (which is essentially the current standard when no additional information is available).

1.2 Study area

The presented study areas are close to Norway's capital Oslo (Figure 1). One in the municipality of Eiker, 40 km south-west of Oslo, the other around Nes in Romerike, around 60 km north-east of Oslo. We observe post-glacial geomorphology typical for the Norwegian low-lands: exposed bedrock (high electrical resistivity), moraines (high resistivity), valleys filled with massive glaciofluvial deposits (medium resistivity), large expanses of glaciomarine clay (very low resistivity), and even instances of quick clay (low resistivity). The bedrock geology is largely comprised of metamorphic rock types. Some igneous rocks are present in the north-eastern corner of Nes, and some shales and limestones are present at Eiker.

2 NES CASE STUDY: HIGHWAY PLANNING

2.1 Project background

Extensive ground investigations for a proposed expansion of the E16 highway along a 30-km segment northeast of Oslo began in late 2012. A resistivity model was created based on 178 line-km of AEM surveys flown in January 2013 both along the road alignment and on an additional grid at two river crossings (Vorma and Uåa). Bedrock models were delivered in spring 2013 using two different methods: First, bedrock depths were chosen from a simple threshold resistivity (i.e. the shallowest occurrence of values greater than a fixed resistivity value was assumed to be bedrock). Second, an expert manually picked bedrock depths from the resistivity models. At the time, approximately

400 boreholes were available to both help guide the manual picks and to guide the choice of an appropriate threshold resistivity.

However, both methods had their limitations. Even though 100 Ωm was the threshold resistivity that worked best, its performance was still poor due to the heterogeneous sedimentary composition (Figure 2). Though the manual interpretation could adjust to local heterogeneities, it was time consuming, subjective, and strongly influenced by the way data was visualized. In our new analysis, we created many new models with ANNs. We show results from three examples in this article: 1) a neural network trained with five boreholes that were manually picked to be well distributed, 2) a neural network trained with 50 randomly selected boreholes, and 3) a neural network trained with all 1107 boreholes

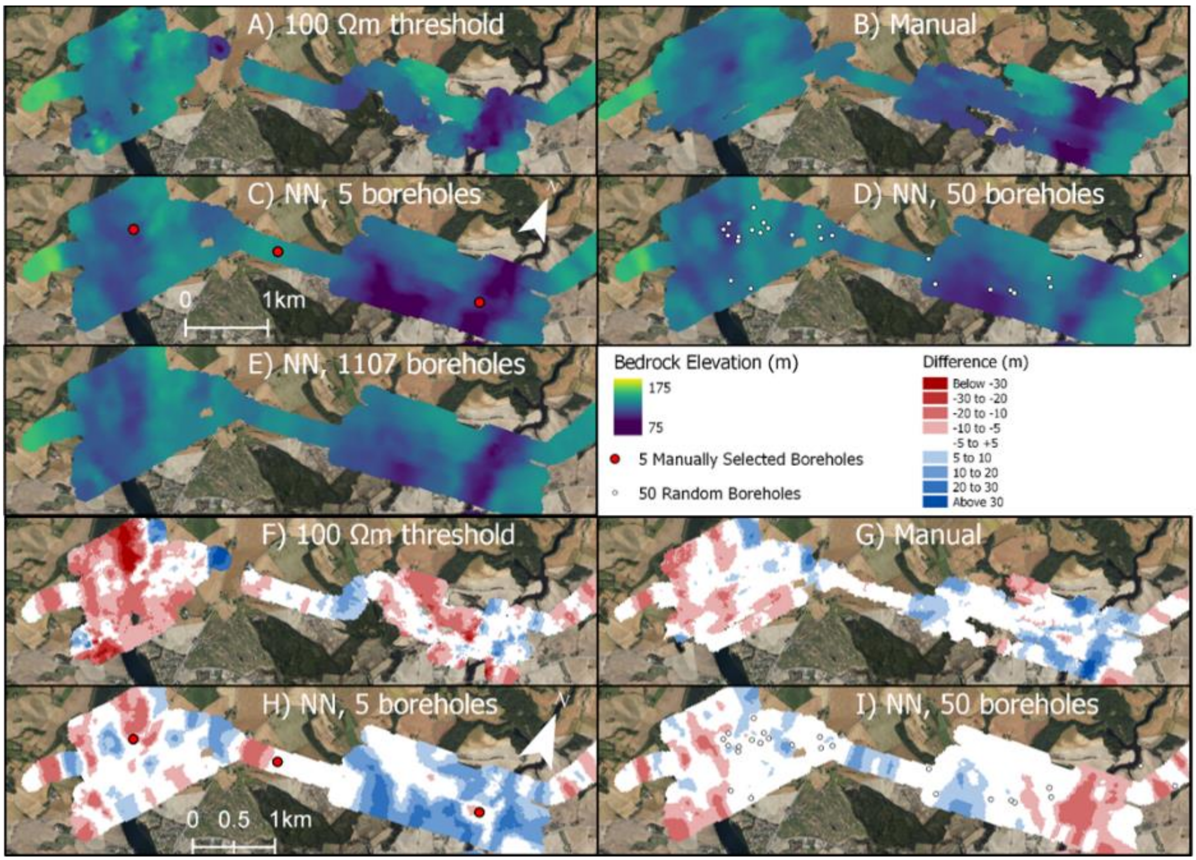

Figure 2: Bedrock elevation models produced from five different methods, focusing on the river crossing at Vorma and Uåa as well as differences between the most accurate model (NN using 1107 boreholes) and the other four models. Negative values indicate that the final model is lower, and vice versa.

2.2 Results

The bedrock model based on only five boreholes outperforms the threshold resistivity method, but has higher average errors than the manual interpretation (Figure 2 and Table 1). However, a neural network with only 50 boreholes outperformed the manual method that relied on several hundred boreholes to guide the expert's interpretation. The neural network trained on all 1107 has the best performance overall, having a median error of 14%. This error is due to both 1) errors due to interpolation of resistivity model from AEM sounding points to boreholes location and 2) due to the imperfect correlation between training data and the target output (i.e. *network loss*).

Table 1. Overall performance of each bedrock modelling method. Errors represent the difference between the model and overlapping borehole measurements

Method	**Median (m)**	**Mean (m)**	**Median (%)**	**Median (%)**
100 Ωm	6,0	7,9	43 %	48 %
Manual	4,6	5,8	28 %	41 %
5 BH	5,7	7,4	37 %	64 %
50 BH	4,0	5,5	24 %	38 %
1107 BH	2,5	3,2	14 %	28 %

Both the 5-borehole and 50-borehole neural networks perform poorly in areas of particularly high and particularly low bedrock elevation where they lack training data to justify the more extreme values (Figure 2). However, these errors tend to be more evenly distributed and random compared to the two models from 2013 and agree more closely with the main trends in the final borehole measurements. Even the five-borehole neural network outperforms the older two methods in one location where a thick body of conductive clays masks the high resistivities of the bedrock below despite not having any training boreholes in this vicinity (Figure 3).

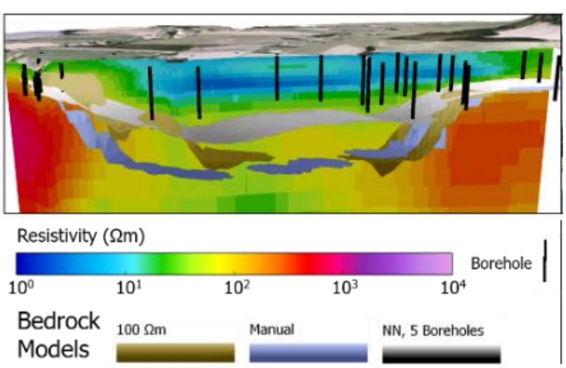

Figure 3: Comparison bedrock models derived from three different methods: threshold resistivity (brown), manual interpretation (purplish blue), and a neural network trained on five boreholes (grey). Boreholes and a sample of the resistivity model are also shown. Vertical exaggeration: 10x.

The results in Figure 4 further underline the advantage of using neural networks and AEM in early phases of projects where few boreholes are available. For instance, with just 25 boreholes, the neural network averages 4.8 m error (or 30% by depth) compared to 7.0 m error (43%) of a surface produced by simple triangulation of borehole measurements.

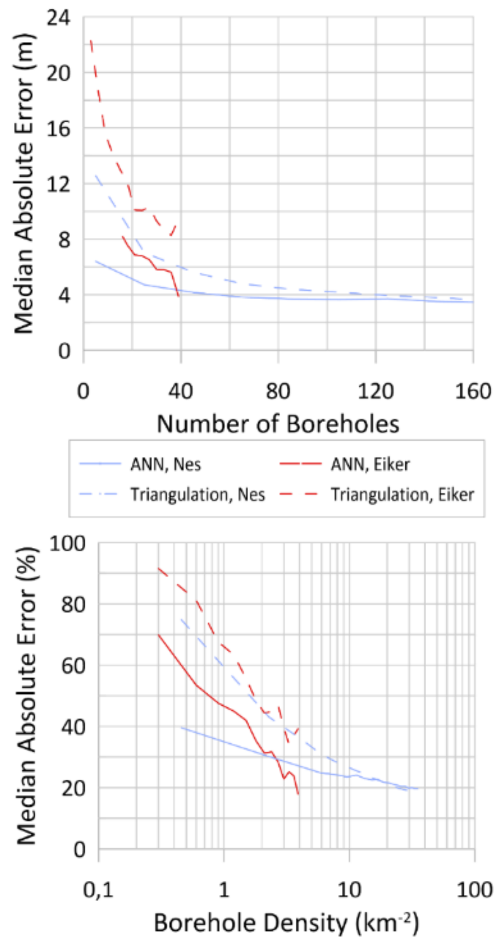

Figure 4: Median absolute error versus the number of boreholes and average borehole density used as training points.

3 EIKER CASE STUDY: RAILWAY PLANNING

3.1 Project background

A new section of highway and high-speed rail is to be built in the Eiker area between the cities Drammen and Hokksund. The helicopter survey covered 17 km^2 with a 100 m line spacing (¨170 line km) within three days in June 2016.

The bedrock model delivered at the time was based on a very sparse borehole set and was constructed by using a linear statistical algorithm (LSI) developed by Gulbrandsen et al. (2015). Measured bedrock positions from boreholes were projected to the nearest flightline. Given the error incurred in projecting, these were not used directly to train LSI. Instead, manual training points were created and the boreholes were considered alongside geologic information and experience with similar airborne data. Even when accounting for these conditions, the linear method was not able to distinguish the various geological situations such as thick sand deposits in the central part of the area. Various manual adjustments were necessary before making the final bedrock model. These issues made this location a good candidate to test ANNs.

3.2 Results

The new ANN method was used to calculate a bedrock surface both for the drilling dataset from 2016 and from the present drilling dataset (Figure 5). We observe a large improvement in mismatch between the two methods (Figure 5 and Figure 4). This improvement can be attributed to two factors. First, as a non-linear method, the ANN can adapt to locally-varying conditions more easily than LSI. Second, accounting for location mismatch of the resistivity and borehole data by interpolation rather than projection improves the correlation between the two datasets.

Interestingly, although no boreholes were available in the deep eastern part of the area in 2016, the ANN method is better able to predict the large depths there, when comparing to the more "true" 2018 model (Figure 5). The geologic situation in the area is quite challenging, the moraine deposits from the southern hillside shades the weak transition to bedrock and makes it almost impossible for a human to identify the bedrock. However, the ANN method, noting this weak correlation between resistivity and bedrock depth, weighs this data less strongly and instead performs a simpler interpolation of the spatial coordinates (Figure 6). The ANN method outperforms the human interpreter in all cases.

4 DISCUSSION AND CONCLUSIONS

The most significant added value of helicopter geo-scanning to an infrastructure project is provided when the survey is carried out in an early project phase. With only a very small number of control boreholes the presented algorithm creates a representative bedrock topography model. The more boreholes are being acquired, the more accurate the model becomes, thus, a frequent update of the derived model is crucial to extract the full value of the survey investment. The ANN provides an objective and consistent analysis of the models outperforming human subjectivity. The human expert can thus instead invest valuable time in quality controlling the ANN results. At a later project stage, when high spatial resolution and high accuracy is needed along the final infrastructure location, the geophysical method's resolution sets limitations. The accuracy of the two bedrock modelling methods (borehole triangulation and AEM resistivity guided ANN) converge at around 20 boreholes per square kilometre (~200 m borehole spacing), which is just slightly more than the footprint of a single AEM sounding (~150 m, Figure 4).

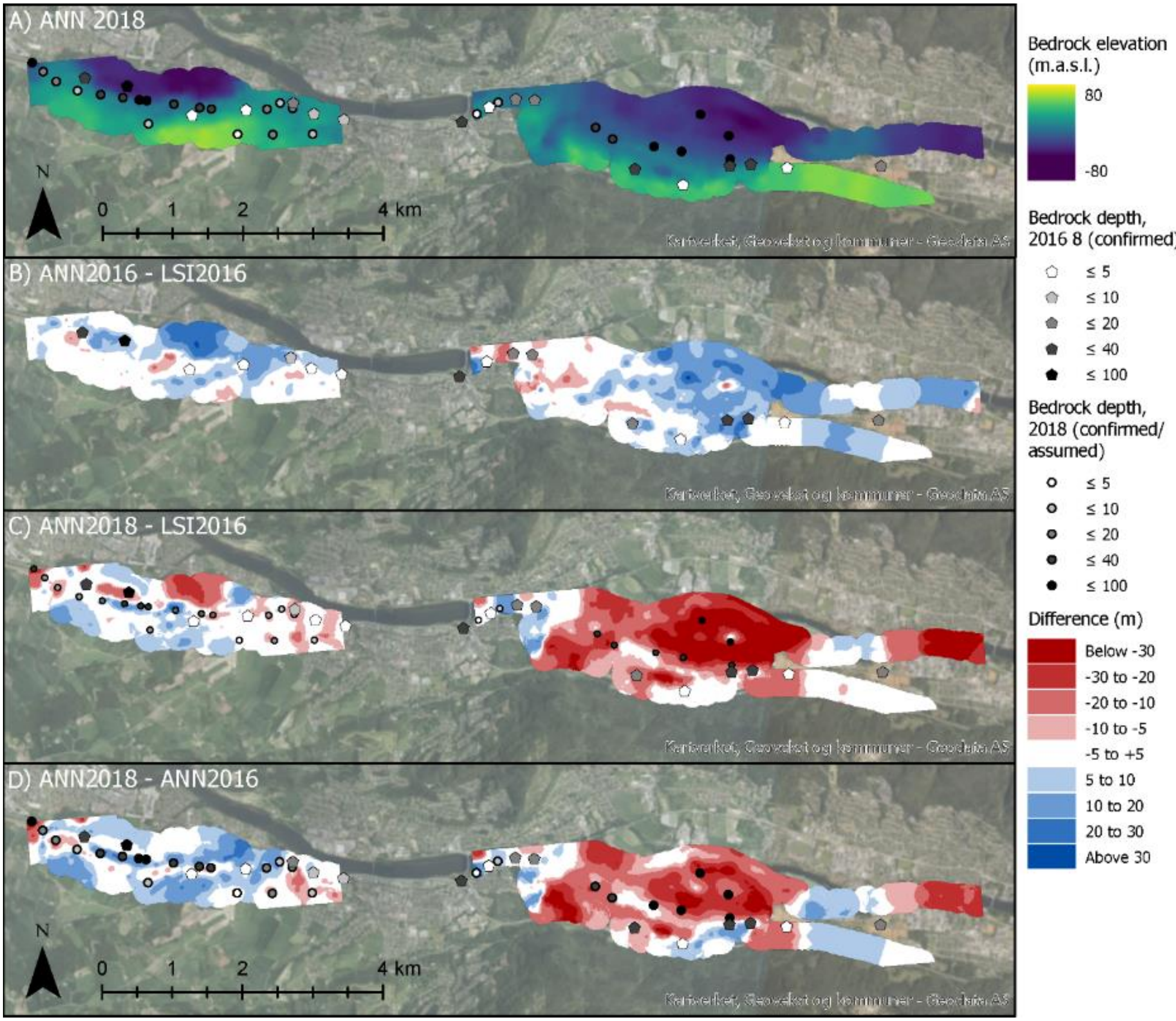

Figure 5: Bedrock elevation model produced from final set of boreholes as well as difference between models from various methods and borehole sets..

However, there is a high variability in performance of neural networks. In the Nes study, the average error of a bedrock model ranged from 28% to 62% when only 5 boreholes were used to train a neural network. Performance is thus highly dependent on the input training data. Early indications are that the neural network performs best where wide range of geological conditions, resistivity models, locations, and depths are represented in a sample. However, further testing is ongoing to understand how to best design a borehole investigation plan based on early AEM models. Further developments aim at ANN based geotechnical interpretation linking the 3D resistivity models to geotechnical soundings and samples.

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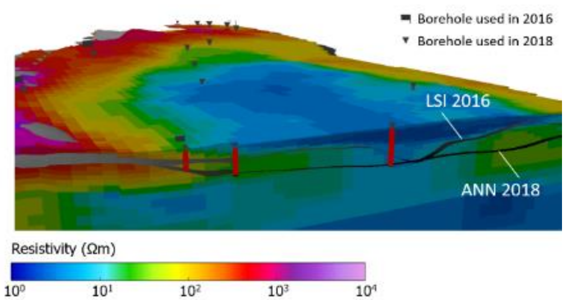

Figure 6: 3D view of helicopter scanning resistivity model, three geotechnical boreholes and the final as well as preliminary bedrock interface.

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