AI IN GEOTECHNICAL ENGINEERING – A GEOPHYSICAL POINT OF VIEW

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Summary in Swedish (see **SUMMARY**)

SUMMARY

Many years ago, we one day asked why "*he*" is such a brilliant geotechnical engineer. The accepted explanation was that *he* had seen it all, *he* had encountered so many different challenges during his career, that *he* intuitively had a solution to the most challenging problems. *He* could see the complex patterns that were hidden to some junior engineers.

Using machine learning in geotechnical engineering may be a key enabler to unlock access to comparable knowledge and experience. ML and AI provide us tools to see the complex patterns between multitudes of data, which are difficult or close to impossible to see for our naked eye. Especially when it comes to truly combining data across technical disciplines, ML can provide powerful tools to extract multiparameter correlations and to provide clarity about key parameters.

Experts have been developing such workflows, that for example enable combining geophysical and geotechnical data to models that focus on key parameters such as geological interfaces and / or mechanical properties. Here, I provide a few examples to illustrate such use cases.

1 INTRODUCTION

In most cases where geophysical methods are applied, the geophysical properties of the ground are not the desired product. They only give the basis to interpret likely models to answer the engineering question at hand. The electrical resistivity of layer X means little to an engineer, geologist, or groundwater resource manager – so, how can we move on from this fundamental limitation? Geotechnical soundings and samples also provide commonly heterogeneous spot information that is challenging to relate to a consistent ground model.

Uncountable numbers of consulting hours have been spent and continue to be spent trying to find "geology" in the geophysical signatures of our earth or to interpret complex geotechnical data. However, increasingly widespread and easy access to machine learning gives us geoscientists a game-changing new way of solving this challenge. We have been seeing an increased use of such tools in all geoscience sectors and we may be at a turning point when it comes to the interpretation of geophysical & geotechnical data and models.

When we have sufficient training data to directly relate geophysical signatures to the actual model parameter of interest through a few direct samples and can quantify its uncertainty, we may consider the geological model the result of the geophysical measurement. The geophysical model is only a proxy, and aids in the quality assurance of the geological model. Can we be confident enough to produce volumes of probabilistic hard vs weak rock or mineralized vs waste rock instead of iso-volumes with high and low resistivity? Or an interface along with quantified uncertainty rather than a gradient of velocities?

I present a few case studies to illustrate these points and hope to start a constructive discussion whether we dare to "unleash" the power of AI to geophysical models and geotechnical data to produce & deliver geotechnical, geological, or hydrogeological models with quantifiable uncertainty.

2 CASE STUDIES

Three cases are briefly described, more details on the case studies are given in the provided references. Topics / targets include 3D quick clay occurrence delineation, bedrock depth assessment and mechanical properties along a railway alignment.

2.1 Quick clay

When it comes to data driven delineation of quick clay deposits, ML can be utilized both to automatically interpret geotechnical sounding and to classify soil volumes as probably quick, based on their geophysical signature and trained by geotechnical classes. This workflow is elaborated in detail by Christensen et al. (2021), consisting of two key steps: First geotechnical soundings (rotary pressure soundings in this case) are classified into probably quick or not quick. This way, enough training data is created for the second step; Classifying each voxel of the geophysical model into probably quick or not quick. This probability model can finally be expressed as iso-volumes with a certain probability threshold, e.g. all material with more than 80% probability to be quick clay.

The provided example (Figure 1) stems from a railway project in Norway, crossing various deep paleochannels filled with marine clays and fluvial sediments. The quick clay occurrence under and close to the planned tracks is a critical factor for design work and safe construction as well as long term management of regional stability.

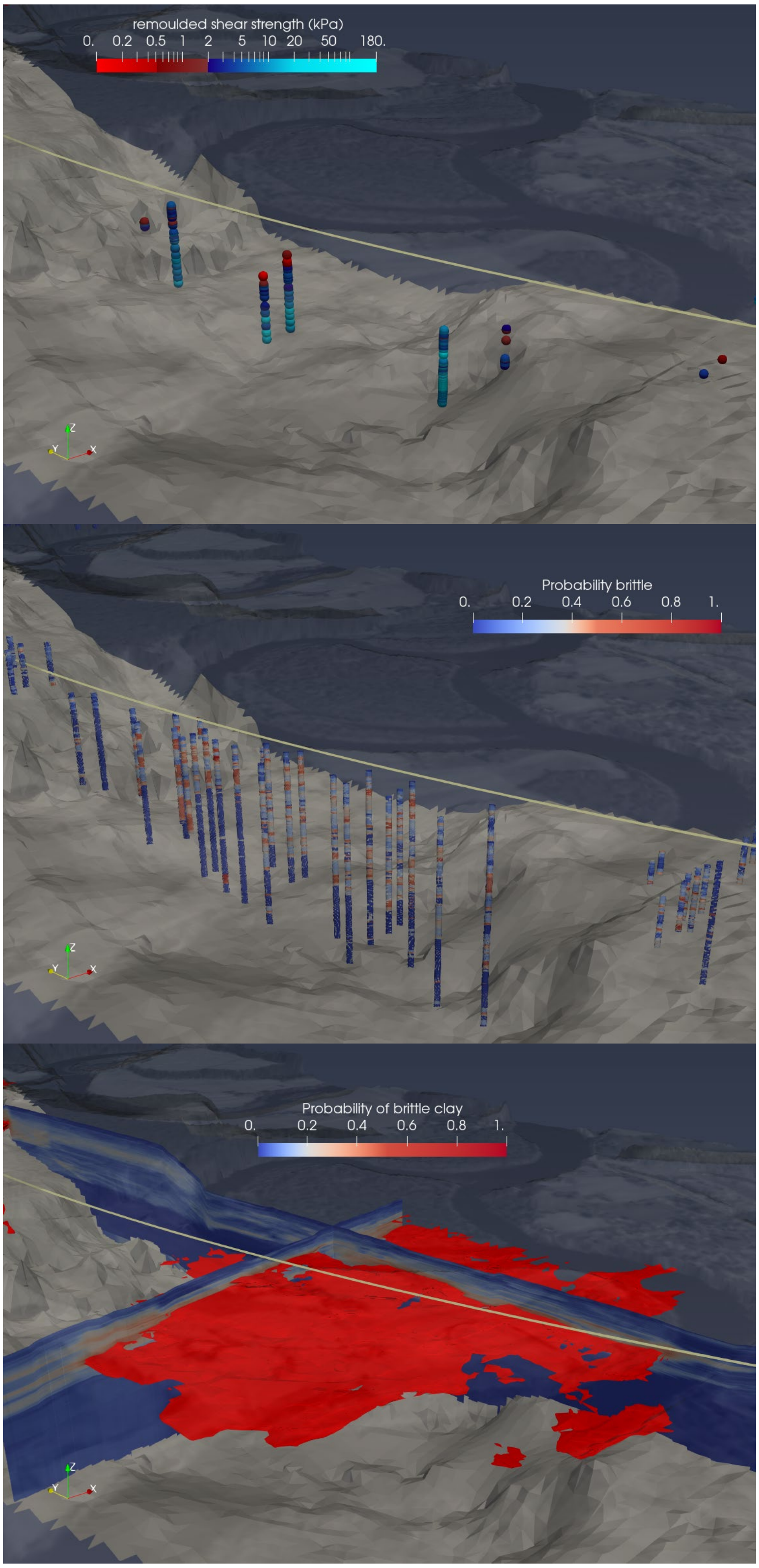

Figure 1: Quick clay deposit throughout a paleochannel filled with marine clay: Top - geotechnical samples, Middle - classified geotechnical soundings, Bottom - delineated volume of more than 80% probable quick clay.

2.2 Top of rock

Most types of sediments have a significant contrast to most types of rock; however, these contrasts are never unique and vary from site to site as well as actual sediment thickness. While simple resistivity thresholds or gradients can be used for small scale projects, real-world geological heterogeneity demands more complex interpretation methods.

Here I show one example along a railway corridor comparing a state-of-practice triangulated bedrock model based on geotechnical boreholes alone (Figure 2 top) vs an integrated model (Figure 2 bottom) that was built using the same boreholes to train an artificial neural network (Lysdahl, et al. 2022) to find the bedrock interface in a 3D resistivity model from processed and inverted helicopter-based time-domain EM data. Each point of the shown surface is accompanied by a calculated uncertainty in meters, allowing the planners to quantify the remaining risks in terms of volumes and costs.

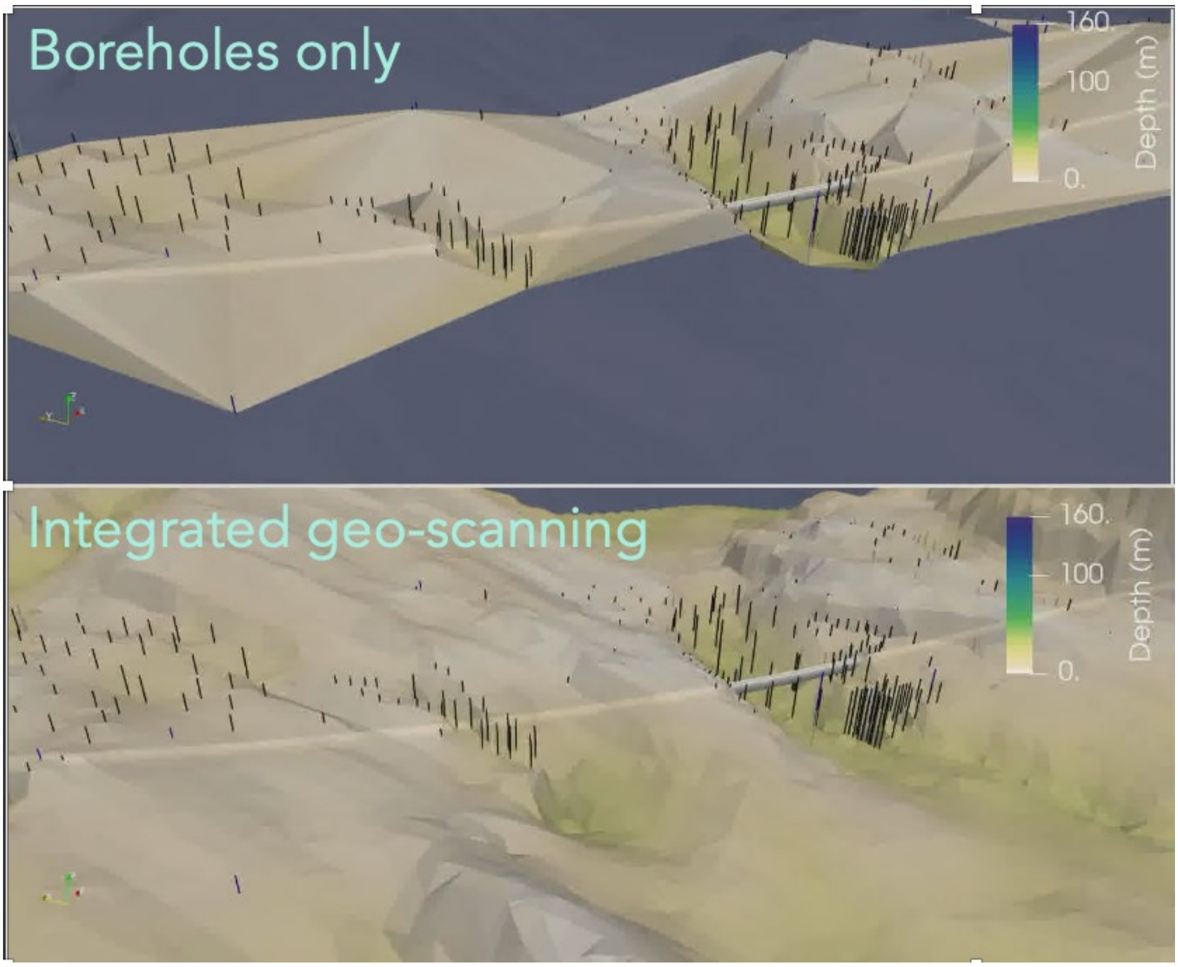

Figure 2: Bedrock topography 3D surface based on boreholes (top) as well as integrated with a wide swath of EM data (bottom).

As such models are purely data-driven, once they have been trained and tuned, they do not rely on expert judgment and can be updated fully automatically as additional drillings or other ground observations become available. Model accuracy increases with number of boreholes, however major features can be revealed with only very few, strategically placed drillings (Figure 3).

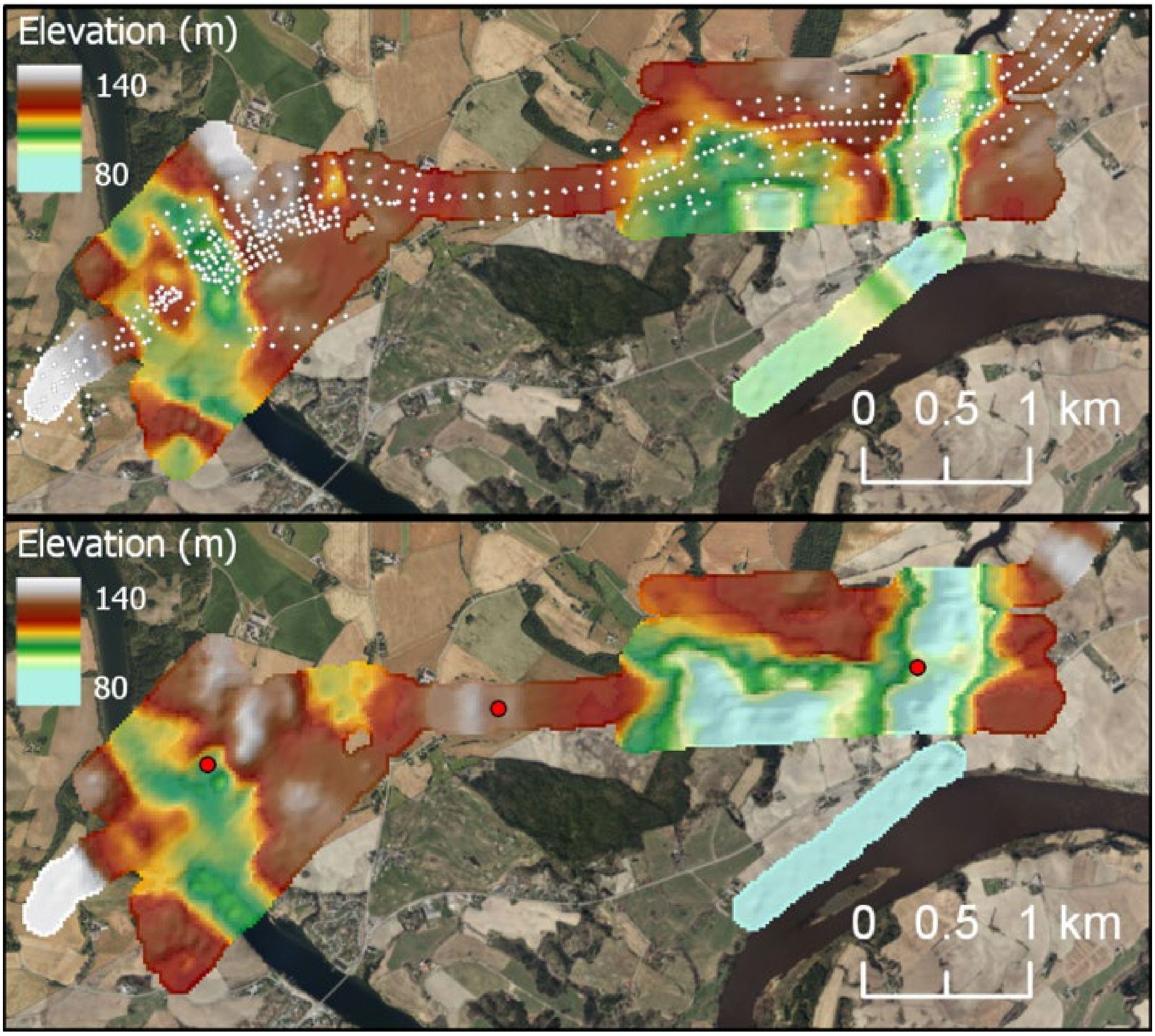

Figure 3: Bedrock topography map derived from geophysical model through ML, driven by 800 and 3 boreholes as training data for the ML.

2.3 Mechanical properties

While general geometries such as bedrock topography and granulometric material classifications (Clay / Silt / Sand) are very useful parameters in planning works, ultimately it is mechanical properties that govern design parameters and excavation costs. Extracting mechanical parameters from geophysical models is arguably the most challenging task, especially when dealing with electrical methods rather than seismic methods. In cases where resistivity and mechanical properties sufficiently correlate, ML based classification can open this Pandora's box and provide seamless models throughout planned groundwork corridors.

In the provided example, Standard Penetration Testing (SPT) counts are the initial basis to classify material from soft (less than 5 hammer blows) to hard or rock (more than 50 hammer blows). These classes have then been applied to the geophysical model, resulting in probabilities for each class at each model voxel. Visualizing the respective most probable class (Figure 4) is on way to inspect such mechanical strength models. Applying these to excavation volume calculations provides mass balance estimates for the different materials (Christensen, et al. 2024).

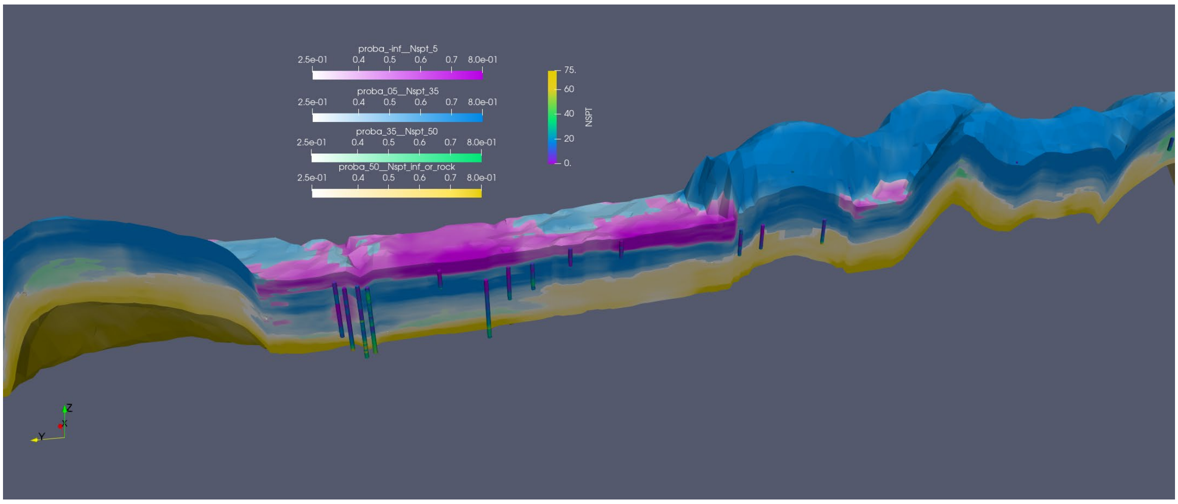

Figure 4: Cut through a sediment model along a railway corridor classified according to mechanical strength from soft (purple) to hard (yellow). Geotechnical soundings (NSPT) that were used to train the model are visible and color-coded accordingly.

3 CONCLUSIONS

The provided examples illustrate the potential of AI in geotechnical engineering, in particular when building geological / geotechnical models from complex cross-discipline data sources. A particular strength is that machine learning workflows typically include uncertainty estimates, enabling the quantification of the reliability of models. Care must be taken to respect fundamental limitations and not to fall for "black box" AI. The trustworthiness of results stands and falls with the fundamental physical relations between data that gets integrated.

4 REFERENCES

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