

Rock and groundwater surface modelling using artificial intelligence

Modellering av berg- och grundvattenniåver med artificiell intelligens



Chunling Shan

Abbas Abbaszadeh Shahri

Stefan Larsson



Scientific achievements

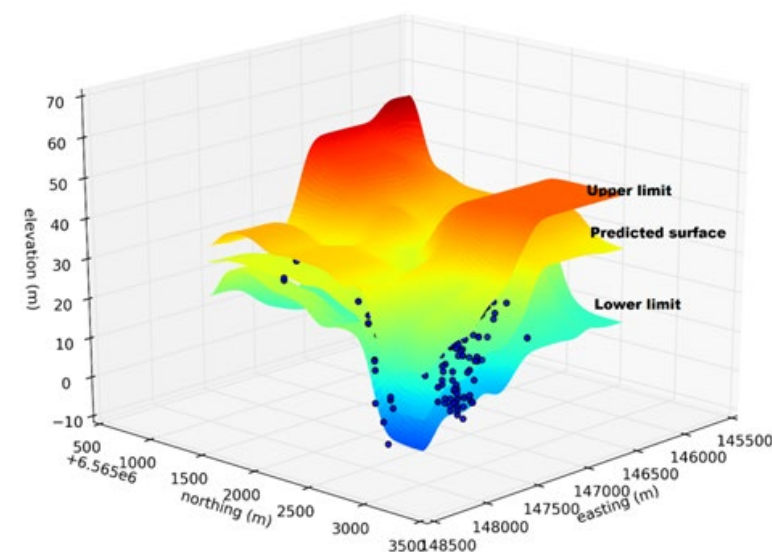
1. Spatial distribution modelling of subsurface bedrock using a developed automated intelligence deep learning procedure: A case study in Sweden (2021). *Journal of Rock Mechanics and Geotechnical Engineering*, 13(6):1300-1310, <https://doi.org/10.1016/j.jrmge.2021.07.006>.
2. A new approach to uncertainty analysis using automated predictive deep learning in groundwater (2022). *Accepted* by *Natural Resources Research*.
3. Artificial intelligence-based models to predict the spatial bedrock levels for geoengineering application (2020). Proc. 3RD Conference of the Arabian Journal of Geosciences (CAJG), *Springer Nature*.
4. Uncertainty analysis of an optimum predictive neural network model in subsurface bedrock level modelling (2021). In proc. 3rd International Symposium on Machine Learning and Big Data in Geoscience. *Machine Learning & Risk Assessment in Geoengineering, MLRA 2021*, 48-52, Wroclaw, Poland.
5. Visualisering av bergtopografi med artificiell intelligens (2022). *Bygg & Teknik*, 114(1):44-46.
6. 3D modeling and uncertainty analysis of DTB using hybrid automated deep learning. *First draft*.

Background

- Understanding the subsurface of our earth is important for many different applications within the geosciences. In Sweden the soil-rock soundings are usually carried out to get the bedrock level. It is an accurate method to determine the exact level of the bedrock, but the disadvantage is the high cost of drilling, besides it is a time-consuming process and only gives the bedrock level at sparse points. To estimate the depth of the bedrock at unsampled locations, interpolation and extrapolation is often needed.
- Over the past several decades, the use of groundwater modelling has increased for better evaluating the complexities inherent in hydrogeological calculations. Information required for groundwater modelling is for example elevation of soil and bedrock layers and groundwater level. This data is usually collected in a limited number of sample points, both due to practical and economic reasons. In order to approximate values in unknown points, known values in measured sample points can be interpolated over the study area.
- In recent years, artificial intelligence (AI) techniques have shown remarkable computational and learning capabilities in addressing geotechnical problems. As depth to bedrock (DTB) and groundwater table (GWT) modelling deals with various uncertainties, the subcategories of AI such as machine learning, neural networks, evolutionary computational and deep learning techniques are appropriate alternatives to overcome the limitation and simplifications.

Aims

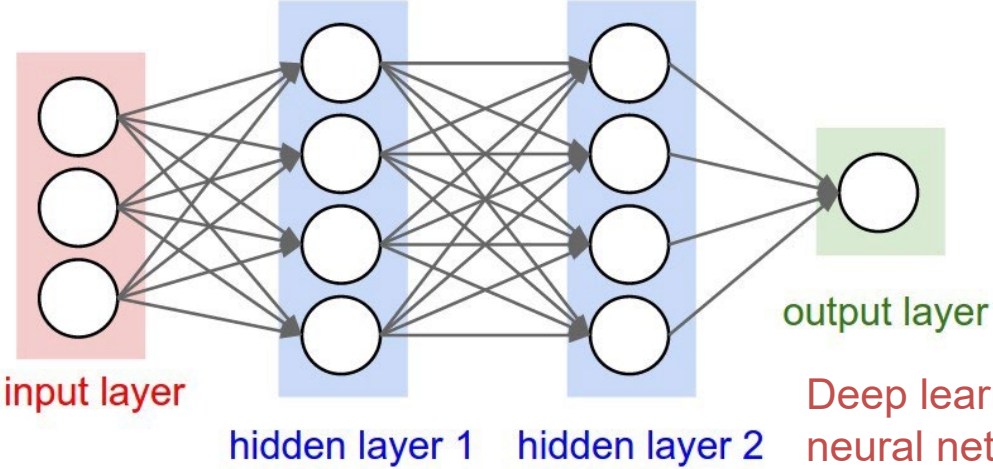
- Automatically analyze and model different types of geo-data including the geotechnical sounding, geophysical and groundwater level data to study the spatial distribution of bedrock and groundwater surfaces with artificial intelligence
- Estimate the uncertainties of estimated groundwater and bedrock levels
- Compare the AI modelling method with traditional interpolation method such as geostatistical method Ordinary Kriging



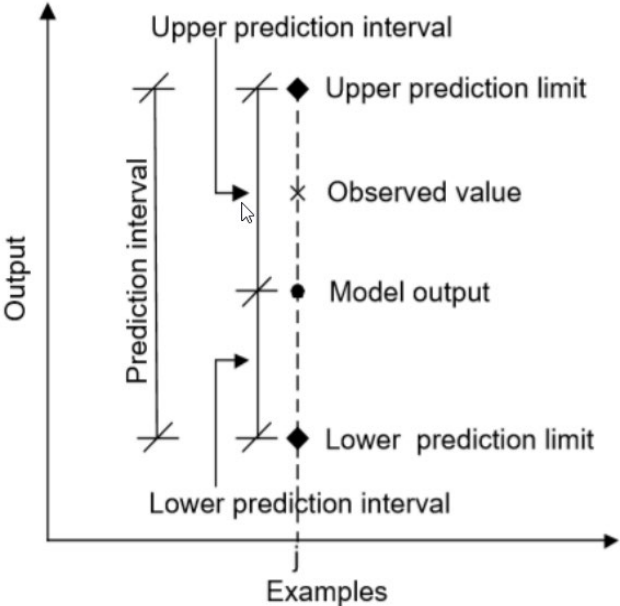
Methodology

Deep learning is part of the broader family of machine learning methods based on artificial neural networks. It attempts to mimic the human brain and enables systems to cluster data and make predictions with high accuracy. In this study, the prediction of deep learning is used through all the studies to predict bedrock levels and groundwater levels at unsampled points. The input layers contain 3 variables: X (northing), Y (Easting), Z (Ground surface level). We developed an automated process with ability in checking numerous structures subjected to different number of neurons, model arrangements and internal hyper parameters.

Since we lack the sureness about the predicted value (interpolated levels), there is always uncertainty imbedded in the predictions. These uncertainties can be caused by lack of bedrock information and knowledge, errors in the measured data and the mathematical modelling process. Estimating the uncertainties of predicted bedrock levels is very important for infrastructure building projects nowadays due to the impacts of uncertain bedrock levels.



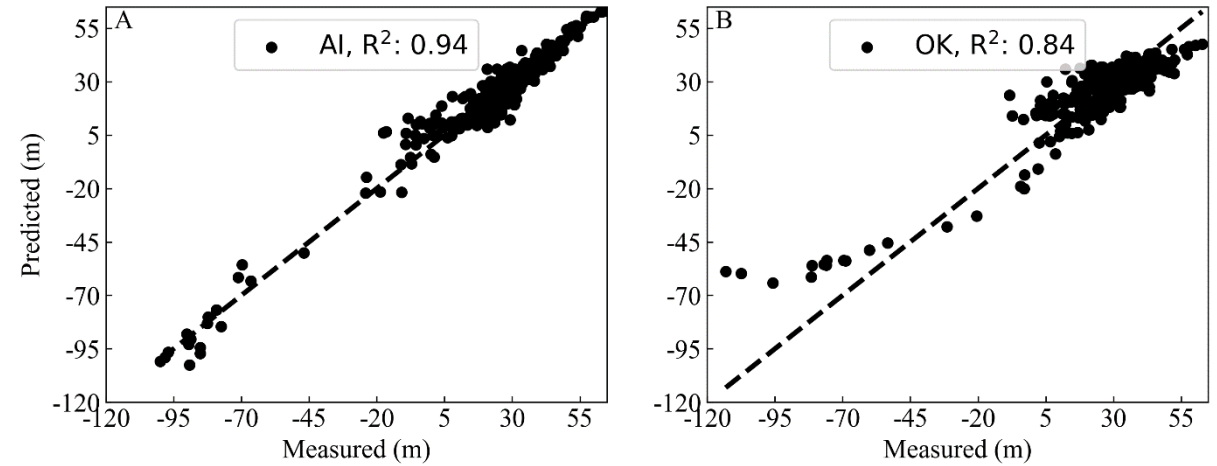
input layer hidden layer 1 hidden layer 2 output layer
Deep learning neural network With two hidden layers



Definition of prediction interval for uncertainty quantification

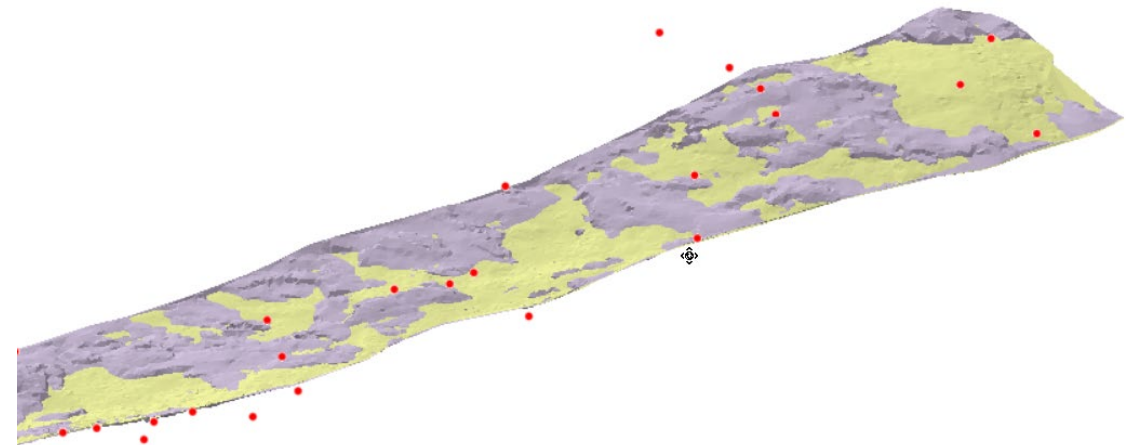
Results

The AI model was applied on the collected geotechnical data to predict bedrock levels at unsampled locations. Figure to right shows the fitting between the measured and predicted bedrock levels of the validation dataset. It can be observed that Ordinary Kriging (OK) has significant lower fitting degree than the AI modelling.



The fitting between measured and predicted values and comparison of the predictability of AI (A) and OK (B)

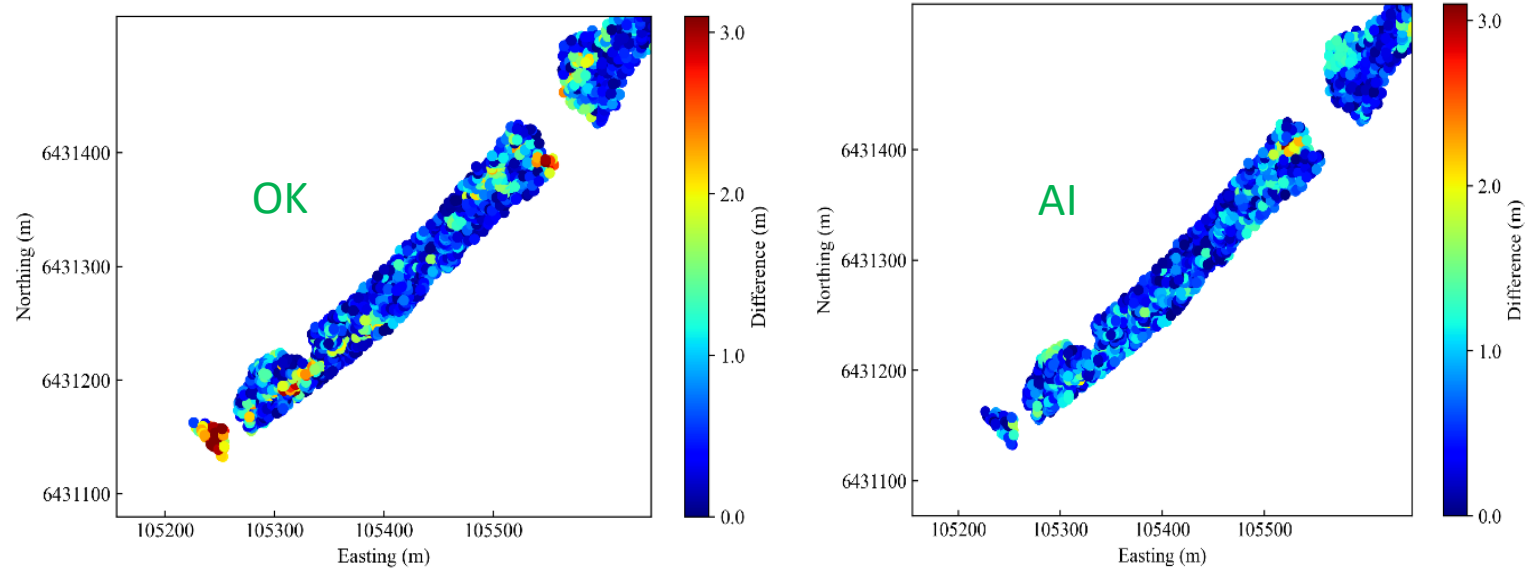
Since the dataset has the true bedrock surface scanned, it possible to compare the predicted and true bedrock levels at exactly the same locations and thus quantify the accuracies of the optimum model with the scanned true surface. The red points show the input data used for deep learning to predict the surface.



A 3D view of scanned true bedrock surface (grey) and the predicted bedrock surface (yellow) from the measured data (red dots)

Results

Figure to the right shows the difference (true – predicted values) comparison of AI and OK methods. It is observed that OK has higher differences at more places than AI.



The difference plot between the predicted/estimated bedrock levels and the true bedrock levels

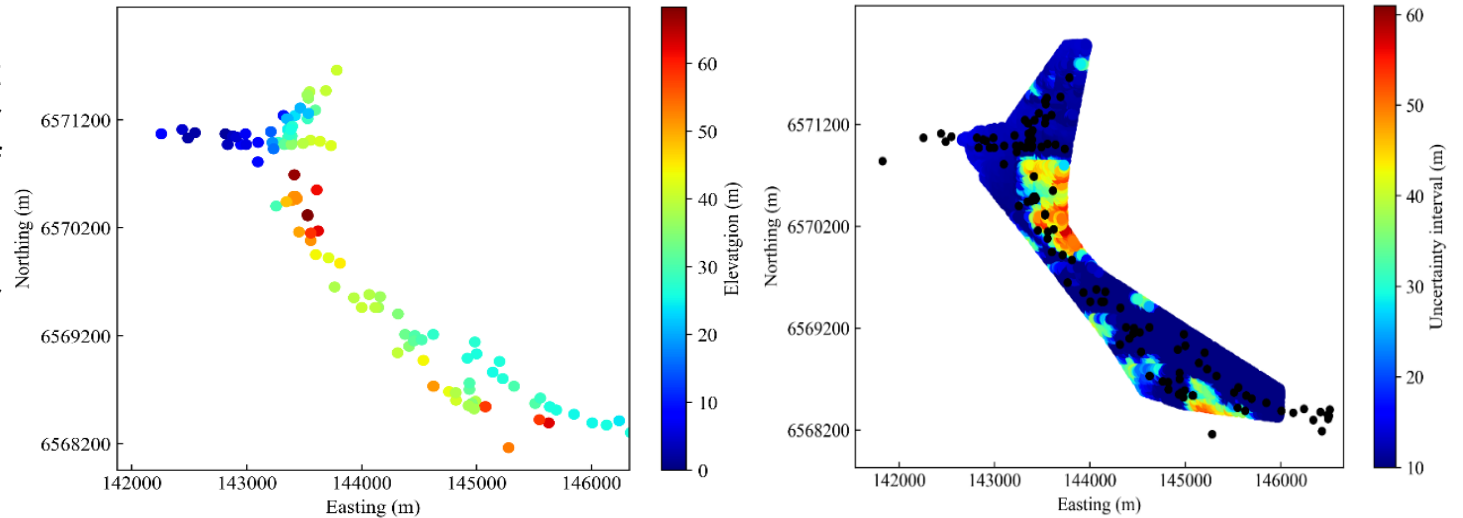
Summary of differences between the predicted and true bedrock levels

Method	Total absolute difference (m)	Average difference/point (m)	Improvement from OK (%)
Ordinary Kriging	31470	0.69	0%
AI	27787	0.61	12%

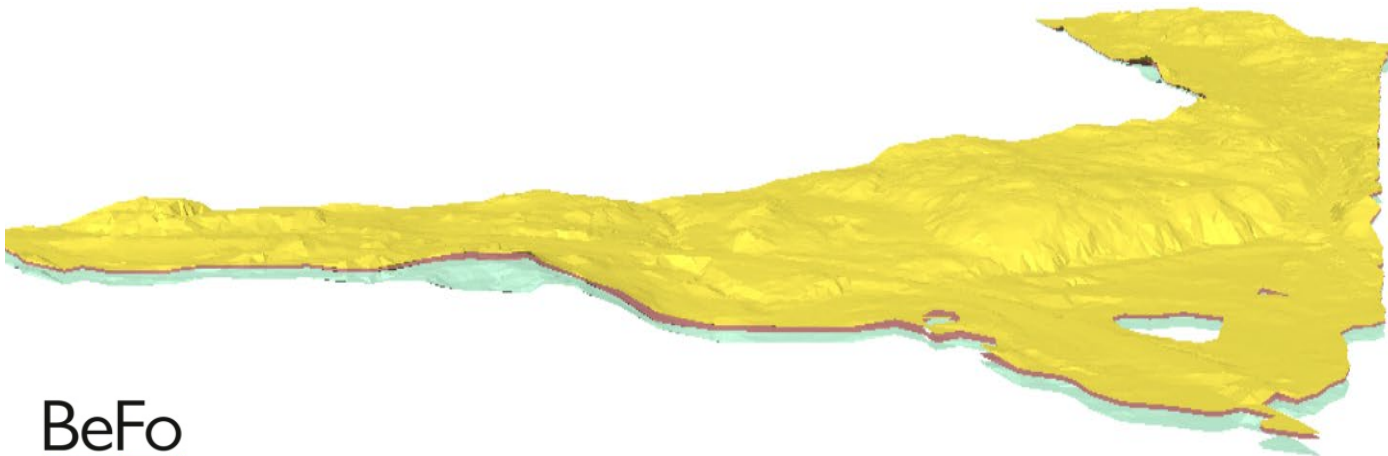
Table to the left shows the summary of the differences between predicted and scanned true values for 45667 points. The Total Absolute Difference is the sum of the absolute difference of each point and the total absolute difference of AI is smaller than OK. The Average Difference/point is the total absolute difference divided by total number of points (45667). The AI has lower value than OK. The Improvement from OK column shows how much better the predicted bedrock surfaces of AI than OK.

Results

Figure to the right shows the groundwater table (GWT) in color and the 95% uncertainty intervals estimated for the studied area. It provides the distribution of different uncertainty levels and gives indication of the reason for high uncertainties, e.g., if they are coming from the lack of observed data or from the sudden big changes in the groundwater levels. The location of the boreholes and the levels of groundwater can be observed from the color plot. As we see that at a few areas the uncertainties are ~ 50 meters. This is due to the lack of data points and sudden GWT changes (up to 40 meters level difference between adjacent boreholes). This map can help in planning for future data collection and borehole drilling locations to reduce the high uncertainties in estimating the groundwater surface.



Color map of the measured GWT data (left) and estimated uncertainty intervals using the measured GWT data (black dots) for a small part of the project area (right).



A 3D view of the estimated groundwater surface (brown, middle) for the study area together with the upper (yellow) and lower (light blue) boundaries.

Summary and Conclusions

- Deep learning was applied to model, analyse and produce the 3D spatial distribution of the depth to bedrock (DTB) and groundwater table (GWT) surfaces in Stockholm, Sweden and at the same time evaluate the uncertainties.
- The comparison between AI deep learning and OK on DTB modelling shows that deep learning can generate a surface that is closer to the true surface. The uncertainty quantification by deep learning also shows superior performance, better estimation of uncertainties and covers more true values than the quantified uncertainty from OK.
- The achieved outcomes and interpreted results indicate that the developed AI models are feasible, cost-effective, economic and sufficiently accurate to be applied for geospatial DTB and GWT surface predictions. The automated deep learning modelling approach can provide more reliable 3D models that can help geoengineers gain better insights into crucial structural elements in the design stages.
- The result of this project was also implemented/integrated with a GeoBIM system to create an automated process for 3D bedrock surface modelling. The users of GeoBIM perform their own 3D bedrock surface modelling. This can assist all geotechnicians, rock engineers and engineering geologists who use bedrock surface models for decision making and project planning.