Bedrock and groundwater modelling using artificial intelligence

2022-03-25

Chunling Shan

Budget and time

Tyréns		KTH	
Sven Tyréns Stiftelse 400 000 kr	Stiftelsen för Bergteknisk Forskning (BeFo) 2 000 000 kr	KTH 100 000 kr	Branschsamverkan i grunden (BIG) 1 850 000 kr

Time: 2020-01 to 2021-12

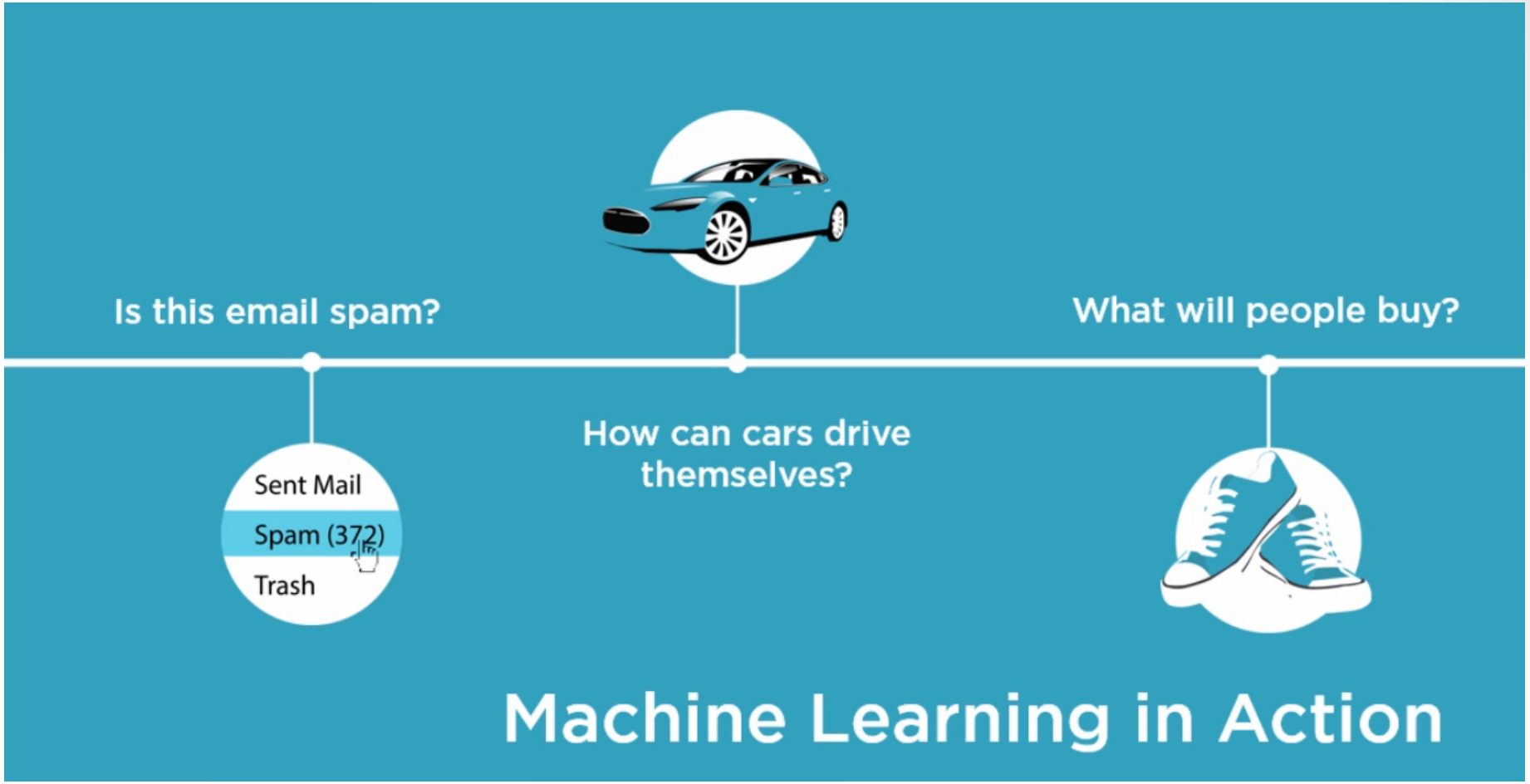
Scientific achievements

1. Spatial distribution modelling of subsurface bedrock using a developed automated intelligence deep learning procedure: A case study in Sweden (2021). *Published by 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). *Published* by In 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. *Published by Machine Learning & Risk Assessment in Geoengineering, MLRA 2021, 48-52, Wroclaw, Poland.*
5. Visualisering av bergtopografi med artificiell intelligens (2022). *Published by Bygg & Teknik.*
6. 3D modeling and uncertainty analysis of DTB using hybrid automated deep learning. *First draft.*

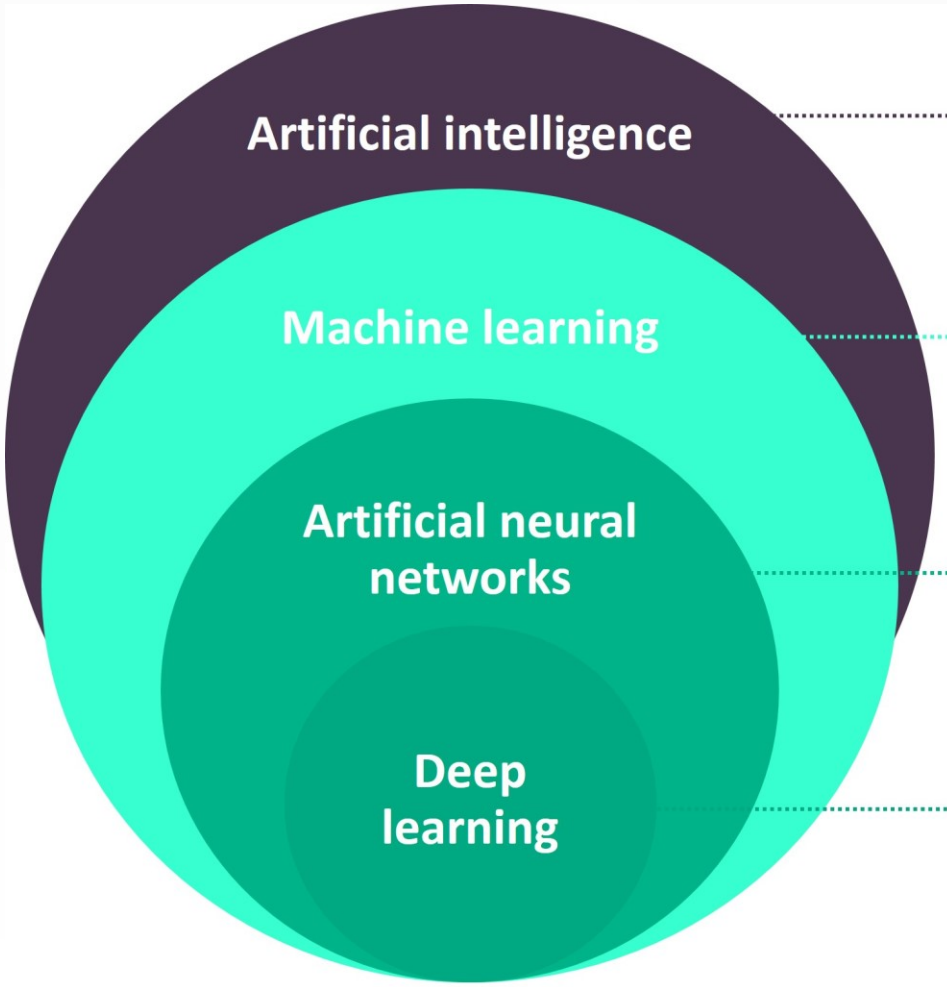
Agenda

1) Short introduction of Artificial Intelligence
2) Background of the project
3) Goal of the project
4) Datasets
5) Methodology
6) Results
   - Comparison of AI results with traditional geostatistical results for bedrock surface modelling
   - Groundwater surface modelling and uncertainty analysis
7) Implementation of results
8) Conclusions

Short introduction of AI



Short introduction of AI



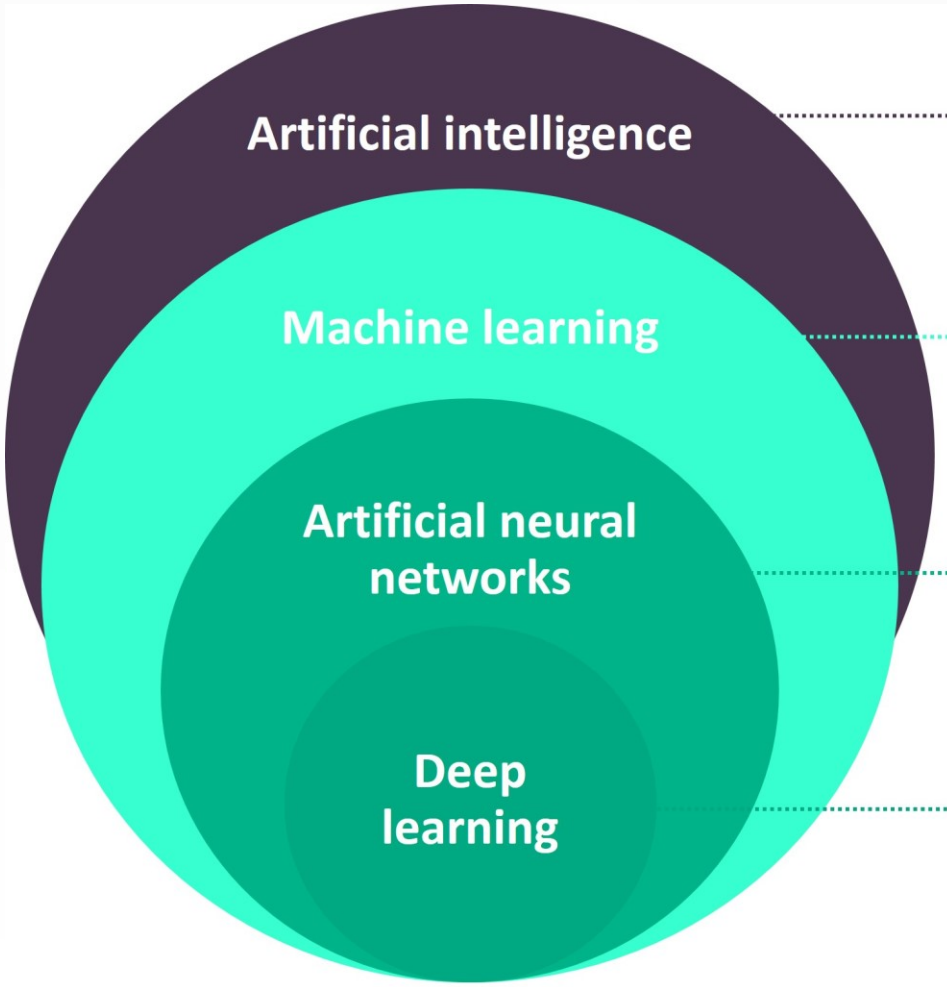
Artificial intelligence (AI)
Any techniques that enable machines to solve a task in a way like humans do

Machine learning (ML)
Algorithms that allow computers to learn from examples without being explicitly programmed

Artificial neural networks (ANN)
Brain-inspired machine learning models

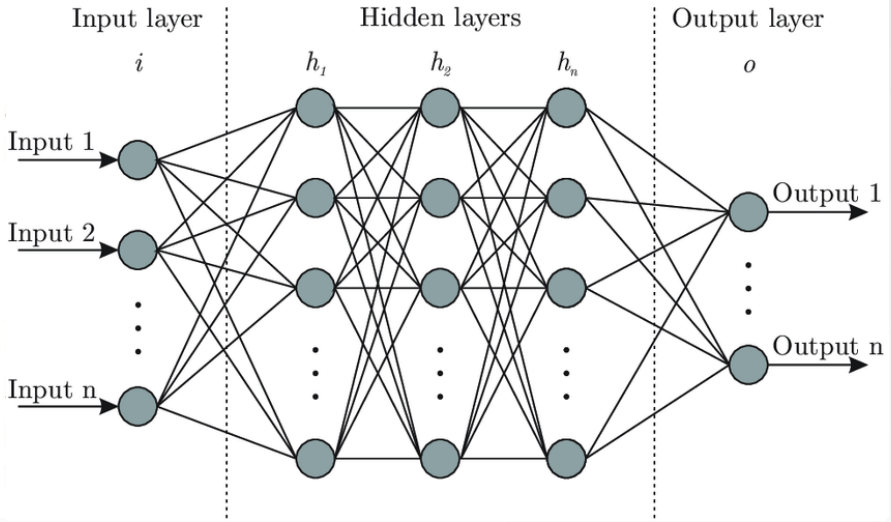
Deep learning (DL)
A subset of ML which uses deep artificial neural networks as models and automatically builds a hierarchy of data representations

Short introduction of AI

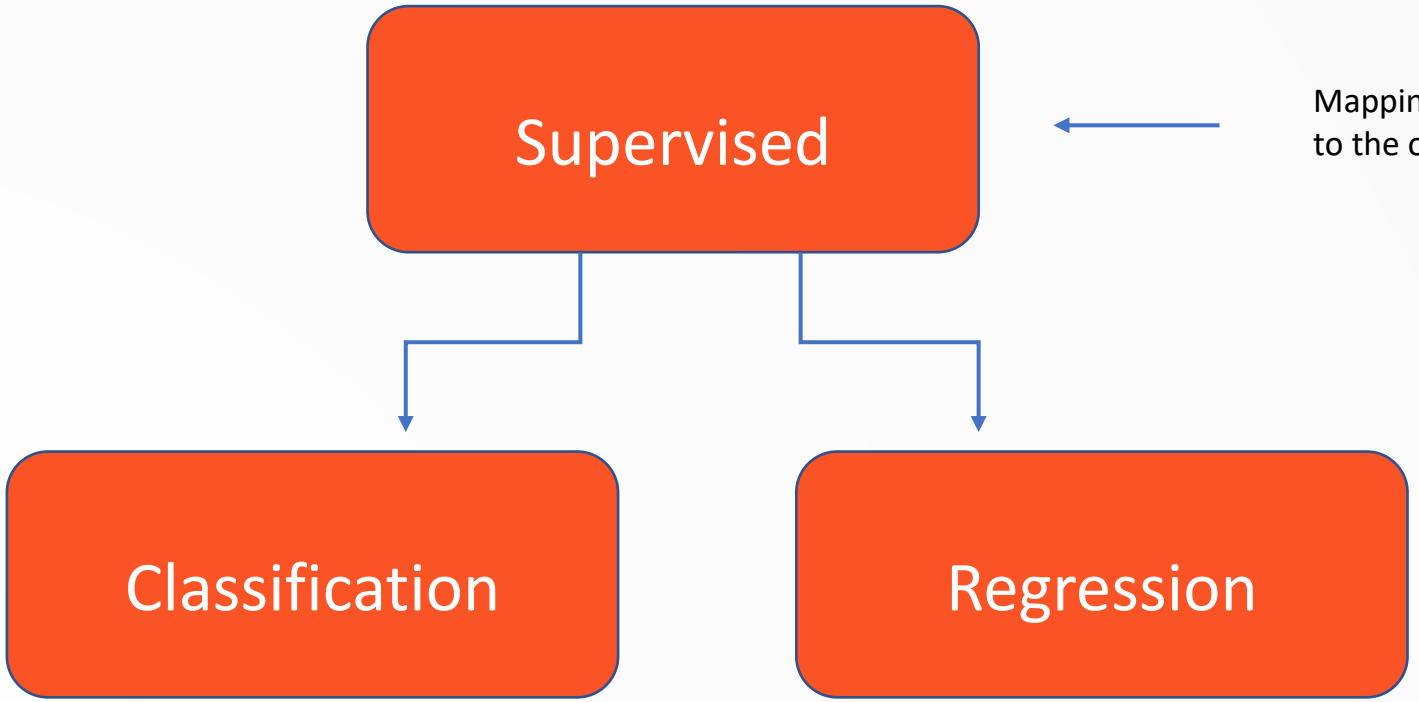


Artificial intelligence (AI)
Any techniques that enable machines to solve a task in a way like humans do

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Algorithms that allow computers to learn from examples without being explicitly programmed



Short introduction of AI



Mapping between the input variable X to the output Y, Y = f(X).

A classification problem is when the output variable is a category, such as “red” or “blue” or “disease” and “no disease”.

A regression problem is when the output variable is a real value, such as stock price.

Background of the project

- Need to understand the bedrock occurrence but have limited bedrock level information



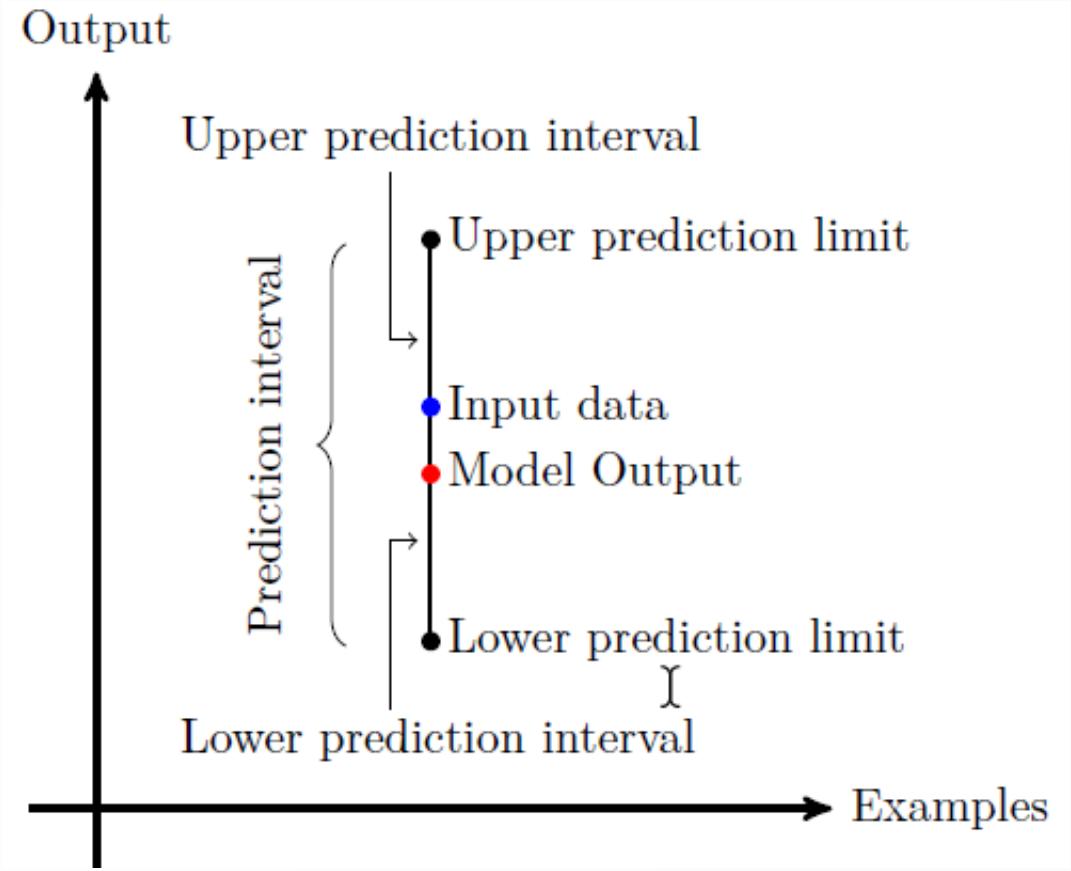
Background of the project

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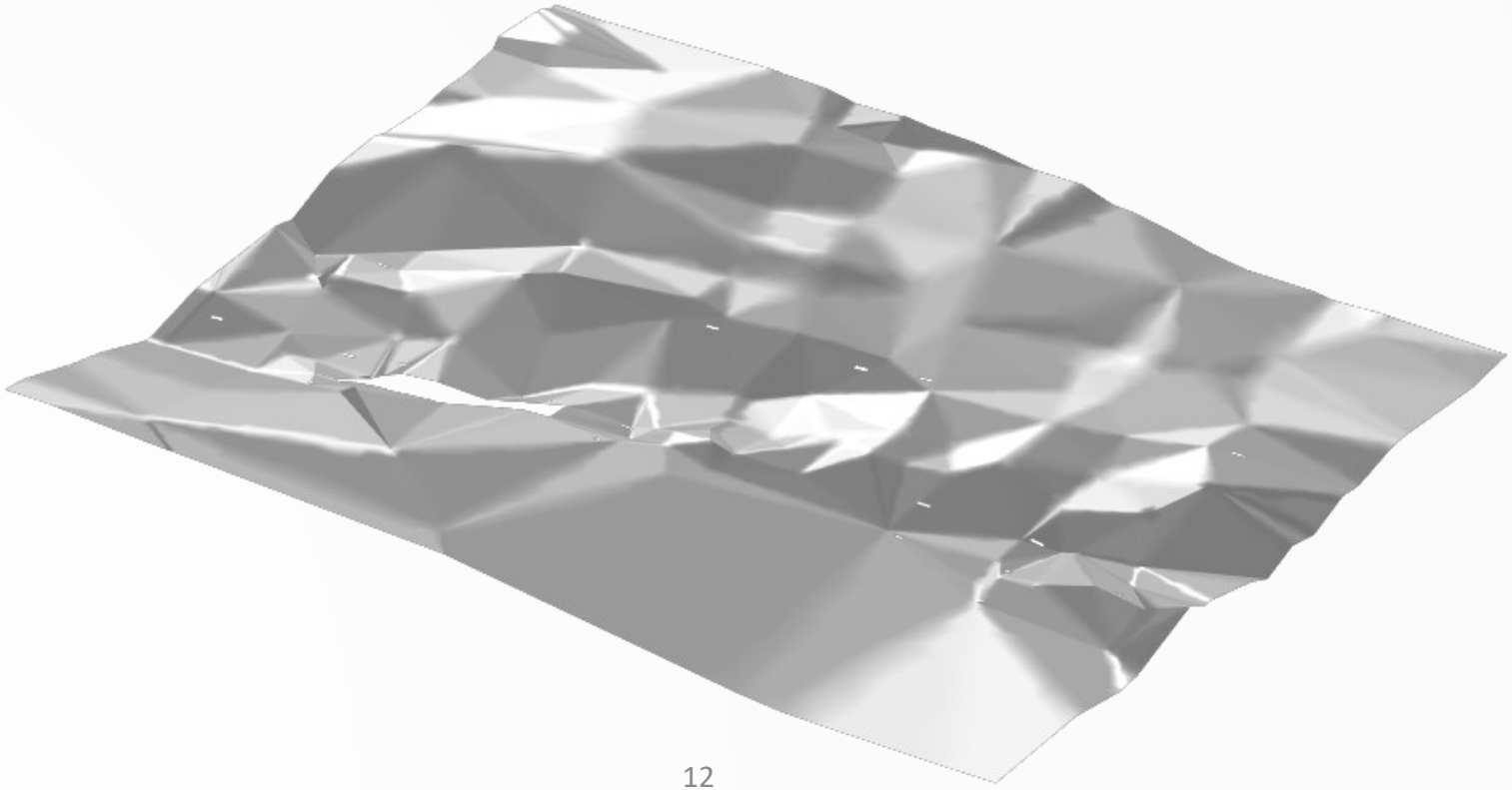
Background of the project

- Need interpolation and extrapolation to build bedrock surface
- The uncertainty of estimated bedrock levels is important



Background of the project

- Current bedrock mapping techniques:
  - Surface triangulation (projects like Ostlänken, Mälarbanan)

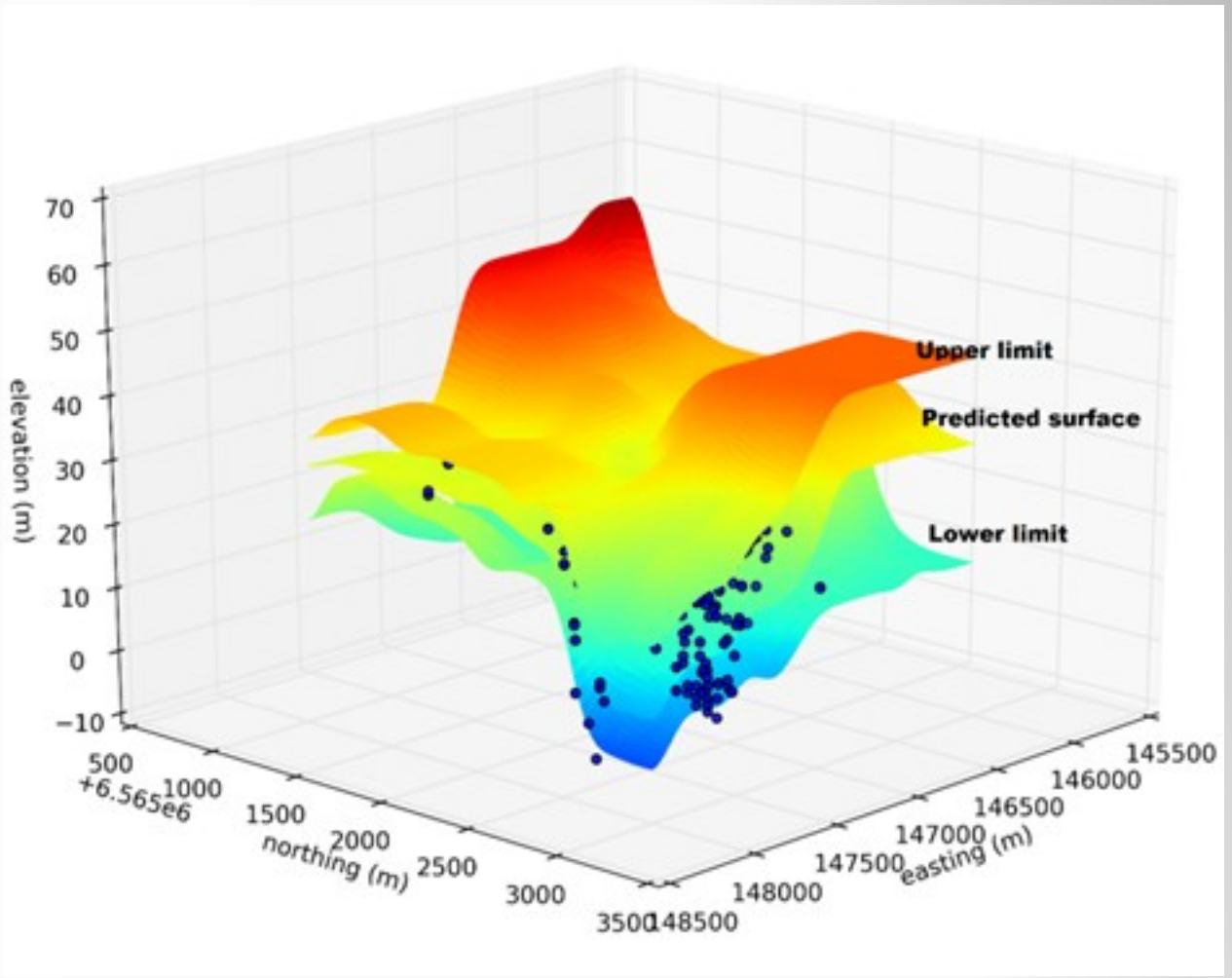


Background of the project

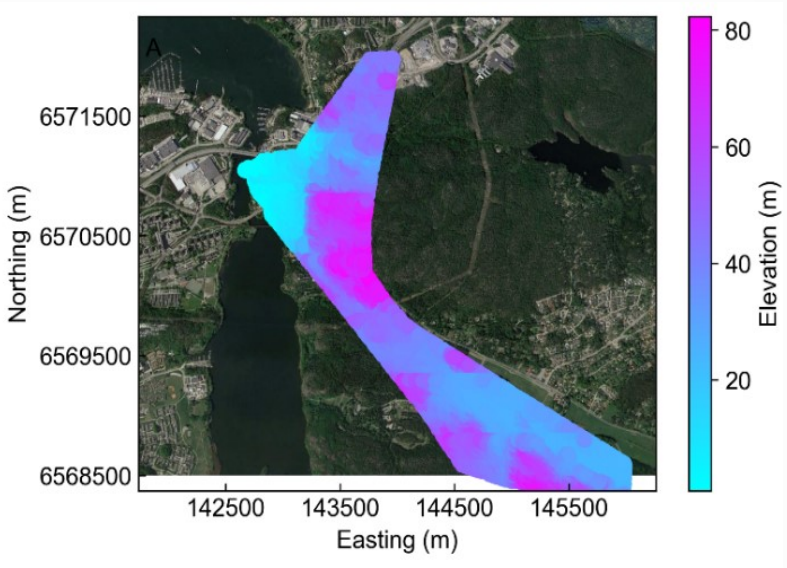
- Current bedrock mapping techniques:
  - Surface triangulation (projects like Ostlänken, Mälarbanan)
  - Geostatistical methods such as Kriging, Inverse distance weighting … …
  - Artificial intelligence (deep learning)

Goal of the project

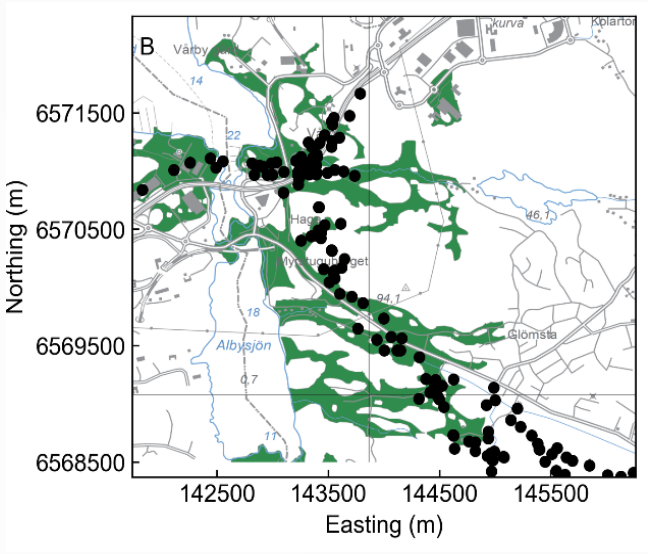
- Build bedrock surfaces and groundwater surfaces with higher accuracies than the methods used today
- Estimate uncertainties of the predicted bedrock levels and groundwater levels



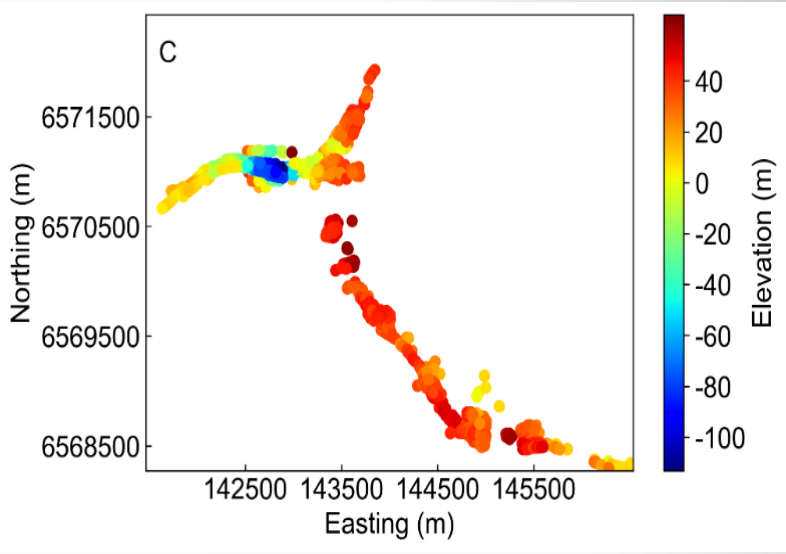
Dataset - Tvärförbindelsen



Digital elevation map

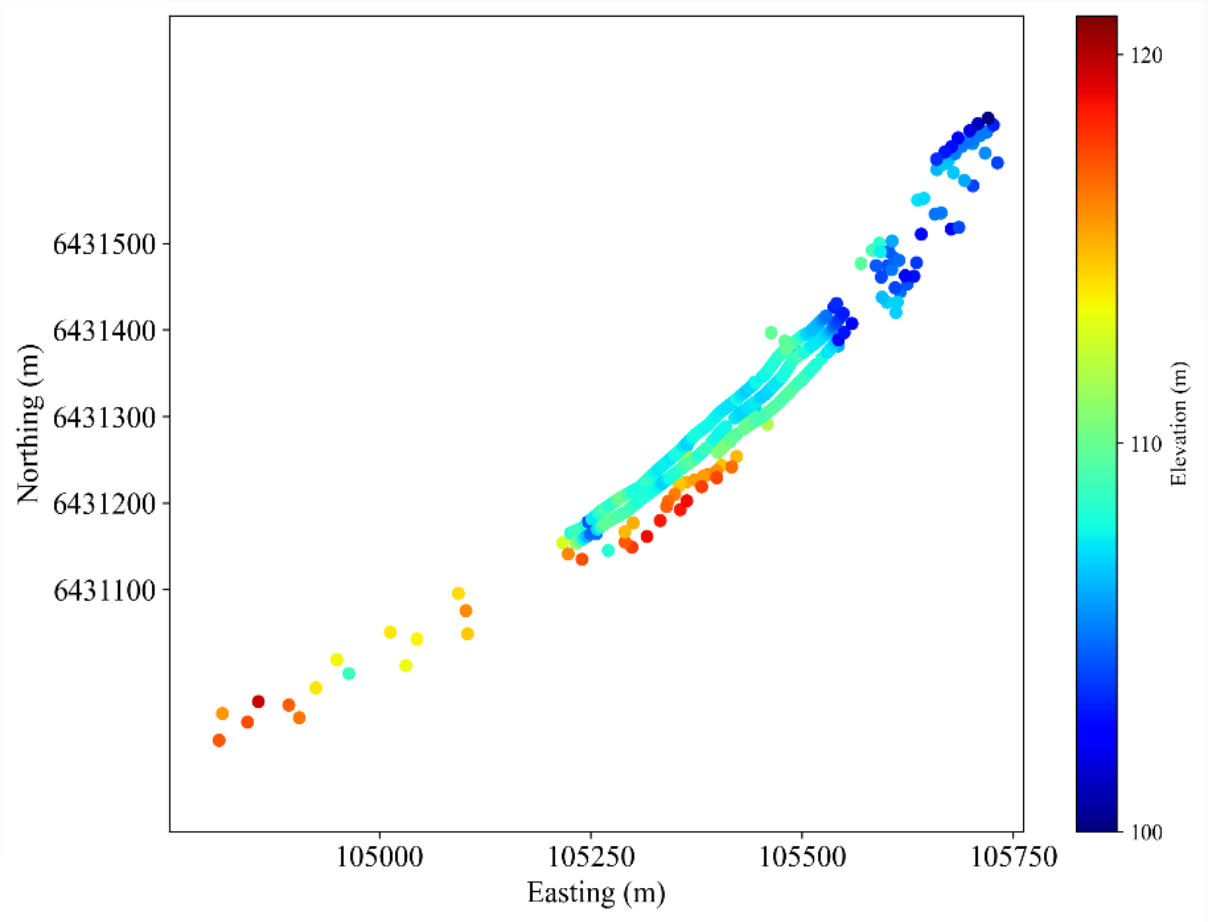


Monitored GWT data



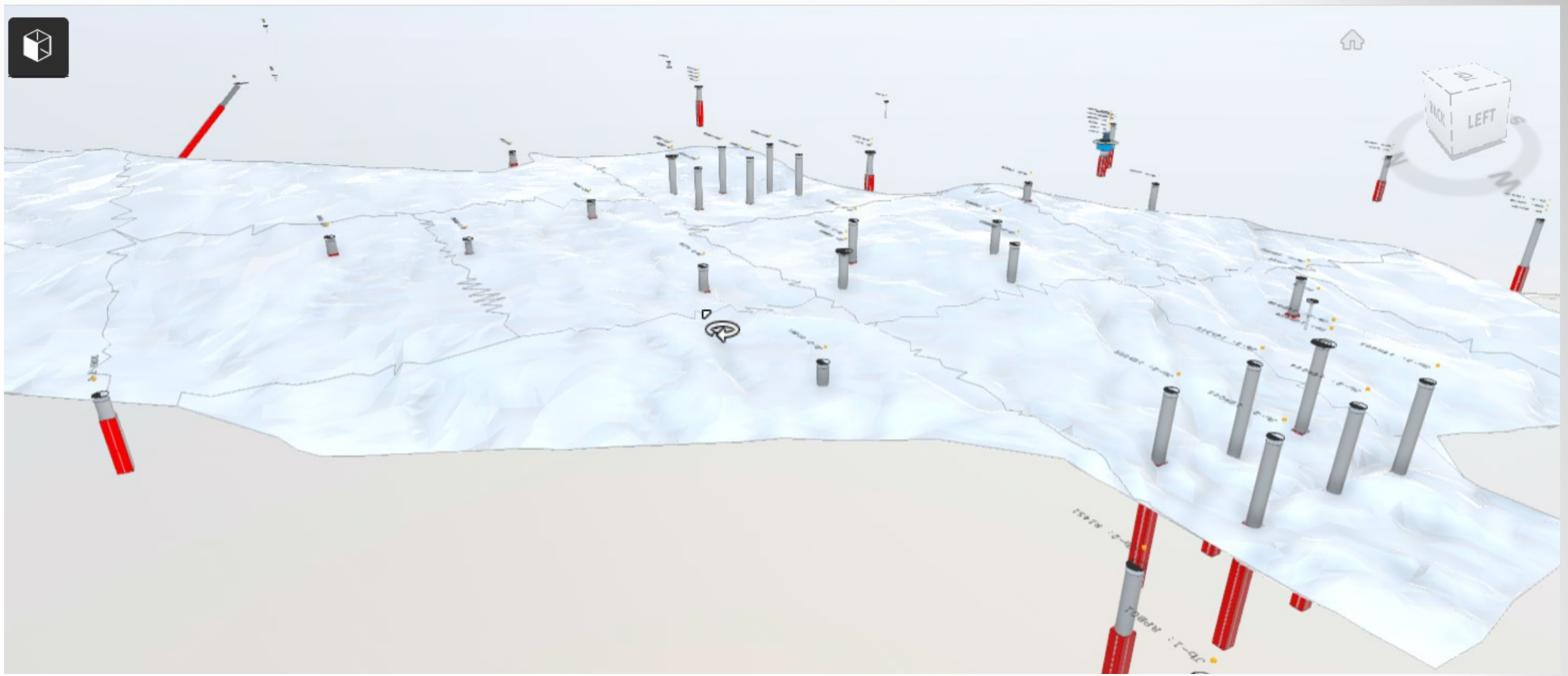
Geotechnical boreholes

Dataset – E20 Bälinge-Vårgårda



Spatial distribution of soil-rock sounding and geophysical profiles

Dataset – E20 Bälinge-Vårgårda



Scanned bedrock surface after excavation of overlaid soil

Data

1	Id	X	Y	MarkYta	BergNivå	Typ	Stopp	Jord	Berg
2	17T1058	6571021,564	142831,156	2,307	-98,793	b3 HfA Pr	95	101,1	4,05
3	18T1116	6568370,379	146683,65	29,292	20,772	b2 Tolk	95	8,52	2,63
4	18T1189	6571109,576	142440,707	4,674	-18,726	b3 HfA Pr	95	23,4	6
5	18T789	6569877,047	143725,733	43,786	32,736	b3 Vim Pr	95	11,05	3,95
6	18T793	6569862,675	143778,927	44,276	31,956	b3 Tolk	95	12,32	3,5
7	18T819	6569652,339	144010,505	43,29	39,91	b2 Vim Hf	95	3,38	2,75
8	18T873	6569048,764	144290,862	43,735	37,585	b2 Tolk	95	6,15	3,9
9	18T874	6569063,987	144328,444	40,918	33,848	b2 Tolk	95	7,07	4,9
10	18T876	6569124,118	144414,718	33,944	24,494	b2 Vim Pr	95	9,45	3,07
11	19T002	6571064,398	142450,748	8,648	-20,522	b2 HfA Pr	95	29,17	3,13
12	19T003	6571047,498	142449,248	7,76	-10,87	b2 HfA Pr	95	18,63	4,15
13	19T006	6571061,076	142487,283	8,987	-34,063	b2 Prov T	95	43,05	3,1
14	19T007	6571058,452	142477,526	2,133	-31,967	b3 Cpt Hf	95	34,1	5,91
15	19T011	6571084,026	142609,755	1,937	-68,063	b3 Cpt Hf	95	70	5
16	19T012	6571074,036	142708,553	1,826	-87,074	b3 Cpt Hf	95	88,9	3,47
17	19T013	6571069,112	142757,119	2,26	-91,34	b3 Cpt Hf	95	93,6	6
18	19T014	6571031,729	142753,405	2,342	-86,358	b3 Cpt Hf	95	88,7	1,84
19	19T015	6571065,77	142815,29	1,792	-101,808	b3 Cpt Hf	95	103,6	3,94

Methodology

Input data from geotechnical information

Deep learning (ANN)

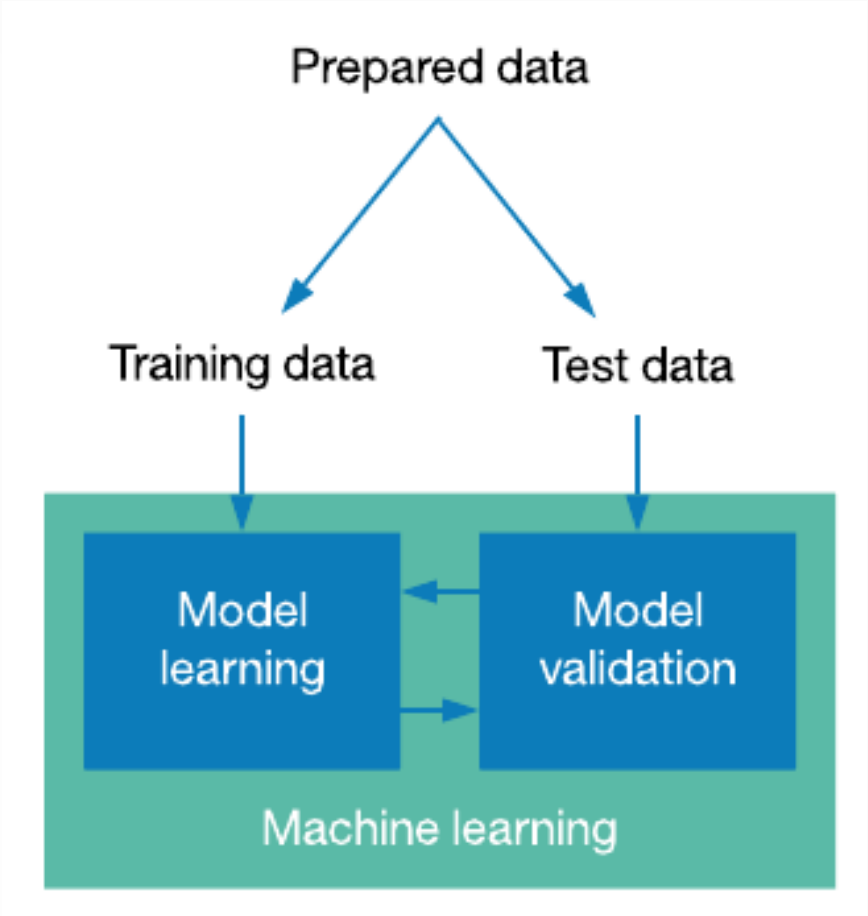
The ANN that is best suited for the input data is found by trying different combinations of:

- *Number of hidden layers*
- *Number of neurons in each layer*
- *Training algorithm*
- *Activation functions*
- *Weight matrix*
- *…*

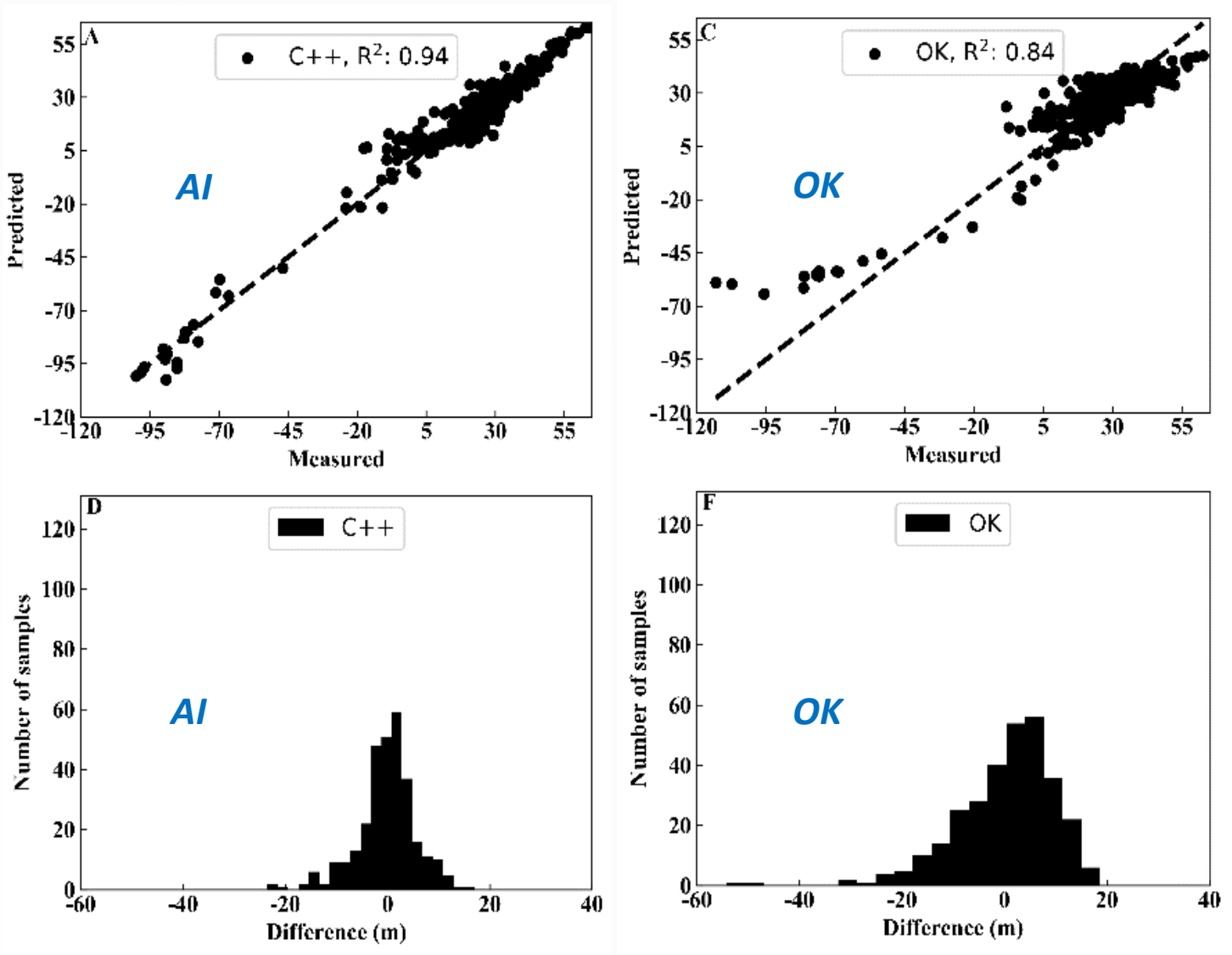
3D bedrock surface and groundwater surface

$$BL = f(x,y,z)$$

Methodology

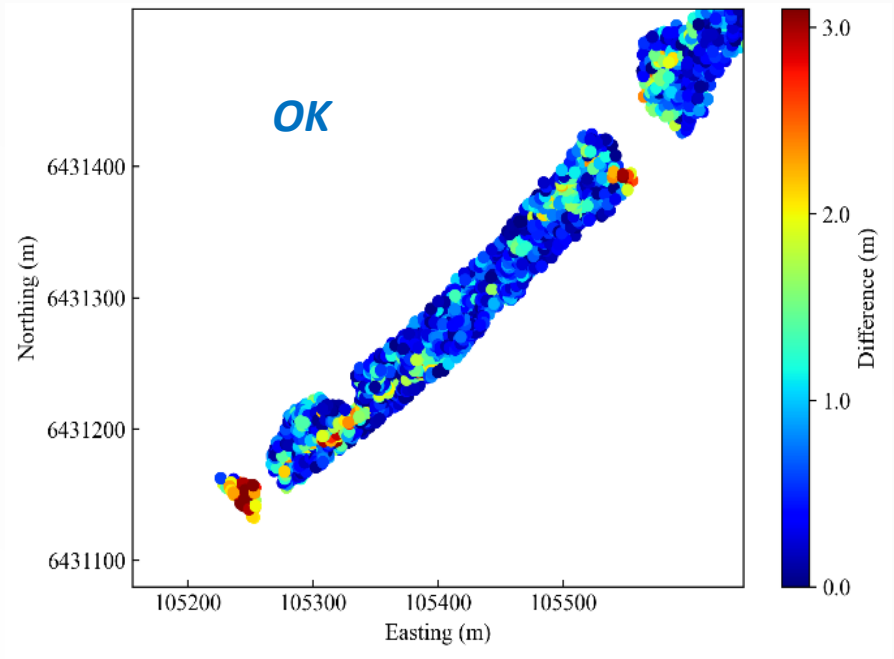


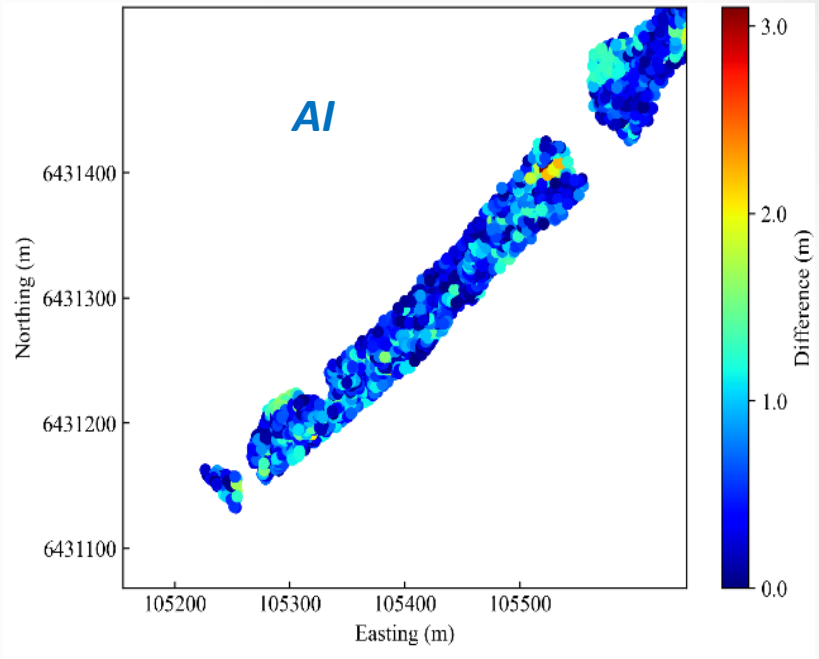
Results ➔ Compared performance of AI and OK for bedrock surface modelling



The fitting and difference between measured and predicted values and comparison of the predictability of AI and OK modelling on bedrock dataset from Tvärförbindelsen.

Results ➔ Compared performance of AI and OK for bedrock surface modelling





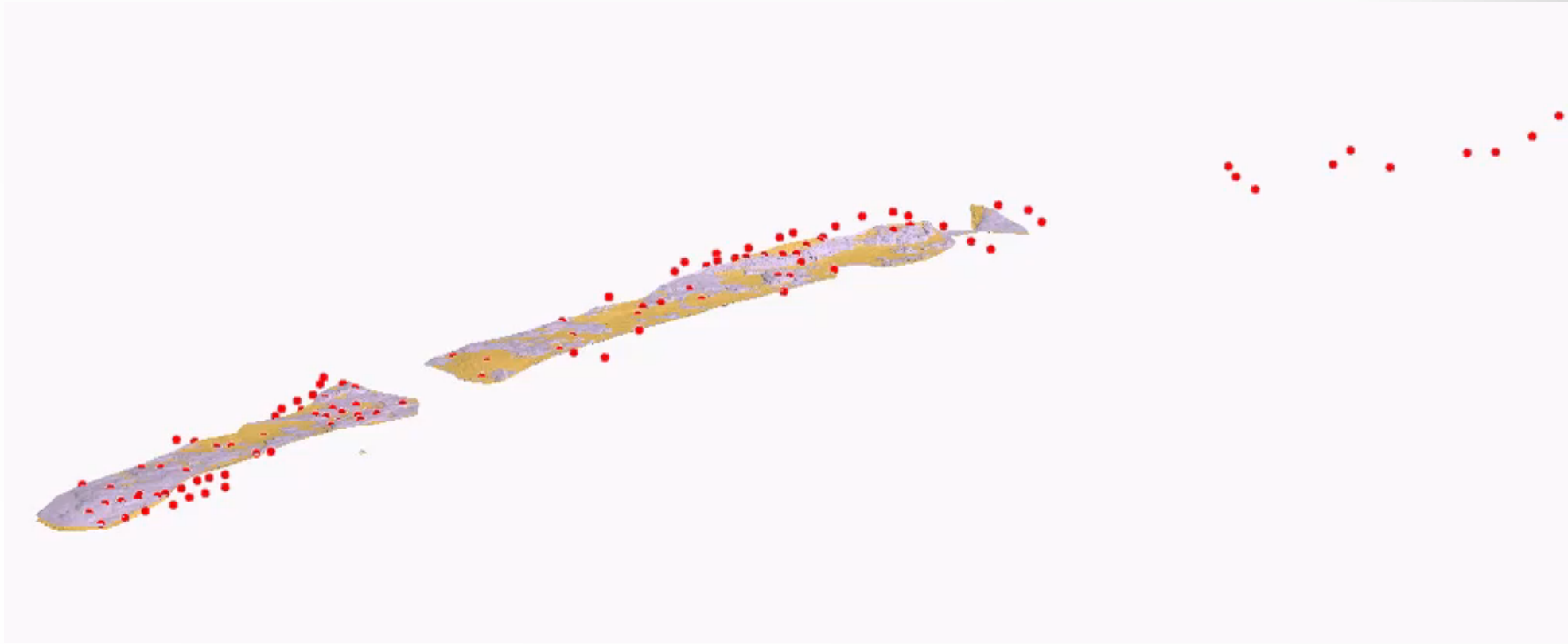
The difference plot between the predicted/estimated bedrock levels and the true scanned bedrock levels for E20 Bälinge-Vårgårda

Results ➔ Compared performance of AI and OK for bedrock surface modelling

Summary of differences between the predicted and true bedrock levels from E20 Bälinge-Vårgårda dataset

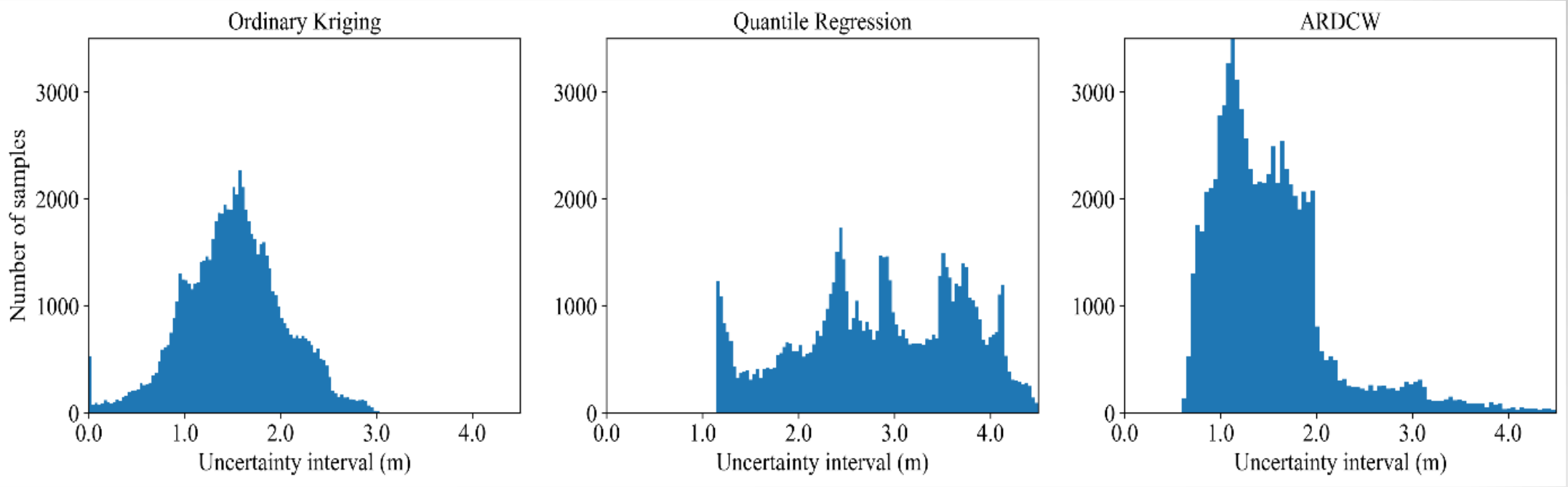
Method	Total absolute difference (m)	Average difference/point (m)	Improvement from OK (%)
Ordinary Kriging	31470	0.69	0%
AI	27787	0.61	12%

Results ➔ Comparison of predicted and true bedrock surfaces



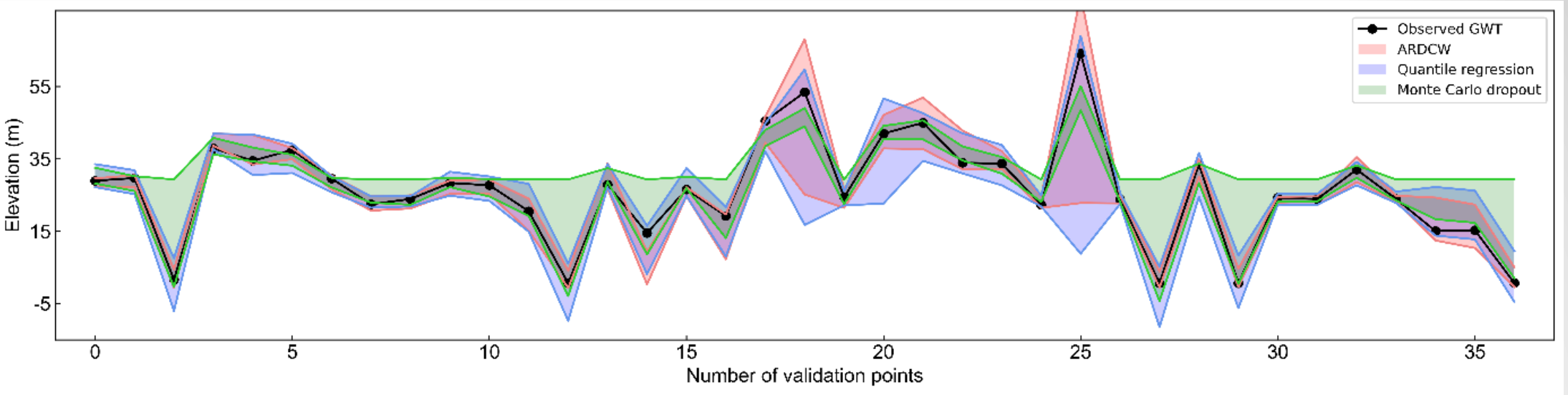
3D view of the comparison between true and predicted bedrock surface
E20 Bälinge-Vårgårda

Results ➔ Compared uncertainty analysis of AI and OK for bedrock surface modelling



Method	Ordinary Kriging	Quantile Regression (AI)	ARDCW (AI)
Number of measured points laying inside the uncertainty intervals	73%	78%	77%

Results ➔ Groundwater surface modelling and uncertainty analysis



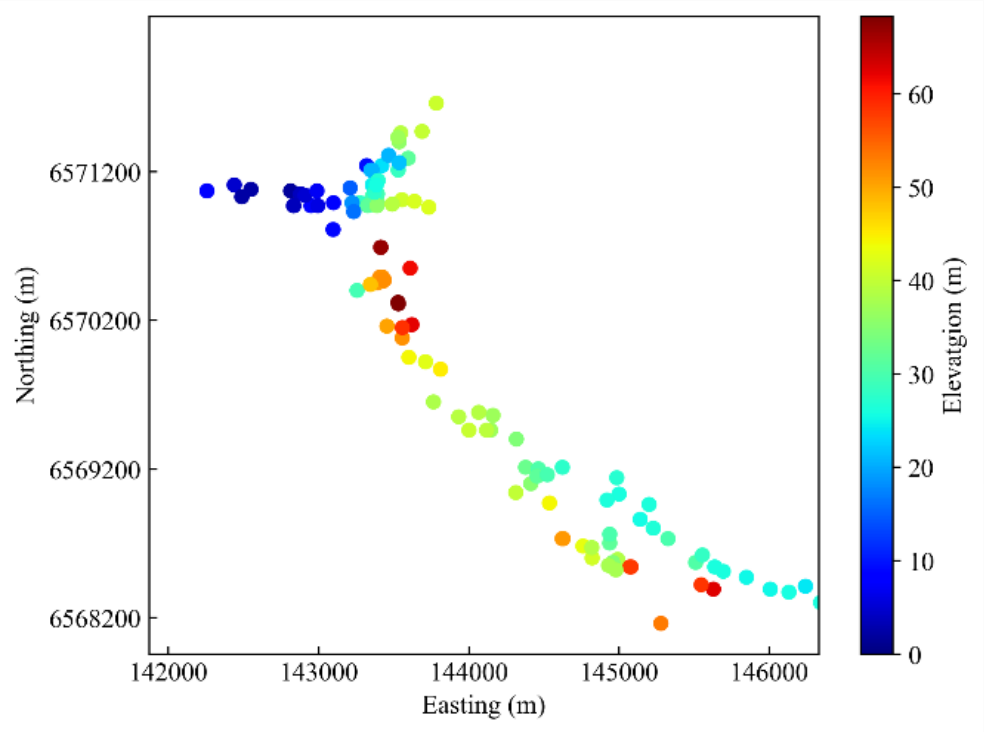
Compared $\boldsymbol{P_{CI}^{95\%}}$ of three models using validation dataset

Results ➔ Groundwater surface modelling and uncertainty analysis

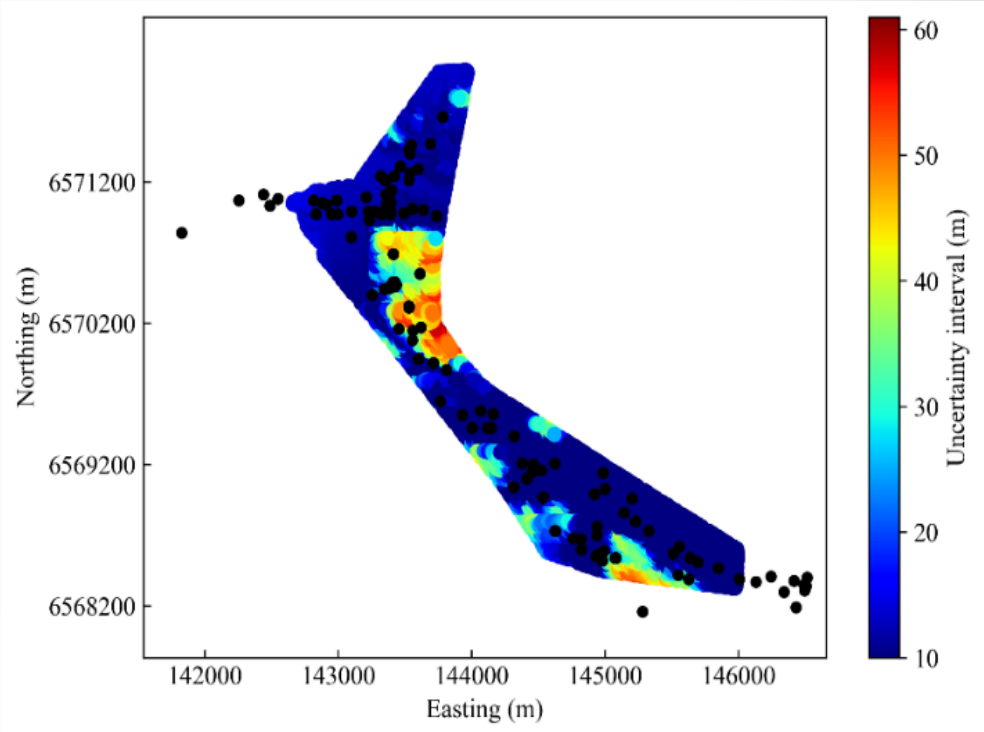
Compared statistical criteria of the three uncertainty methods

Performance criteria						Ranking of criteria						
Model	E_c	RMSE	IA	R^2	$P_{PI}^{95\%}$	E_c	RMSE	IA	R^2	$P_{PI}^{95\%}$	Total rank	Sort order
ARDCW	0.97	2.51	0.99	0.97	8.2	3	3	3	3	3	15	3
QR	0.96	2.99	0.99	0.96	11.6	2	2	3	2	1	10	2
MCD	0.94	3.5	0.98	0.94	9.4	1	1	1	1	2	6	1

Results ➔ Groundwater surface modelling and uncertainty analysis

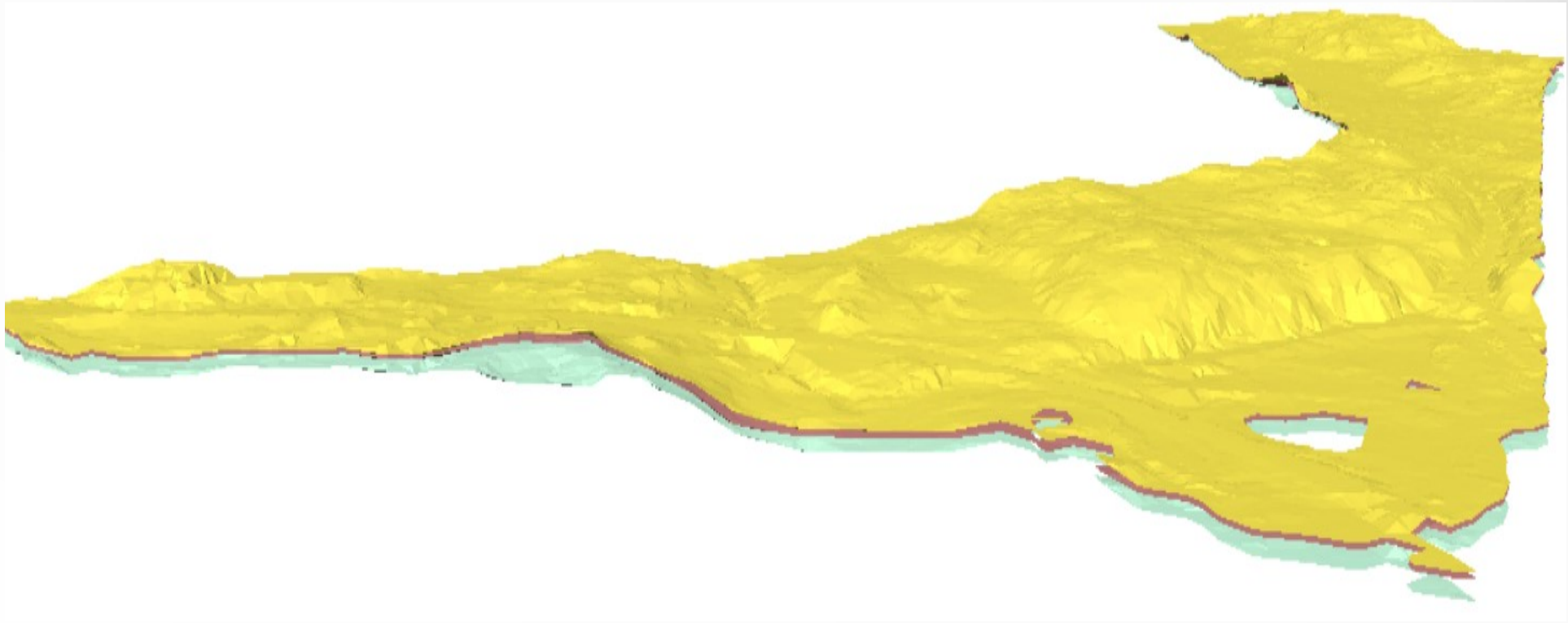


Color map of the measured GWT data



Estimated uncertainty intervals

Results ➔ Groundwater surface modelling and uncertainty analysis

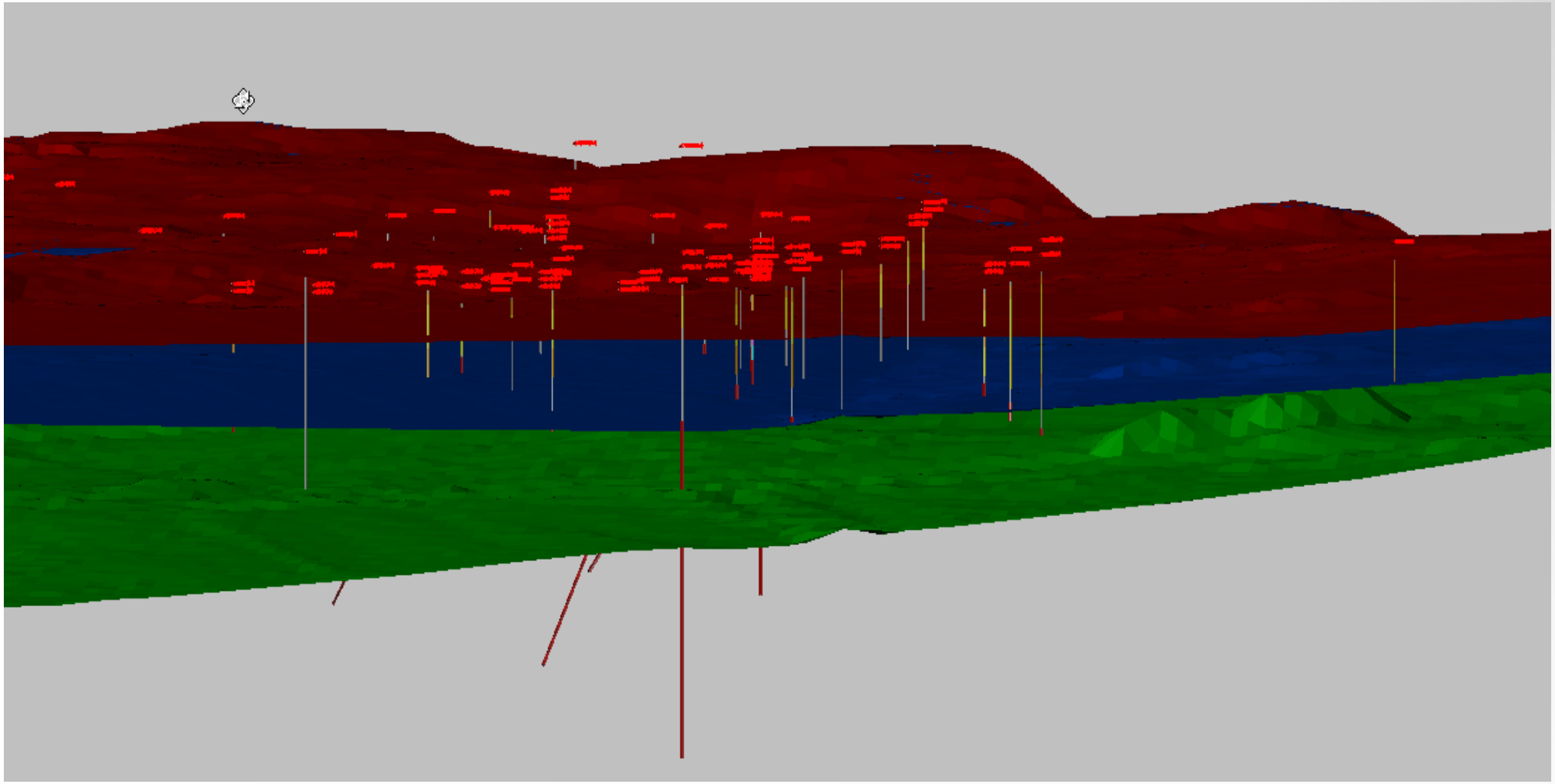


3D view of the estimated groundwater surface (brown, middle) together with the upper (yellow) and lower (light blue) boundaries.

Implementation of results

- Our results are published in open access journals
- The results were implemented in GeoBIM system that can automatically produce 3D bedrock/groundwater surfaces together with estimated uncertainties
- This facilitates the geotechnicians and engineering geologists with their modelling work
- Planning to make our Python code open access in GitHub so that it is available for everyone to use on their own data

Implementation of results



Conclusions

- AI methods are accurate enough tool to be applied for geospatial bedrock and groundwater surface predictions.
- The comparison between deep learning and Ordinary Kriging shows that deep learning can generate a more accurate surface.
- The uncertainty quantification using deep learning also shows superior performance and better estimation of the uncertainties than the geostatistical method Ordinary Kriging.

Thank you

Results ➔ Uncertainty analysis

Monte-Carlo Dropout	**Quantile Regression**
• Randomly disable a certain number of neurons • Run training process n times • Able to estimate mean and variance of predictions • Requiring computation time and is expensive to apply on large datasets	• Implemented as loss function • Estimate only at two quantiles • Less computation time