BIG projekt nummer: A2022-08

A 3D settlement predictive CPT-based intelligent model







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Aim and objective of the project

Increasing the knowledge of applying AI for solving geotech problems

Developing cost-effective AI approach to build **more accurate 3D CPTu-based settlement** model supplemented by:

1) CPTu and subsurface soil classes (Slide 3)

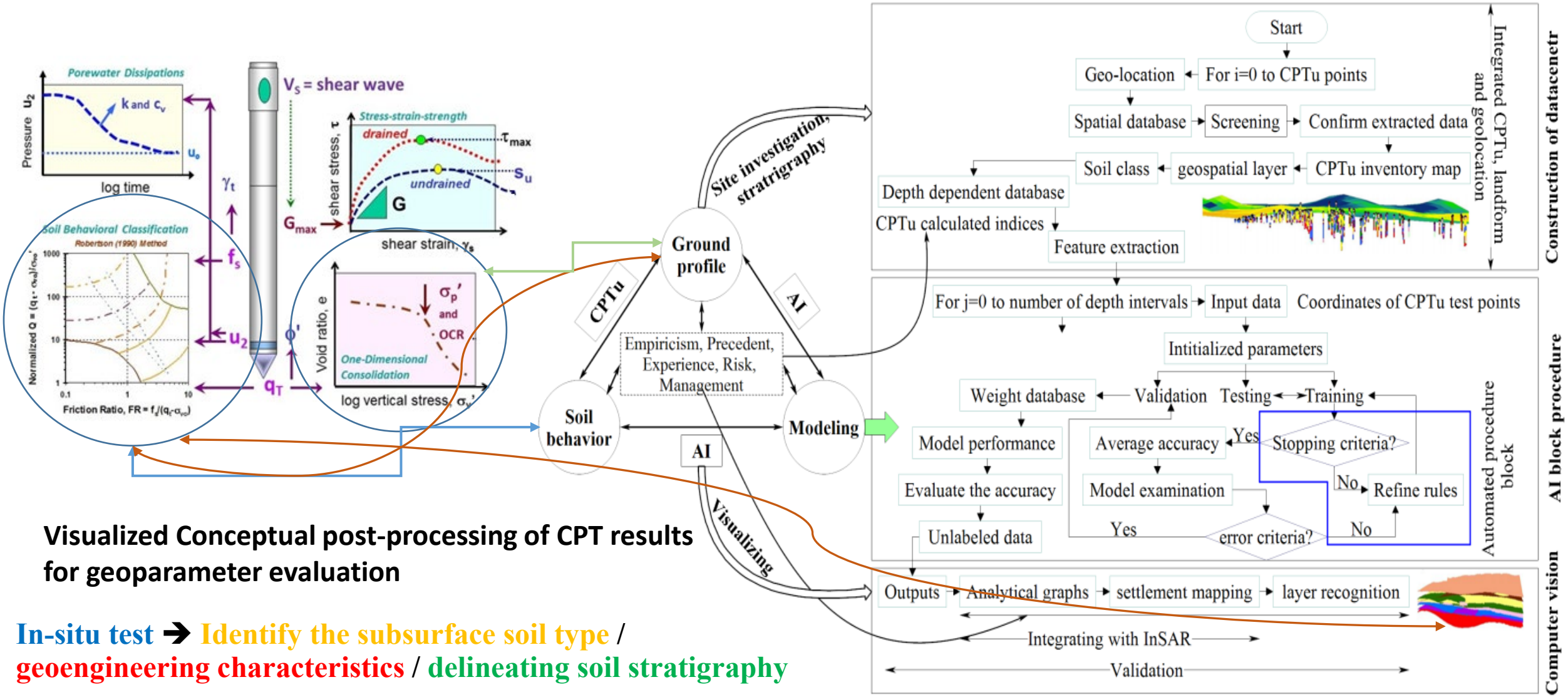
2) Settlement prediction (Slides 4-14)

3) 3D automated modeling details (results, analyses, comparisons…) (Slides 15-19)

4) Advantage and limitations (Slide 20)

5) Concluding and remarks (Slide 21)

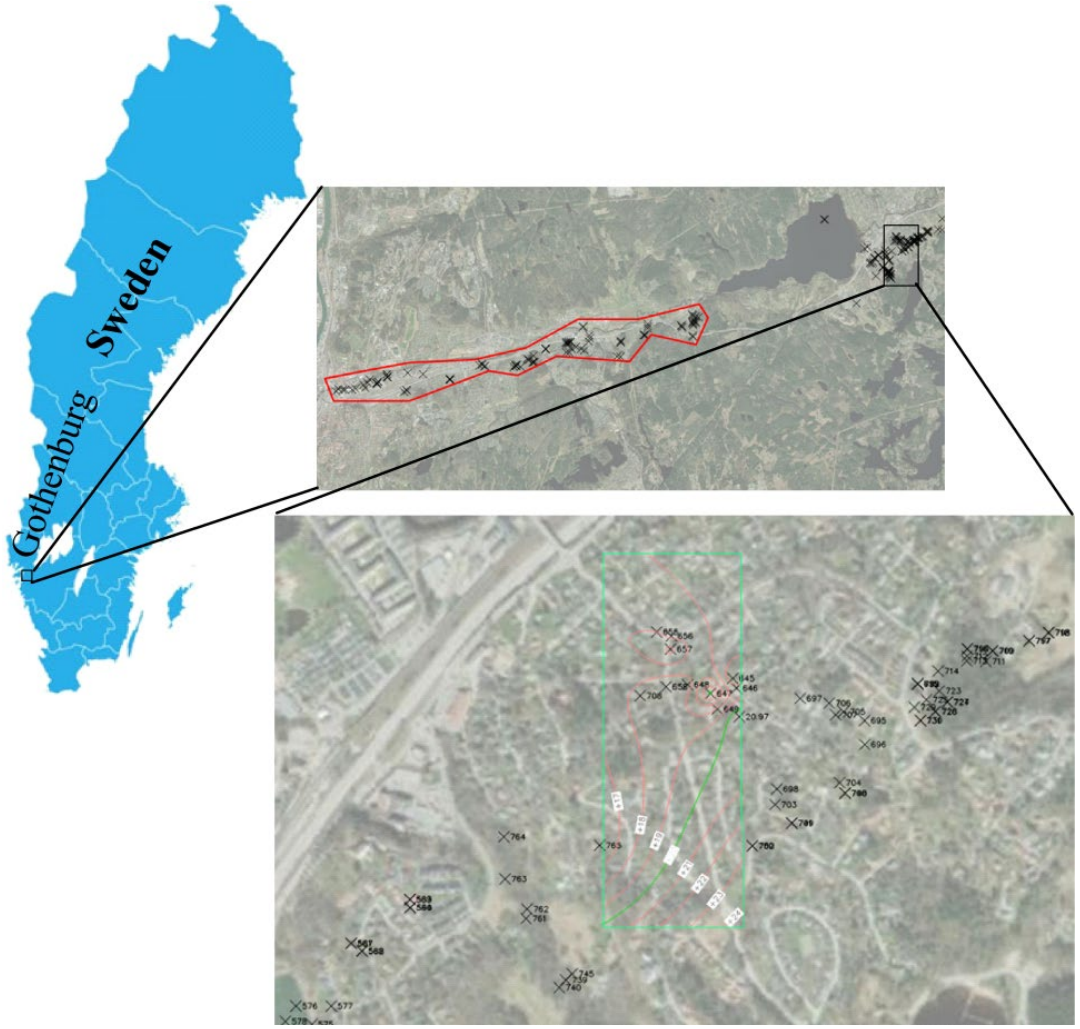
Overview of the Project and embedded automating process



Visualized Conceptual post-processing of CPT results for geoparameter evaluation

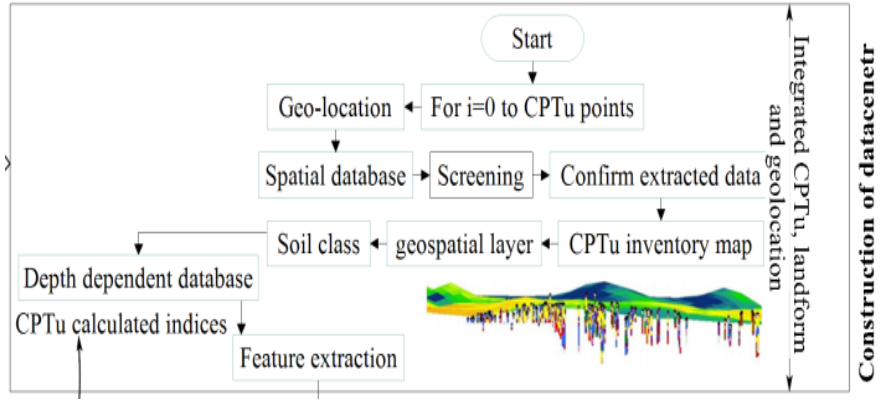
In-situ test ➔ Identify the subsurface soil type / geoengineering characteristics / delineating soil stratigraphy

Study area

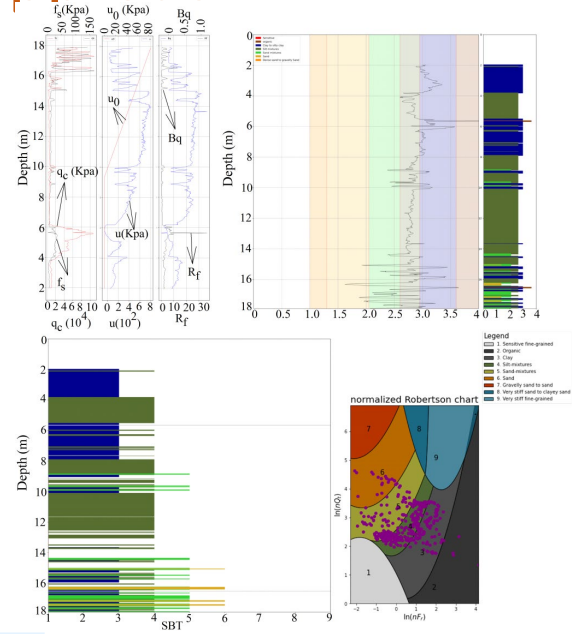


total number of 262 CPTu points

Simple overview of carrid out steps from engineering feature extraction to 3D computer vision model using proposed automated approach

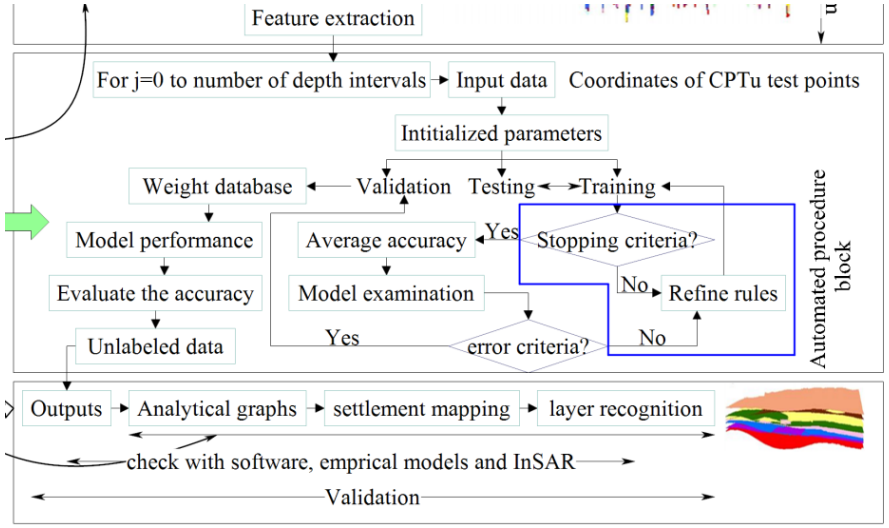


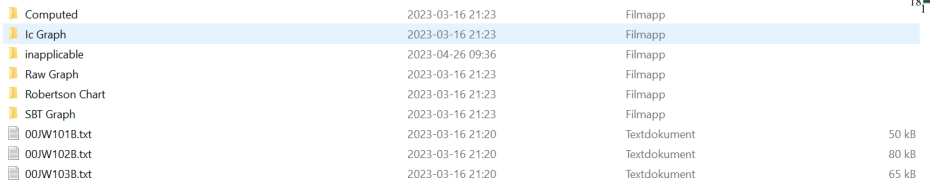
1. Raw data plots
2. Basic geo-parameter calculations
3. Data visualization
4. Stress history parameters



Database construction

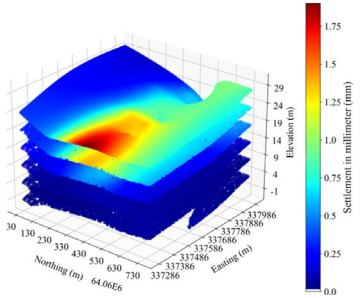
Settlement analysis and calculation





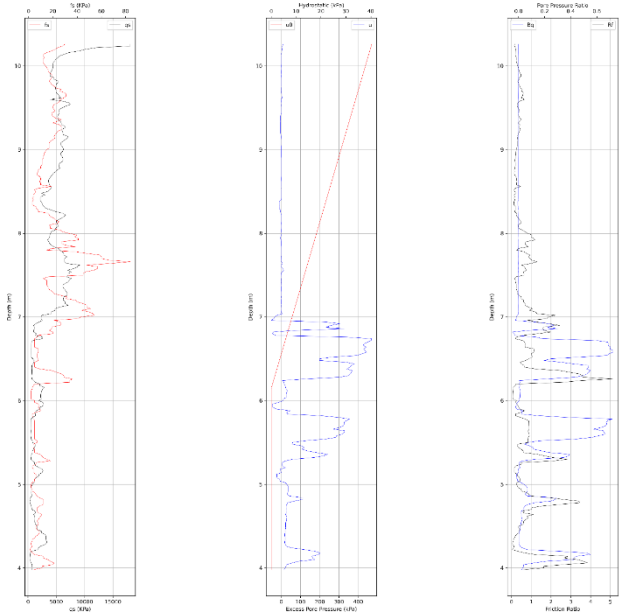
Computed	2023-03-16 21:23	Filmapp	
Ic Graph	2023-03-16 21:23	Filmapp	
inapplicable	2023-04-26 09:36	Filmapp	
Raw Graph	2023-03-16 21:23	Filmapp	
Robertson Chart	2023-03-16 21:23	Filmapp	
SBT Graph	2023-03-16 21:23	Filmapp	
00JW101B.txt	2023-03-16 21:20	Textdokument	50 kB
00JW102B.txt	2023-03-16 21:20	Textdokument	80 kB
00JW103B.txt	2023-03-16 21:20	Textdokument	65 kB

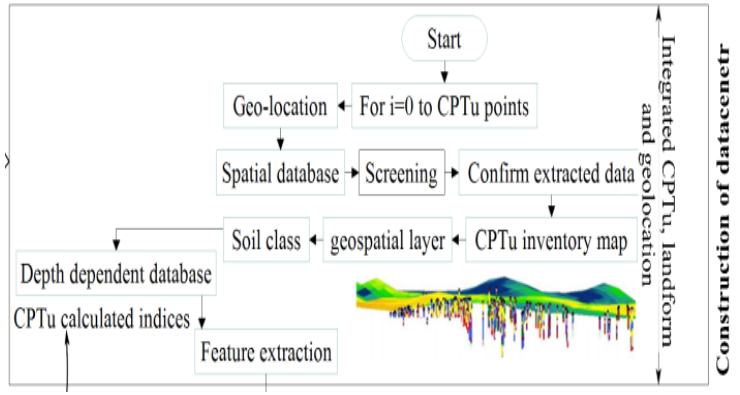
3D computer vision model



Automated data processing and feature extraction

1. Raw data plots





2. Basic Parameters

qt: corrected cone tip resistance (KPa)
Rf: Friction Ratio (%)
ϒ: Soil unit weight (KN/m3)
σv: Total vertical overburdun stress(KPa)
σ'v: Effective verical overburdun stress (KPa)
Qt: Normalized cone resistance
FR: Normalized Friction Ratio (%)
Bq: Porepressure ratio
Ic: Soil Tpe Index
Su: undrained shear strength (Kpa)
Qtn:Normalized cone resistance based on soil type and stress level
Sen: sensitivity
N60: SPT blow count
FC: Fine contenet (%)

3. Stress history parameter

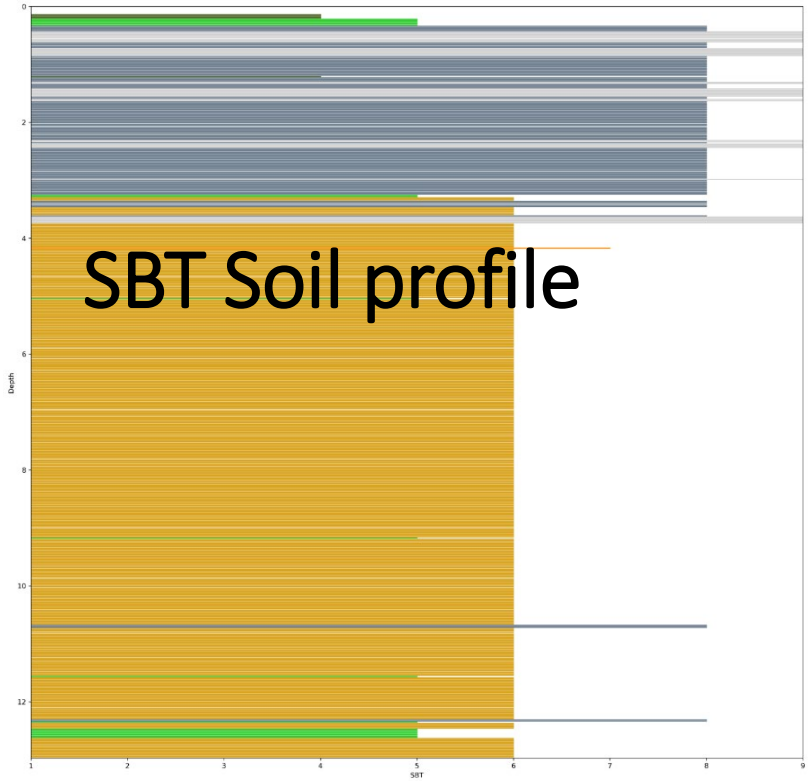
Spp: Preconsolidation stress(effective yeild stress)
YSR: yield stress ratio (Normalized Spp)
OCR: over consolidation ratio
σ'v: Effective verical overburdun stress (KPa)
φ: Friction angle
Ko: Insitu stress ratio (Lateral stress coefficient)
E: Elastic modoulus
Ep: Equivalent E
K: Hydraulic conductivity
M: Constrint Modulus
n: Porosity
Dr: relative density
SH: Horizonatl earth pressure

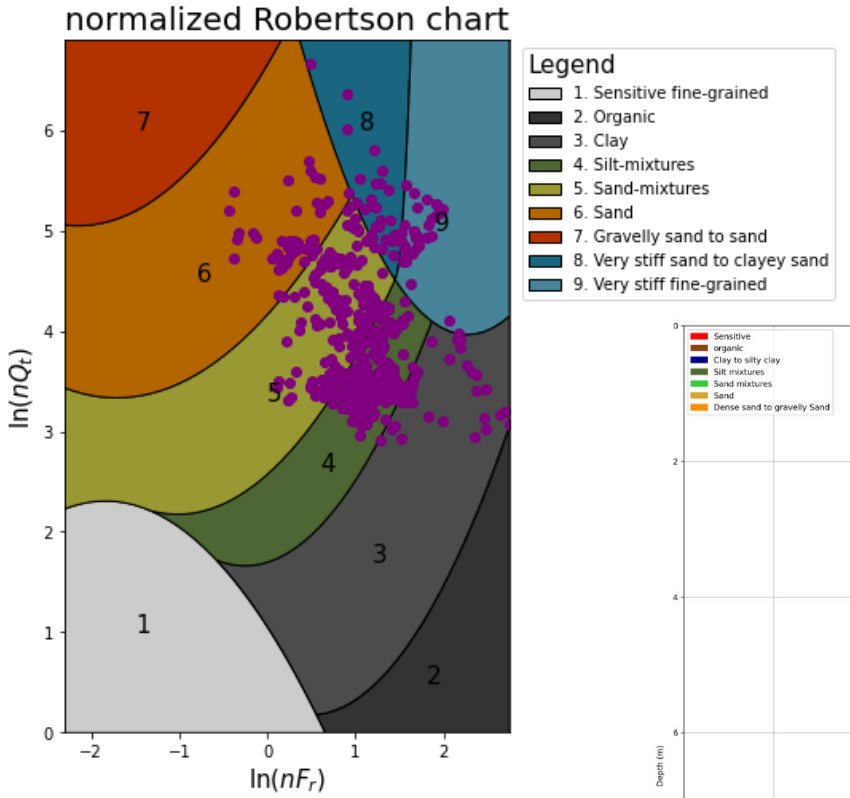
Visualizing results

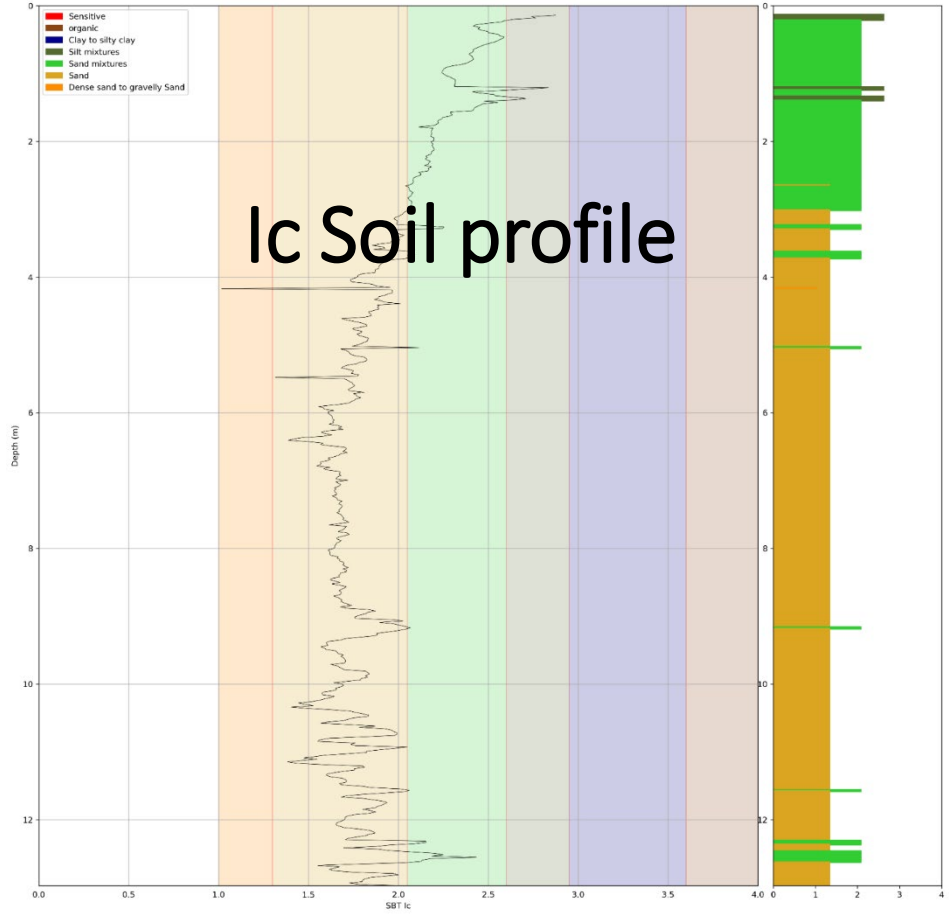
depth	qs	fs	u	u0	qt	Rf%	gama	Sv	Spv	Qt	FR	Bq	Qtn	n	Ic	Nkt	Su	SBT	N60	t/pa)(/N6	Su(rem)	FC
0.14	597	1	0	1.3734	597	0.167504	12.30211	1.722295	0.348895	1706.181	0.167989	0	1249.944	0.535542	2.873834	5.076963	79.8853	4	2.350153	2.515109	2.866193	67.04462
0.16	526	2	0	1.5696	526	0.380228	13.21255	2.114007	0.544407	962.3052	0.381762	0	554.46	0.501169	2.740616	7.572552	53.30132	4	1.908331	2.729044	3.67372	61.39377
0.18	509	1	0	1.7658	509	0.196464	12.28172	2.21071	0.44491	1139.082	0.197321	0	674.0781	0.536311	2.763972	5.566208	63.62336	4	1.872979	2.690689	2.247644	62.3845
0.2	473	3	0	1.962	473	0.634249	13.74723	2.749447	0.787447	597.184	0.637958	0	296.7446	0.480982	2.639199	9.133544	42.53771	4	1.614933	2.899914	3.809782	57.09188
0.22	482	3	0	2.1582	482	0.622407	13.74964	3.024921	0.866721	552.6287	0.626337	0	255.2362	0.480891	2.591125	9.077658	43.48834	5	1.599597	2.983425	3.46132	55.0527
0.24	491	5	0	2.3544	491	1.01833	14.4467	3.467207	1.112807	438.1107	1.025572	0	203.7405	0.454574	2.571184	10.57676	40.45924	5	1.610503	3.018552	4.49314	54.20682
0.259	737	7	0	2.54079	737	0.949796	14.95781	3.874072	1.333282	549.8654	0.954816	0	232.6791	0.435277	2.495031	10.35944	61.56752	5	2.312582	3.15536	5.250201	50.97656
0.279	983	8	0	2.73699	983	0.813835	15.17712	4.234415	1.497425	653.6323	0.817356	0	255.9722	0.426998	2.43216	9.886879	84.45412	5	2.974942	3.27155	5.342503	48.30971
0.299	1063	10	0	2.93319	1063	0.940734	15.49234	4.63221	1.69902	622.9283	0.944851	0	244.7518	0.415096	2.415946	10.32754	89.0389	5	3.187389	3.301998	5.885745	47.62198
0.319	1010	15	0	3.12939	1010	1.485149	16.04107	5.117102	1.987712	505.5476	1.492711	0	217.8191	0.394379	2.453204	11.71783	78.76704	5	3.093745	3.232328	7.546366	49.20237
0.339	983	16	0	3.32559	983	1.62767	16.12605	5.466732	2.131142	456.5477	1.636778	0	196.474	0.391171	2.441343	11.99792	75.64952	8	2.990625	3.254394	7.472649	48.69922
0.359	966	20	0	3.52179	966	2.070393	16.42972	5.816771	2.376481	407.0014	2.067312	0	180.9967	0.379706	2.460538	12.73099	71.99662	8	2.971462	3.218738	8.415804	49.51345
0.379	939	26	0	3.71799	939	2.768903	16.78594	6.361872	2.643882	352.7533	2.787791	0	171.9075	0.366257	2.497037	13.61682	67.55431	8	2.949844	3.151702	9.834024	51.06165
0.399	975	30	0	3.91419	975	3.076923	16.98708	6.777846	2.863656	338.1071	3.098462	0	168.2658	0.358663	2.50061	13.93802	69.31248	8	3.069277	3.145192	10.47612	51.21322
0.419	904	38	0	4.11039	904	4.20354	17.30182	7.249461	3.139071	285.6738	4.237522	0	155.3444	0.346781	2.553655	14.88978	62.13975	8	2.934909	3.049667	12.10549	53.46328
0.439	922	43	0	4.30659	922	4.663774	17.47401	7.671089	3.364499	271.7578	4.702903	0	151.4231	0.34028	2.562776	15.20656	62.71823	9	3.009351	3.033449	12.78051	53.85017

Excell format output

Possibilty to plot each desired parameter based on depth or Vs. each other to check the correlation and dependencies


SBT Soil profile


normalized Robertson chart
Legend
1. Sensitive fine-grained
2. Organic
3. Clay
4. Silt-mixtures
5. Sand-mixtures
6. Sand
7. Gravelly sand to sand
8. Very stiff sand to clayey sand
9. Very stiff fine-grained
ln(nQt)
ln(nFr)


Ic Soil profile
Sensitive
organic
Clay to silty clay
Silt mixtures
Sand mixtures
Sand
Dense sand to gravelly Sand
Depth (m)
SBT Ic

Settlement prediction

- Review of applied methods
- Mathematical formula analysis
- Settlement calculation
- Automated deep learning development
- Result analysis → **1)** code monitoring
  2) Generated 3D model
  3) accuracy metrics analyses using InSAR data
  4) Comparison with commercial packages (Conrad)

1) Classified CPTu-based approaches in analyzing the settlement

Applied method	Reference	pros	cons
Empirical correlations	Jefferies and Davies (1993); Robertson and Campanella (1983); Robertson and Cabal (2022); Qi et al., (2023); Schmertmann (1978)	simple/quick for preliminary assessments	soil homogeneity assumptions/rough estimate/case-based/unable to capture complex soil-structure interactions
Analytical methods	Lunne et al, (1997); Mayne and Kulhawy (1982); ASTM (2012); Mihálik et al., (2023); Eslami and Mohammadi (2016)	well-established theories; quick estimations under certain conditions	soil homogeneity assumption/not account for complex soil stratigraphy or non-linear behavior
Numerical modeling	Arel and Can Mert (2021); Valikhah and Eslami (2019); Roy and Robinson (2009); Wang et al., (2023); Liu et al., (2022)	captures complex SSI/handles non-linear behavior/useful for detailed settlement analysis	significant computational resources/ experts/simplification and assumptions/ accuracy dependency to input qualities
Semi-empirical methods	Schmertmann (1978); Juang et al., (2008); Jones and Rust (1991); Wu et al., (2022); Bullock et al., (2019)	balance between empirical and analytical principles/more refined predictions than purely empirical	different assumptions in the use of correction factors
Probabilistic methods	Thoft-Christensen and Baker (1982); Collico et al., (2023); Collico et al., (2024); Costa and Beck (2024); Winkelmann et al., (2021)	Probability assessment/counting for uncertainties in input parameters	distribution of uncertainties/sensitive to the chosen probability distributions
Field monitoring and back analysis	Randolph and Gourvenec (2011); Giretti et al., (2018); Comodromos and Randolph (2023); Wang et al., (2020)	incorporates real-time data/empower the reliability of predictions	Time consuming/sensitive to external factors affecting settlement
AI-based approaches	Wu et al., (2021); Gupta et al., (2023); Rauter and Tschuchnigg (2023); Lo et al., (2022); Nghia-Nguyen et al., (2023)	Able to handle heterogeneous media and non-linear relations/adaptability for complex site conditions/accuracy improvement with large datasets	sufficient high-quality training data/ physical interpretation of underlying soil mechanics

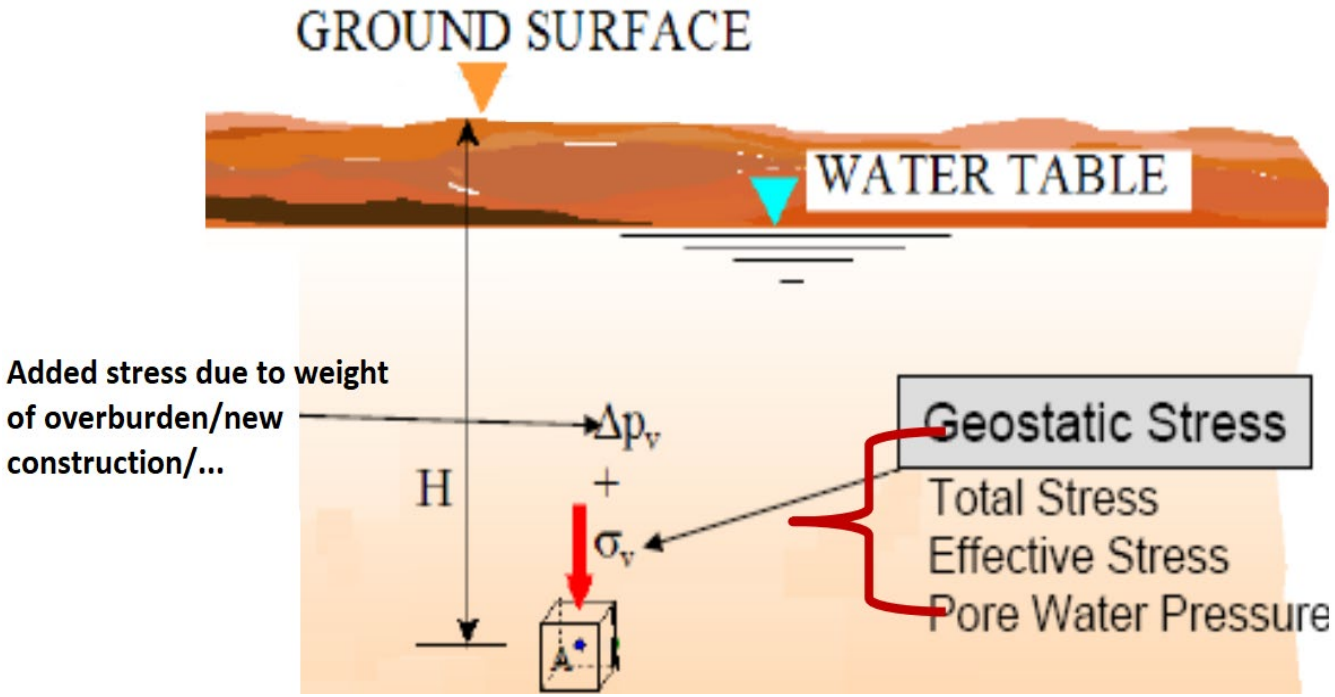
2) Derived empirical equation in predicting the settlement using CPTu data

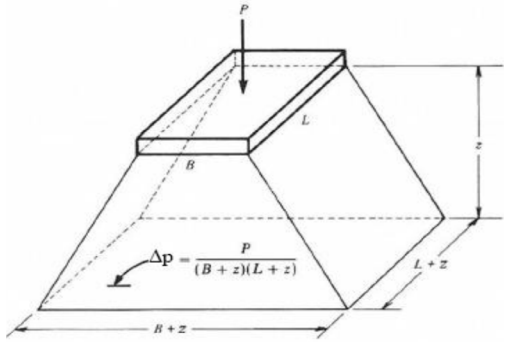
Equation	Reference(s)
$\Delta S = \left(\frac{q_c}{c_c}\right)(1+e_0)\log(N)\ ; N = f_s \times A_r$	Robertson 2009; Rindertsma et al., 2018; Robertson and Cabal, 2014 and 2022; Dagger et al., 2018; Sakleshpur et al., 2021a, b)
$\Delta H = \left(\left(\frac{q_c}{s_u}\right) - a\right) b,\ \ S_{u(Kpa)} = \left(\frac{q_t - \sigma_v'}{10.57 + 7\log\left(\left(\frac{f_s}{q_c - \sigma_{vo}}\right)\times 100\right)}\right)$	
$\Delta S_c = (C_c - C_r)\log\left(\frac{\sigma_1 + \Delta\sigma}{\sigma_1}\right) + \Delta e_{avg}\left(1 + e_{avg}\right)H$	
$\Delta S = (q_c N_c + f_s N_s)\left(1 + e_0 \log\left(\frac{t_v}{t_o}\right)\right)$	
$\Delta S = \left(\frac{q_c N_c}{(1+e_0)}\right)\left(1 - exp\left(\frac{-B_{q_c}}{\sigma_v' N_\gamma}\right)\right)$	Schmertmann (1978)
$\Delta S = \frac{\left((q_c - \sigma_v')P_a\right)N_c}{1+e_0}\left(1 - exp\left(\frac{-B_{q_c}}{\sigma_v' N_\gamma}\right)\right)$	Schmertmann et al., (1978)
$S = \sum_0^n \Delta z\left(\frac{2.3}{1.5\left(\frac{q_c}{\sigma_v'}\right)}\right)\log\left(\frac{\sigma_0' + \Delta\sigma'}{\sigma_0'}\right)$	DeBeer (1965)
$\Delta S = \frac{\left((q_c - P_a)\sigma_v'\right)N_c}{1+e_0}\left(1 - exp\left(\frac{-B_{q_c}}{\sigma_v' N_\gamma}\right)\right)N_c N_s$	Modified Schmertmann (Lutenegger and DeGroot, 1995)
$\Delta S = C_c N_c \sigma_v' \log\left(\frac{t_v}{t_0}\right) + \left(C_s N_s \sigma_v' log\left(\frac{t_v}{t_v}\right)\right)$	Menard (1975)
$\Delta S = \left(\frac{q_c}{2\pi\sigma_v' R_f}\right)\left(1 + e_0\, log\left(\frac{t_v}{t_v}\right)\right)$	Robertson (2009)
$\Delta S = \frac{\left(0.0045\left(\frac{q_c}{\sigma_v'}\right)^{0.5}\left(\frac{L}{D_f}\right)^{0.25}\left(1 + 0.45\frac{H_f}{D_f}\right)\left(1 + e_0\, log\left(\frac{t_v}{t_v}\right)\right)\right)}{1+e_0}$	Seed et al., (1983)
$\Delta S = \left(\frac{q_c}{\sigma_v'}\right)\left(1 + e_0 \log\left(\frac{t_v + t_1}{t_1}\right)\right)$	Seed et al., (1983)
$\Delta S = \left(\frac{q_c(1+e_0)}{2\sigma_v' C_c}\right)\left(1 - exp\left(\frac{-2C_c\sigma_v' N_\gamma}{q_c}\right)\right)$	Bishop's simplified method (1954)
$\Delta S = \left(\frac{q_c}{\sigma_v'}\right)\left(1 + \left(\frac{e_0}{1-e_0}\right)\log\left(\frac{t_v + 0.1}{t_0}\right)\right)$	Janbu and Senneset (1974)

3) Settelement calculation

- Required sub steps

Depth conversion➔ Center and thickness ➔ Cc: Consolidation coeeficient ➔ Δσv: Verical overburden stress ➔ Δσ'v: Verical effective overburden stress ➔ Calculation of stress change based on depth interval





$$\sigma_z = \frac{P}{(B+z)(L+z)}$$

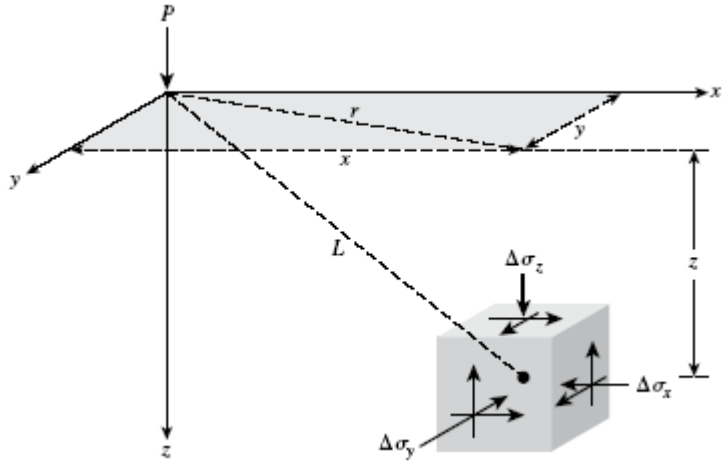
Used formula for calculation

Settlement formulation using:

1. S-Sch : Schmertmann
2. S_LPDC: LPDC (low pressure die casting)
3. S_E: Elastic modulus
4. S_e: void ratio
5. S_Iz: Stress influence factor Iz
6. Sc_e: Consolidation Settlement using void ratio
7. Ss: Secondary Sett
8. S_Rob: Robertson

➔ St: Total average Settlement

The most important original solution was given by BOUSSINESQ (1885)



$$\sigma_z = \frac{P}{(B+z)(L+z)}$$

$$I_1 = \frac{3}{2\pi}\frac{1}{[(r/z)^2+1]^{5/2}}$$

$$\Delta\sigma_z = \frac{P}{z^2}\left\{\frac{3}{2\pi}\frac{1}{[(r/z)^2+1]^{5/2}}\right\} = \frac{P}{z^2}I_1$$

Settlement output

Code results

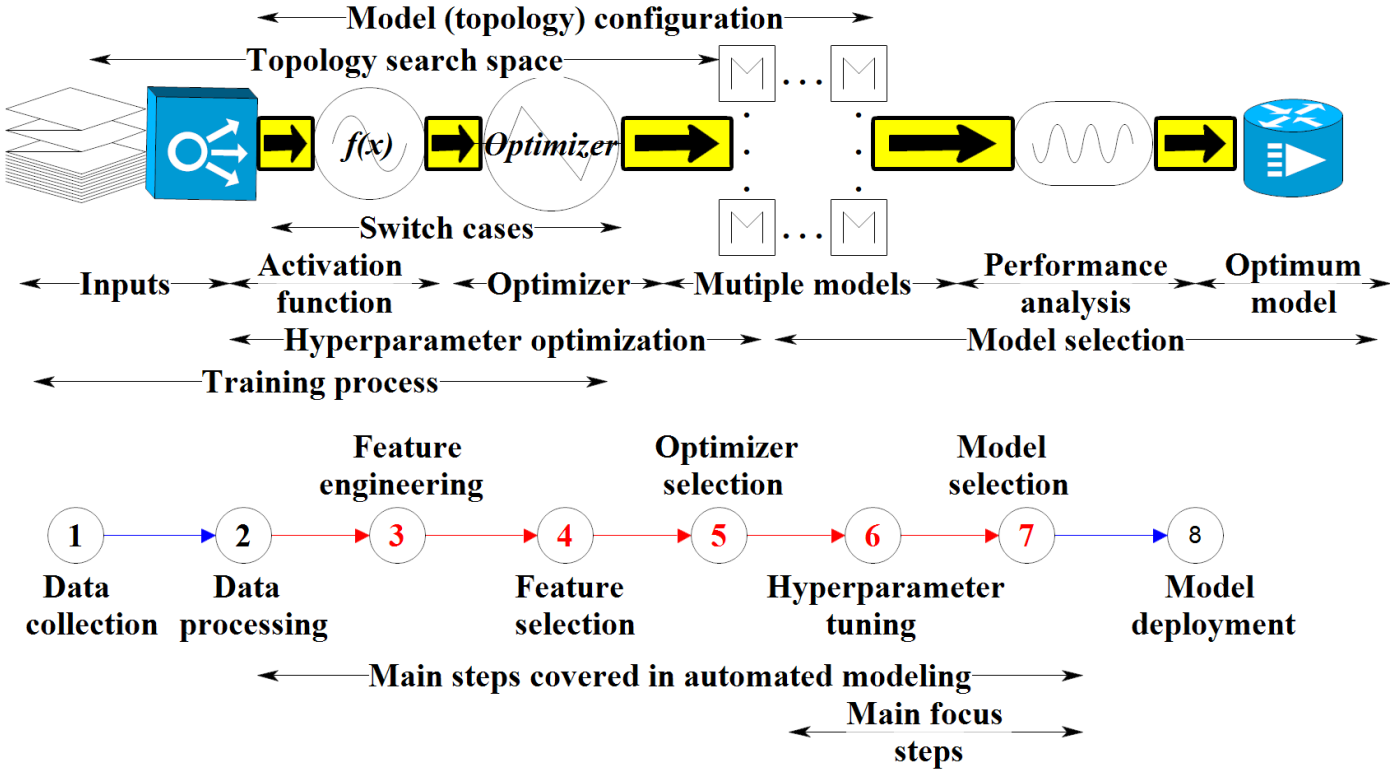
X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK
center	thickness	Cc	delta-Sv	delta-Spv	dP	dP+Spv	S_Sch	S_E	S_e	S_Rob	S_ave	Ss	S_tot
0.15	0.02	1.4E-05	1.845316	0.471916	111.4744	111.9464	0.017431	0.000138	0.010711	0.000268	0.007137	3.92E-05	7.175807
0.17	0.02	3.12E-05	2.246133	0.676533	107.7277	108.4042	0.002885	0.000179	0.010023	0.000294	0.003345	4.4E-05	3.389394
0.19	0.02	2.56E-05	2.333527	0.567727	104.1667	104.7344	0.01197	0.000174	0.010726	0.000294	0.005791	4.3E-05	5.833995
0.21	0.02	5.7E-05	2.886919	0.924919	100.7794	101.7043	0.001356	0.000213	0.00962	0.000306	0.002874	4.65E-05	2.92017
0.23	0.02	8.12E-05	3.162418	1.004218	97.55463	98.55885	0.001411	0.000215	0.009618	0.000291	0.002884	4.42E-05	2.928054
0.2495	0.019	9.51E-05	3.604451	1.250051	94.63239	95.88244	0.022785	0.000201	0.008637	0.000263	0.007972	4.07E-05	8.012295
0.269	0.02	0.000244	4.02365	1.48286	91.69595	93.17881	0.011348	0.00015	0.008706	0.000179	0.005096	2.8E-05	5.123646
0.289	0.02	0.000505	4.386186	1.649196	88.8941	90.5433	0.002661	0.000118	0.00854	0.00013	0.002862	2.04E-05	2.88267
0.309	0.02	0.000612	4.787134	1.853944	86.21874	88.07268	0.001356	0.000109	0.008302	0.000116	0.002471	1.84E-05	2.489183
0.329	0.02	0.000448	5.277512	2.148122	83.66236	85.81048	0.000497	0.000106	0.007888	0.000119	0.002153	1.91E-05	2.171622
0.349	0.02	0.000473	5.627992	2.302402	81.21801	83.52041	0.000327	0.000108	0.007823	0.000119	0.002094	1.91E-05	2.113491
0.369	0.02	0.000406	6.062568	2.540778	78.87924	81.42002	0.000397	0.000105	0.007594	0.000117	0.002053	1.9E-05	2.072445
0.389	0.02	0.000306	6.529732	2.811742	76.64006	79.4518	0.000398	0.0001	0.007325	0.000117	0.001985	1.92E-05	2.004466
0.409	0.02	0.000309	6.947716	3.033526	74.49489	77.52841	0.000617	9.4E-05	0.007173	0.00011	0.001999	1.8E-05	2.016705
0.429	0.02	0.000198	7.42248	3.31209	72.43854	75.75063	0.000161	9.27E-05	0.006936	0.000115	0.001826	1.91E-05	1.845341

Possiblity to plot the Settlement based on depth

Producing a light version of develped code for data processing in an Excell sheet

Layout of automated process for model configuration in this project

Definition: automated modeling is a dynamic design of advanced techniques from data feeding to model building and configuration.

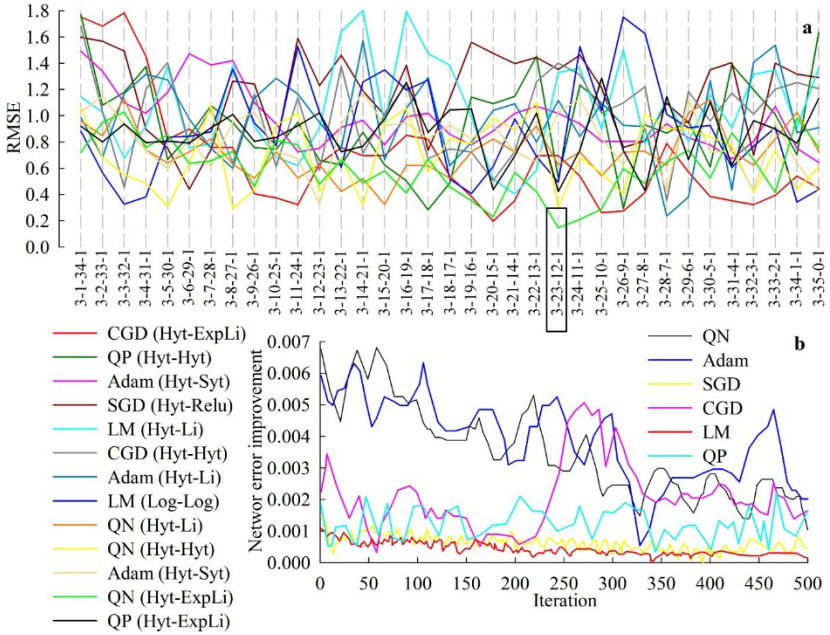


Applied approach: automated neural search topology based on advanced hyperparameters optimization in a search space

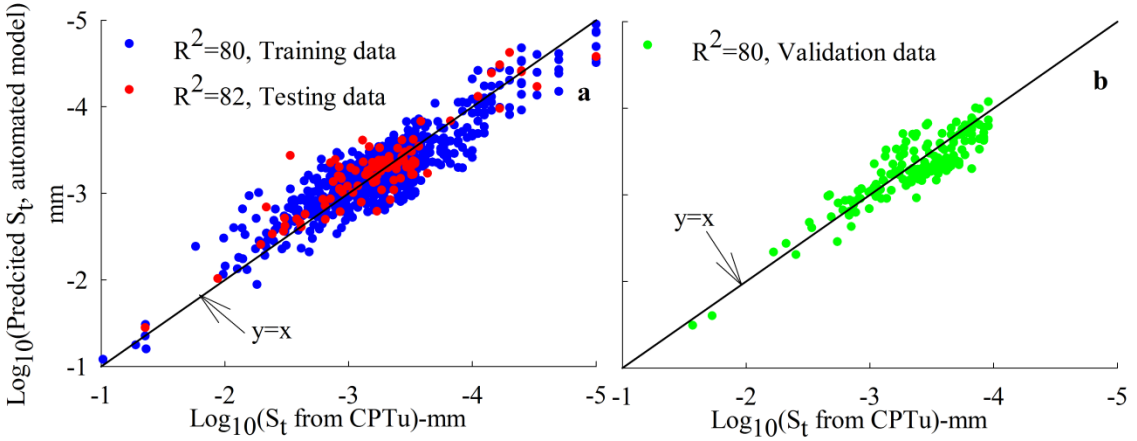
Results analyses

1) Code monitoring

Serach space and hyperparameters➔ 6 optimizers (QP, CGD, Adam, QN, LM, SGD), 1-7 hidden layers, 1-80 neurons, 6 activation functions (Hyt, Li, Relu, ExpLi, Syt, Log) and 0.05 step size incremental learning rates within [0.001-1] interval

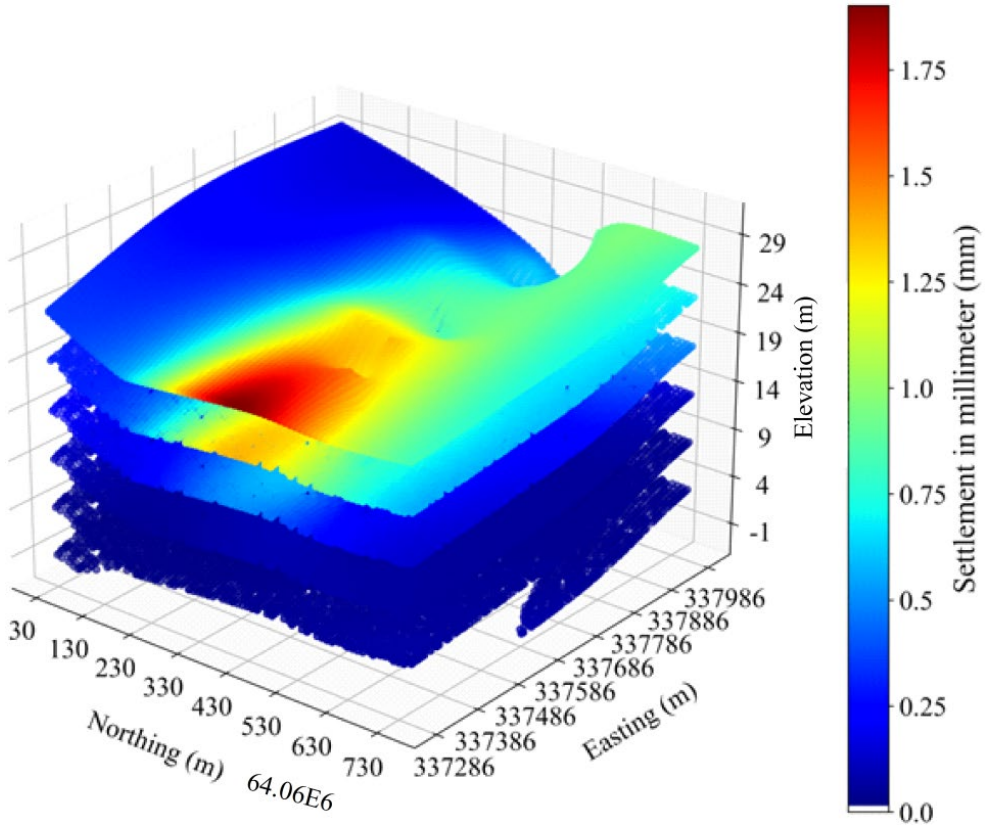


Performance control for the monitored topologies subjected to various hyperparameters (a), and error improvement analysis of the optimizers using optimal topology (b).



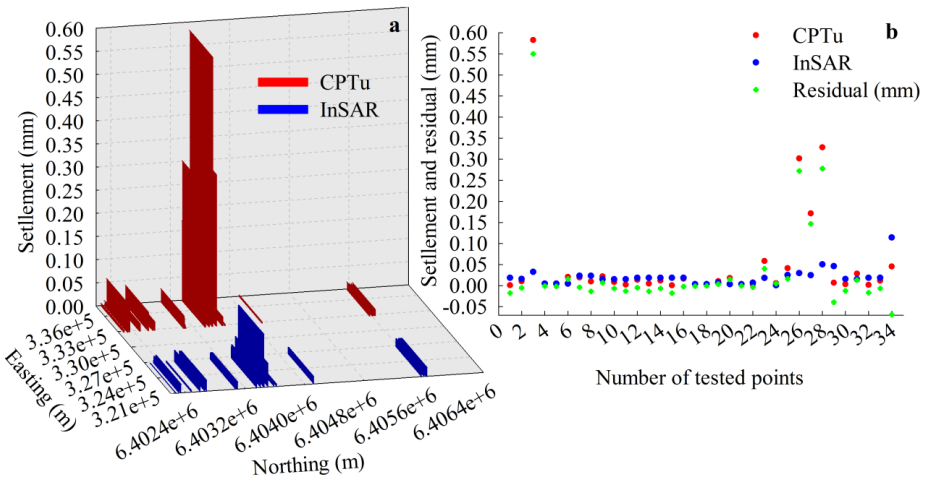
Calculated settlement using CPTu data Vs. predicted values

2) Generated 3D computer vision depth-based interval model

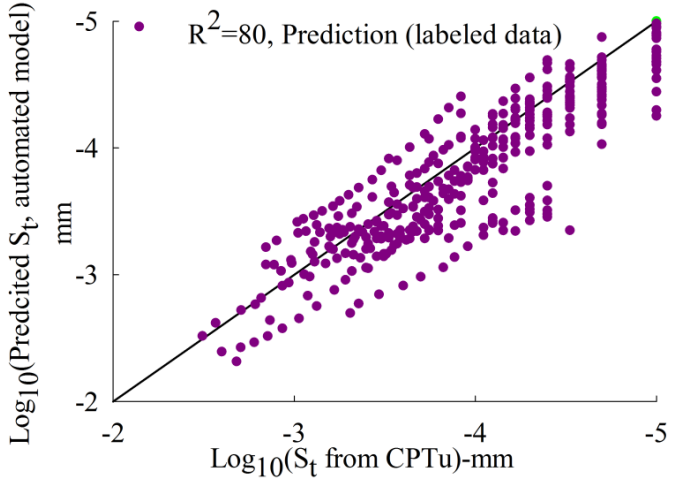


The 3D visualized perspective of predicted settlement based on the depth interval in the studied site

3) Accuracy metric analyses using InSAR data



Comparison between the calculated settlement from CPTu test points and InSAR data (a) and corresponding calculated residuals (b)



Predictability of the model using unseen data and the weight database of the optimum topology

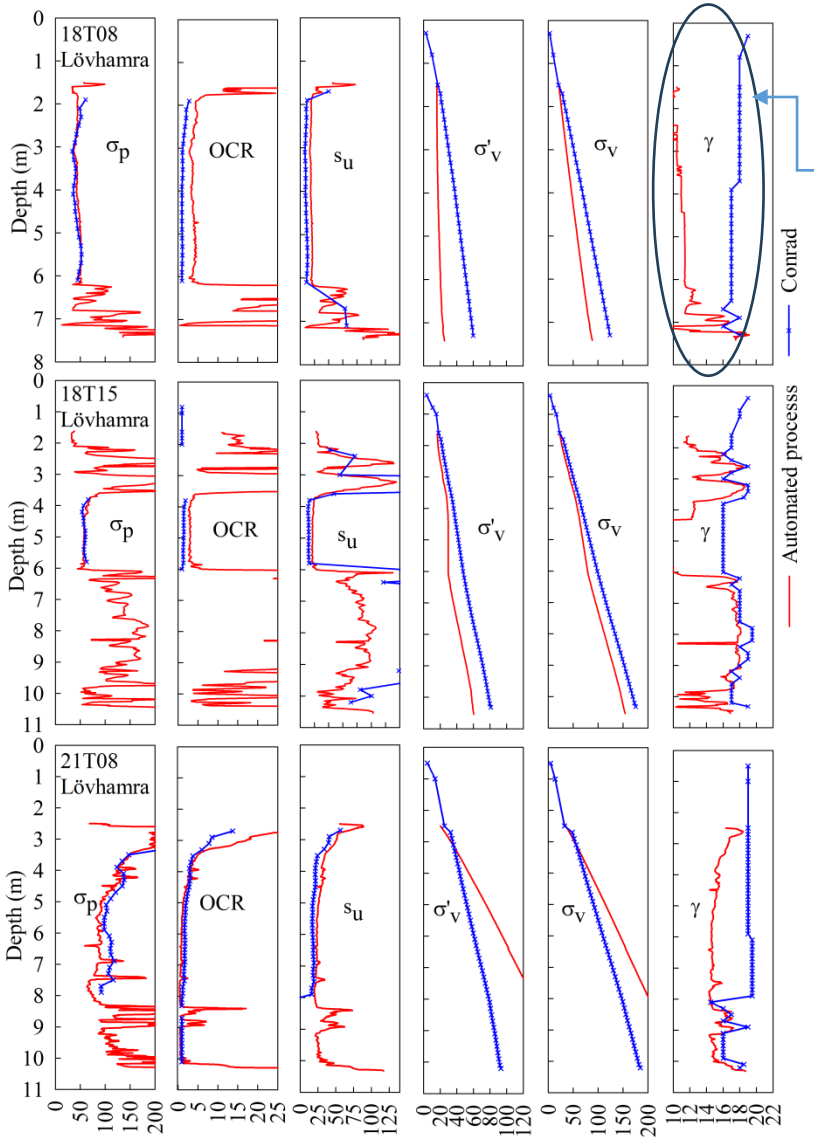
Model	Reference	Metrics			
		RMSE	MAE	WAPE	RS
$S_{ci} = \frac{1}{E}\Delta\sigma_v . z_i$	Terzaghi (1943)	0.0138	0.011	0.815	[-0,0061, 0,0235]
$\Delta S_s = \left(\left(\frac{u_2}{\sigma'_v}\right)\left(\frac{q_c}{P_a}\right)^{-0.15}\right)$	Hardin (1985)	0.7087	0.662	0.997	[-1,2942, 0,0135]
$\Delta S_s = 0.15\left(\left(\frac{q_c}{P_a}\right)\left(\frac{OCR}{2}\right)^{-0.25}\right)$	Mesri et al., (1994)	0.1148	0.084	0.991	[-0,3586, 0,0135]
$\Delta S_s = \left(\left(\frac{q_c}{100}\right)^{0.3}\left(\frac{OCR}{2}\right)^{-0.14}\right)$	Burland et al., (1985)	1.269	1.226	0.996	[-1,7633, 0,0135]
This study		0.0126	0.009	0.574	[-0,0402, 0,0178]

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}$, $MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i|$, $WAPE = \max\left[\frac{|P_i - O_i|}{P_i}\right]$, $RS = [min/\max(O_i - P_i)]$

n: number of samples, P_i and O_i: predicted and observed value, $\bar{P}$ and $\bar{O}$: the average value of predicted and observed value

Comparing the metrics between this study and empirical equations based on InSAR data

4) Comparison with commercial software in Sweden (Conrad)



Mismatching between the calculated σ_v and σ'_v can be assigned to assuming a constant user defined soil unit weight (γ) in Conrad and this physically can be interpreted as neglecting the soil layer variations in the test point. The calculation of the proposed automated process is dependent to the record intervals and therefore variation in identified soil layers. Despite the similar trend their differences at the most depth intervals cannot be ignored.

Close compatible results in other parameters with Conrad can be interpreted as the capability of our automated approach in deriving the different soil parameters **with a higher speed, better flexibility and cost-effective.**

Our approach in comparison with Conrad, **provides real time continues estimation of desired soil parameters without cumbersome manual adjustments for simultaneously feeding a large batch number of CPTu test points**. From geotechnical point of view, the depth- dependent parameters like σ_v is calculated based on variation of γ instead of a constant value and this increases the accuracy of the estimated parameters.

Advantage, limitation, future works

Limitation:

1) Settlement prediction using CPTu data is not always accurate due to high variability of soil behavior ➔ The accuracy of prediction using any formula depends on the **selected method,** its **assumptions, quality** and **reliability** of the **input data.**
2) Recommended to use multiple settlement prediction methods and compare the results to ensure the reliability of the predictions.
3) The empirical equations are only valid for homogeneous and isotropic soil layers that are not subjected to loading for a long time (not consider the changes in soil properties over time) ➔ in challenging problems, cross validation using advanced numerical models/perform laboratory or field tests may be necessary.

Advantages:

1) **Cost-effective** and **high-speed** platform for simultaneous process/extract/analyze large volumes of real-world derived geo-parameters from CPTu data.
2) Facilitating for **patterns recognition**, trend analyses and **establishing relationships** that may be challenging using traditional methods.
3) Significant improvement in **modeling efficiency**, save time, reduce the need for deep expertise,
4) **customizability for generalization** to meet different site conditions and required outputs
5) Quick decision-making during field investigations due to **real-time assessment** of factors like ground settlement, deformation, and pore water pressure, enhancing early warning systems
6) A) Can be applied to analyze data from sensors and monitoring devices installed in geotechnical structures, B) quantify uncertainty in geotechnical predictions

Concluding remarks

1) **Developing** an enhanced end-ot-end CPTu-based predictive automated modeling approach for 3D visualization via advanced neural search topology and hyperparameter optimizations.
2) **Successful application** to a real case study in Sweden➔ empowered visualized depth dependent settlement features leading to geotechnically site characterization, i.e., safer project design.
3) Efficiency, cost effectiveness, consistent performance, customizability, high speed and real-time analysis of simultaneous feeding of big data are some **remarks** of this approach **over traditional Geotech softwares**.
4) Providing more possibilities to capture the subsurface complexities via digitization of geometric/topological feature of geo-data ➔ better technical communication between geoengineers and decision makers in both economy and construction aspects.
5) **Adaptable** with new data for modification/re-training
6) In **comparison** with **formulations** and **Conrad package** the dedicated more capability in feature extractions for generating more detailed 3D model
7) Comparison with **InSAR data** showed low residual and thus **close predictability** of our approach, i.e., allows to be further supplied with other acquired combinations of geo-data to reflect more details of the subsurface features.
8) The comparisons showed that the **accuracy** of predicted settlement **strongly depends on the quality of the input data and validity of the selected method**. This reason tightly is dependent to considered assumptions and thus corresponding induced limitations in both current formulations and software packages.
9) Meaningful model **interpretation still requires domain-specific knowledge.**

Automated Deep learning for 3D modelling of setllement

Data base construction ✓

Depth interval ✓

Geographical coordinates of test points ✓

Developed of code platform ✓

Succesfull analyses ✓

Thank you

TRAFIKVERKET

Branschsamverkan i Grunden

A2022-08 – A 3D settlement predictive CPT-based intelligent model

- Benefits of obtaining *reliable* (AI-trained) 3D-settlement results while driving the CPT cone into the ground, in real-time.
  ⇒ Opportunities for proactive decision-making while the drill rig is on-site.

THIS SHOWS….

1. AI applications within Geotechnical engineerings are possible within reasonable limits;

2. Replicatable in other geotechnical computational areas (e.g. bearing capacity checks; shallow foundation design; design of simple retaining wall structures; stability and settlement calculations) while performing site-investigations in real-time.

OTHER ISSUES?

- Suitability? Representativity?
- ”Large-scale & general” vs ”Small-scale & complex”
- Implications of utilising geotechnical data?

CHAT
Webbinarium 20240322 AI - CPT

[fredag 12:29] Tornborg, Johannes

Question from the room at Chalmers: what is creating the settlement in your model?

[fredag 12:37] Paulina Bakunowicz

Thank you for presentation! I am interested in more details in the InSAR check with your model. Which period of InSAR measurements did you consider for the comparison? Did you consider check with monitoring results like precise leveling or 3D monitoring for surface settlement or extensometers results to check settlement by depth?

[fredag 12:49] Leyla Nik

Thank you for presentation!

[fredag 12:50] Tornborg, Johannes

Thank you Abbas!