Convolutional Neural Network for Identifying Effective Seismic Force at a Domain Reduction Method Layer for Rapid Reconstruction of Shear Waves

Shashwat Maharjan, Bruno Guidio, PhD, and Chanseok Jeong, PhD

CENTRAL MICHIGAN UNIVERSITY

AGENDA

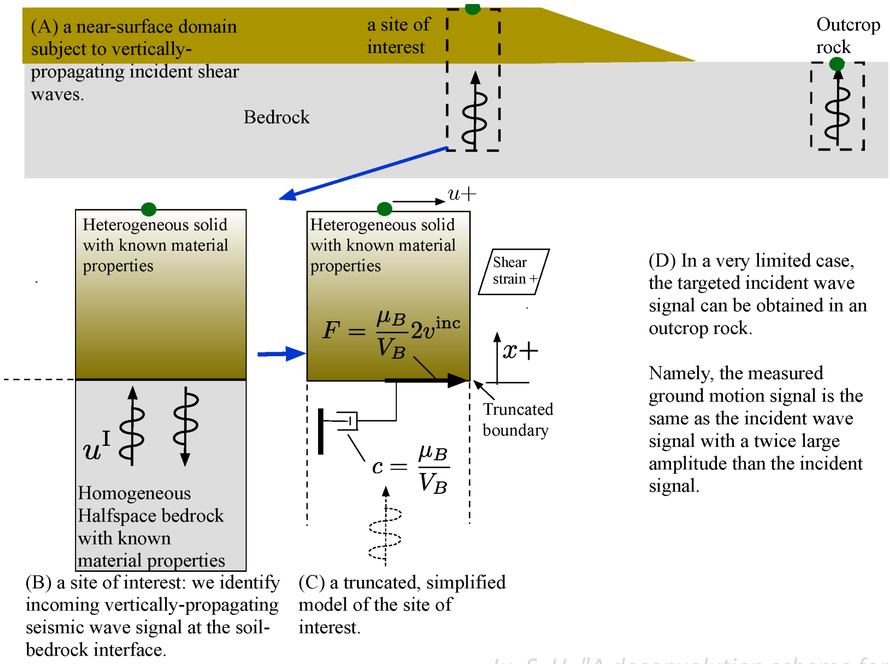
- Existing Methods and Limitations
- Problem Description
- Synthetic Data Generation
- Convolutional Neural Network
- Numerical Results
- Discussion

RESEARCH QUESTION

Is it possible to develop a highly accurate method for reconstructing seismic ground forces from sparse ground motion data that is less computationally intensive and suitable for real-time predictions?

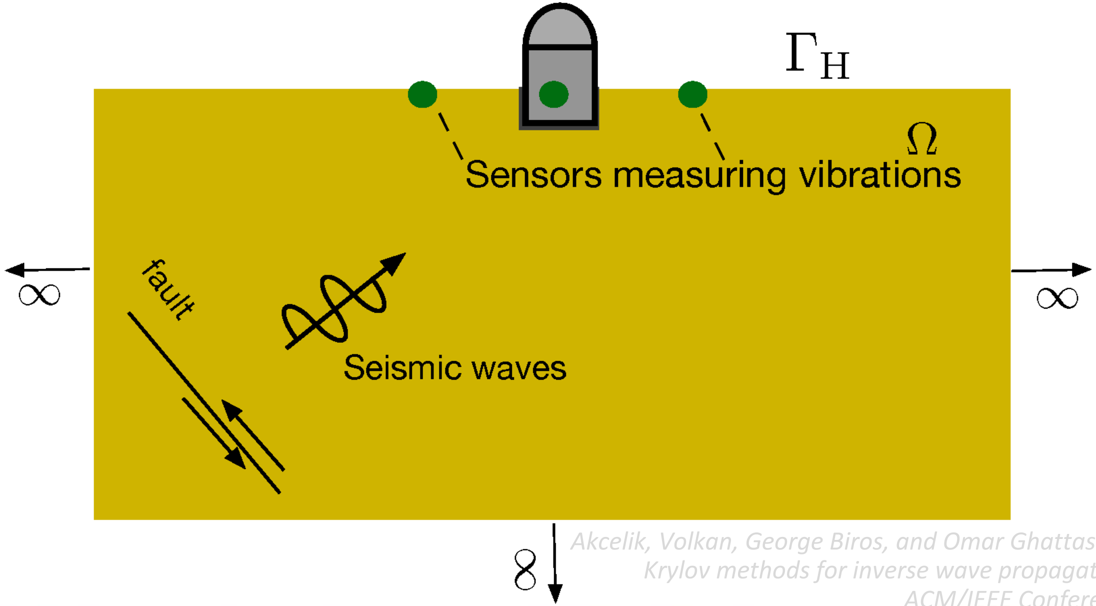
EXISTING METHODS AND LIMITATIONS

DECONVOLUTION



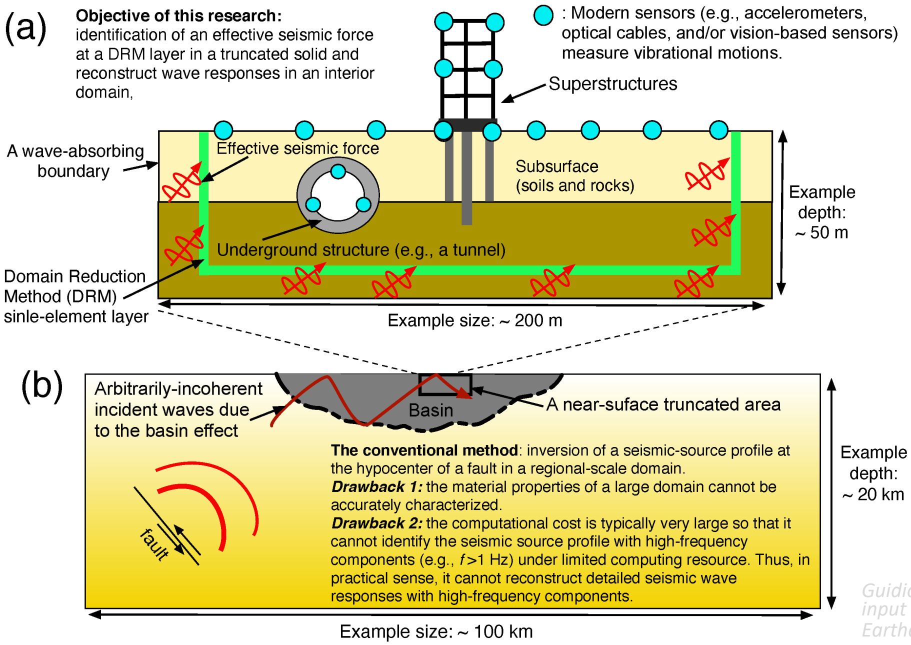
Ju, S. H. "A deconvolution scheme for determination of seismic loads in Bulletin of the Seismological Society of America 103.1 (2013): 258-267.

SEISMIC SOURCE IDENTIFICATION IN A LARGE DOMAIN



Akcelik, Volkan, George Biros, and Omar Ghattas. "Parallel multiscale Gauss-Newton-Krylov methods for inverse wave propagation." SC'02: Proceedings of the 2002 ACM/IEEE Conference on Supercomputing. IEEE, 2002.

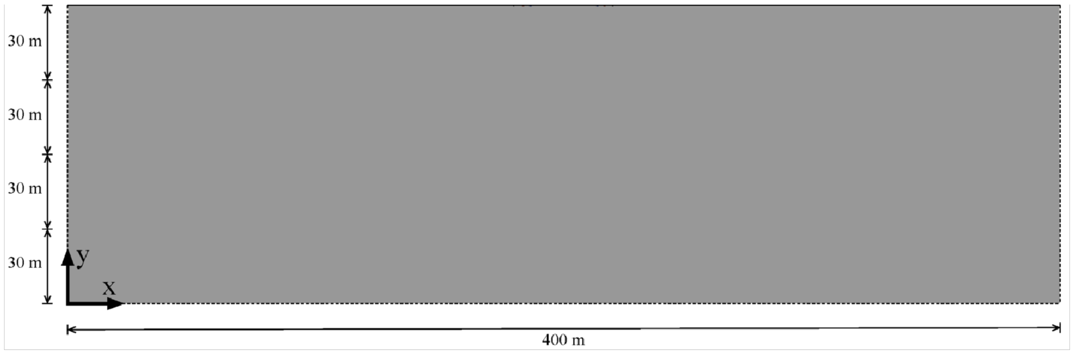
PARTIAL DIFFERENTIAL EQUATION CONSTRAINED OPTIMIZATION



Guidio, Bruno, et al. "Passive seismic inversion of SH wave input motions in a truncated domain." Soil Dynamics and Earthquake Engineering 158 (2022): 107263.

PROBLEM DESCRIPTION

WHAT ARE WE TRYING TO DO?



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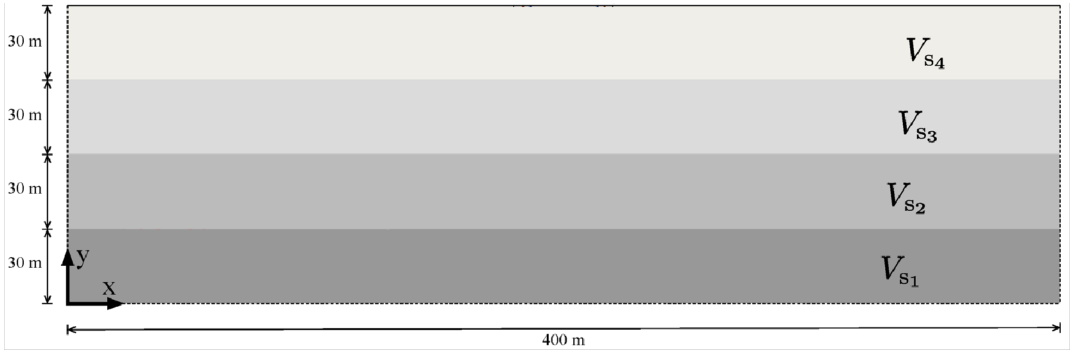

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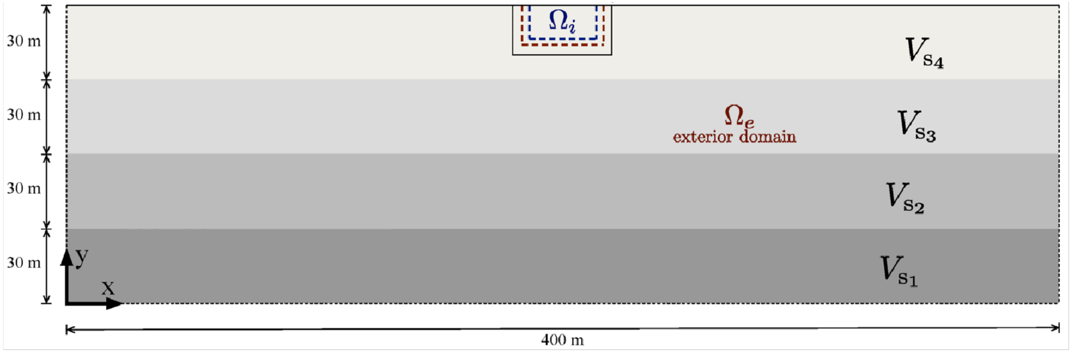

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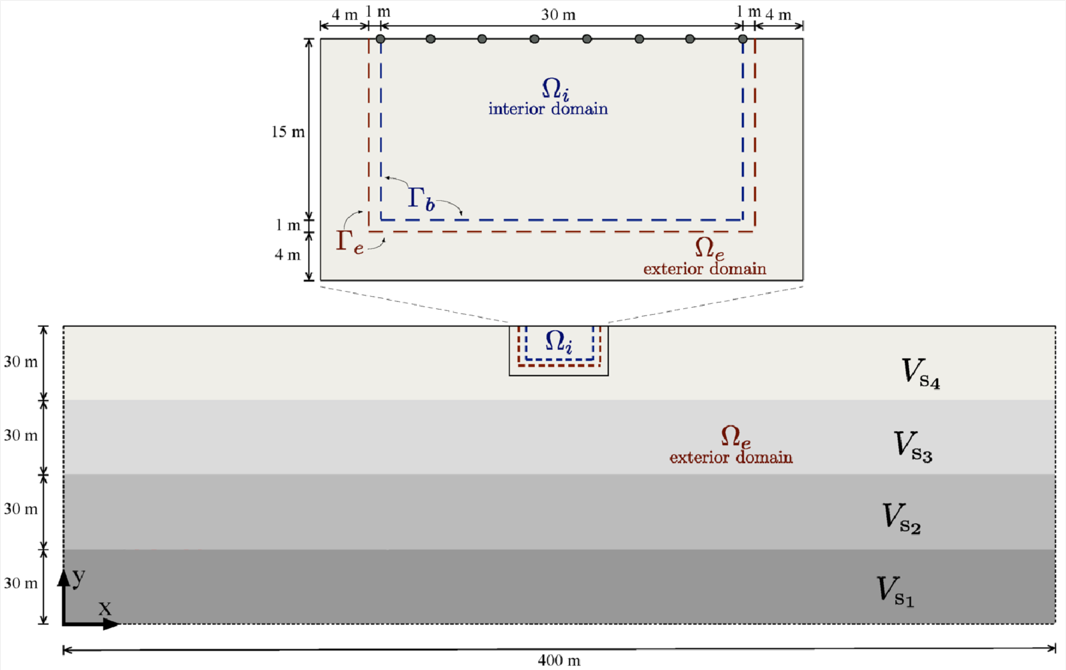
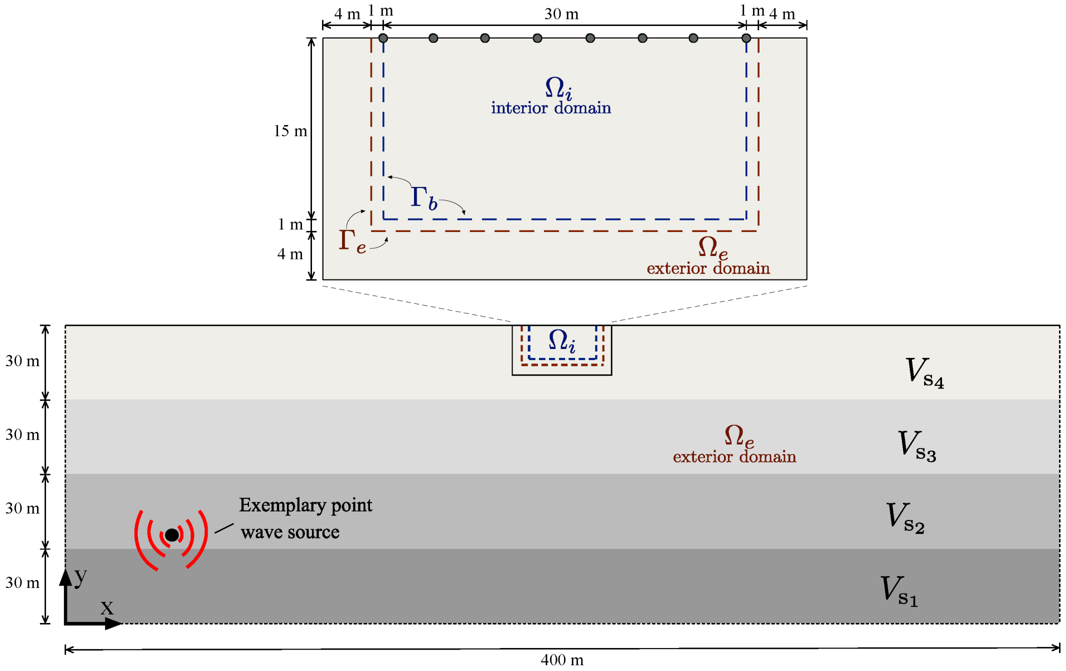


SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE



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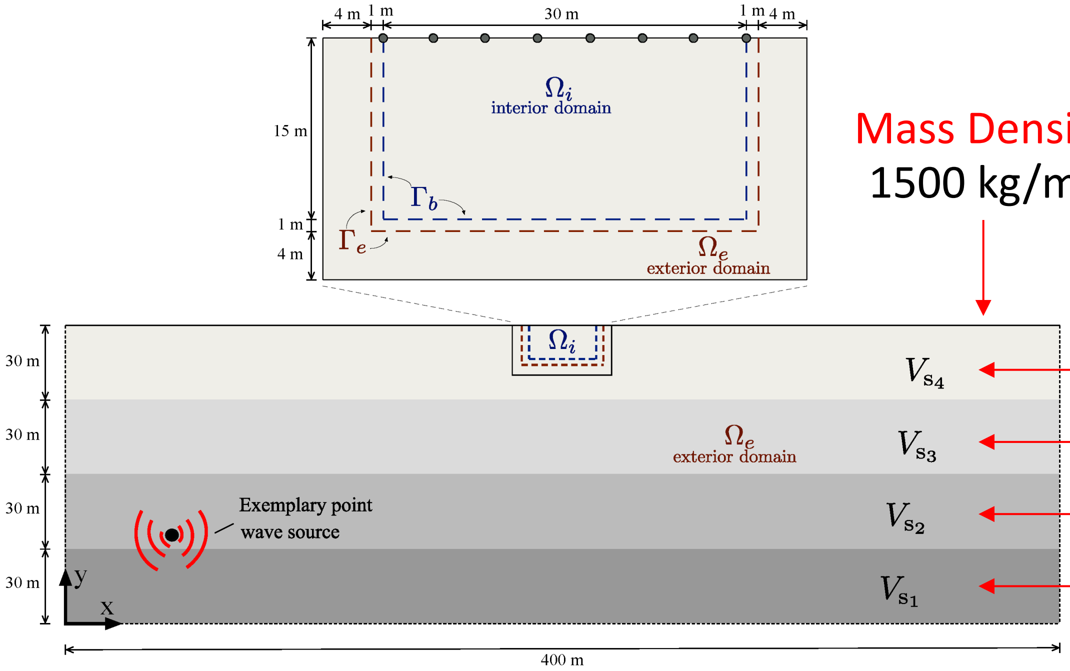


Mass Density
1500 kg/m3

Shear Wave Velocities

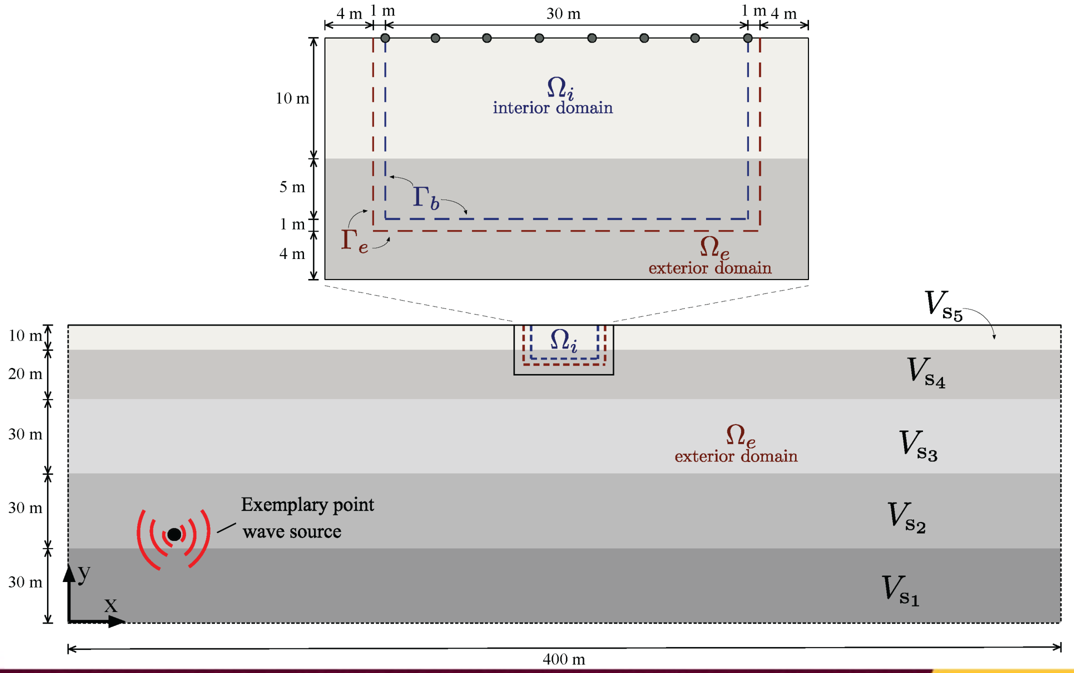
200 m/s

300 m/s

1500 m/s

1800 m/s

SITE PROFILE 2
HETEROGENEOUS SOIL PROFILE



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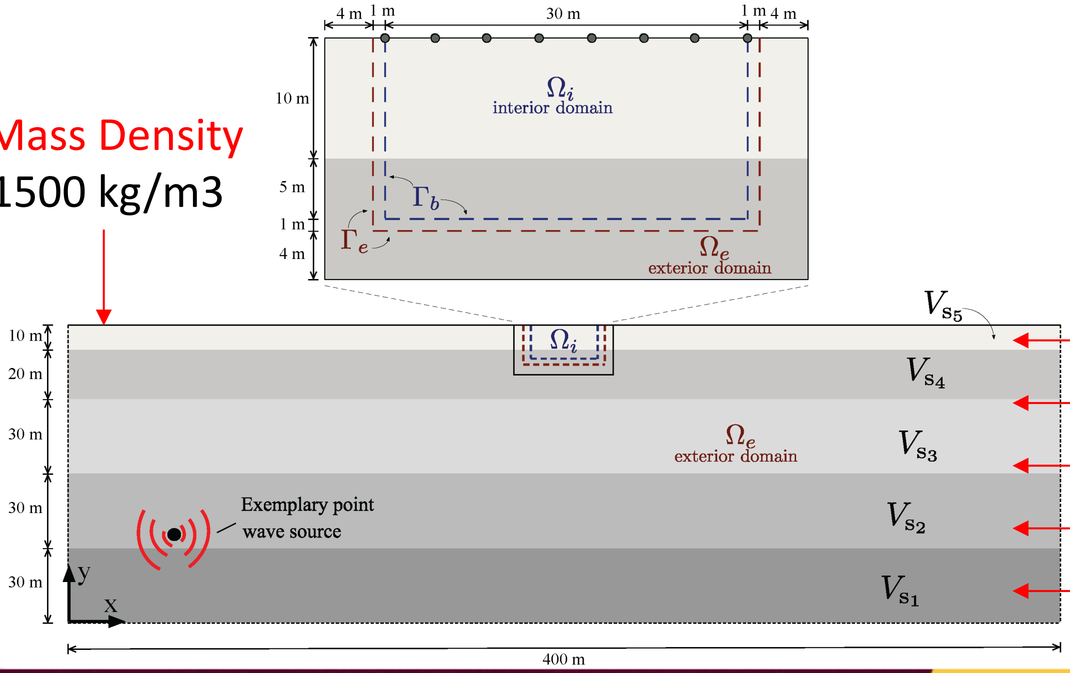
1500 kg/m3



Shear Wave Velocities

200 m/s

250 m/s

300 m/s

1500 m/s

1800 m/s

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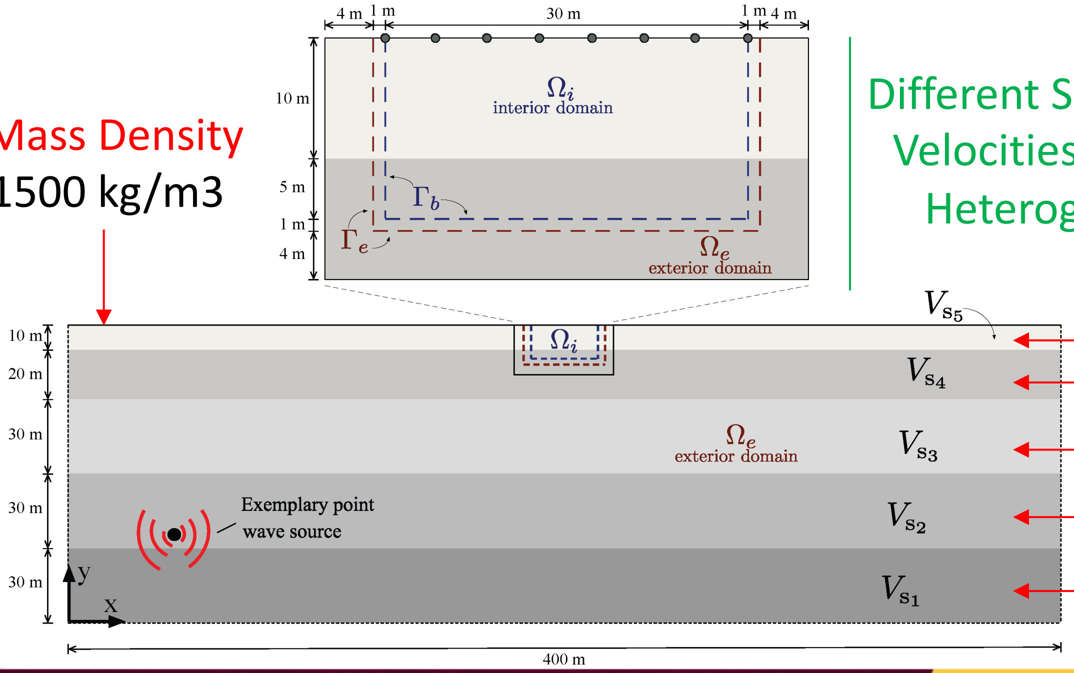


Different Shear Wave Velocities Makes It Heterogeneous

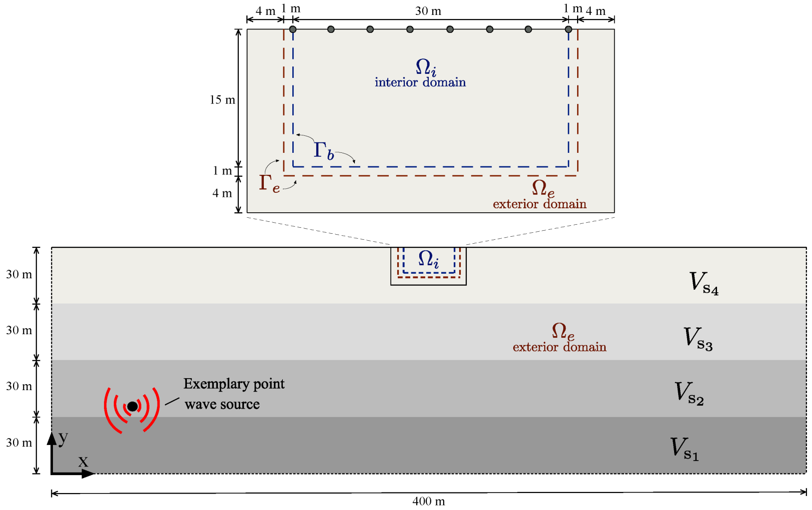
Shear Wave Velocities

200 m/s
250 m/s
300 m/s
1500 m/s
1800 m/s

SYNTHETIC DATA GENERATION

WAVE SOURCE

- Randomly chooses between 1- or 2-point wave sources (N_p)
- Randomly selects parameters for each source:
  - start time (t_p)
  - peak amplitude (A_{peak})
  - frequency (f)
  - location (x_s, y_s)



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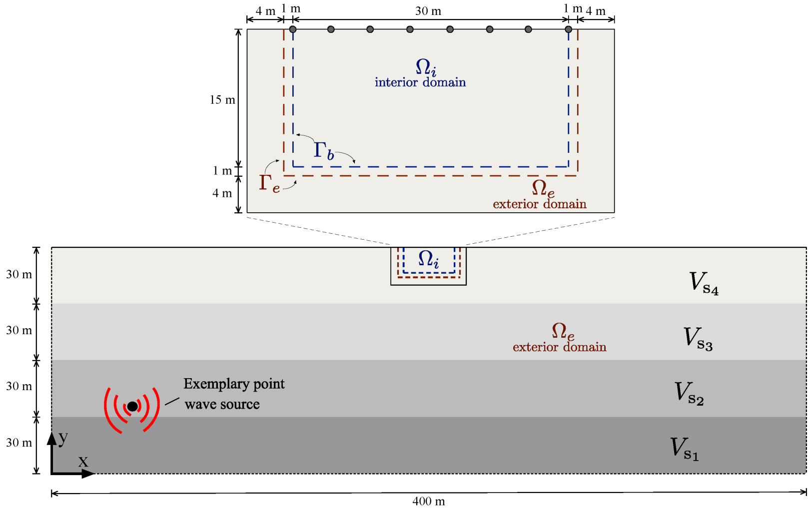

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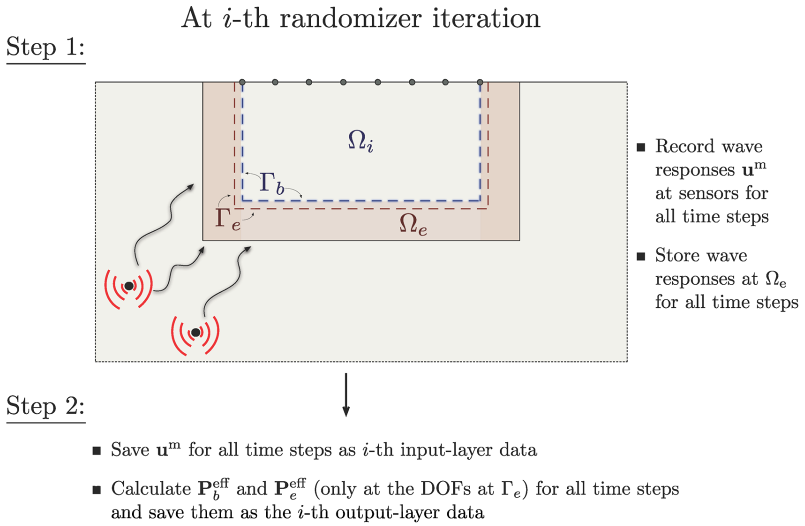
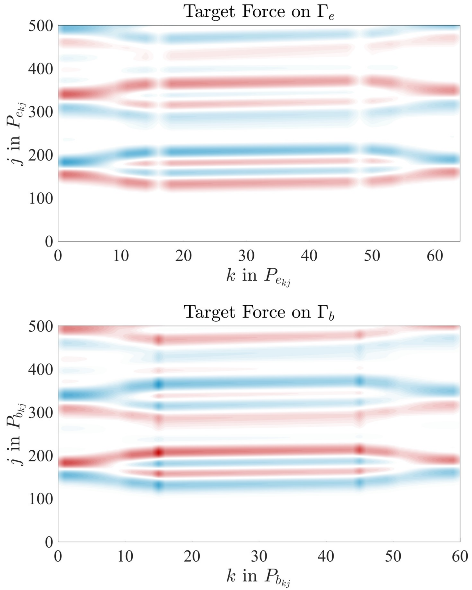
FORWARD SOLVER

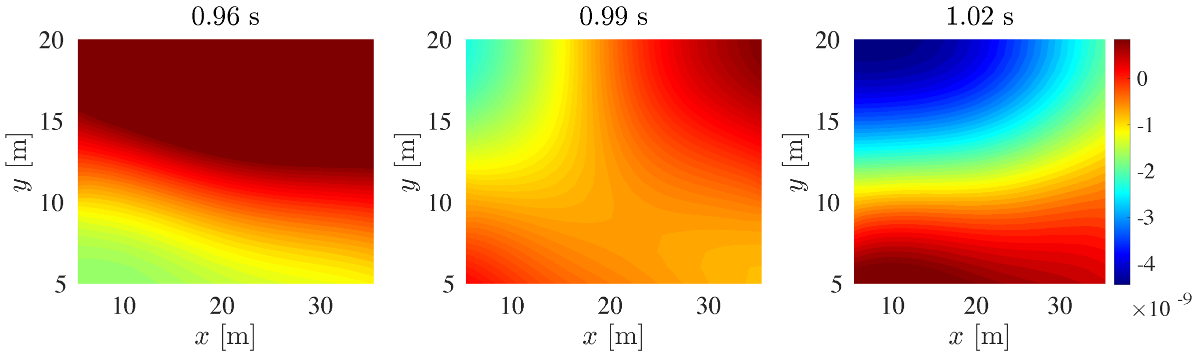
- Solves the 2D wave propagation problem in an enlarged domain using the randomly generated source parameters
- Saves displacement data at sensor locations on the surface as input-layer features
- Saves effective nodal forces on DRM layer boundaries (Γ_b and Γ_e) as output-layer features
- Repeats this process 20,000 times to generate a large dataset for training and evaluating the CNN model



FORWARD SOLVER...

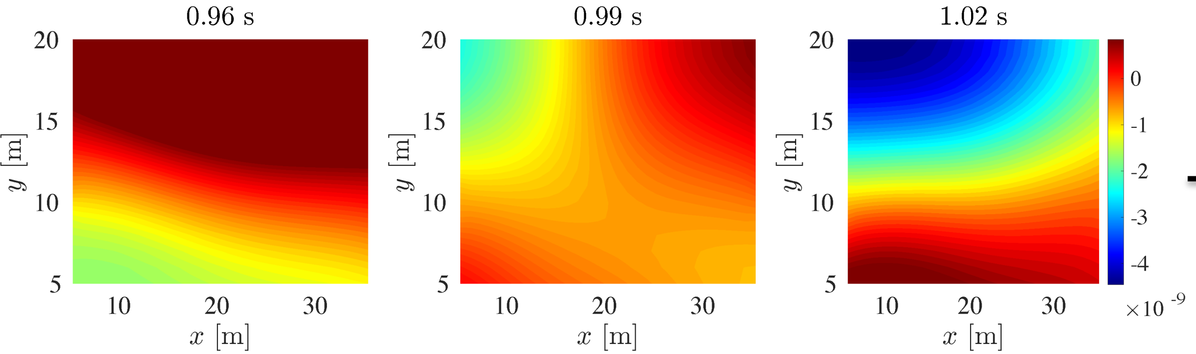


INDUCED DRM FORCES



DISPLACEMENTS IN INTERIOR DOMAIN
AT THE SENSOR LOCATIONS
DUE TO THE Γ_e and Γ_b forces

USING MACHINE LEARNING...



DISPLACEMENTS IN INTERIOR DOMAIN
AT THE SENSOR LOCATIONS
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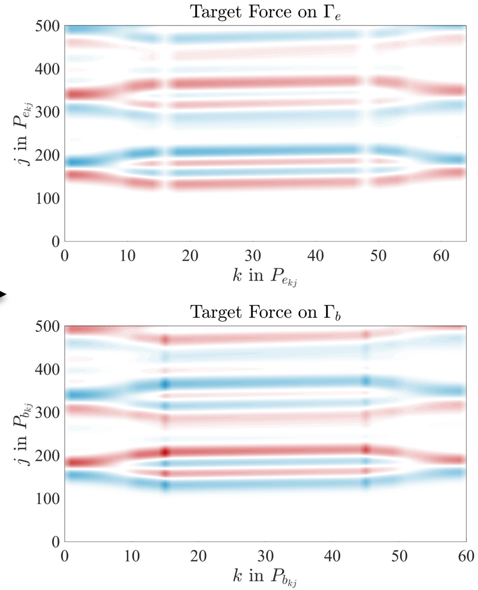

INDUCED DRM FORCES

CONVOLUTIONAL NEURAL NETWORK

WHY CNN?

- Automatic feature extraction for streamlined processing.
- Efficiently identifies prominent features automatically.
- Less computationally demanding than fully-connected layers.
- Preserves spatial data characteristics effectively.

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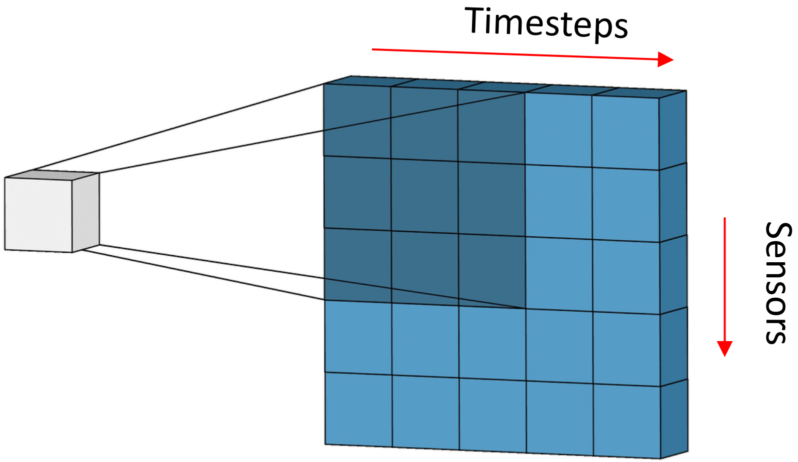
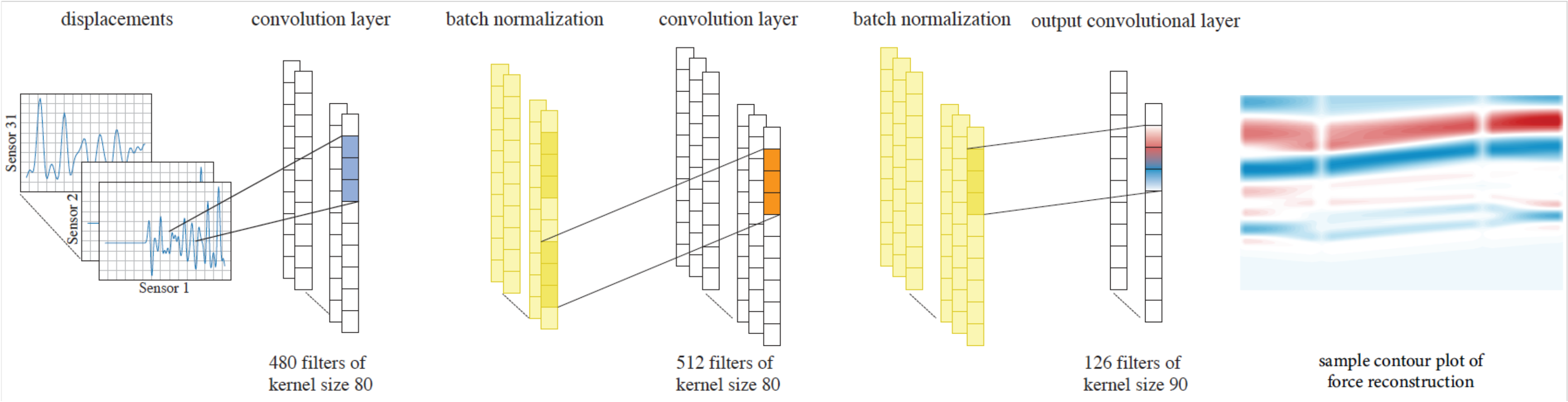
APPPLICATION TO OUR DATA

- Convolution enhances spatial data capture by operating on timestep values.
- CNNs provide automatic feature extraction, strengthening their selection.
- CNNs enable superior and efficient processing with massive data sizes.



CNN ARCHITECTURE



NUMERICAL RESULTS

ERROR METRICS

- Mean Absolute Error = $|Target - Predicted|$
- Mean Squared Error = $(Target - Predicted)^2$
- Sample Percent Error = $\left|\frac{Target - Predicted}{Target}\right| \times 100\%$

SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE

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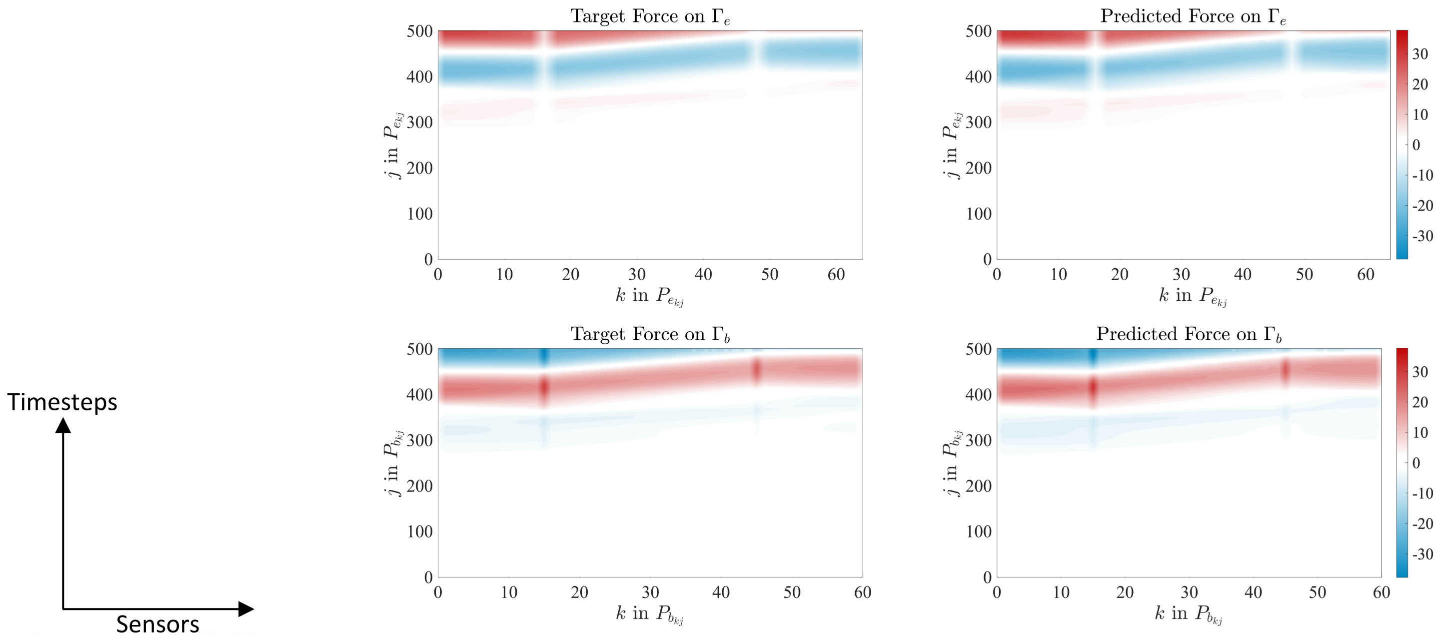
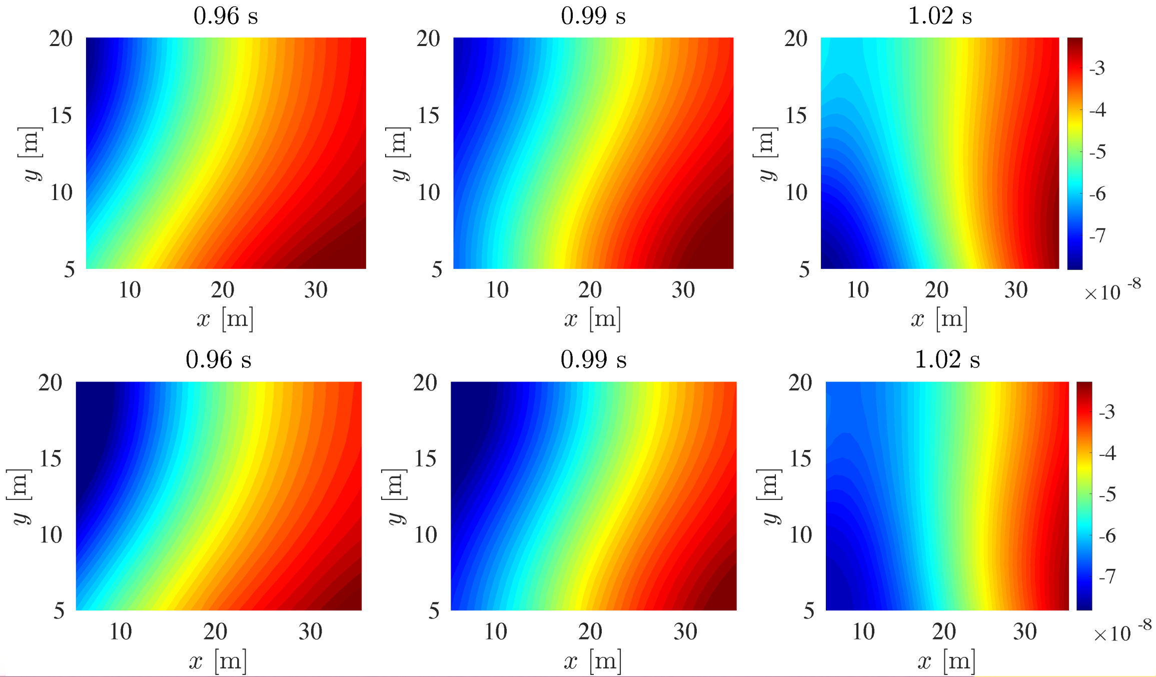
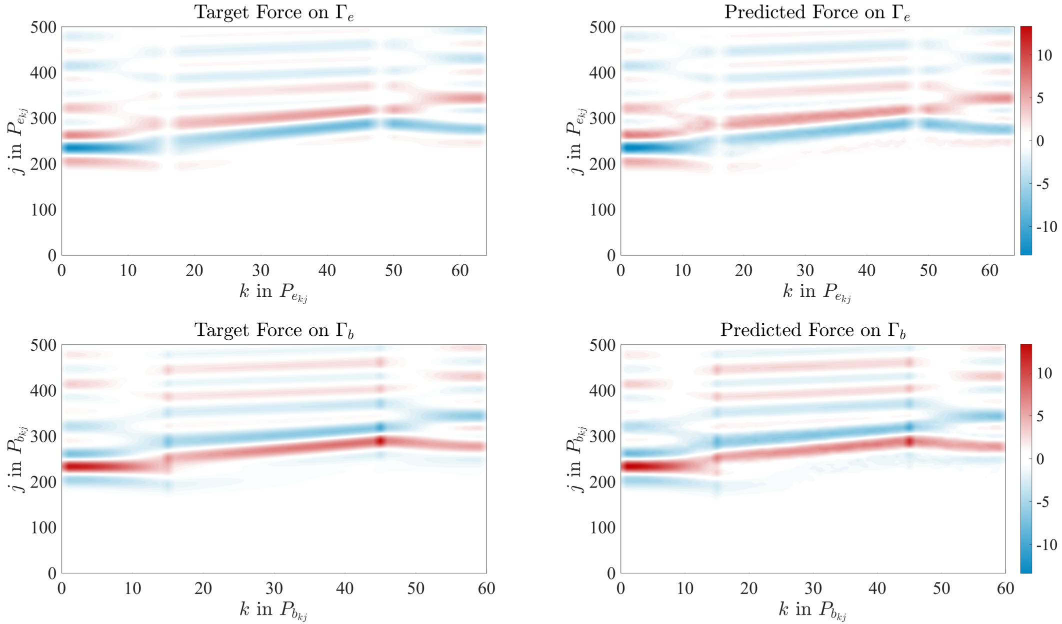
HOMOGENEOUS SOIL PROFILE
BEST FORCE PREDICTION (0.73%)

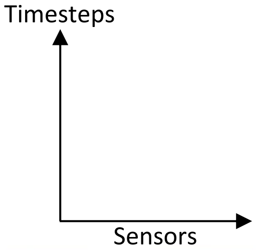


SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (0.69%)

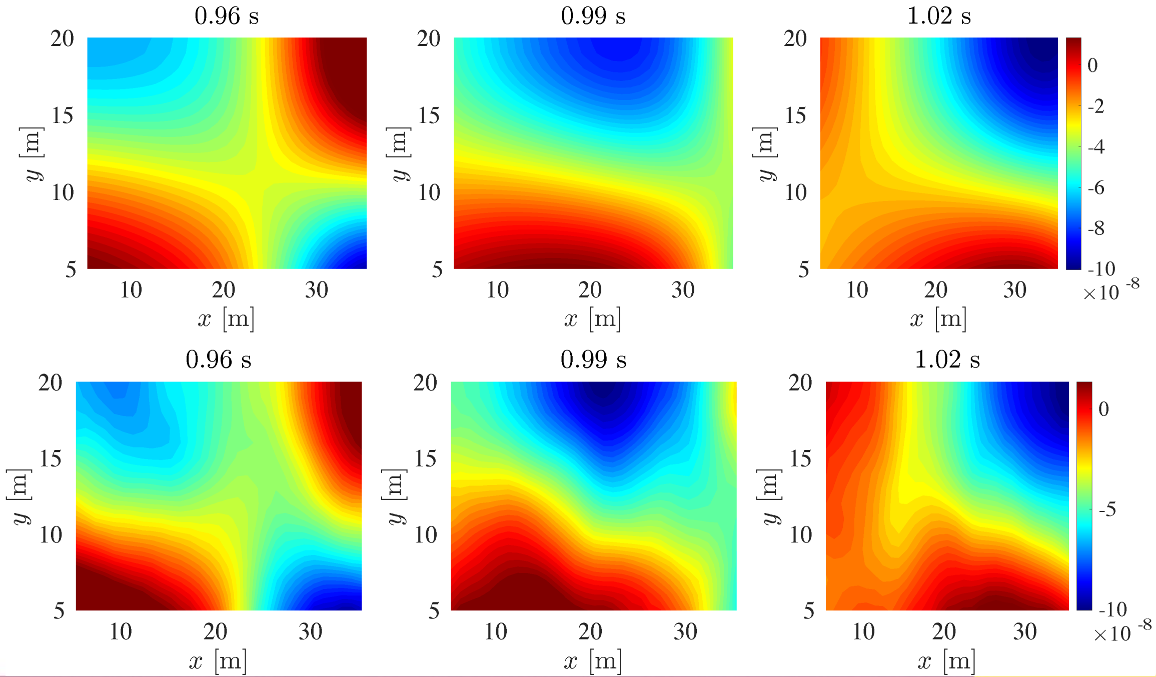


SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE
50TH PERCENTILE FORCE PREDICTION (2.01%)

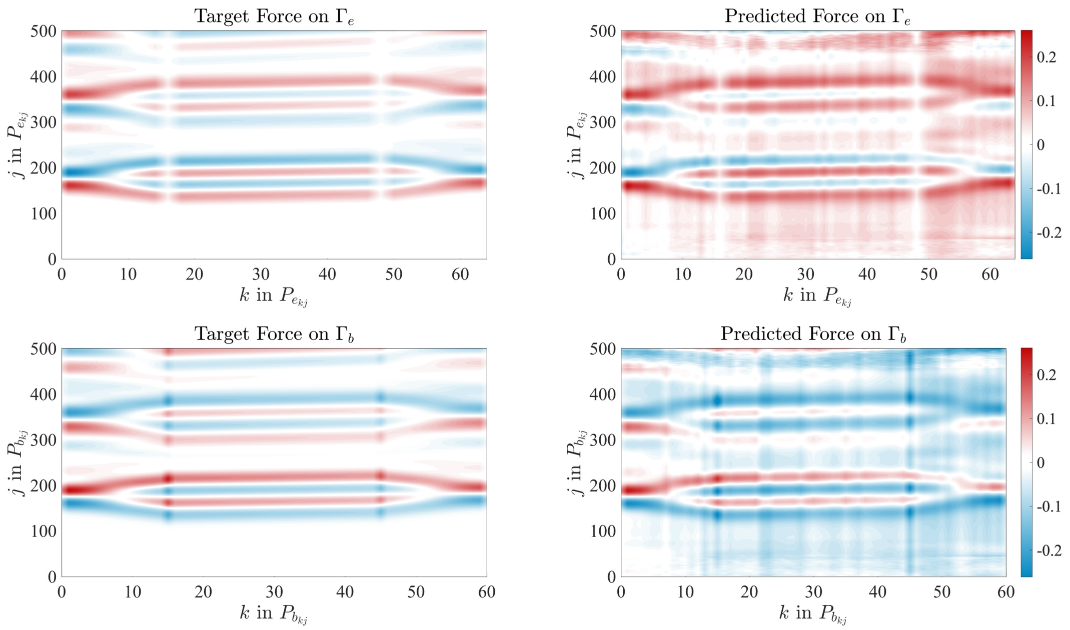


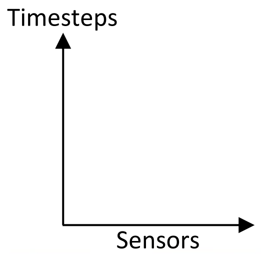


SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (1.58%)

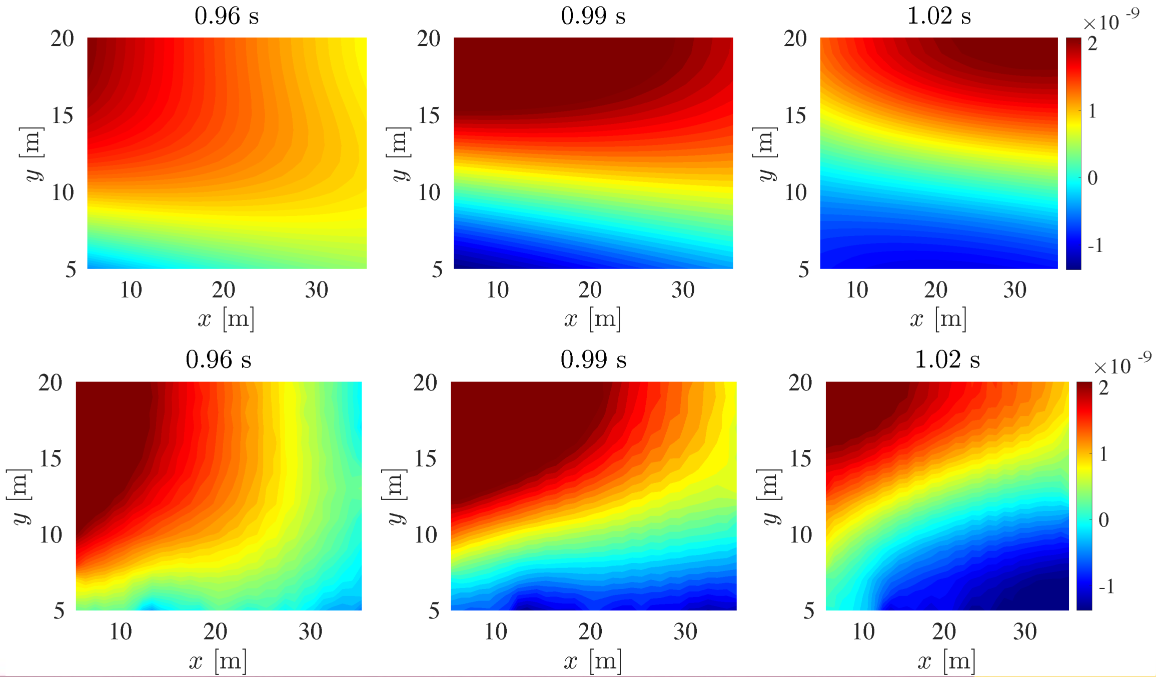


SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE
WORST FORCE PREDICTION (35.32%)



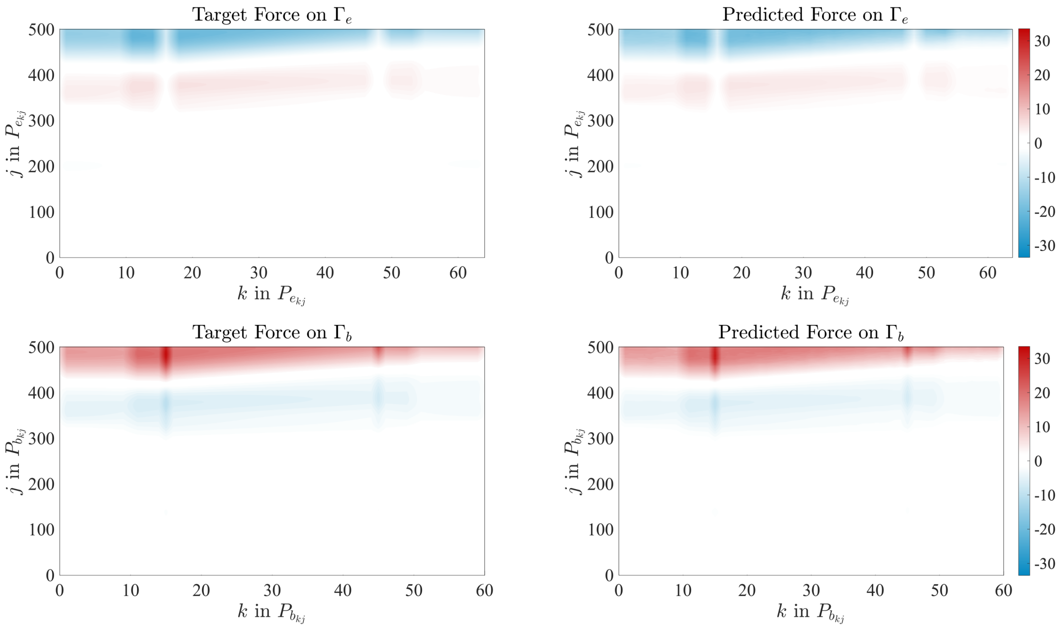


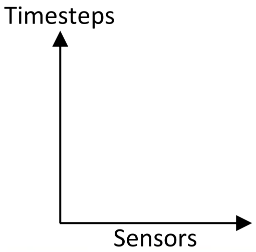
SITE PROFILE 1
HOMOGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (18.86%)



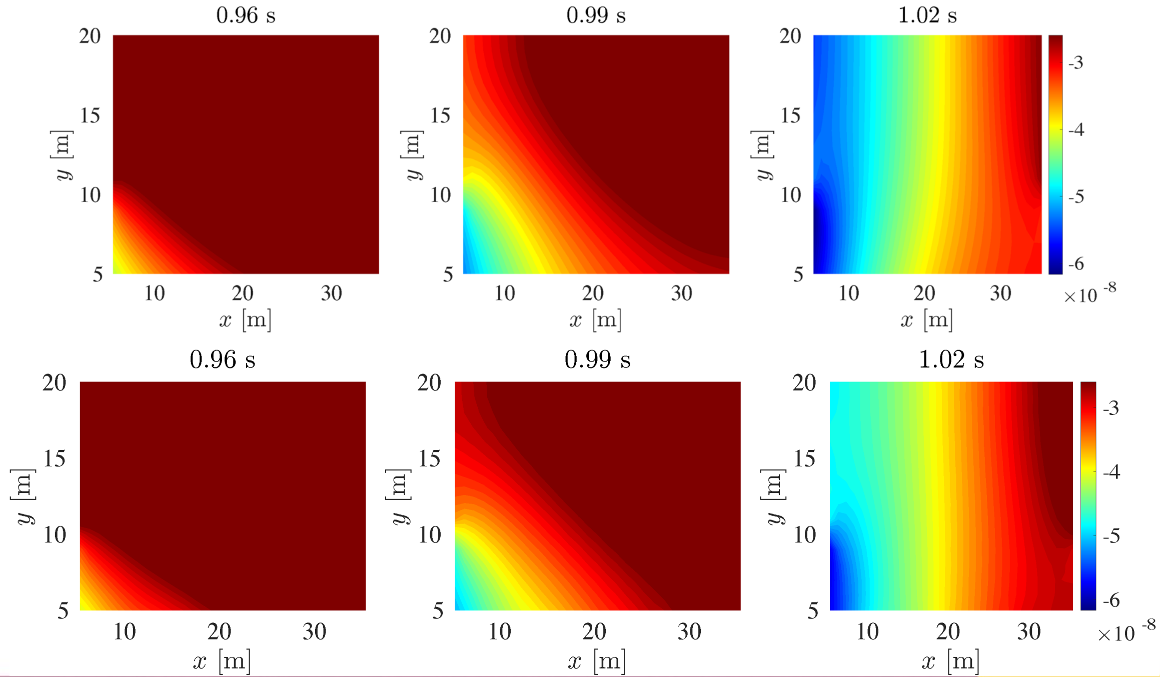
SITE PROFILE 2
HETEROGENEOUS SOIL PROFILE

SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
BEST FORCE PREDICTION (0.22%)

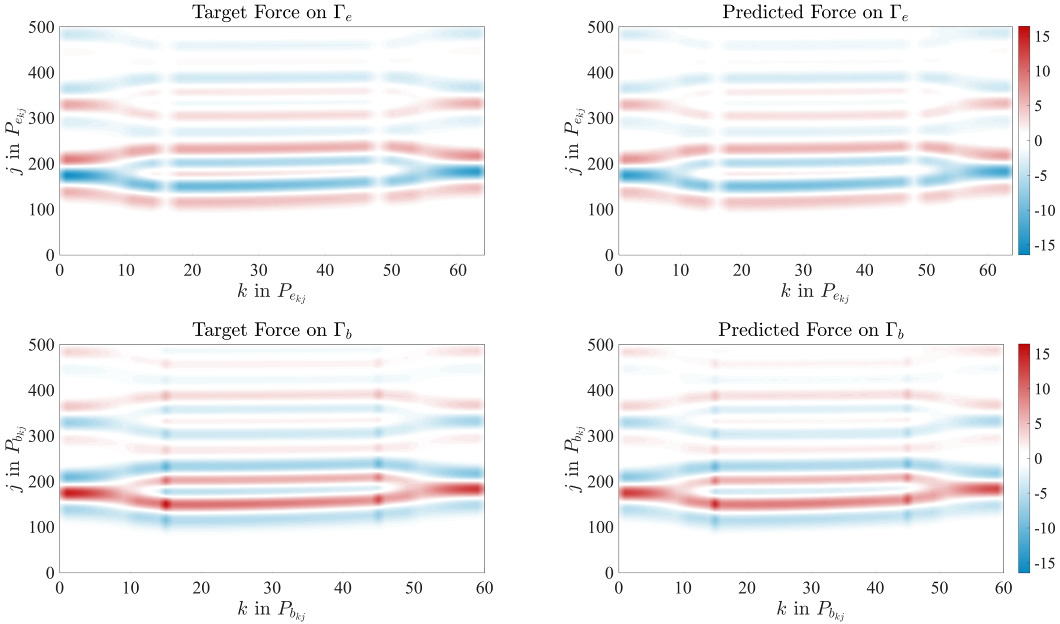


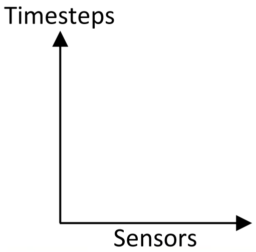


SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (0.20%)

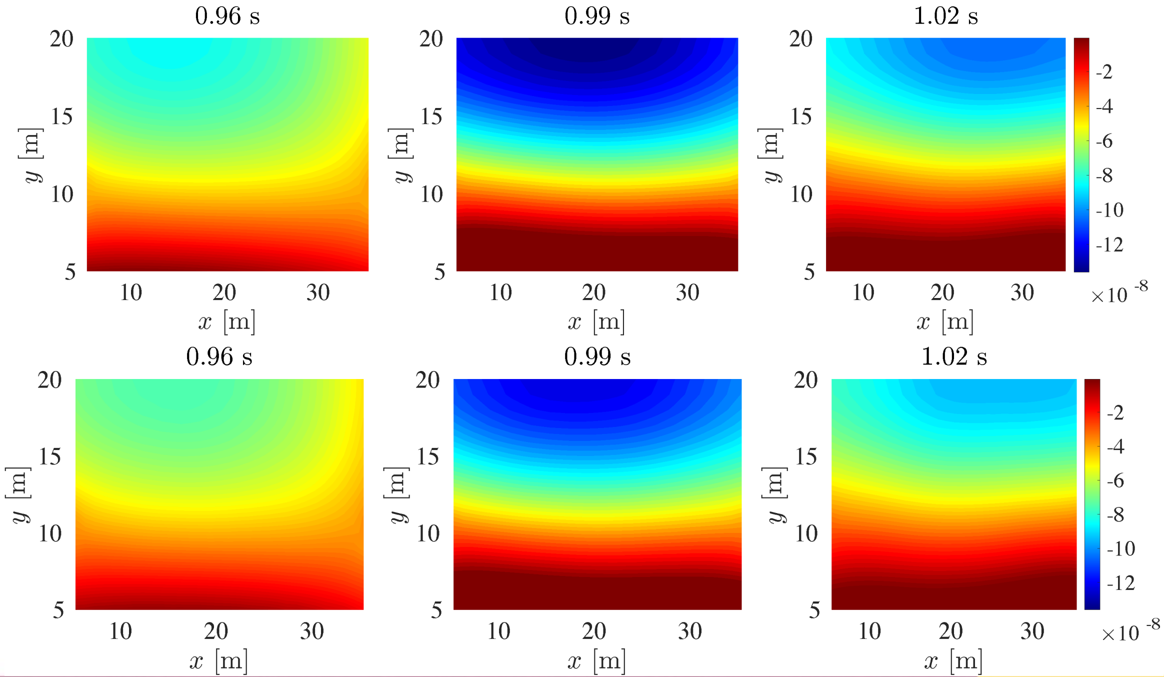


SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
50TH PERCENTILE FORCE PREDICTION (1.12%)

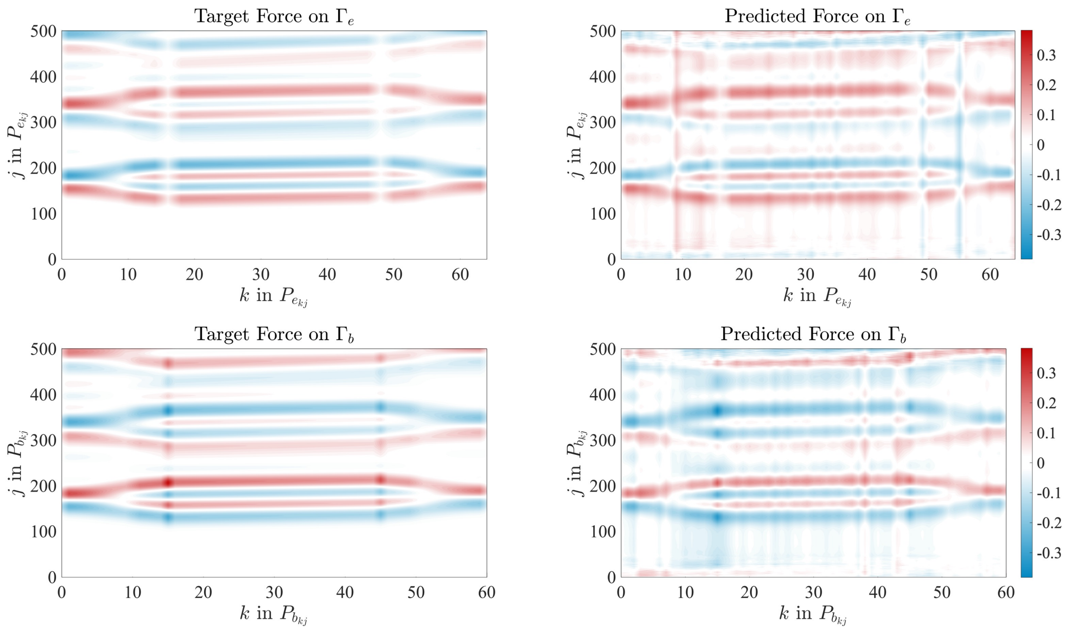


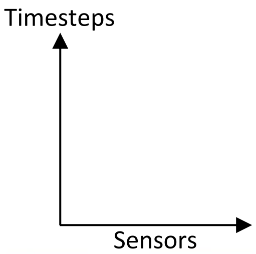


SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (0.82%)

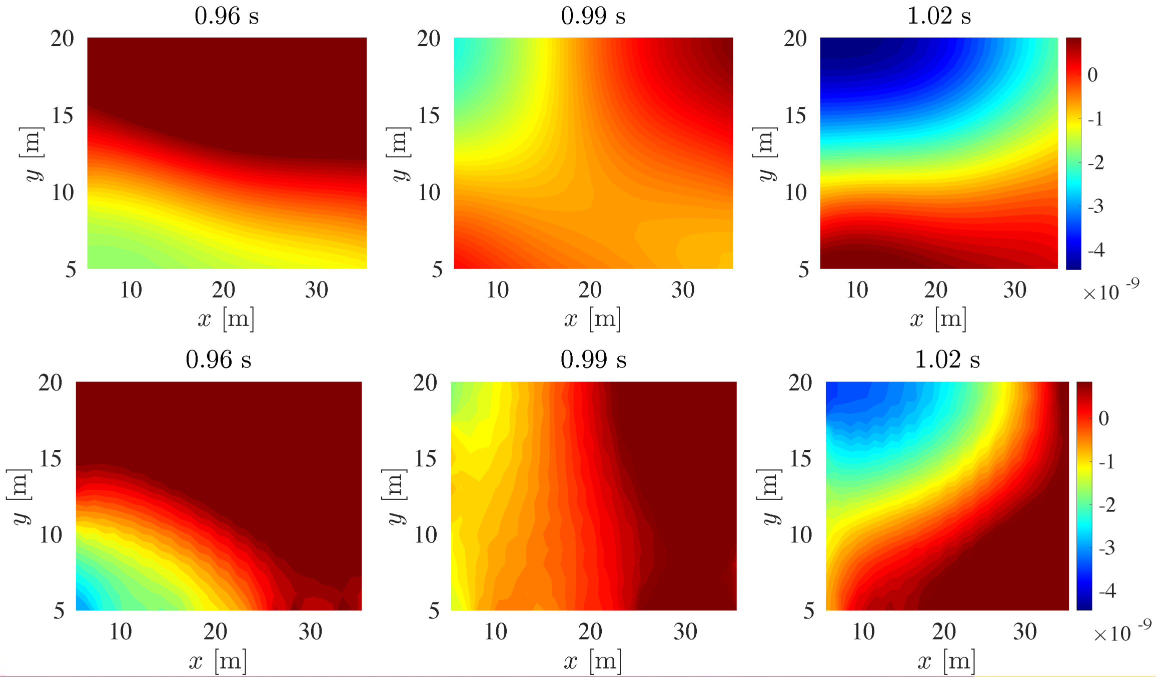


SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
WORST FORCE PREDICTION (24.52%)

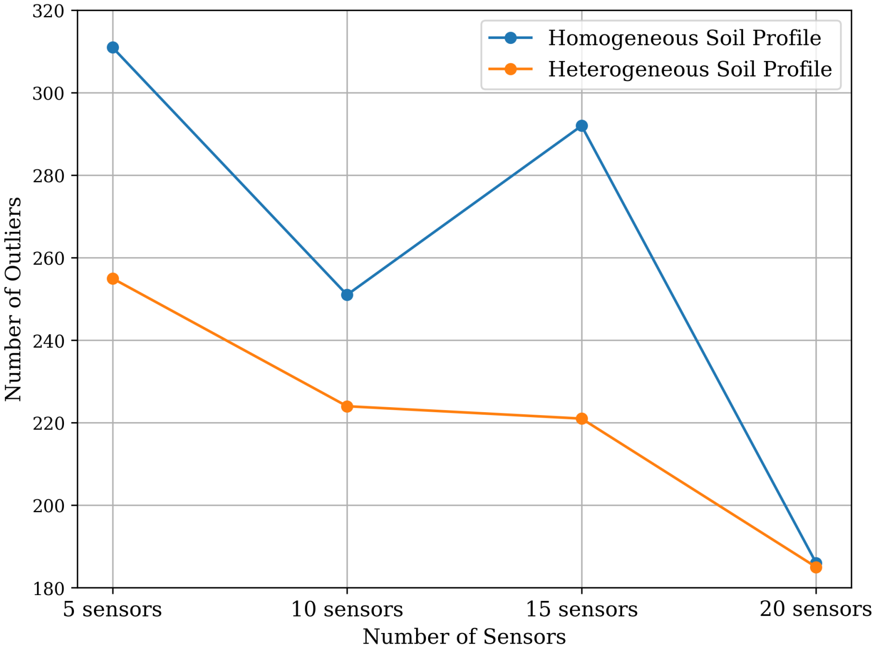




SITE PROFILE 1
HETEROGENEOUS SOIL PROFILE
CORRESPONDING RESPONSE PREDICTION (29.79%)

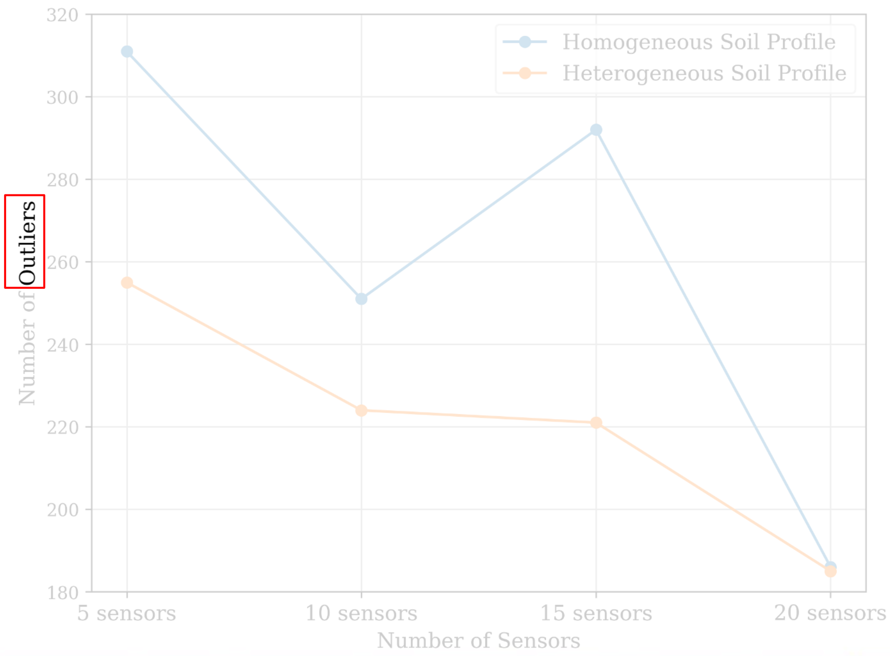


PARAMETRIC STUDY
NUMBER OF SENSORS



PARAMETRIC STUDY
NUMBER OF SENSORS

Outlier
In this case, it refers to a particular sample data that deviates significantly from the normal trend of data used to train the neural network.



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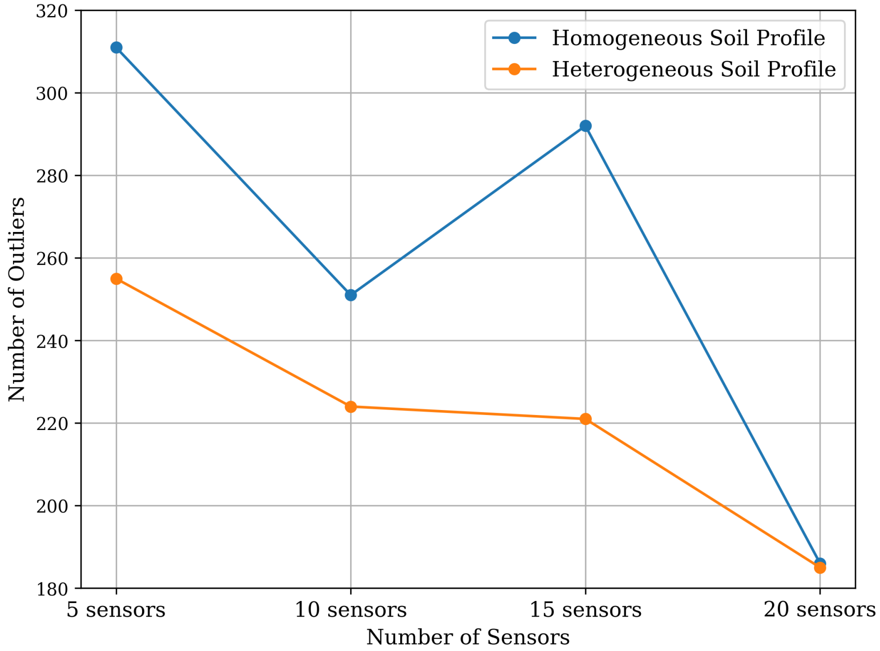
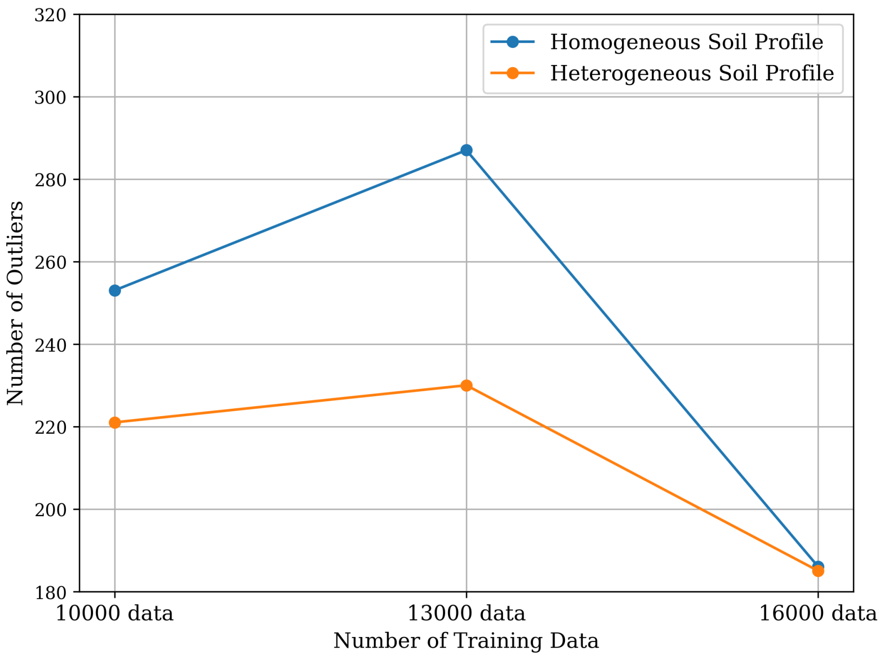


PARAMETRIC STUDY
NUMBER OF TRAINING DATA



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DISCUSSION

SOURCES OF ERROR

- Effective in predicting active areas but struggles with near-zero displacement values.
- Heterogeneous soil profiles feature complex 5-layer structures, introducing uncertainty versus simpler homogeneous profiles.

DISCUSSION

- Our CNN-based approach accurately identifies seismic forces at DRM layer boundaries in diverse soil profiles, expediting ground motion reconstruction from measured signals at the sensors.
- The CNN model surpasses PDE-constrained optimization in processing time, requiring only 0.15 seconds per test sample versus approximately an hour for the optimization method.

FUTURE DIRECTIONS

- Expanding the approach to tackle complex three-dimensional soil profiles and wave propagation scenarios.
- Investigating uncertainty quantification of the CNN model.

REFERENCES

- Akcelik, Volkan, George Biros, and Omar Ghattas. "Parallel multiscale Gauss-Newton-Krylov methods for inverse wave propagation." *SC'02: Proceedings of the 2002 ACM/IEEE Conference on Supercomputing*. IEEE, 2002.
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- Maharjan, Shashwat, Bruno Guidio, and Chanseok Jeong. "Convolutional neural network for identifying effective seismic force at a DRM layer for rapid reconstruction of SH ground motions." *Earthquake Engineering & Structural Dynamics* 53.2 (2024): 894-923.

QUESTIONS?