Sandia National Laboratories

Using Deep Learning Models to Characterize Subsurface Physical Parameters at Modeled Underground Chemical Explosion Sources

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Motivation

- Physical characteristics at the source affect discriminants as well as source time function (STF) and yield estimates
- Machine learning (ML) can potentially learn these near-source characteristics from seismic waveforms/spectra

Fig. 1: Local discriminant thresholds are affected by hard vs. soft rock

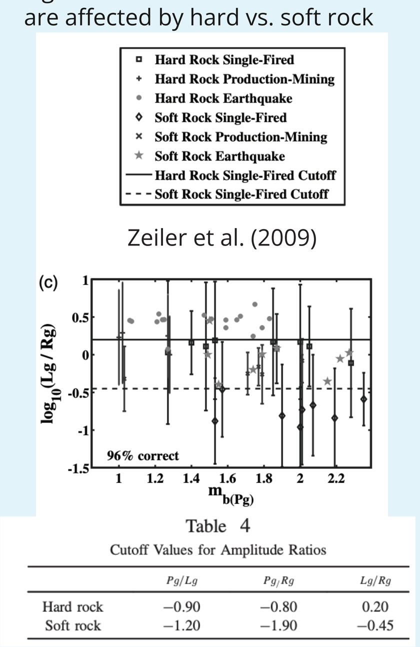


Fig. 2: STFs are affected by ground material and source emplacement

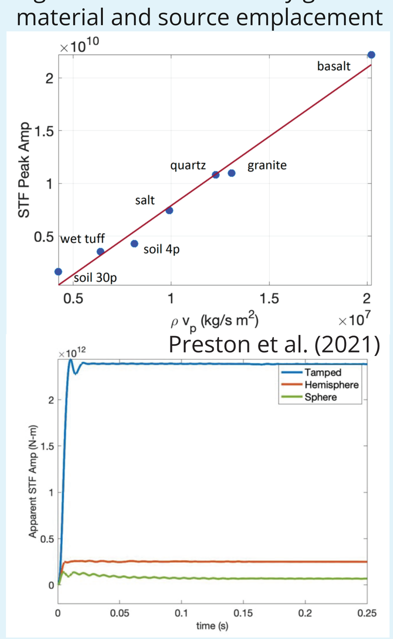


Fig. 3: ML can estimate depth of burial from far-field waveforms

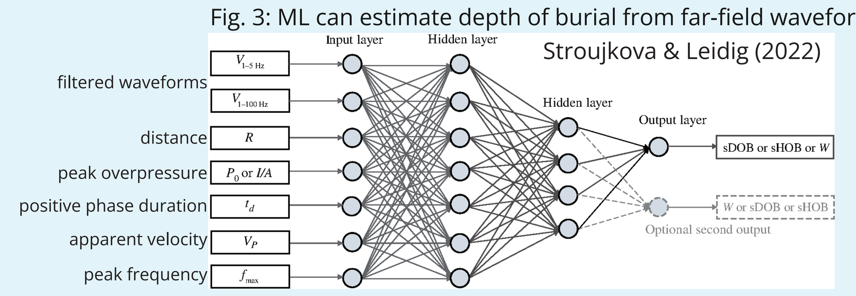
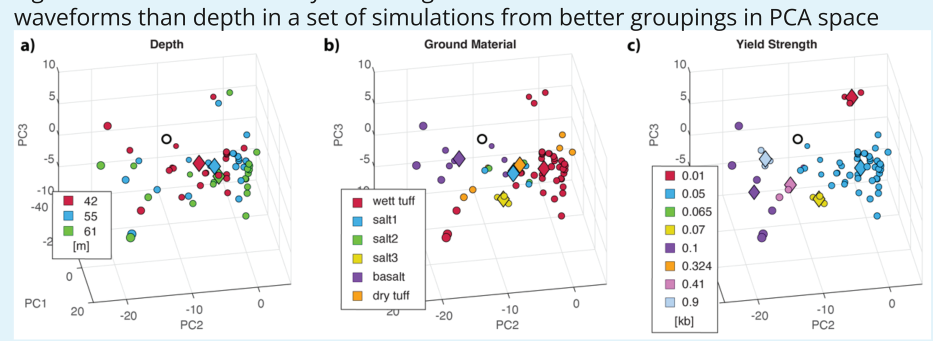


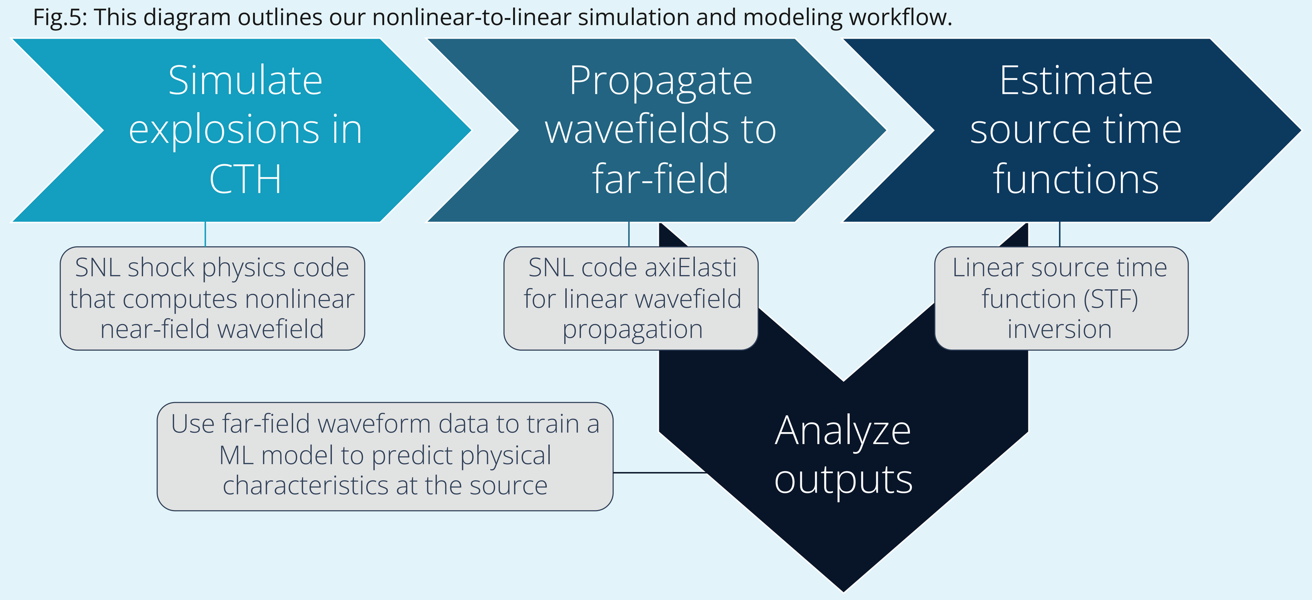
Fig. 4: Ground material and yield strength were shown to be more influential to far-field waveforms than depth in a set of simulations from better groupings in PCA space



Underground Explosion Simulations

- We use a nonlinear-to-linear modeling scheme to simulate buried explosions and their resultant far-field waveforms
- We vary the properties of a homogeneous half-space earth model for the same size source, such as:
  - ground material
  - yield strength
  - fracture pressure
  - source depth
  - Poisson's ratio
  - strength model and model parameters

Fig.5: This diagram outlines our nonlinear-to-linear simulation and modeling workflow.



Far-Field Waveform Dataset

- We generated a preliminary (and growing) dataset consisting of far-field waveforms recording identical chemical explosion sources in a variety of subsurface models
- We will look at 71 simulations and focus on ground material and emplacement

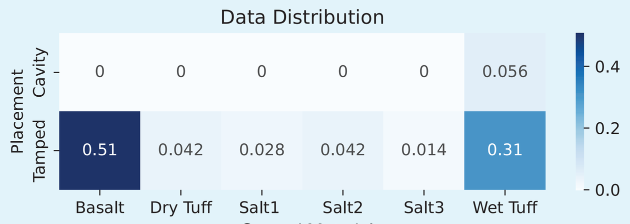


Fig.6: Our distribution of placement and ground material in simulated waveforms data is not balanced.

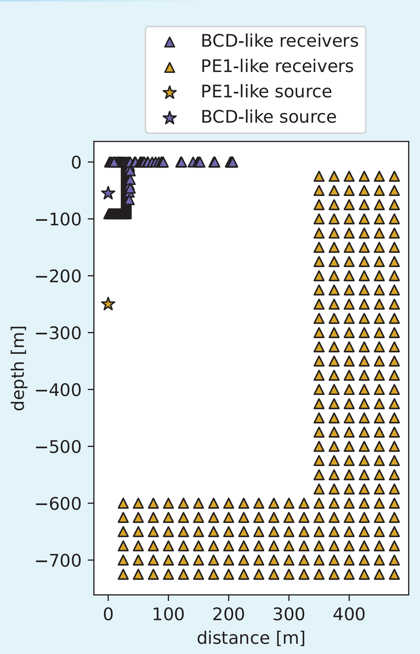


Fig.7: We have two types of simulations with different source depths and receiver locations based on two different experiments.

- 2-channel waveforms record vertical and radial velocity (axi-symmetric simulations)
- Waveforms are filtered to 0.001 to 4,500 Hz and resampled to a sample rate of 10,000 Hz
- We output discrete frequencies to 750 Hz using a fast Fourier transform

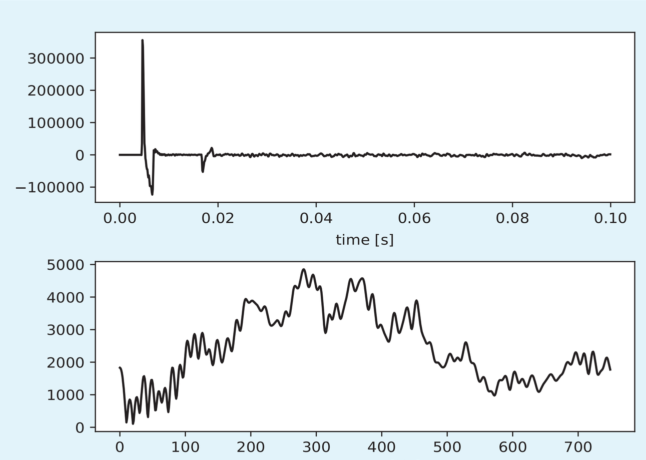


Fig.8: The top panel shows the filtered and resampled far-field waveform from a BCD-like simulation and the bottom panel shows the spectra to 750 Hz that will be used for ML training.

Deep Learning Multi-Output Classification

We train a fully connected neural network (FCNN) to classify emplacement and ground material

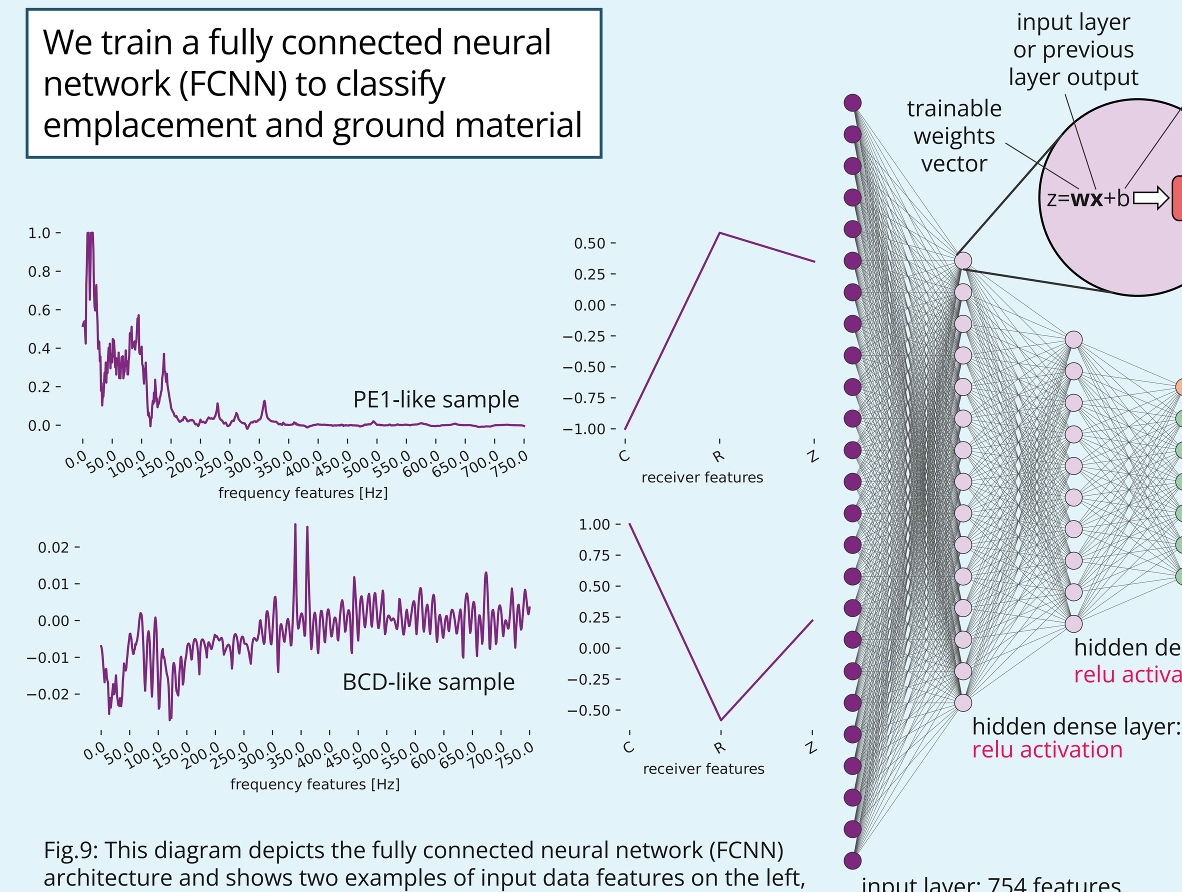


Fig.9: This diagram depicts the fully connected neural network (FCNN) architecture and shows two examples of input data features on the left, which are demeaned and normalized frequencies and receiver channel and location.

Activation functions

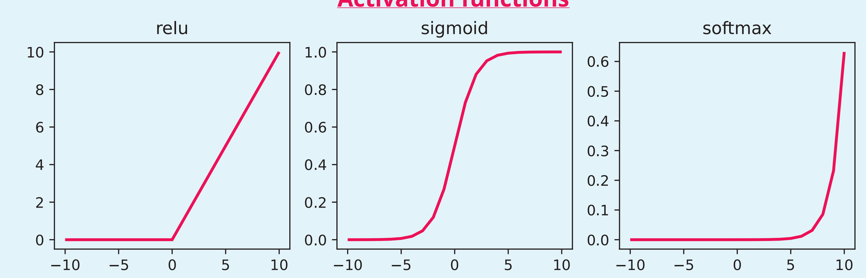


Fig.10: These plots show the activation functions used in the FCNN.

Loss functions

binary cross-entropy loss function

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(p_i) + (1-y_i)\log(1-p_i)$$

number of samples; true class; class probability

categorical cross-entropy loss function

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(p_{ij})$$

number of classes

- We split the input data into a train and validation set 70/30 (shuffled by individual spectra, not simulation cases)
- We use a batch size of 200 and train for 80 epochs
- The loss weight for the ground material and emplacement is 2 and 1, respectively
- training takes ~4 min. on an NVIDIA V100S-4Q 4 GiB GPU

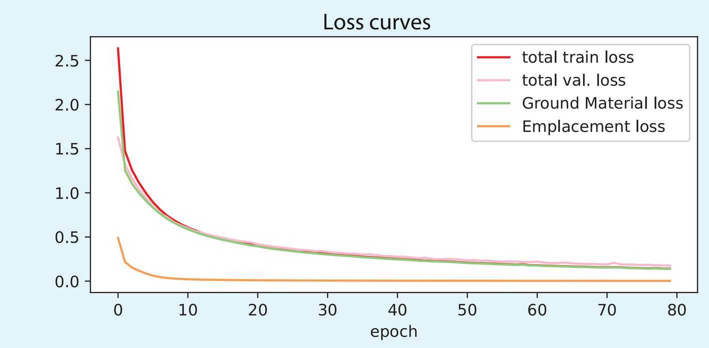


Fig.11: This plot shows the loss over epochs during training, with total train loss in red, total validation loss in pink, ground material train loss in green and emplacement train loss in orange.

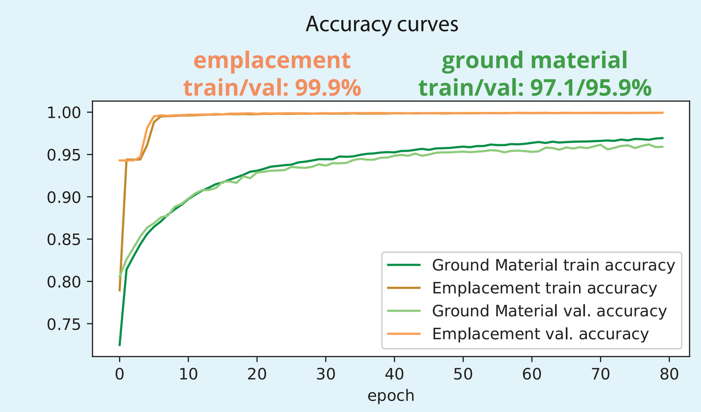


Fig.12: This plot shows the accuracy over epochs during training, with ground material in greens, emplacement in oranges, train in darker colors, and validation in lighter colors.

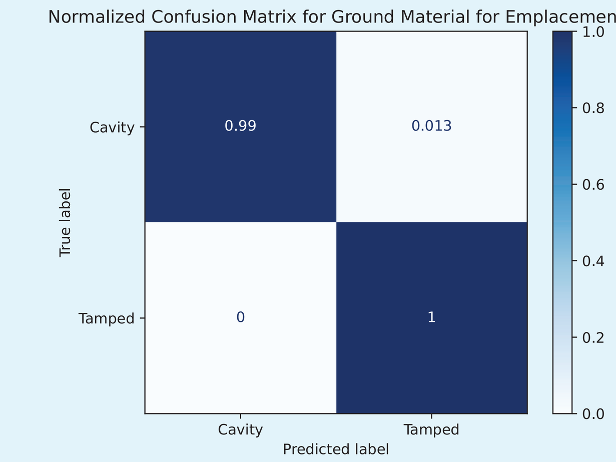


Fig.13: This plot shows a confusion matrix showing the emplacement class accuracy by class, normalized by true class (rows).

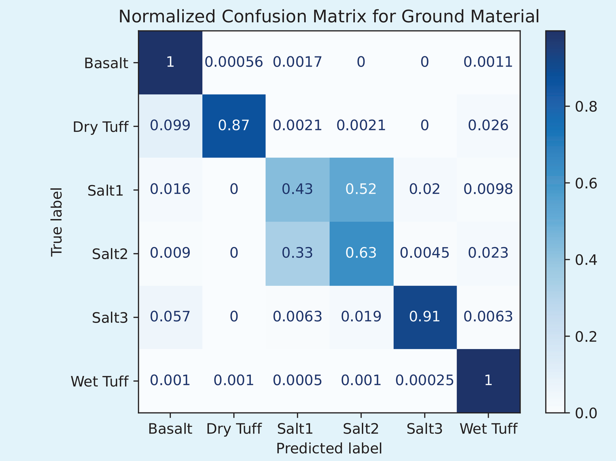


Fig.14: This plot shows a confusion matrix showing the ground material class accuracy by class, normalized by true class (rows)

Sensitivity Analysis

- Leveraging the differentiability of the FCNN architecture, we can compute the Jacobian for a set of input samples and calculate the sensitivities of outputs to inputs
- We use the NeuralSens package (Pizarroso et al., 2022)
- This is a good tool for better understanding and trusting the ML model and evaluating the important data features within a dataset (not necessarily generalizable yet)
- We see differences in input feature utilization for classifying emplacement vs. ground material
- There is little reliance on higher frequencies (>350 Hz) nor receiver features

Sensitivity Metrics

	single neuron:	multiple neurons:
mean sensitivity:	$S_{ik}^{avg} = \frac{\sum_{j=1}^{N} s_{ik}\lvert_{x_j}}{N}$	$S_i^{avg} = \frac{\sum_{k=1}^{n} S_{ik}^{avg}}{n^L}$
sensitivity standard deviation:	$S_{ik}^{sd} = \sigma\left(s_{ik}\lvert_{x_j}\right); j \in 1,\dots,N$	$S_i^{sd} = \sqrt{\frac{\sum_{k=1}^{n}\left(\left(S_{ik}^{sd}\right)^2 + \left(S_{ik}^{avg} - S_i^{avg}\right)^2\right)}{n^L}}$
mean squared sensitivity:	$S_{ik}^{sq} = \sqrt{\frac{\sum_{j=1}^{N}\left(s_{ik}\lvert_{x_j}\right)^2}{N}}$	$S_i^{sq} = \left(\frac{\sum_{k=1}^{n}\sqrt{S_{ik}^{sq}}}{n^L}\right)^2$

i: input variable; N number of j samples; n: number of k output neurons

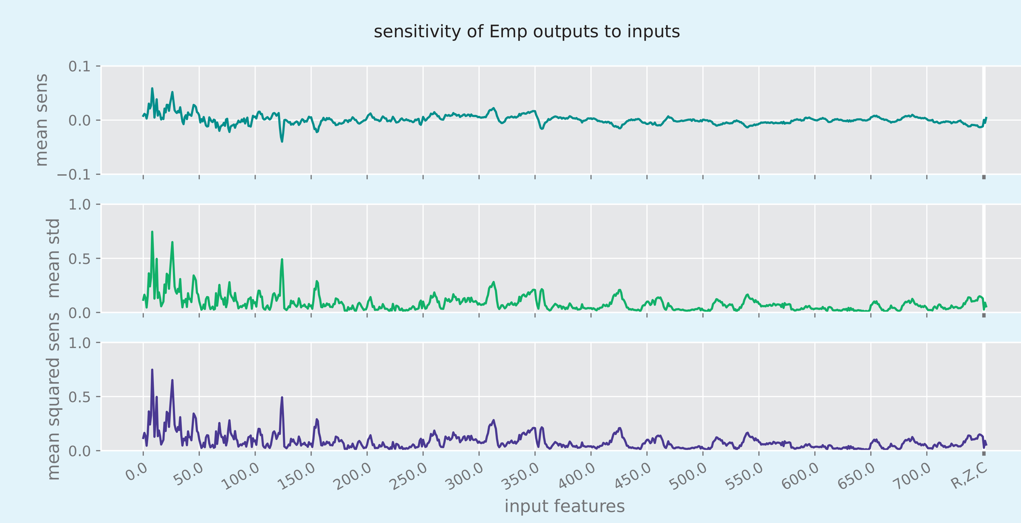


Fig.15: These plots show the mean (top), standard deviation (middle) and mean squared (bottom) sensitivity of the emplacement output neuron to all the input features.

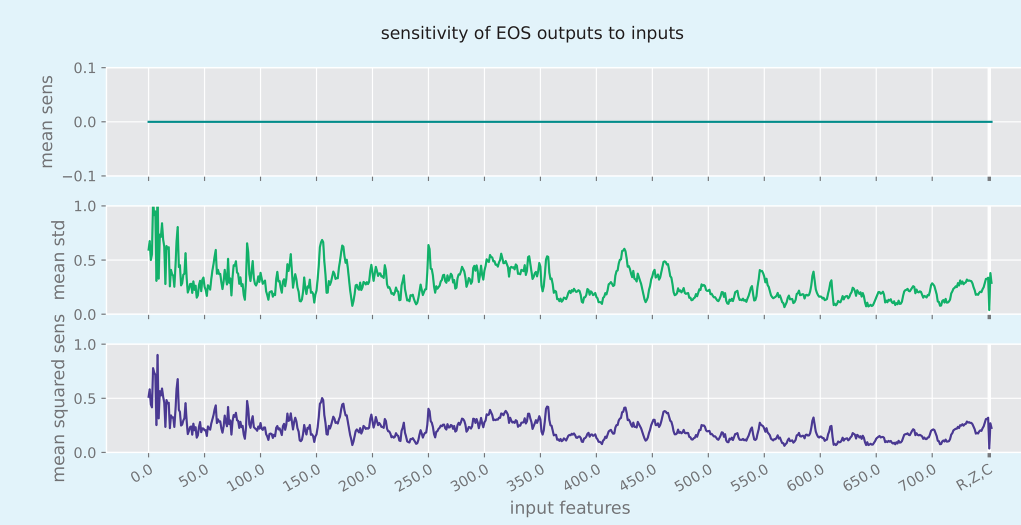


Fig.16: These plots show the mean (top), standard deviation (middle) and mean squared (bottom) sensitivity of the ground material output neuron to all the input features.

Acknowledgments

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