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Implicit elastic full waveform inversion: application to the Snowflake dataset

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Abstract

In 2018, the Consortium for Research in Elastic Wave Exploration Seismology executed a 3D walkaway-walkaround VSP survey, integrating both three-component accelerometers and DAS fibres. This investigation employs implicit full waveform inversion to determine the baseline model based on 2018's accelerometer data. This implicit elastic full waveform inversion harnesses neural networks to produce elastic models. The neural network's weights are optimized to generate refined elastic models that minimize data misfit, obviating the need for precise initial models. A comparison of inversion outcomes with well-log data is encouraging, and the alignment between synthetic and observed data further underscores its promise.

Introduction

The standout advantage of the IFWI method is its independence from precise initial models when computing FWI. Nevertheless, it does mandate the well-log data of the area under investigation. This data offers a comprehensive overview, particularly the mean and standard deviation of the desired elastic parameter. Such information ensures that the resulting elastic models yield values within an acceptable and plausible range. Also, inversion results' uncertainty quantification(UQ) is relatively cheap. In this MLP-based EIFWI, we can use the dropout method, which randomly mutes the weights in the neural network during the forward passing of the neural network, which can provide computationally efficient methods for sampling models around the inversion results.

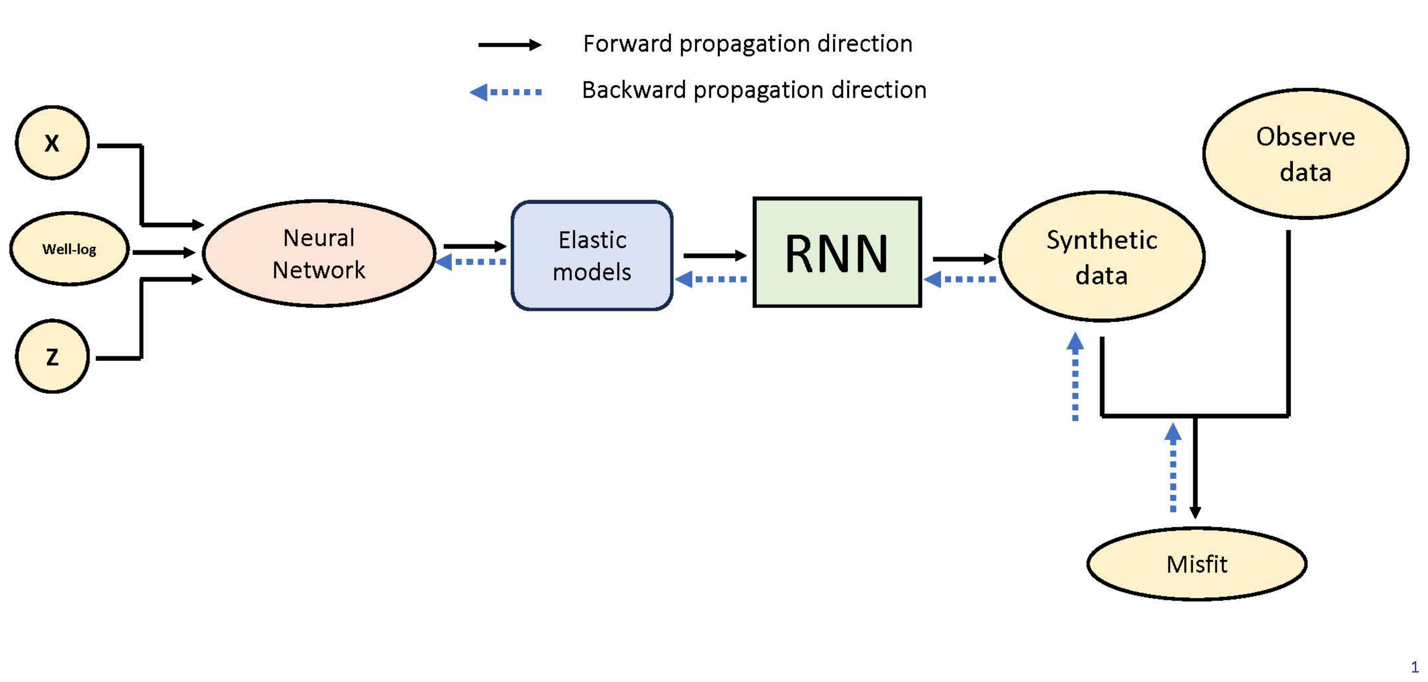

Figure 1: Training diagram of IFWI. Weights in the neural network are optimized to generate better elastic models to decrease the data misfit. The network's input is the coordinates of the x and z directions and the well log. The well-log will help the neural network generate elastic models within the reasonable value range. The generated elastic models will be sent to the RNN for synthetic data. Data misfit can be calculated with the distance between the observed and synthetic data, and we will update the weights in the neural network to generate elastic models that decrease the data misfit.

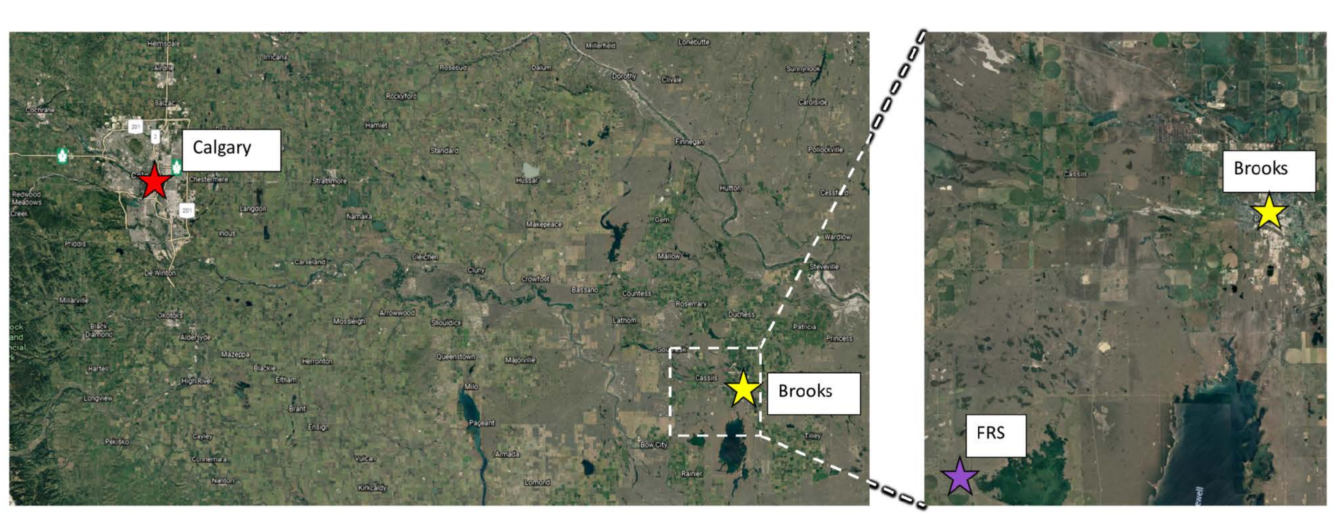

Figure 2: The location of investigation area

MLP-based EIFWI field data inversion results

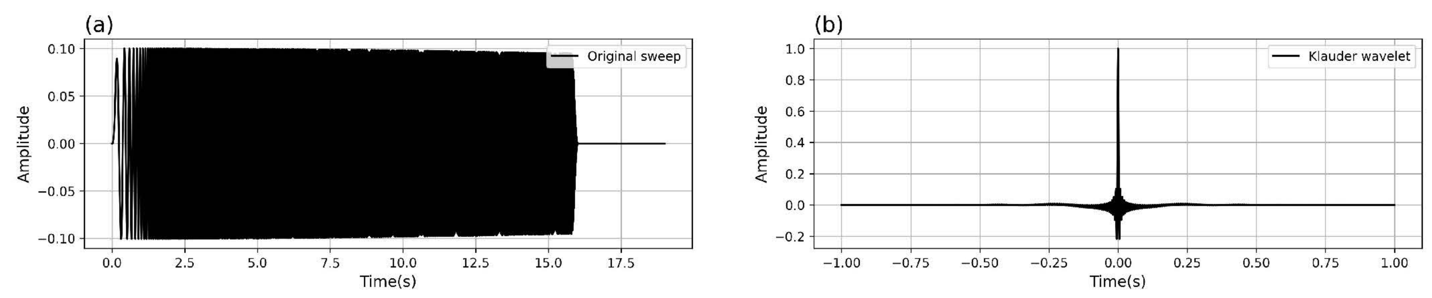

Figure 3: The Original seep (a) and the Klauder wavelet(b).

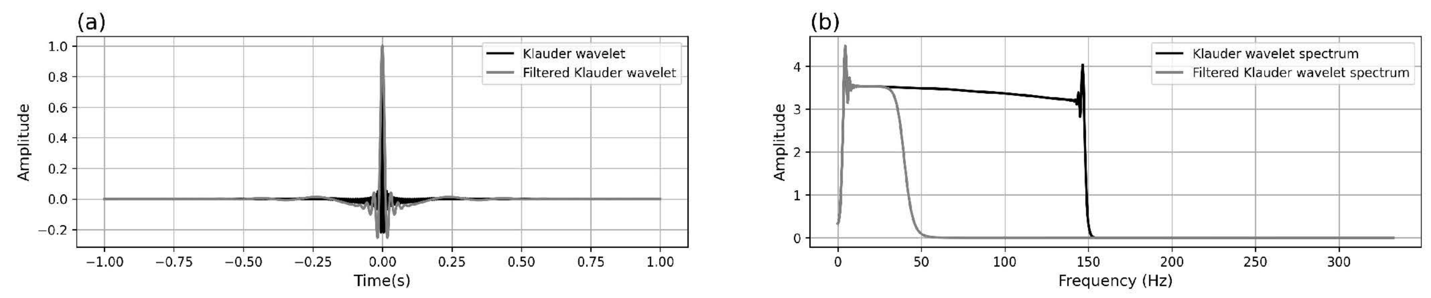

Figure 4: Filtered Klauder wavelet (a) and their spectrums(b).

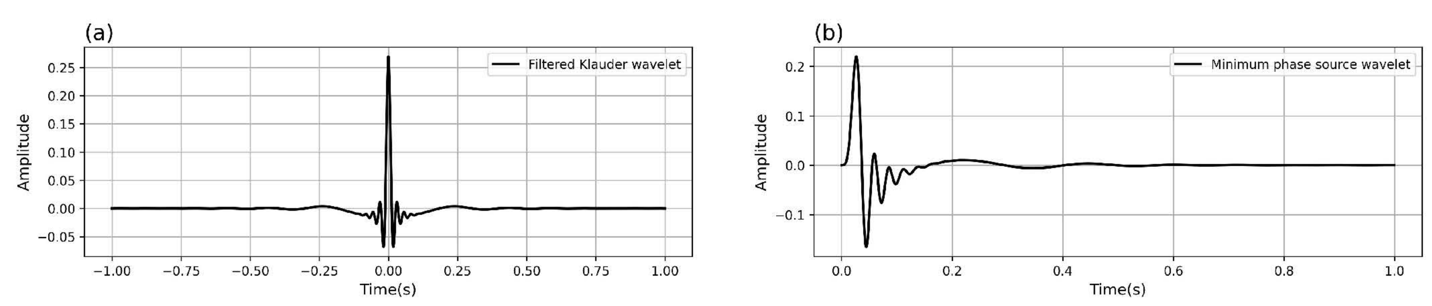

Figure 5: Based on the minimum phase assumption, transforming the zero-phase wavelet(a) into the minimum phase wavelet(b).

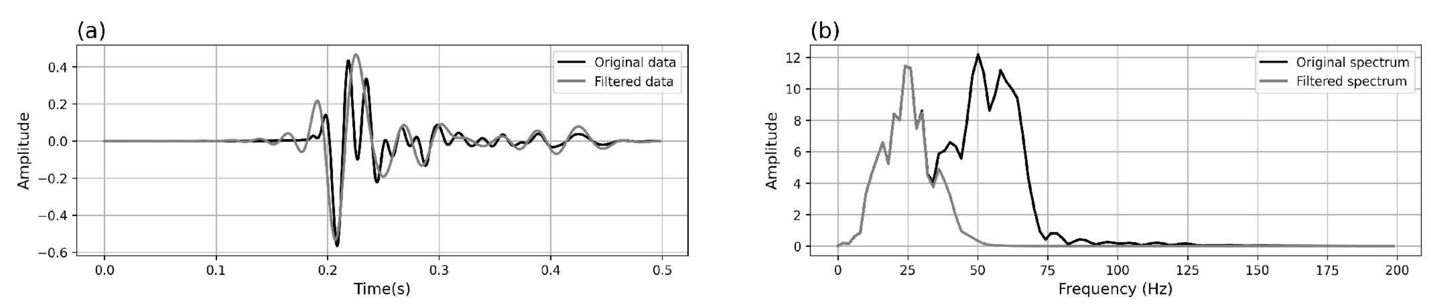

Figure 6: Original and filtered data in the time domain (a) and the frequency domain spectrum(b).

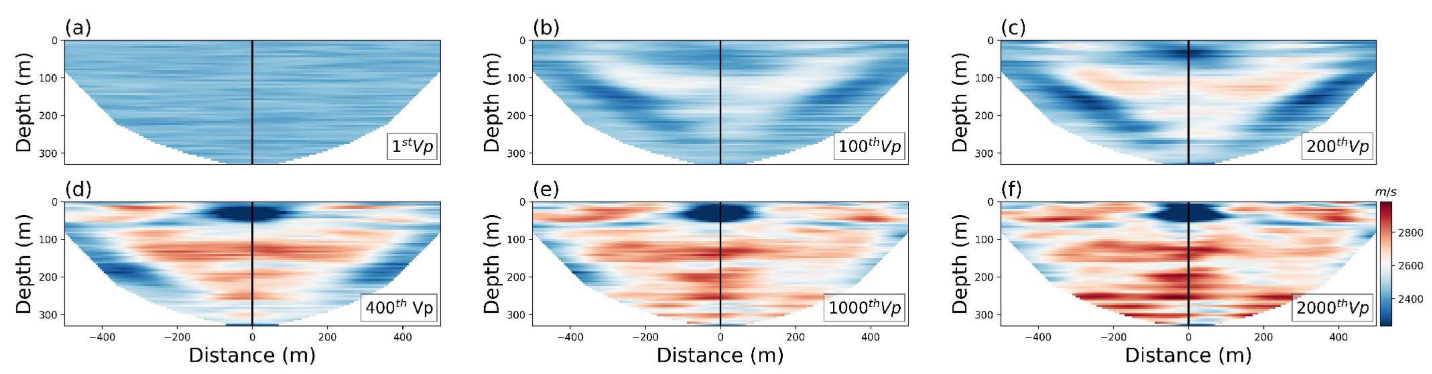

Figure 7: MLP-based EIFWI results for the V_p model.

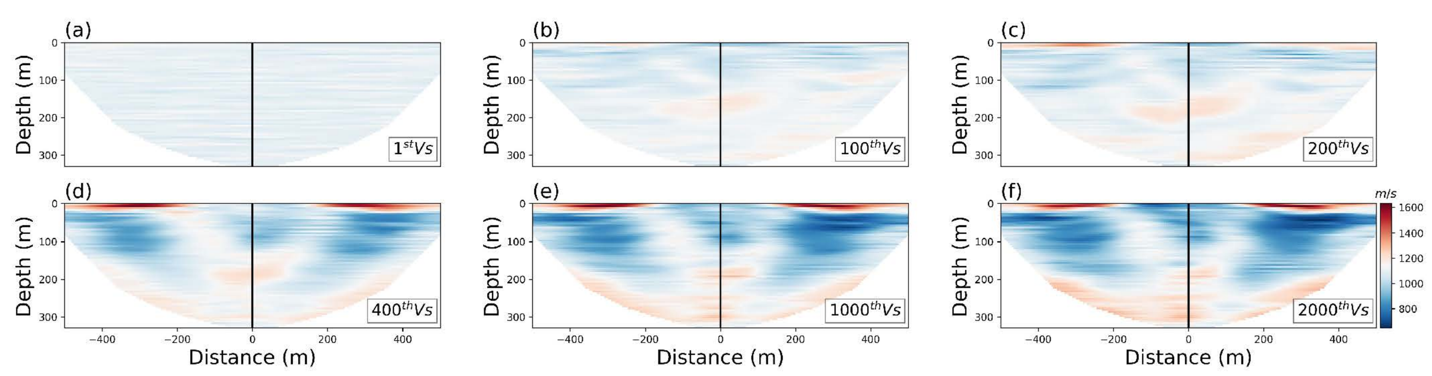

Figure 8: MLP-based EIFWI results for the V_s model.

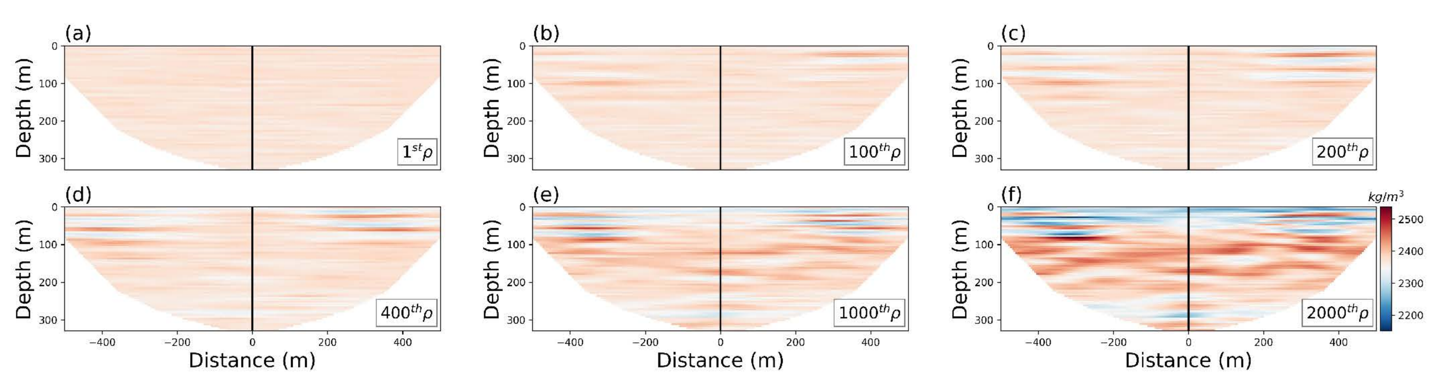

Figure 9: MLP-based EIFWI results for the ρ model.

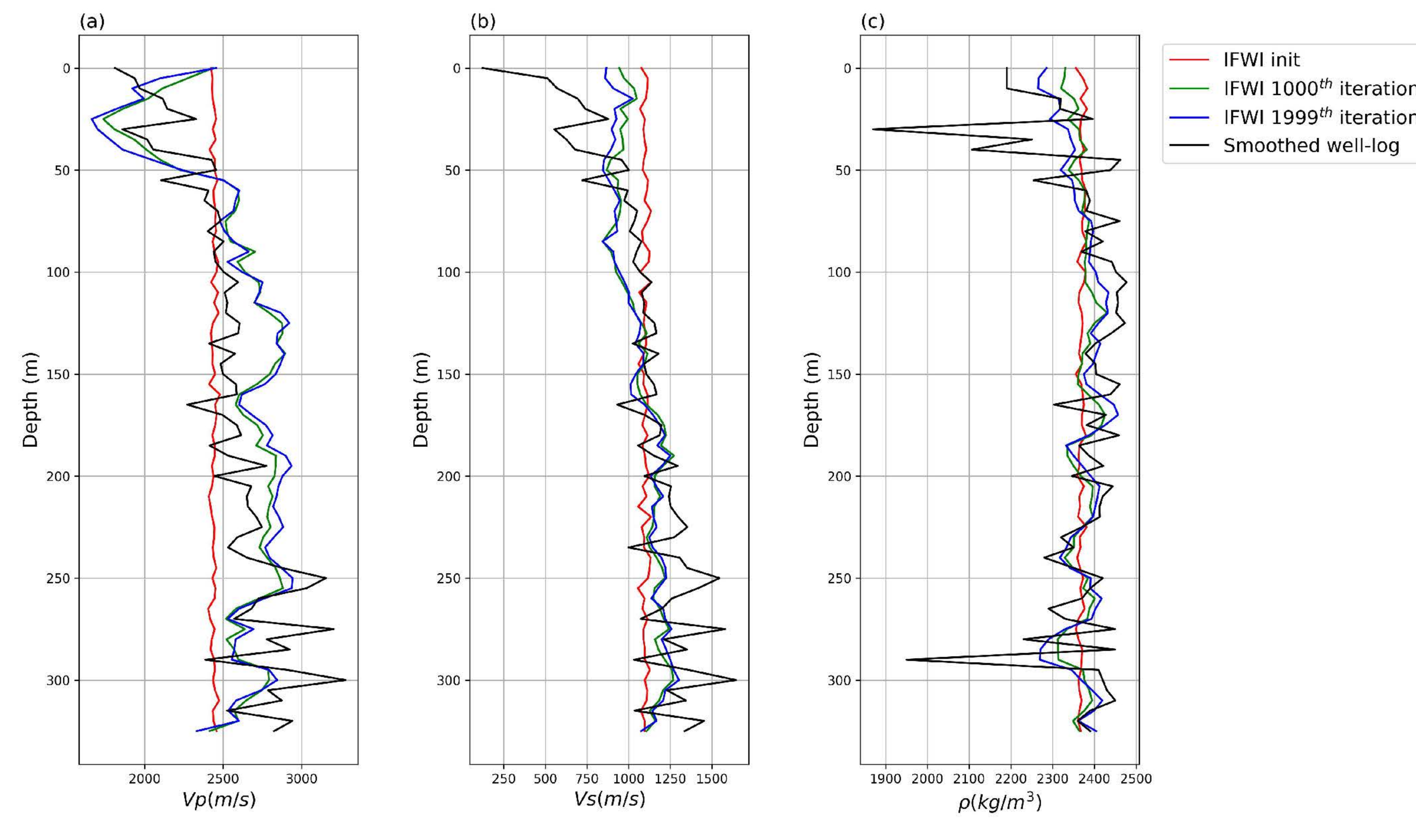

Figure 10: MLP-based EIFWI results in comparison with the well-log. Red lines are the initial value, and green lines are the IFWI inversion results at 1000 iterations. The blue lines are the final IFWI prediction results.

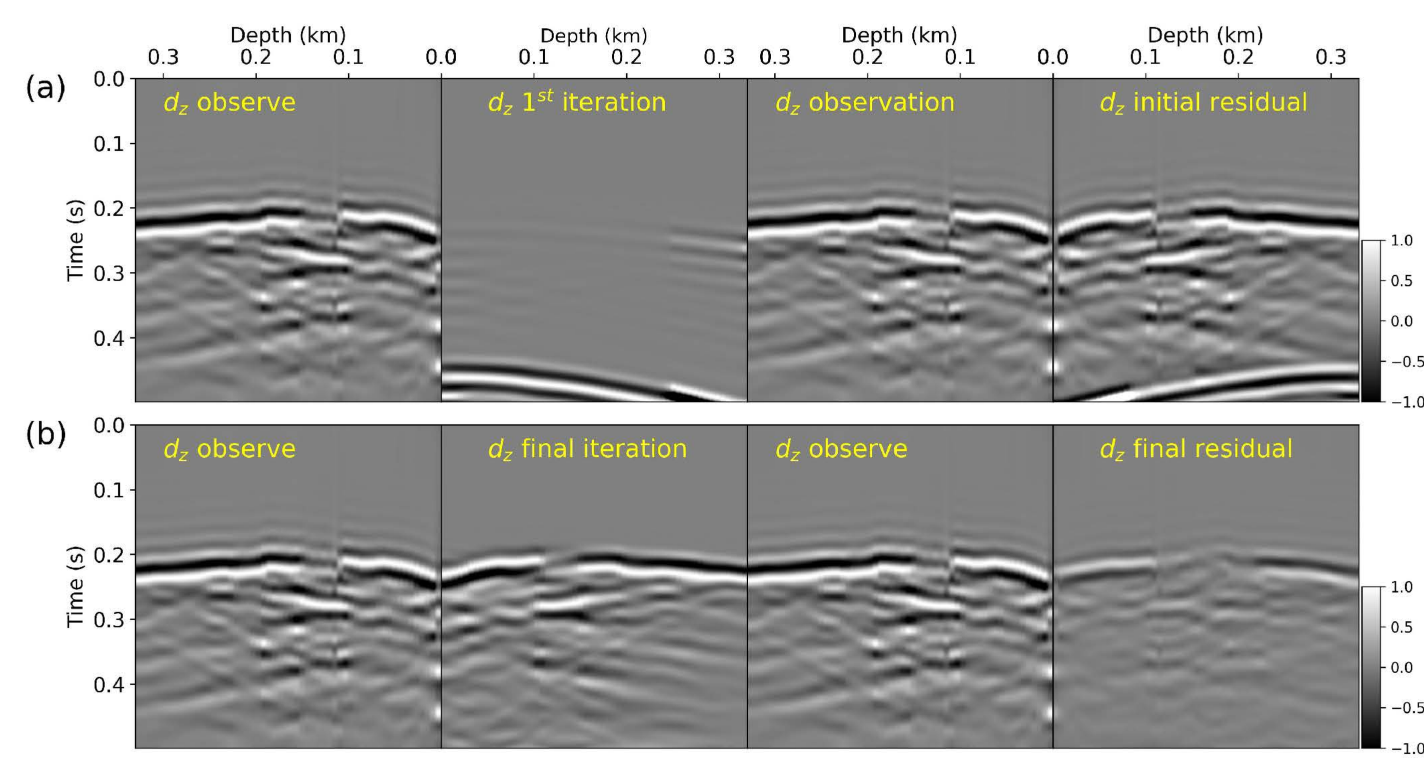

Figure 11: . MLP-based IFWI vertical component data comparison. (a) Observe accelerometer data of the vertical component, with amplitude normalization, initial IFWI vertical component, and the initial residual of the Vertical components are plotted from left to right. (b) Observe accelerometer data of the vertical components, final IFWI vertical components, and the final residual of the vertical components are plotted from left to right

Uncertainty quantification

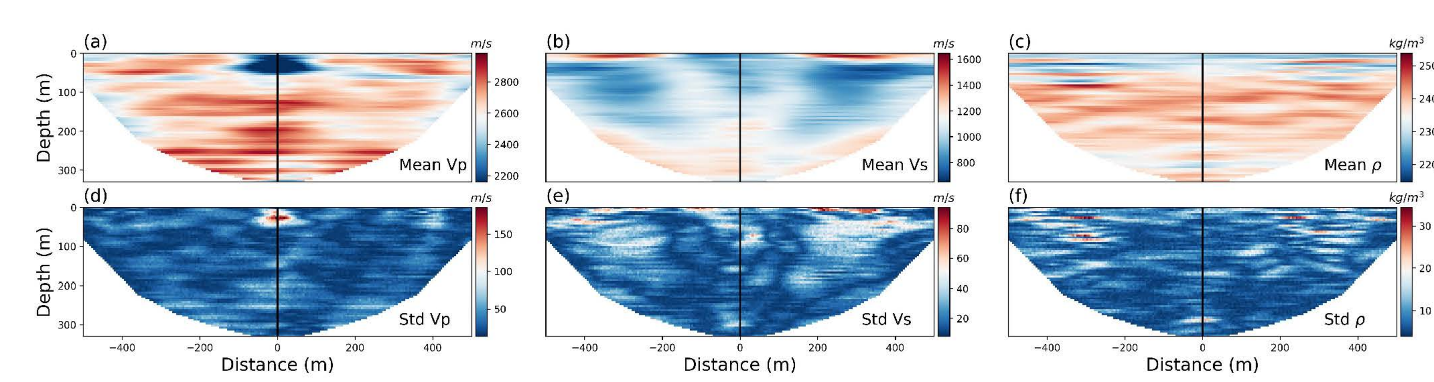

Figure 12: MLP-based IFWI uncertainty quantification. The UQ of the IFWI results is obtained by forward passing the well-trained network 1000 times and calculating the predicted models' mean and standard deviation. (a), (b) and (c) are the mean model of the predicted Vp, Vs, and ρ model, respectively. (d), (e) and (f) are the standard deviation of the predicted models for Vp, Vs, and ρ, regarded as the uncertainty quantification of the inversion results.

Conclusions

- (The inversion results of the MLP-based EIFWI has good correlation with the well-log data),
- (The inversion results of the MLP-based EIFWI synthetic data align well with the observed data)
- (No accurate initial models are utilized.)

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