Well-log parameterized full waveform inversion at the CMC Newell County facility

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Summary

Prior information in elastic full waveform inversion tends to aid model convergence by prioritizing relevant features of the modelled medium. Considering a trendline that was constructed based on a strong relationship observed between density, P and S-wave velocity in well-logs at the Carbon Management Canada Newell County facility, in this investigation, we advocate the inclusion of a second term to describe the trendline and parameterize the inversion. This term was formulated by combining concepts of spatial geometry and principal component analysis with the intention of capturing more data variation to expand the applicability of a preceding single-term parameterization. To test our method, we examined the changes in density, P and S-wave velocity associated with an injection program of carbon dioxide at the study site. Although our current results demonstrate some level of underestimation in several modelled parameters, our method helped us to reconstruct superior models than those obtained using the single-term parameterization for the same application.

Introduction

Multi-parameter full waveform inversion (FWI) relies on finding a good approximation to a metric (e.g., data fit) between a set of true observations and a set of simulated observations. To find this solution, it iteratively optimizes a misfit function that can be further separated into a data-fitting term and a model-fitting term. Both parts are suitable for the inclusion of prior information during the inversion. However, the former uses it when simulating the wave propagation in expressions relating simultaneously data and model information, whereas the latter uses it to penalize model features, usually through a weighting term.

At the Carbon Management Canada (CMC) Newell County facility, Eaid et al. (2021) demonstrated by crossplotting well-log information that there is a strong correlation between S-wave (V_S) and P-wave velocity (V_P), and between density (ρ) and P-wave velocity. This relationship was quantified through a nonlinear trendline, bounding V_S and ρ parameters with respect to V_P by modelling a single parameter during the inversion. Though the estimated trendline helped to mitigate the effects of cross-talk in FWI, it also restricted the degrees of freedom that each parameter had in an isotropic-elastic model. This assumption helped to reproduce plausible V_P, V_S and ρ models for the study site using real distributed acoustic sensing (DAS) and vertical seismic profile (VSP) data corresponding to a baseline stage in an injection program of carbon dioxide (CO_2).

In this investigation, we advocate adding a second modelling term in FWI to expand the applicability of the existing single-term parameterization in a time-lapse setting. We argue that the introduced parameter will help to capture more amount of data variation, especially from values that deviate further away from the trendline that bounds V_P, V_S and ρ. This is likely to increase as the injection of CO_2 continues at the CMC facility, as suggested by well-log crossplots created from projections for the study site (Macquet et al., 2019). To formulate the second parameter, we combined concepts of spatial geometry and principal component analysis (PCA). Then, we evaluated our method by modelling three stages of CO_2 injection using a VSP configuration consistent with the permanent experiment deployed at the CMC facility. These experiments helped us make comparisons between the single and the two-term reparameterization for the same application.

Method

To describe any well-log sample considering a differentiable trendline that expresses the relationship between modelling parameters (e.g., V_P, V_S, ρ), we assume that its position in space can be explained as the sum of two terms. The first term (η) will be defined on the tangent direction of the trendline, describing most of the data variation. Whereas our proposed second term (κ) will be defined in a normal direction from the tangent, and it will help to describe a significant amount of data variation omitted by the first term. Equation 1 summarizes our suggested reparameterization:

$$Log\ sample = \hat{\eta} + a\hat{\kappa} \tag{1}$$

While Eaid et al. (2021) proposed that η can be estimated by parameterizing the trendline using the arc-length in a V_P–V_S–ρ space, we formulated κ based on a coordinate system transformation. The latter was achieved following four steps for every sample along the trendline:

Step 1: define a fixed vicinity of interest along the trendline.

Step 2: project every value that appears within the established vicinity into a normal plane, assuming that the latter should be defined from the tangent plane.

Step 3: estimate the most significant direction from the trendline using the projected values from Step 2 with PCA.

Step 4: Use the first principal component (PC1) estimated in Step 3 to define κ.

Once η and κ are determined, we can map values between V_P–V_S–ρ space to η-κ space by updating the elastic tensor elements (e.g., c_{11}, c_{44}) and density. This will lead to updating the FWI sensitivities using the estimated η and κ values, incorporating prior information in the data-fitting term of the objective function of FWI.

Although we recognize that Step 1 from our proposed workflow can be achieved through different methodologies, we suggest using a cylinder of fixed measurements centred on the trendline to define the cutoffs for the coordinate transformation. By modifying the length and radius of the cylinder, we can customize the number of samples that meet the established cutoffs, varying on the relative value of κ and lateral smoothness of the inverted velocity and density models.

Results

To investigate the difference between a single and two-term log-guided parameterization using the same trendline, we examine the evolution of V_P, V_S, and ρ models in a timelapse application at the CMC Newell County facility. The inverted models for this study correspond to three stages of CO_2 injection from a baseline stage to a mid and final injection stages (Macquet et al., 2019; Hu et al., 2021). These were obtained using a VSP configuration consistent with the permanent experiment deployed at the site, with receivers separated every 5 m between 190 m to 305 m and modelling surface sources with a separation of 60 m. We inverted 8 frequency bands from 4-44 Hz following a multi-scale approach using a frequency-domain wave propagation.

In Figure 1, we show a profile view of the inverted models at a near offset location for the three modelled stages. While in general terms, we observe good model convergence using both parameterizations, the inclusion of a second term demonstrates a better reconstruction of small velocity and density variations. This is more noticeable with increasing depths where changes are more rapid, including the thinned injection target. From the three inverted models, density appears to benefit the most from the inclusion of prior information in the inversion, whereas V_P and V_S are relatively well inverted in every test.

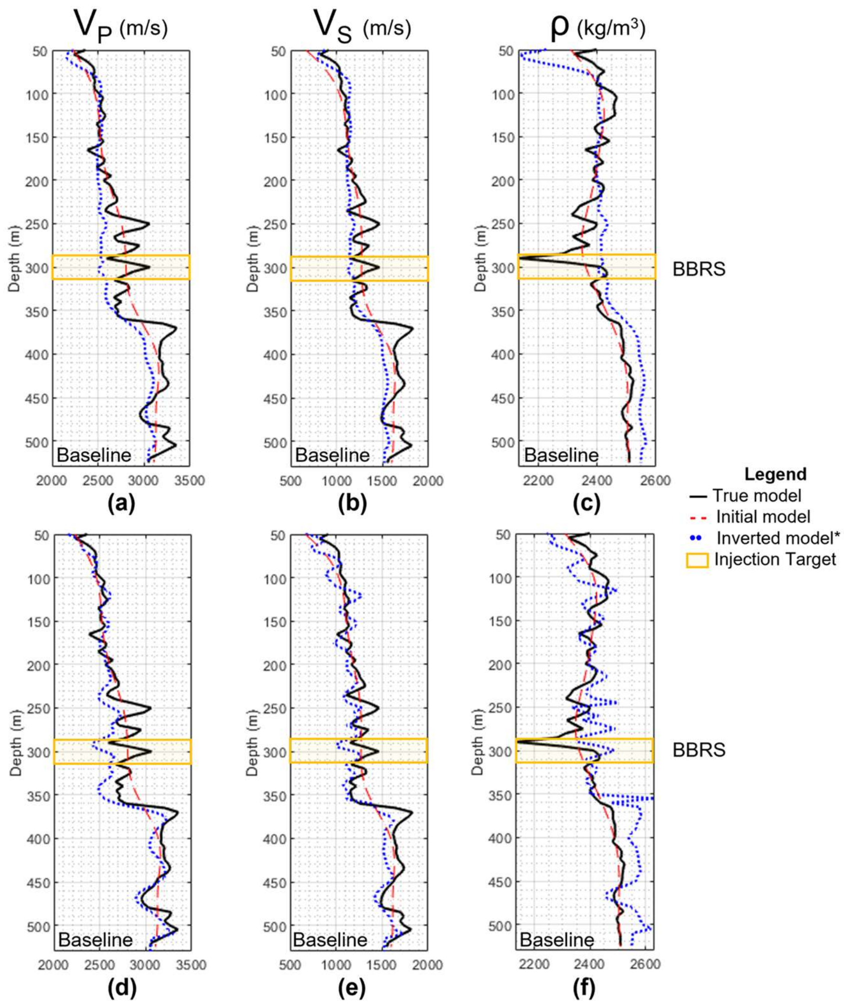

Figure 1. Profile views of the inverted using the well-log guided parameterization at a near offset location. Models in (a), (b), and (c) were estimated using the single-term parameterization, and models in (e), (f), and (f) were estimated using the two-term parameterization. In each graph, the solid black lines are the true model, the red dashed lines are the initial model, and the blue dotted lines are the inverted models after η and κ were mapped back to the V_P–V_S–ρ space.

As previously stated, P-wave velocity was well-estimated independently of the considered reparameterization. However, as quantitatively demonstrated by the estimation of the normalized root-mean-square error (NRMSE) in Figure 2, the model convergence was consistently improved from early frequency bands when we included both, η and κ. While in general terms, we can observe in Figure 2(a)-(c) that with the single-term parameterization, the models eventually converged slightly better at late frequency bands, the estimated NRMSE in those cases is still larger than the models obtained using the two-term parameterization. This remark is consistent for S-wave velocity and density, but we are showing V_P for reference.

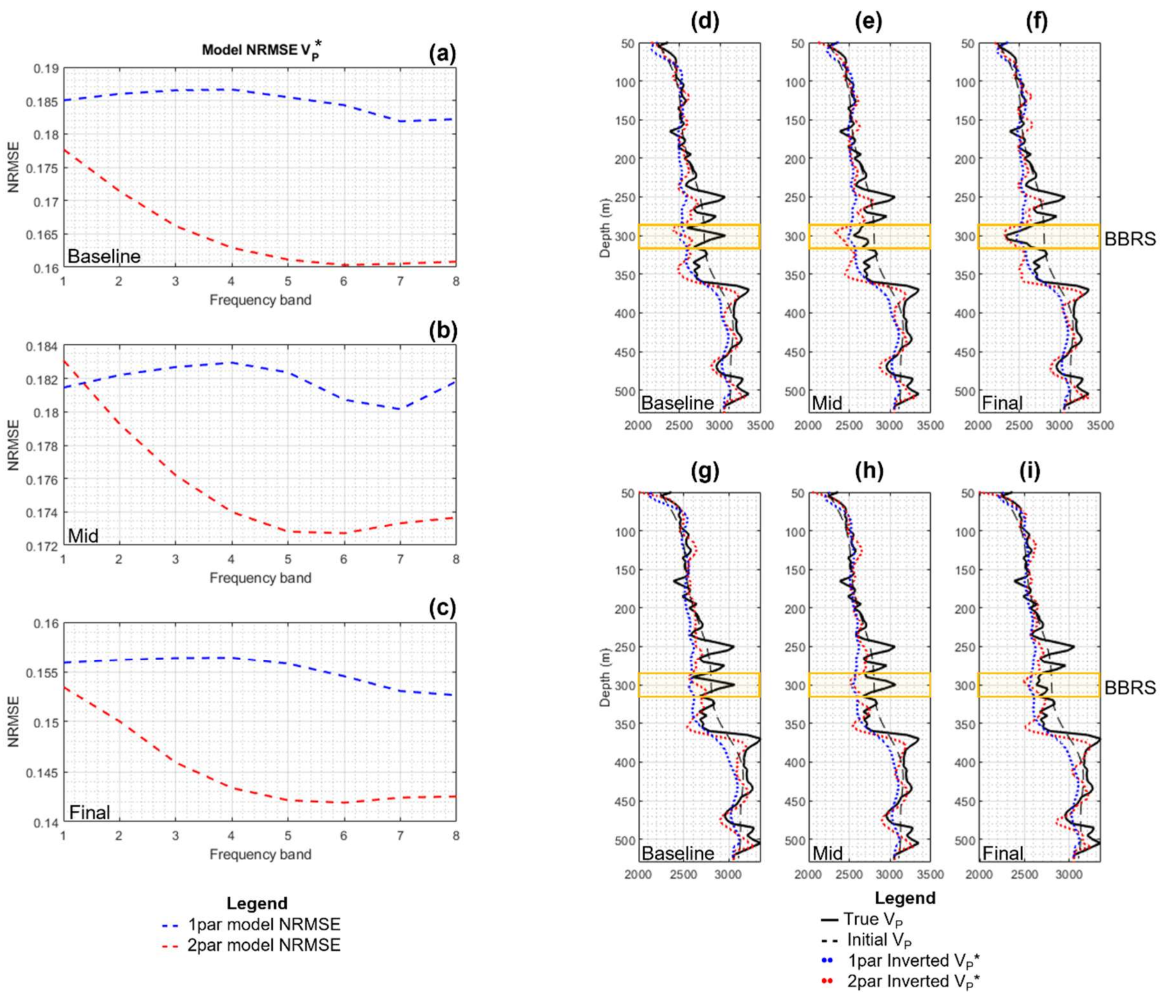

Figure 2. (a), (b), and (c) are history plots for the model NRMSE from the three stages of inverted V_P. The profile views show the inverted V_P at a near location set 40 m from the zero offset in (d), (e), and (f); and at a far location set a 120 m from the zero offset in (g), (h), and (i). The blue dotted and dashed lines correspond to the model obtained using the single term log-guided parameterization, the red dotted and dashed lines correspond to the model obtained using the two-term log-guided parameterization, and the black lines are the true and initial models.

To estimate a time-lapse evolution of the study site, we subtracted the model residuals for the simulated mid and final stages of injection with respect to the inverted baseline. As shown in Figure 3 and Figure 4, we reconstructed the geometry of the expected CO_2 effects with various levels of success. Independently of the number of terms considered in the reparameterization for V_P and density, we observe that the model residuals are less influenced by modelling artifacts. Hence, the boundaries of the injected gas effects are better delineated, even when we cannot fully reconstruct the magnitude of the parameters. Meanwhile for V_S, we observed the appearance of velocity artifacts at various depth levels, especially in the models obtained with the two-term parameterization. This behaviour limits our capacity to confidently denote the edges of the CO_2 effects for the final injection stage, which also occurs when inverting each parameter using established parameterizations like V_P–V_S–ρ and I_P–I_S–V_P (Amundaray, 2023).

Conclusions

In this investigation, we demonstrate the feasibility of using well-log parameterized FWI in a timelapse application for the CMC Newell County facility. Although results using a preceding single-term formulation reproduced interpretable models, our proposed second term helped us to reconstruct more detailed velocity and density variations. This helped in the convergence of V_P, V_S and ρ models for the three modelled stages. Though our estimated models generally showed relative magnitude underestimation and overestimation in the modelled parameters at some depth levels, they helped us to confidently delineate the geometry of the CO_2 effects for V_P and ρ, and with relative success for V_S. Overall, parameter magnitude and model geometry were improved with the addition of the second term in the well-log reparameterization.

Acknowledgements

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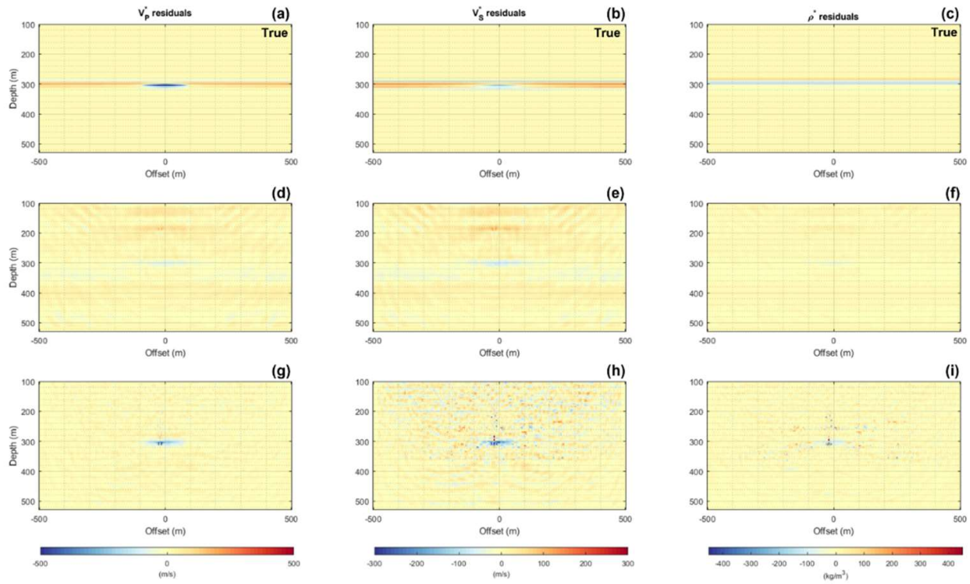

Figure 3. V_P, V_S, and ρ model residuals estimated taking as reference the baseline for the medium stage of CO_2 injection. Models (a)-(c) refer to true models, models (d)-(f) were estimated using the single-term parameterization, and models in (g)-(i) were estimated using the two-term parameterization.

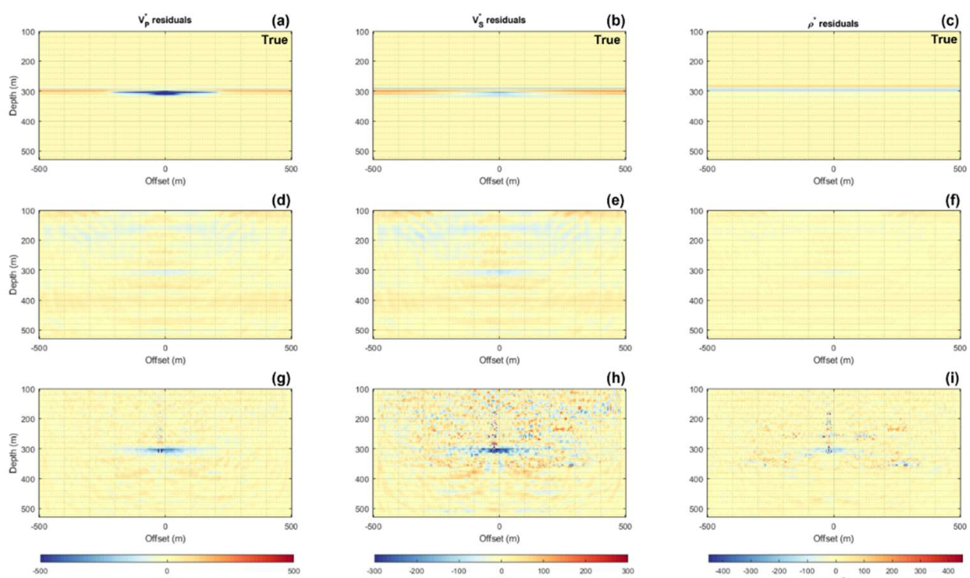

Figure 4. V_P, V_S, and ρ model residuals estimated taking as reference the baseline for the final stage of CO_2 injection. Models (a)-(c) refer to true models, models (d)-(f) were estimated using the single-term parameterization, and models in (g)-(i) were estimated using the two-term parameterization.