

AI-Based Coal Probability Prediction for CCS Seal Characterization

Introduction

Coal produces strong impedance contrasts and high-amplitude reflections that can dominate the seismic response, introducing sidelobe interference, coherent noise, bandwidth attenuation, and interbed multiple contamination (Gochioco, 1991). These effects reduce confidence in seismic imaging and inversion throughout and beneath coal-bearing successions.

This study investigates whether deep learning inversion can provide a geologically meaningful and probabilistic assessment of coal-seam continuity in a carbon capture and storage (CCS) setting. The approach builds on the stratigraphy-guided framework of Heir et al. (2024), combining stratigraphic guidance with a Temporal Convolutional Network (TCN). To provide an estimate of uncertainty, we extend the method to create an ensemble of AI realizations.

The offshore CCS site in a coal-bearing basin is selected for testing the AI method because it can be challenging to prove the continuity of the sealing lithologies. Important seals and reservoirs occur within interval B (Figure 1) where coal is an important component of the sealing system alongside mudstone and shale. The interbedded low-density coals violate the weak contrast assumption of most conventional inversion methods (Aki and Richards, 1980; Lu et al., 2015).

To provide a benchmark for comparison, the AI predictions are evaluated against a constrained seismic simultaneous inversion (SSI) (Rasmussen et al., 2004). Acoustic impedance (I_p) predictions from a single AI realization are compared with SSI at well location, while coal continuity is assessed using an ensemble-derived coal probability volume, $P(\text{coal})$. These comparisons evaluate prediction quality and the value of probabilistic coal characterization for seal-continuity assessment.

Method and Theory

We first train the AI model using data from 10 wells to predict I_p from seismic and stratigraphic input features and then apply an empirical I_p threshold to estimate coal presence. The AI model learns a mapping from the input feature space to the target property space. Let $\mathbf{f}_i \in \mathbb{R}^K$ denote the feature vector for the i -th training sample, where K is the number of input features (e.g. seismic amplitudes, relative geological time), while $p_i \in \mathbb{R}$ denote the target I_p . The trainable parameters, or weights, θ , of the TCN network $H(\mathbf{f}_i, \theta)$ are found by minimizing the mean squared error over N training samples:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \frac{1}{N} \sum_{i=1}^N \|H(\mathbf{f}_i, \theta) - p_i\|_2^2. \quad (1)$$

At inference, the TCN is applied trace-by-trace across the 3D seismic volume where x, y are the inline and crossline coordinates and z is the depth sample index. The network leverages surrounding depth samples to capture local stratigraphic context. This yields a predicted I_p value $\hat{p}(x, y, z)$, for each voxel, based on the input features ($\mathbf{f}_i$) from nearby samples along the trace at (x, y) .

Each voxel is then classified as either coal or non-coal by applying an empirical I_p threshold p_t . This results in a binary coal indicator:

$$c(x, y, z) = \mathbf{1}[\hat{p}(x, y, z) < p_t], \quad (2)$$

where $\mathbf{1}[\cdot]$ equals 1 if the condition is satisfied and 0 otherwise. We chose $p_t = 5000 \text{ g/cm}^3 \cdot \text{m/s}$ as the empirical threshold separating low- I_p coal from non-coal lithologies based on well-log calibration in interval B. For fixed weights θ , this binary output is deterministic.

To estimate coal probability, we use ensemble member variability. We run $M = 10$ independent model realizations under the same modelling setup, each with a different random weight initialization, yielding a binary coal indicator $c^{(m)}(x,y,z) \in \{0,1\}$ at each voxel, for $m = 1, 2, \dots, M$. All realizations use the same training data and hyperparameters, differing only through stochastic initialization of the network weights. Specifically, each realization is initialised from a different random starting point $\theta_0^{(m)}$ prior to optimization via Eq. (1). The resulting solutions $\theta^{*(m)}$ sample different admissible minima of the objective function, reflecting the inherent non-uniqueness of the inverse problem. Ensemble statistics stabilized after approximately ten realizations, consistent with Lakshminarayanan et al. (2017), who reported stabilization at $M = 5$ and diminishing improvements in variability beyond that.

Applying the same I_p threshold to each realization yields a set of binary coal volumes, which are aggregated voxel-wise into a coal probability volume:

$$P(\text{coal})(x,y,z) = \frac{1}{M} \sum_{m=1}^M c^{(m)}(x,y,z). \quad (3)$$

$P(\text{coal})$ represents the fraction of ensemble members that predict coal at a given voxel. A value close to 1 indicates strong agreement among ensemble members, typically corresponding to a thick or well-resolved coal-seam. A value of 0 means no realization predicts coal, suggesting a high-confidence non-coal interval. Intermediate fractions reflect ambiguity in the prediction, arising from thin beds near the resolution limit, transitional I_p responses, or reduced seismic signal quality.

The resulting $P(\text{coal})$ volume gives a geologically coherent, data-driven result of coal-seam continuity confidence, informative for the seal-continuity assessment.

Results and Discussion

At Well 4, the AI I_p realization achieves a correlation coefficient of 0.93 and a mean absolute error (MAE) of 410 g/cm³·m/s, compared with 0.82 and 735 g/cm³·m/s for SSI I_p (Figure 1). Across four wells near the structural crest, the AI I_p realization achieves an average correlation of 0.84 and an average MAE of 540 g/cm³·m/s, compared with 0.76 and 743 g/cm³·m/s for SSI I_p . The AI also shows good generalization in a blind test at Well 8, with I_p correlation of 0.80 and MAE of 724 g/cc·m/s. The AI realization broadly agrees with SSI in preserving the lateral continuity of the main coal package B near the structural crest (Figure 2b). Local lateral discontinuities present in both SSI and AI may reflect faulting, seismic imaging uncertainty, or coal-related wavefield effects.

The differences are most apparent at depth, where Figure 1b shows that SSI exhibits sinusoidal oscillatory behaviour that is not supported by the well log measurement. The oscillations manifest in 3D as laterally continuous cyclic I_p layering and may be mistaken for stratigraphic events. When applying the I_p cut-off to the SSI I_p , the resulting coals are blockier and more discrete laterally than we consider geologically plausible given the depositional setting.

In comparison to SSI, the large parameter space of stratigraphy-guided AI is beneficial to resolve the thin coal units in areas with good well control. First, AI can learn the nonlinear relationship between the large I_p contrast coals and the seismic signal. SSI is limited by the linear approximation to the Zoeppritz equation, which is only applicable at small I_p contrasts (Aki and Richards, 1980). Secondly, the AI can learn to relate high seismic frequencies to the thin units, similar to spectral inversion, while the SSI resolution is limited to $\lambda/8$ by the wavelet frequency assumption (Castagna and Sun, 2006). Thirdly, AI can learn to differentiate signal and noise in the attenuated sub-coal signal.

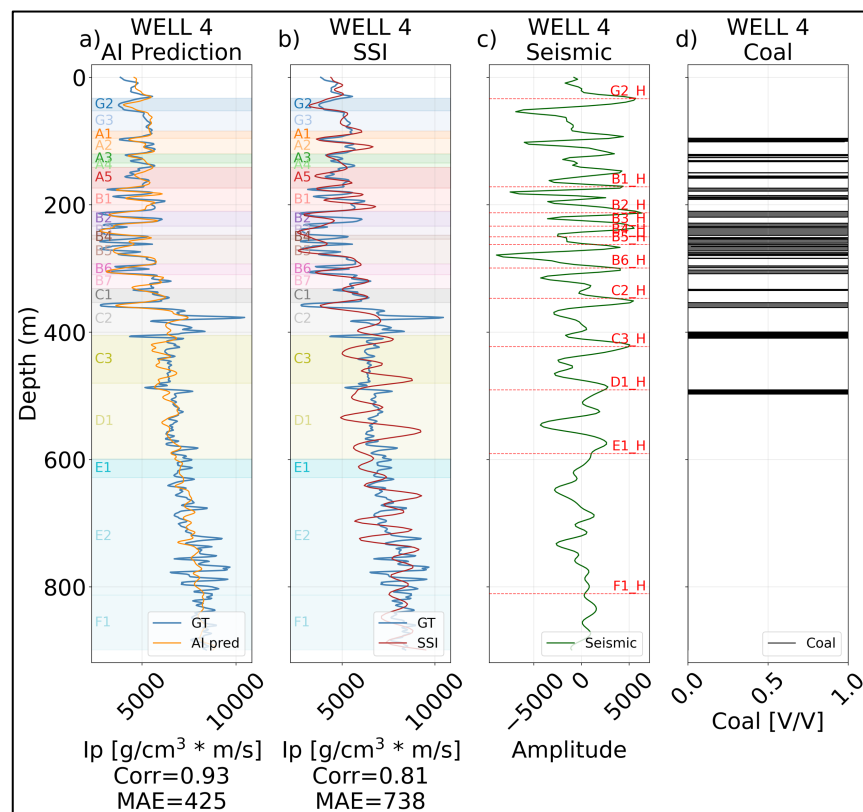


Figure 1 I_p comparison at Well 4 (relative depth datum). AI (1a) and SSI predictions (1b) are compared with the ground truth (GT) measured well log, alongside seismic amplitude (1c) and petrophysical coal flags (1d).

Figure 2 compares coal occurrences derived from an AI realization (2b) and from an AI ensemble (2a). The single AI realization exhibits locally patchy coal predictions, an inherent feature of any single point-estimate solution to a non-unique problem (2b). In comparison, P(coal) provides spatially continuous coal-seams, for example the thin B6 coal, aligning with well control and showing robustness to stochastic variations. We interpret the gradational P(coal) response as more geologically plausible than the SSI blockiness.

Near the structural crest, Well 4 has a gas-related I_p reduction that overlaps with the coal I_p range. To avoid false-positive coal predictions, post-processing removed coal flags from the corresponding unit.

AI training takes one minute, and inference along a 2D line takes less than 20 seconds. A cube of one billion grid cells takes about 5 minutes.

A limitation and natural extension of this work can be to better represent the uncertainty of the I_p -to-coal relation beyond the constant I_p cutoff. For example, separating coal from gas-related low- I_p reservoirs can be addressed using AVO information and V_p/V_s prediction. Second, the ensemble can broaden across varying training/validation splits, features, and hyperparameters, thereby additionally sampling systematic uncertainty. Third, the AI method can be benchmarked with alternative AI approaches.

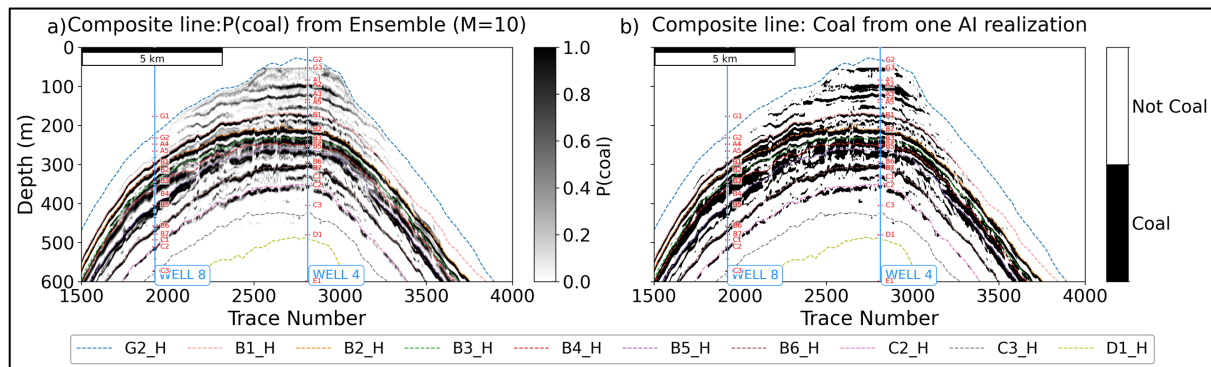


Figure 2 Composite-line through Well 4 and Well 8 showing coal prediction from the AI ensemble (2a) and a single AI realization (2b).

Conclusions

Stratigraphy-guided deep learning inversion provides a geologically consistent and uncertainty-aware approach to I_p prediction and coal characterization in a coal-rich CCS setting. The AI predictions show good agreement with SSI in addition to resolving thinner coals and making more stable predictions in deeper intervals affected by sub-coal attenuation.

The AI approach can provide a complementary and higher resolution view of seal continuity. Used as independent comparisons, the two approaches provide a more complete characterization of the sealing system than either would alone. Probability assessment via $P(\text{coal})$ offers a useful estimate of ensemble-derived AI model uncertainty and confidence for seal-continuity assessment ahead of CO_2 injection.

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