SMART Initiative - Phase 2

Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

ML-Based Rock Properties and Seismic Volume Enhancement

Athos Nathanail, Manika Prasad, Ashish Kumar, Ilya Tsvankin, Maureen James

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NATIONAL ENERGY TECHNOLOGY LABORATORY

U.S. DEPARTMENT OF ENERGY

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Acknowledgment

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Outline

SMART EY23

- Project Overview
  - Key Project participants
  - Project objectives
  - Project performance dates
  - Funding summary
- Project Background
  - Brief Project history
  - Project location(s)
  - Importance of project towards advancing DOE Program Goals
- Technical Approach/Project Scope
  - High-level Project execution plan
  - Project schedule summary, including key milestones
  - Project success criteria/ expected outcomes
  - Summary of high probability and/or high impact project risks, with mitigation strategies
- Current Status of Project and Accomplishments
  - Status of project objectives and tasks (Elements 4.2.2, 2.2.3 and 4.4.2)
  - Summary of significant accomplishments / key findings and their impact
  - Summary of significant challenges and mitigations
- Summary of Lessons Learned to date
- Next Steps

Element 4.2.2 - Machine Learning & Well Log Predictions

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1. Refining Petrophysical and Geophysical Log Predictions – Predict Compressional Velocity (Vp)
2. Training Data used: WOGCC and IBDP well logs
3. Machine learning models used:
   - Random Forest Regression model
   - Multi-Feed Forward Neural Networks (MFNN)
   - Long Short-Term Memory (LSTM) neural network
4. Well logs from the Wyoming Oil and Gas Conservation Commission to find the best model
5. Error criteria used for model assessment:
   - RMSE for average error magnitude
   - R-squared for variance explained
   - MAE for average absolute prediction error
   - Random Forest Model : R^2: 0.96 (Wyoming data)
6. Retrain and apply the best model to IBDP well logs (target – Lower Mt.Simon)
   - Random Forest Model : R^2: 0.95 (IBDP data)

Element 4.2.2 - Machine Learning & Well Log Predictions

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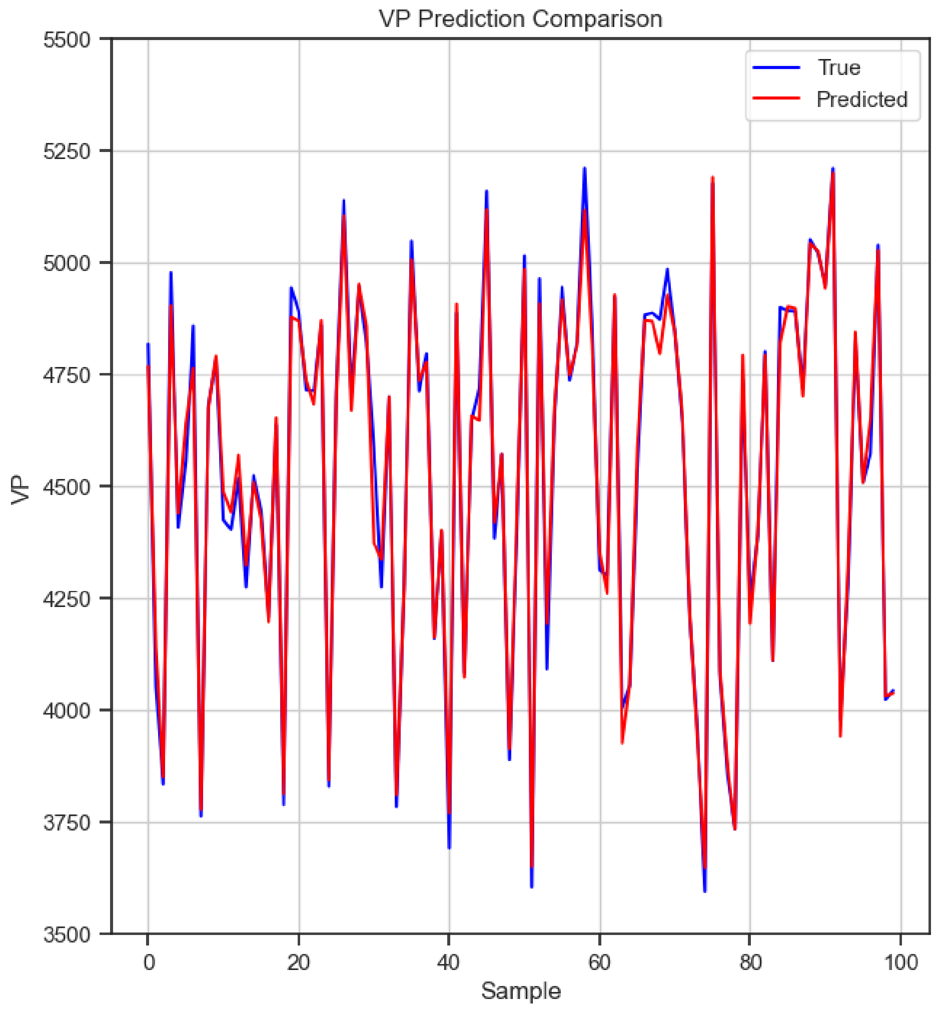

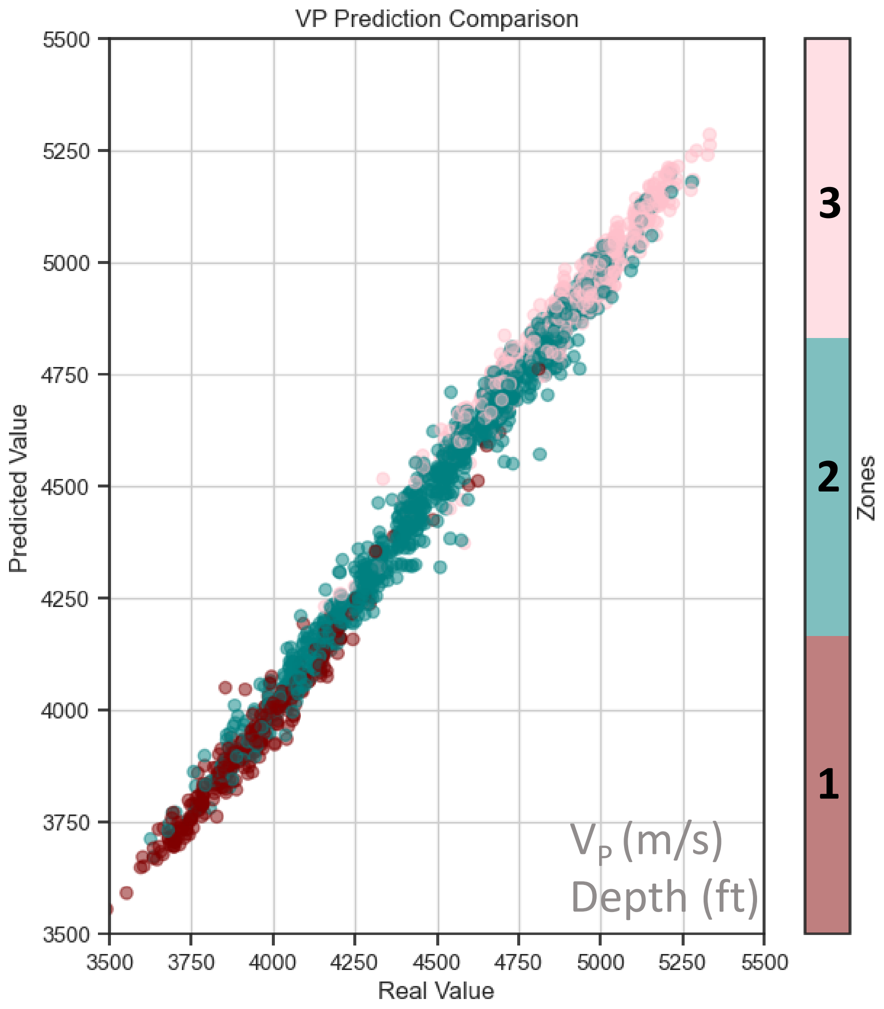

ıpressional Velocity

Dataset	Zone #	Reservoir
IBDP Site (1 well)	1	Upper Mt.Simon
	2	Middle Mt.Simon
	3	Lower Mt.Simon*

Mt.Simon)

Element 4.2.2 - CVAE for CO2 Saturation Prediction

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1. Application of Multiphysics CVAEs for predicting CO2 saturation levels in geological formations at the Illinois Basin Decatur Project (IBDP)

2. Develop and train a CVAE to accurately predict CO2 saturation levels within the IBDP site using both real and synthetic well log data

3. Methodology
    - Data Integration: Import, interpolate, and generate synthetic geological data to create comprehensive training sets
    - Model Training: Train CVAEs with real and synthetic datasets to map injection history, geological properties, and CO2 saturation
    - Evaluation: Assess and adapt neural network performance for real-world CO2 saturation prediction

Element 4.2.2 - CVAE for CO2 Saturation Prediction

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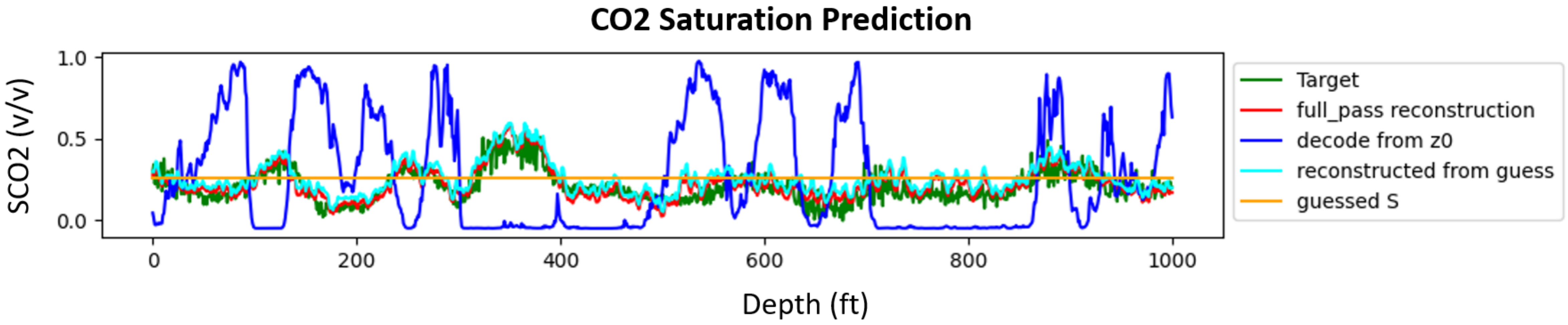

Target is the ground truth for the CO_2 saturation profile from the well logs

Full-pass reconstruction and predictions showcase how the model has learned to replicate the target saturation profile

Z0 represents the latent space

Reconstruction of the saturation profile based on the saturation guess value

Guess for the CO_2 saturation value (constant number)

Element 2.2.3 - Facies-based FWI

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1. **Goal**: Estimation of high-resolution geophysical attributes from elastic full-waveform inversion with lithologic constraints incorporated via machine learning
2. Challenges
   - Low Signal-to-noise Ratio
   - Limited Spatial Data Coverage
   - Parameter Trade-offs
   - Non-linearity Of The Inverse Problem
3. Incorporate additional lithologic constraints

Element 2.2.3 - Facies-based FWI

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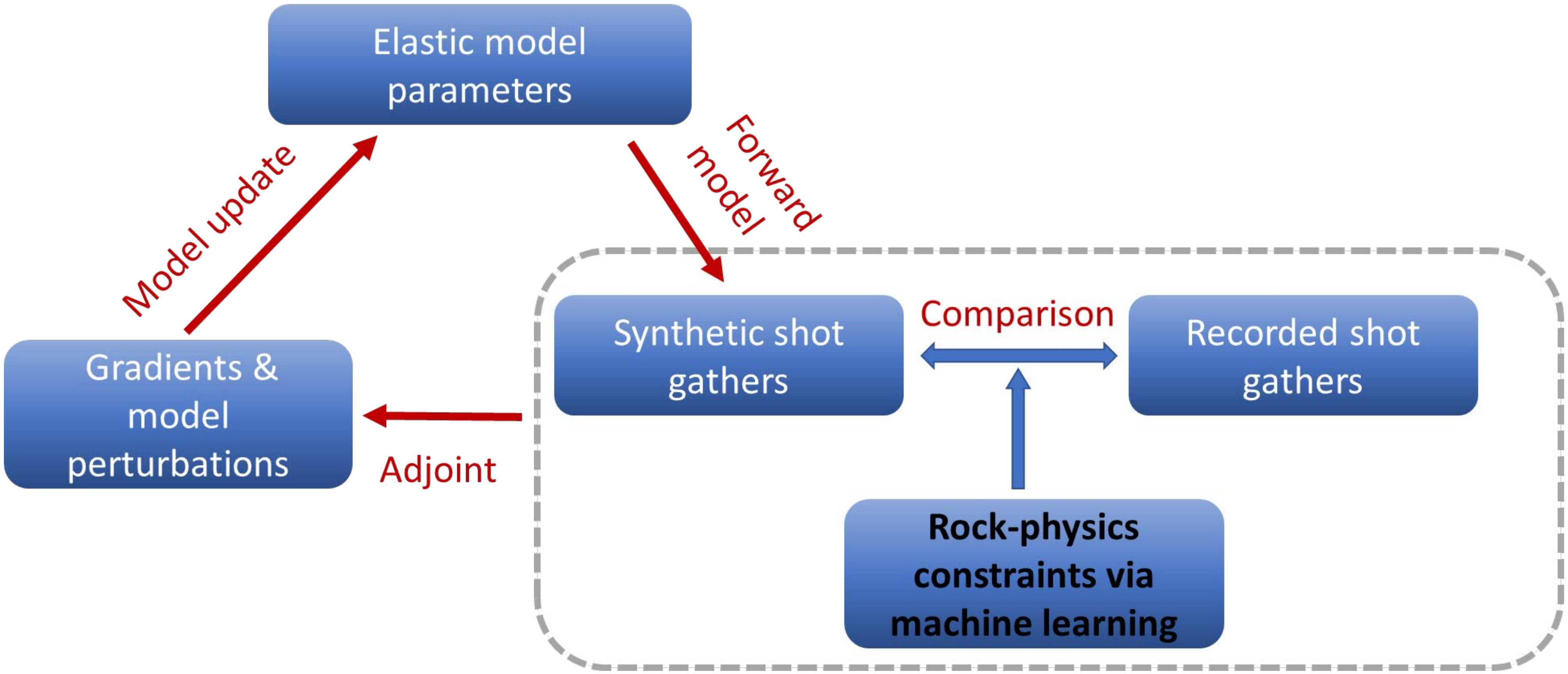
Facies-constrained elastic FWI Workflow



Synthetic example: VTI Marmousi model

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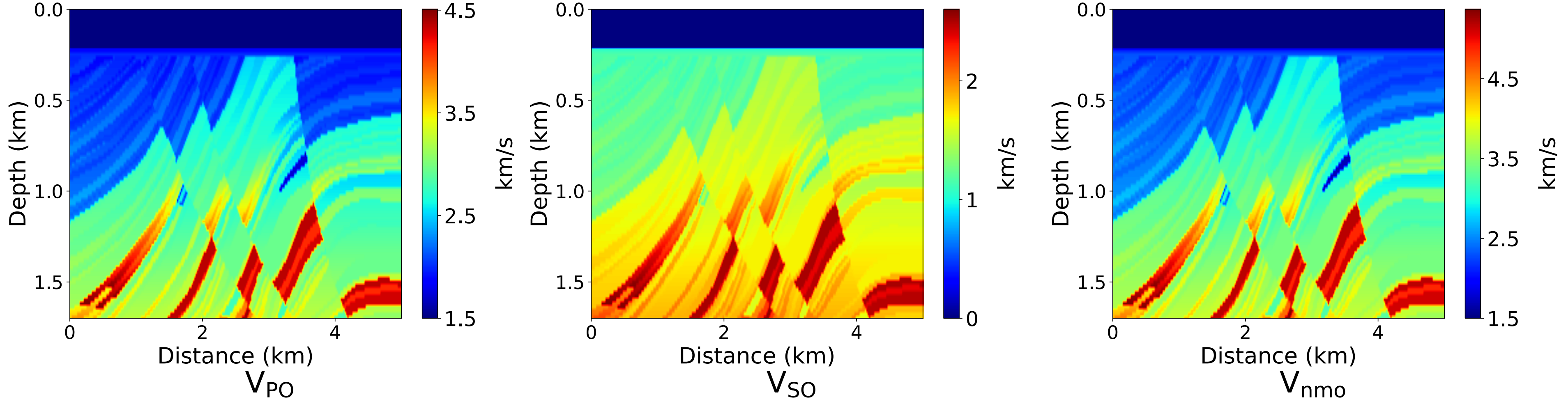

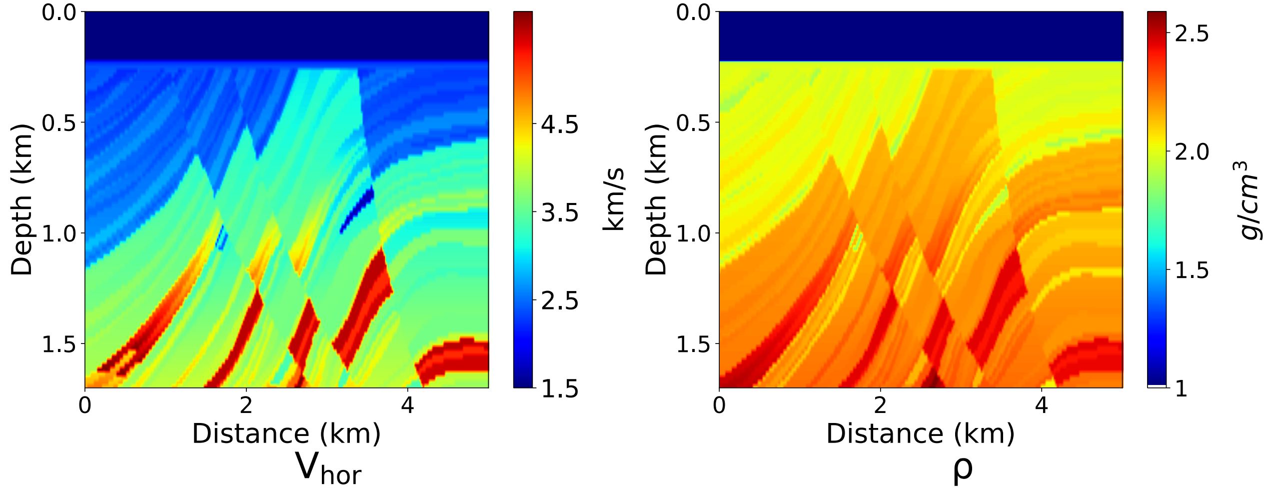

Parameters of VTI media
P-wave vertical velocity (V_{P0})
S-wave vertical velocity (V_{S0})
P-wave normal-moveout velocity (V_{nmo})
P-wave horizontal velocity (V_{hor})
Density (ρ)

Initial Model

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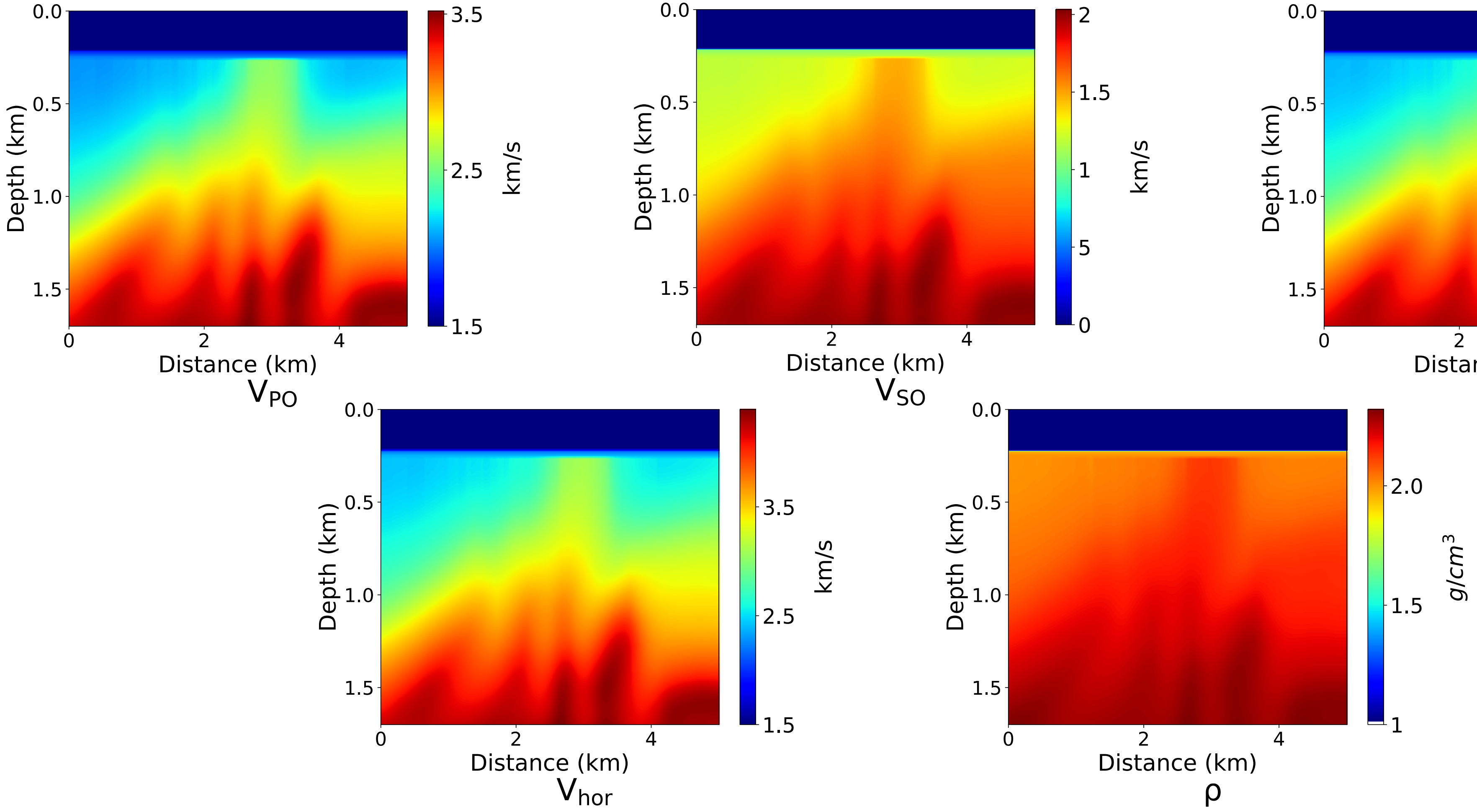

Inverted Model

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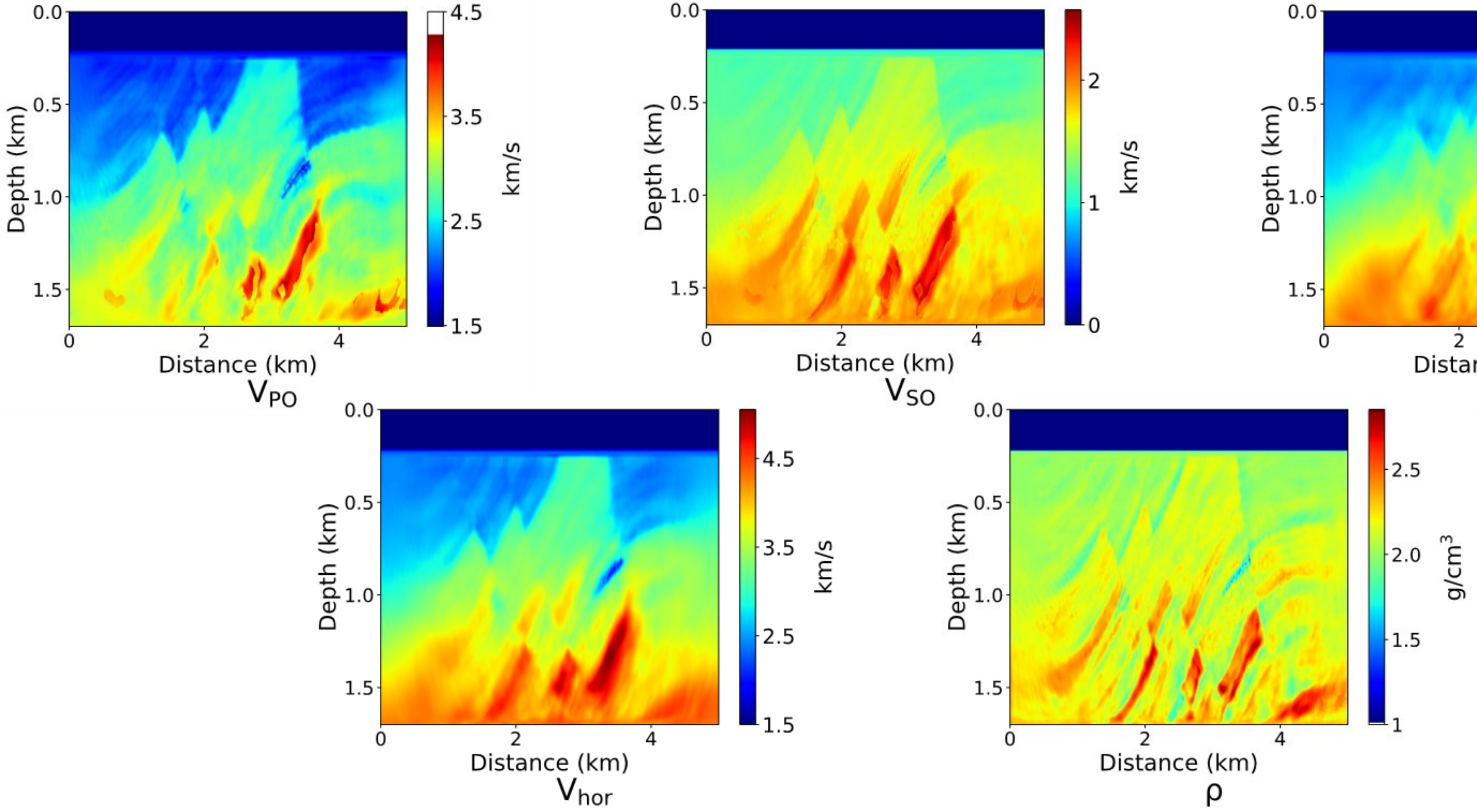

Facies Classification

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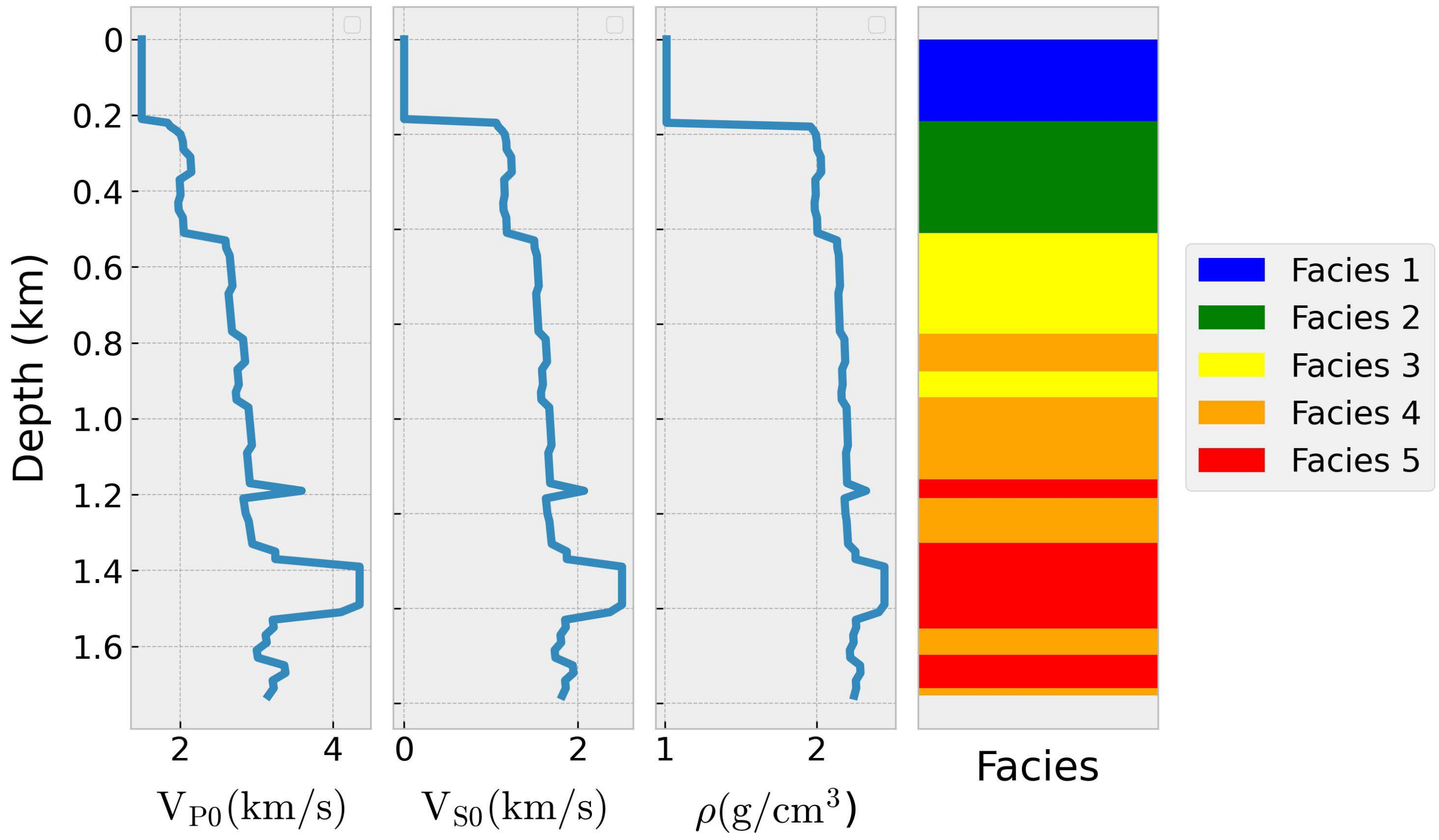

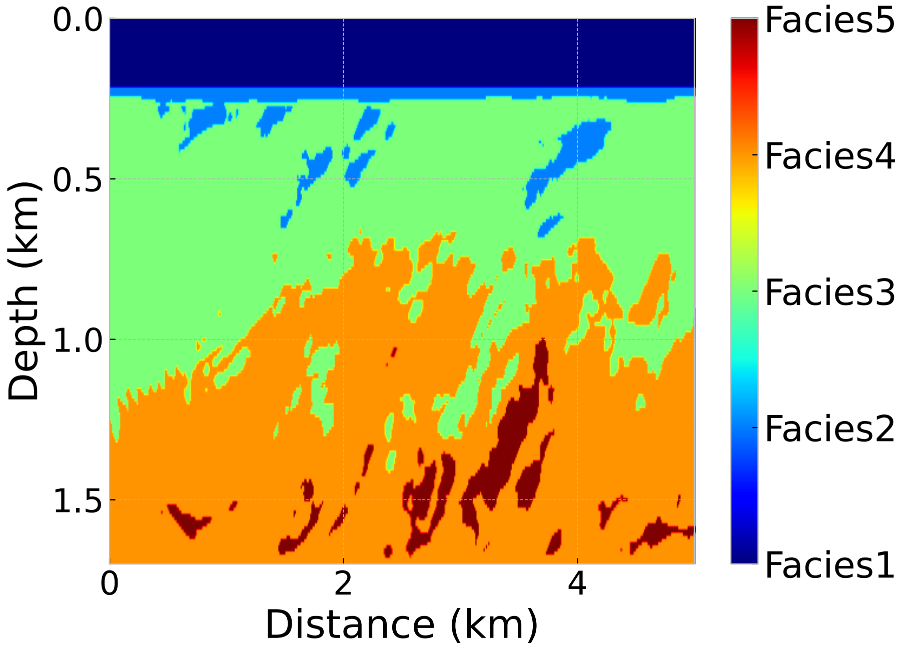

Facies model

ML-Based Facies Prediction

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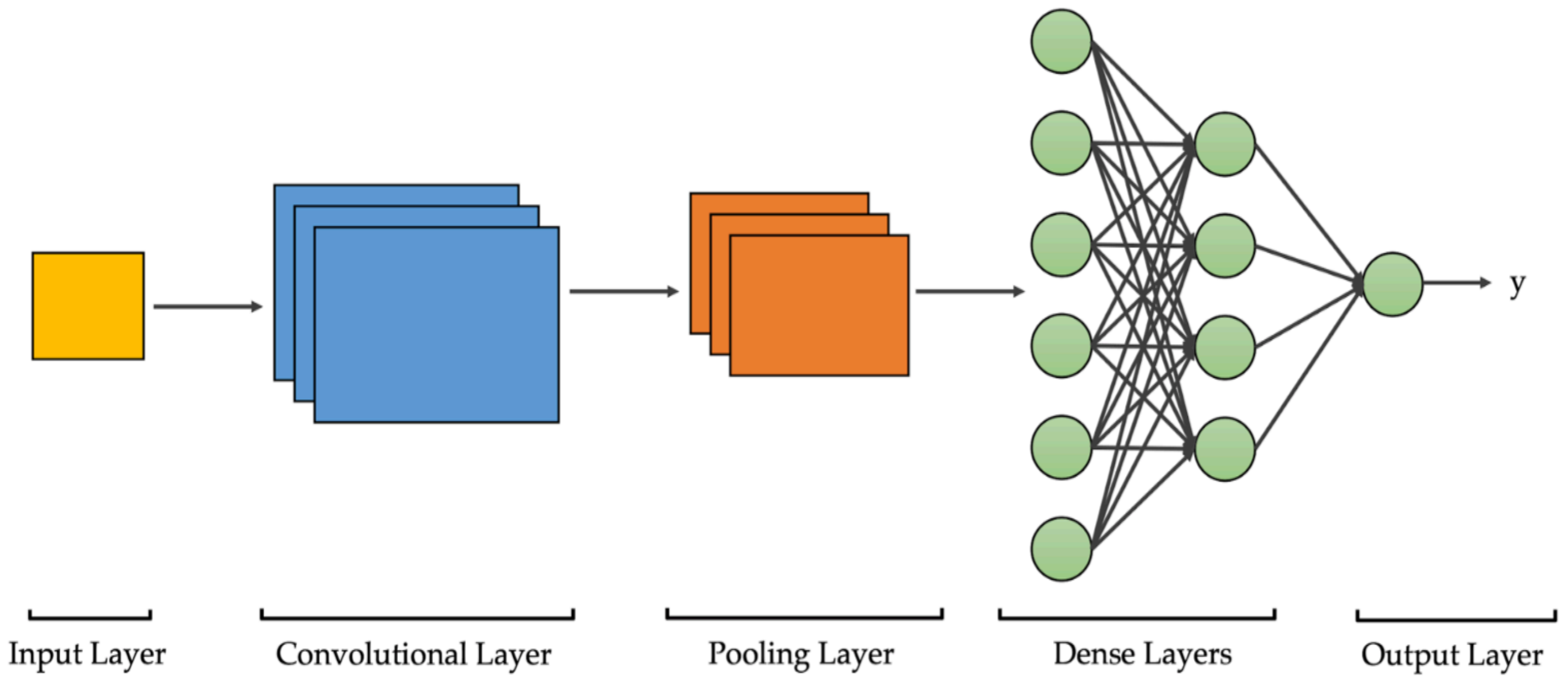
CNN architecture



Initial vs Facies-Constrained Model

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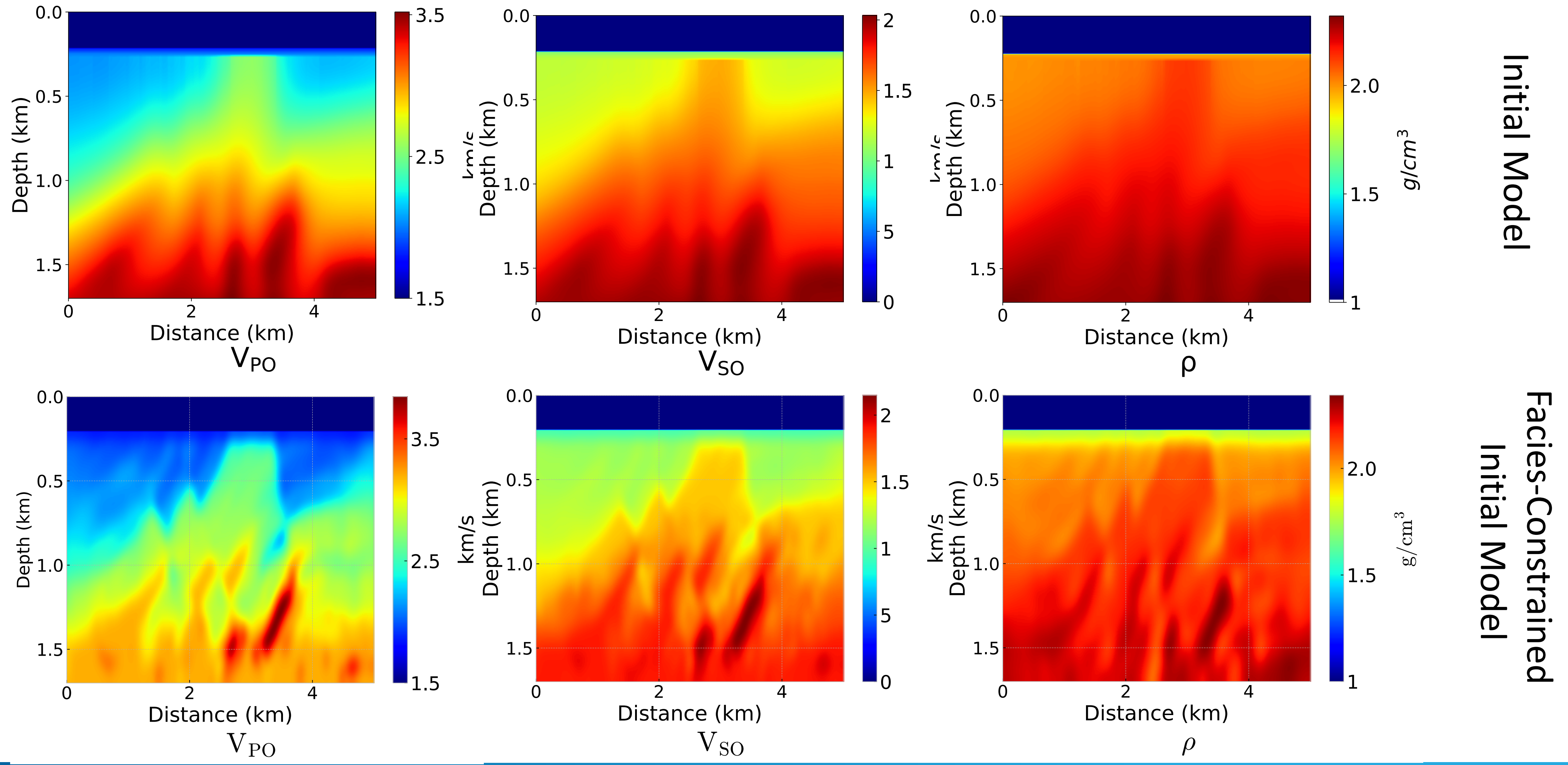

Initial vs Facies-Constrained Model (Vertical Profiles)

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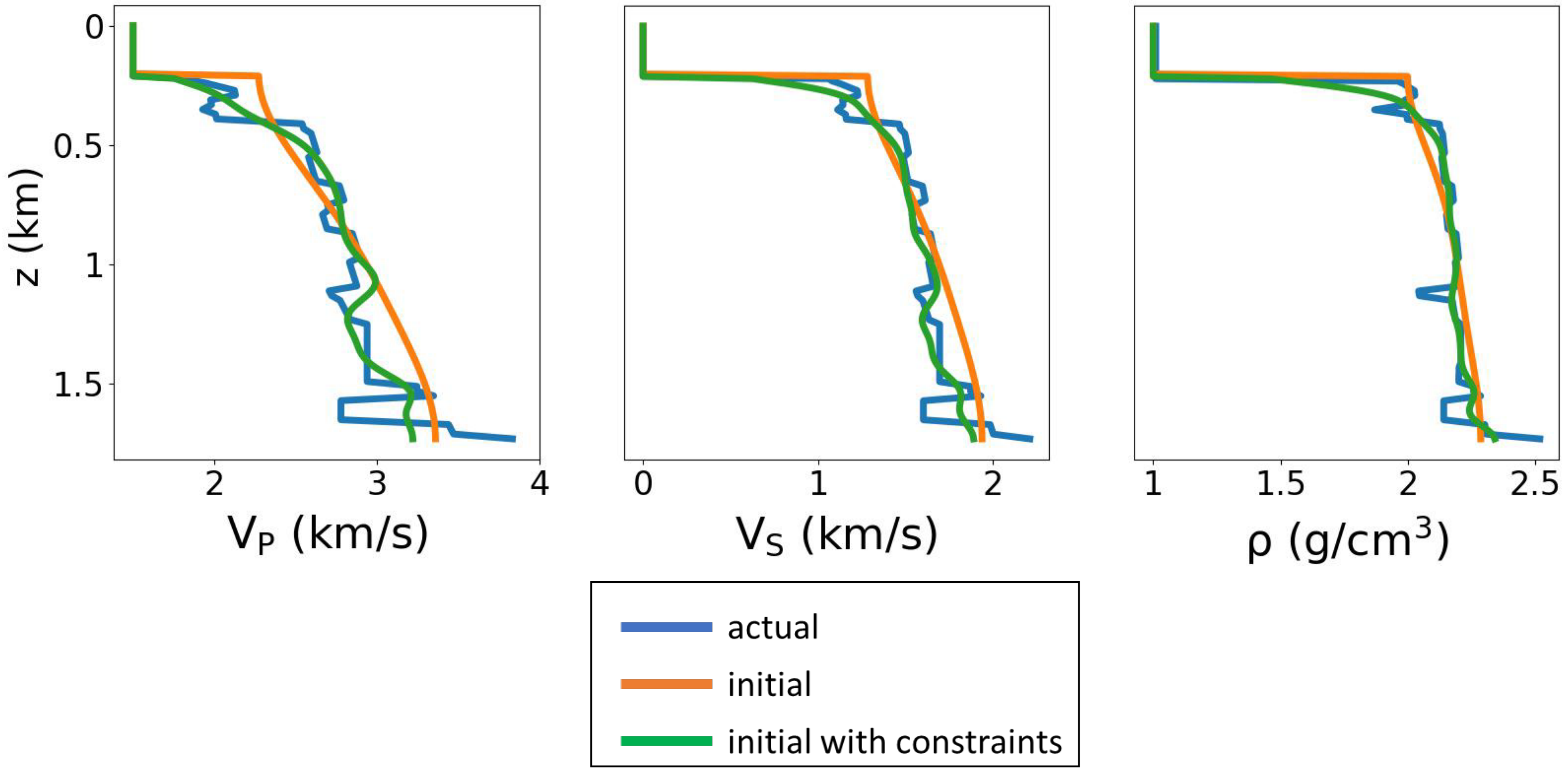

Vertical Profiles

Inversion for VP_0 and VS_0

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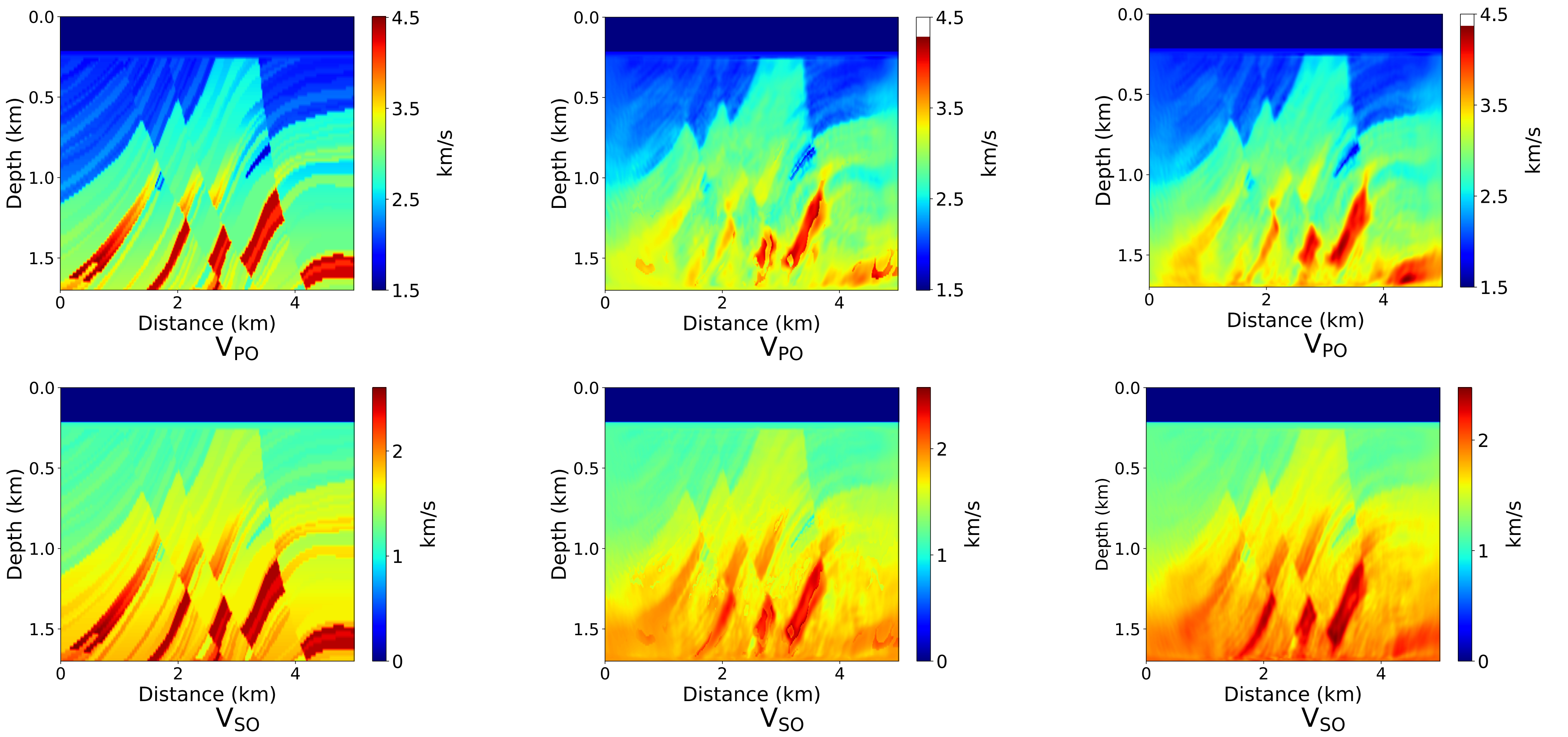
Actual | **Inverted** | **Inverted with constraints**



Inversion for V_{nmo} and V_{hor}

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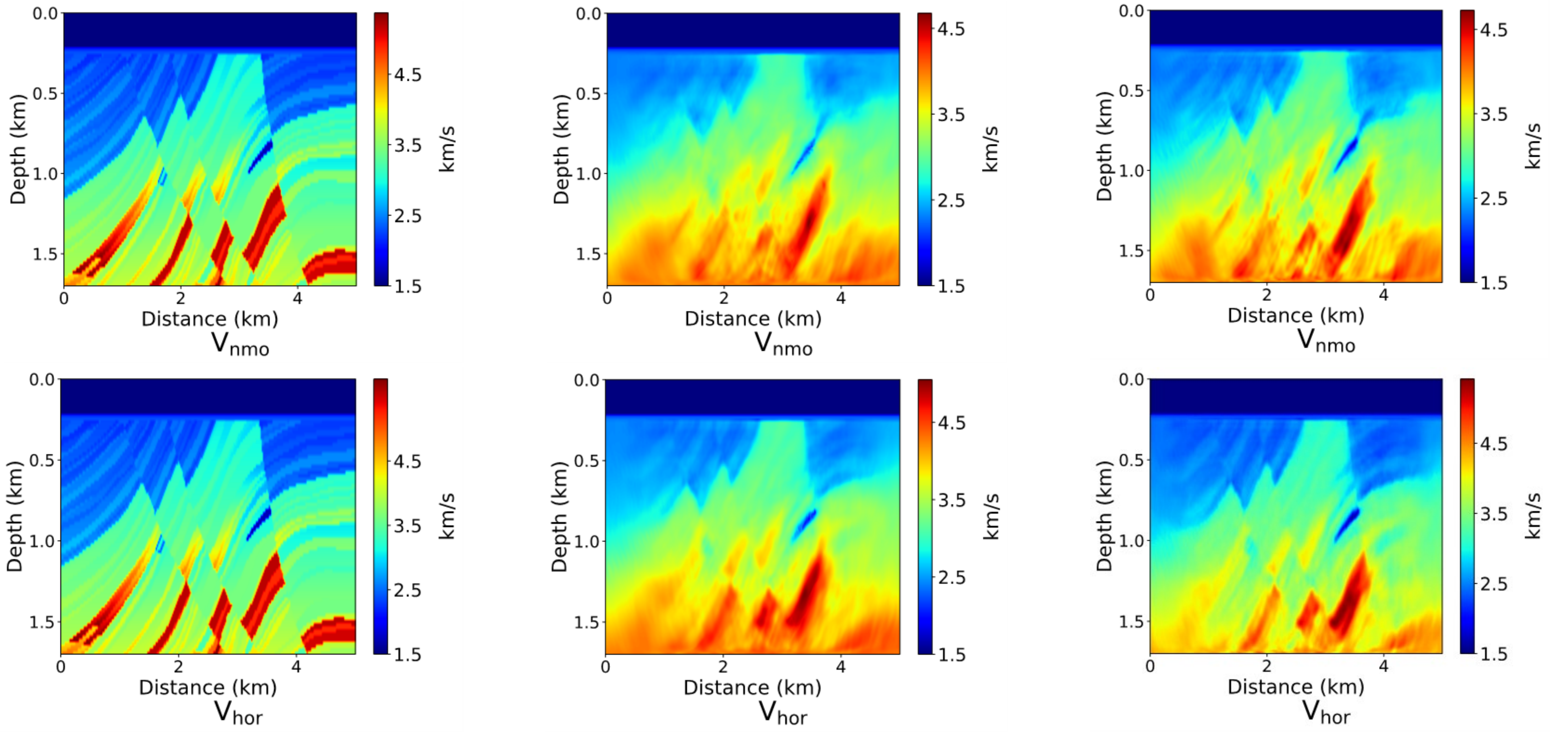
Actual | **Inverted** | **Inverted with constraints**



Inversion for Density

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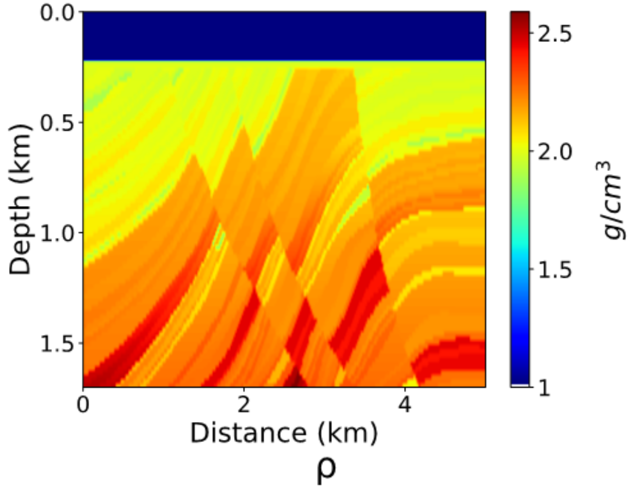
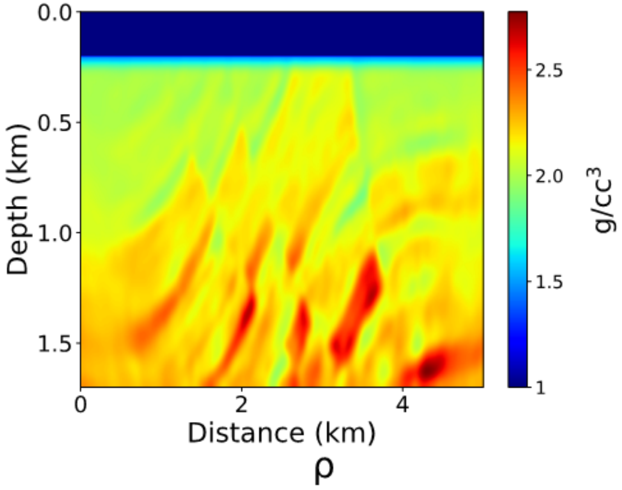
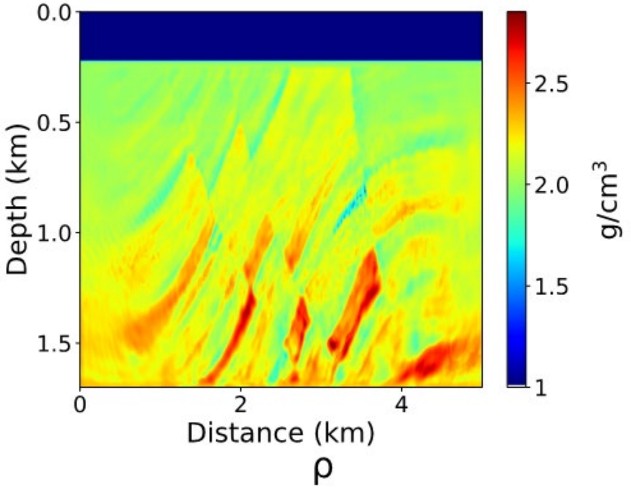
Actual



Inverted



Inverted with constraints



Vertical Profiles – Overall Comparison

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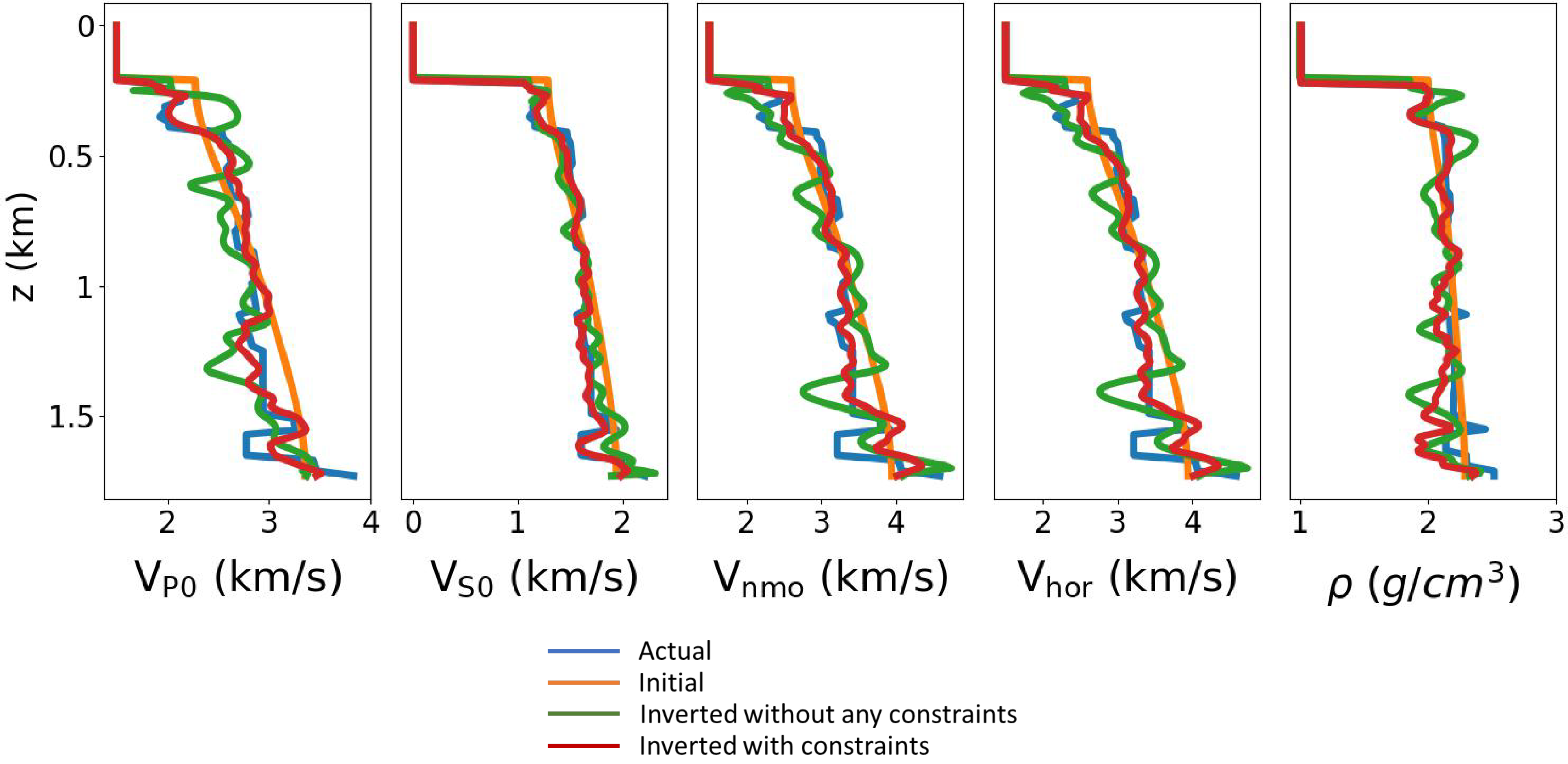

Element 4.4.2 – Enhancement of Seismic Image Resolution

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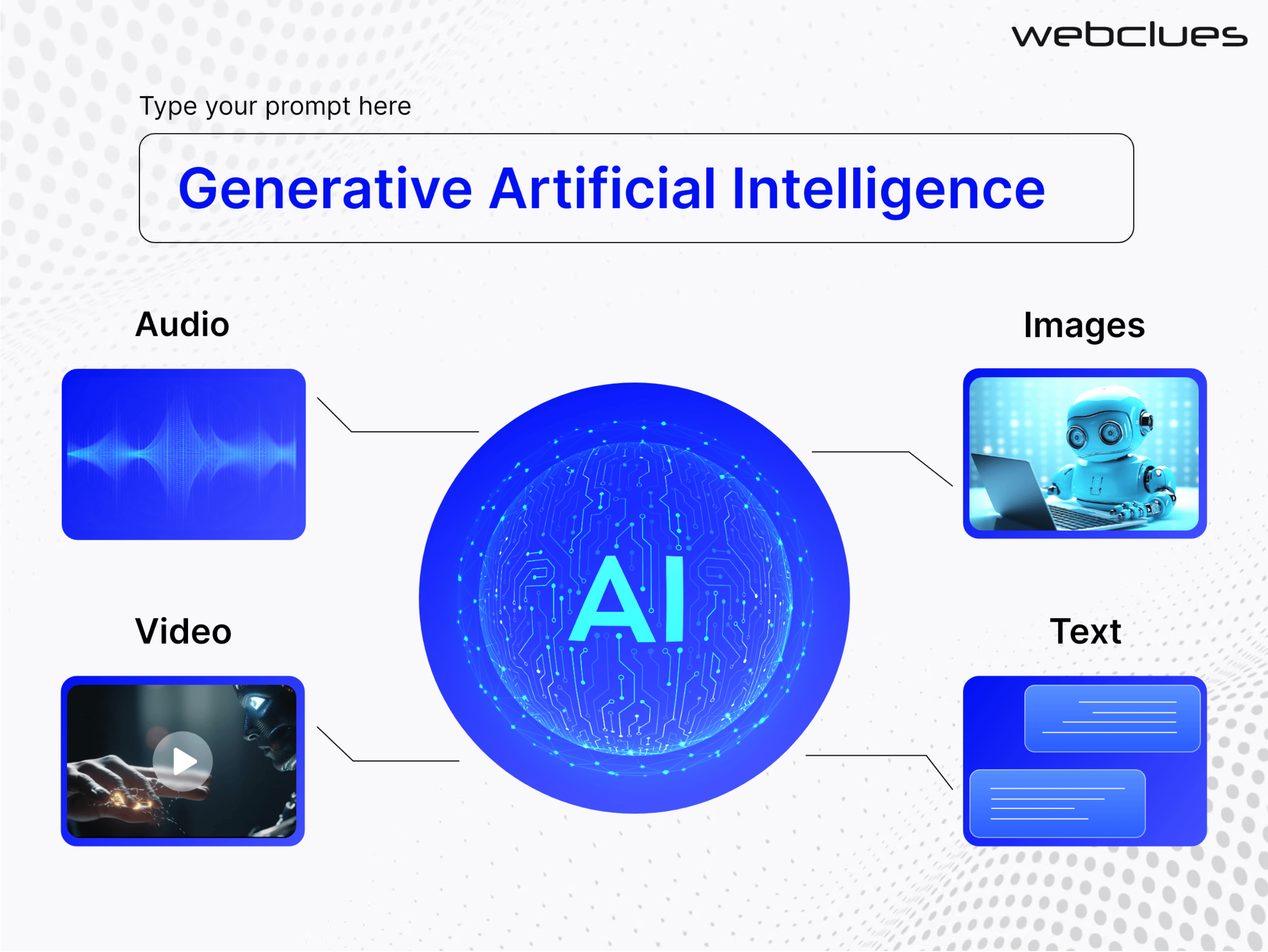

https://www.webcluesinfotech.com/

Element 4.4.2 – Enhancement of Seismic Image Resolution

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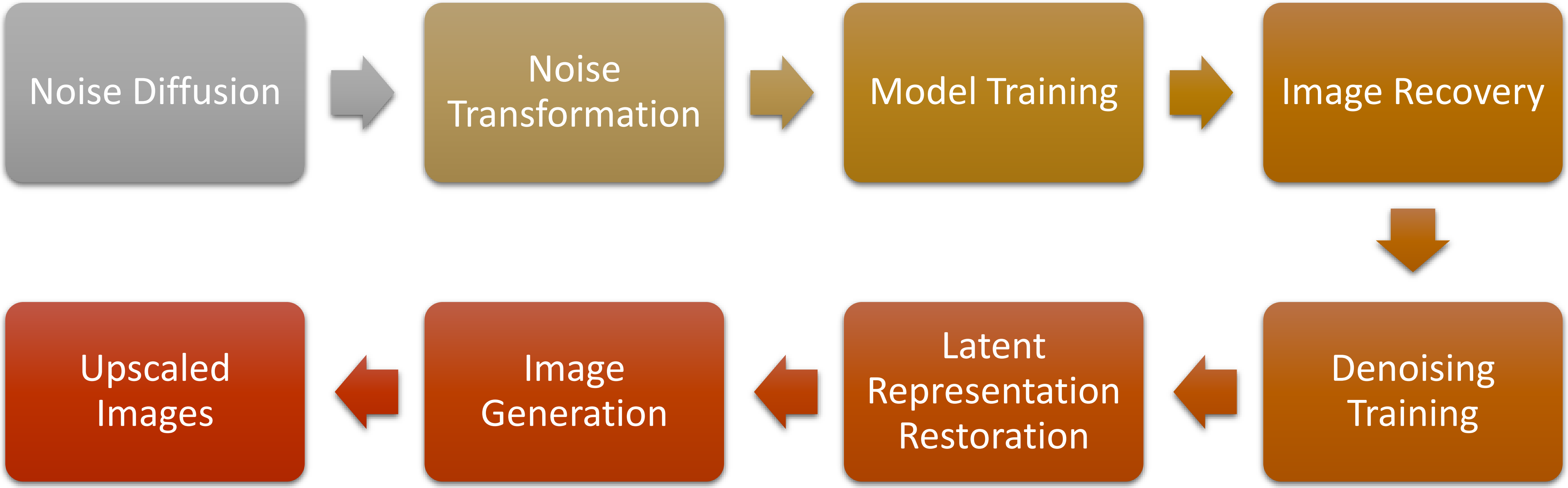
1. Use a Stable Diffusion model to generate upscaled versions of a given image
   - Enhances resolution and quality of seismic images
   - Cost-effective alternative to new seismic surveys
2. How Does it work?



Why Can't We Use Traditional Image Upscalers?

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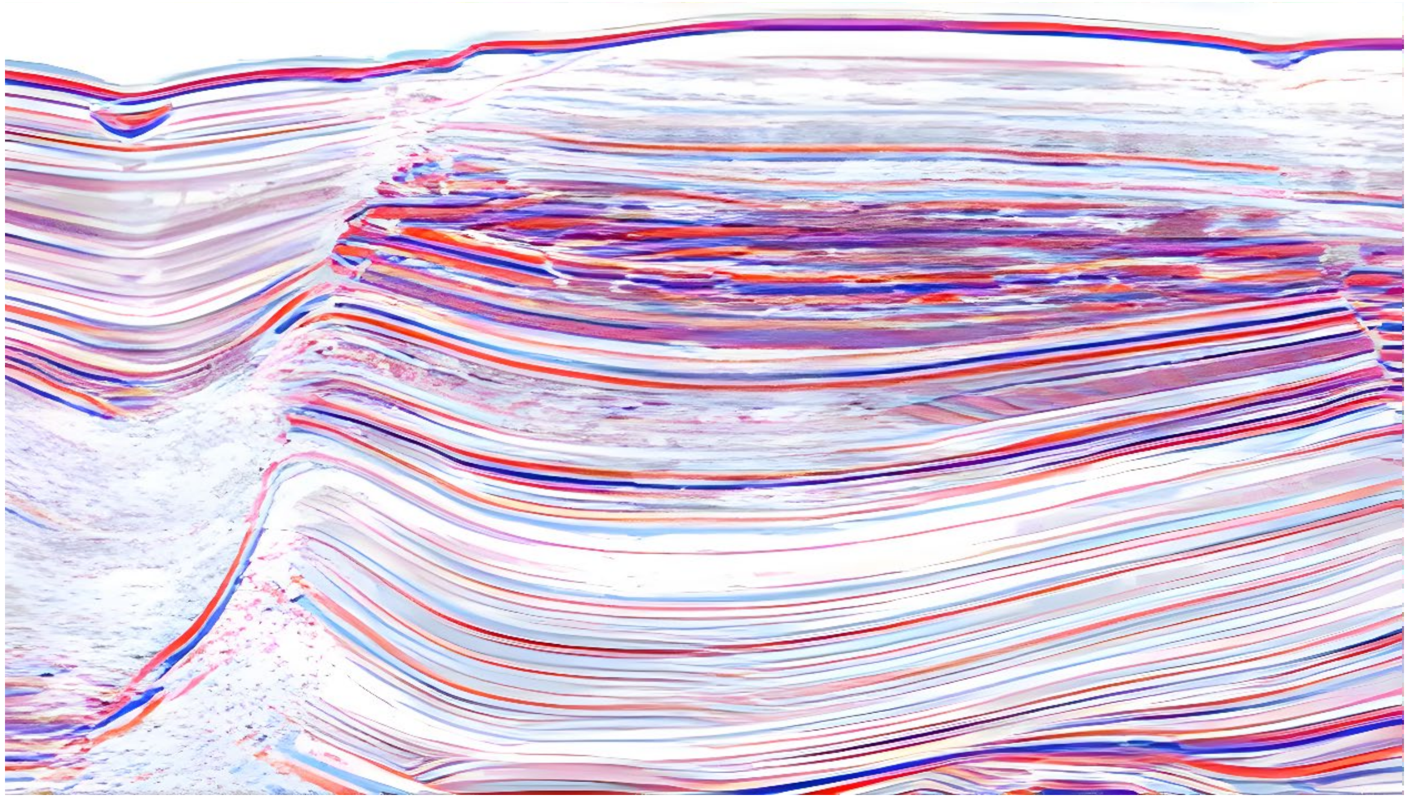
1. Examples of traditional image upscaling techniques
   - Nearest Neighbor
   - Lanczos
   - GANS



http://petroscan.co.uk/

SeismoSynth AI: Enhancement of Seismic Image Resolution GUI

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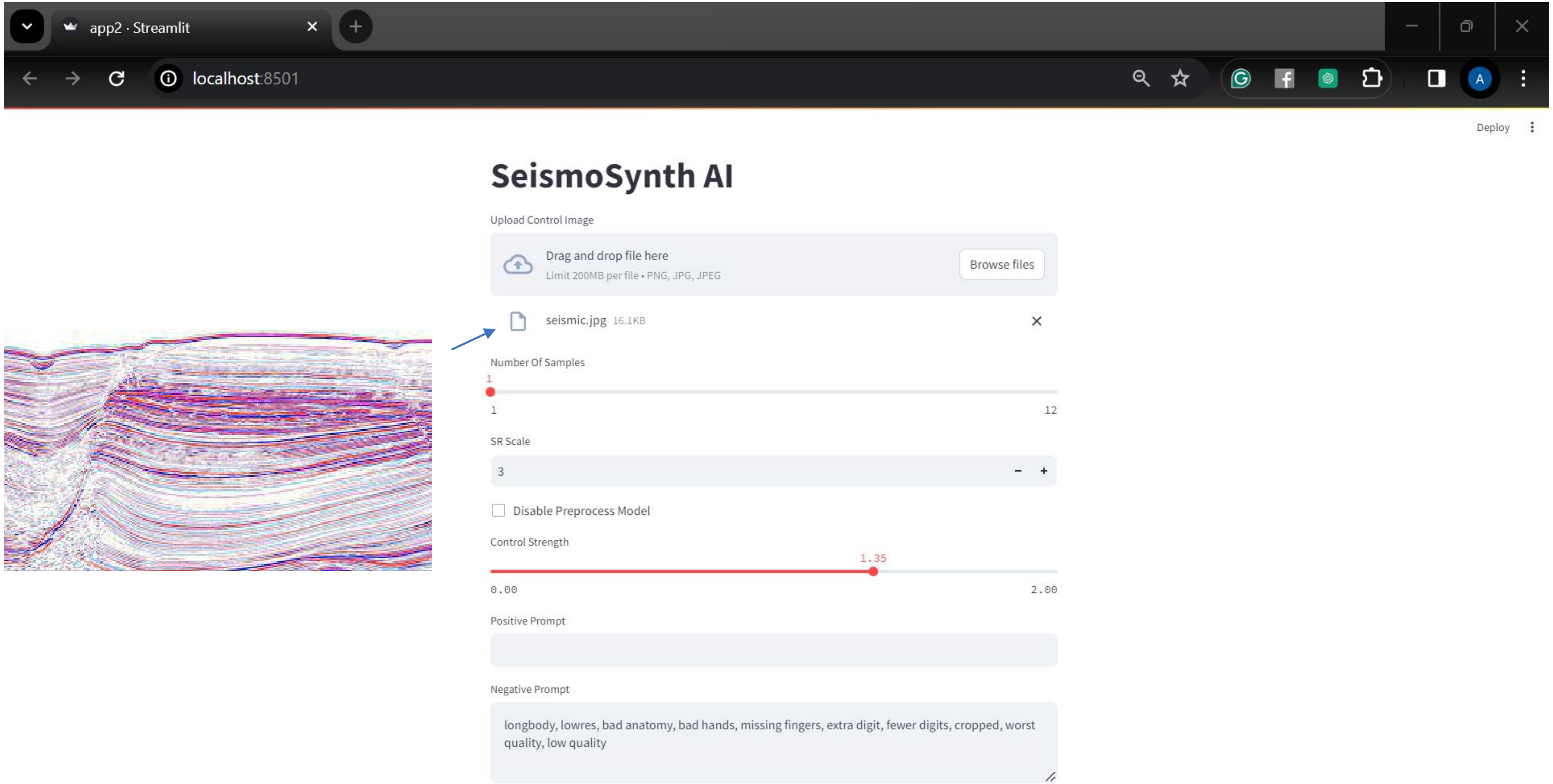

SeismoSynth AI: Enhancement of Seismic Image Resolution GUI

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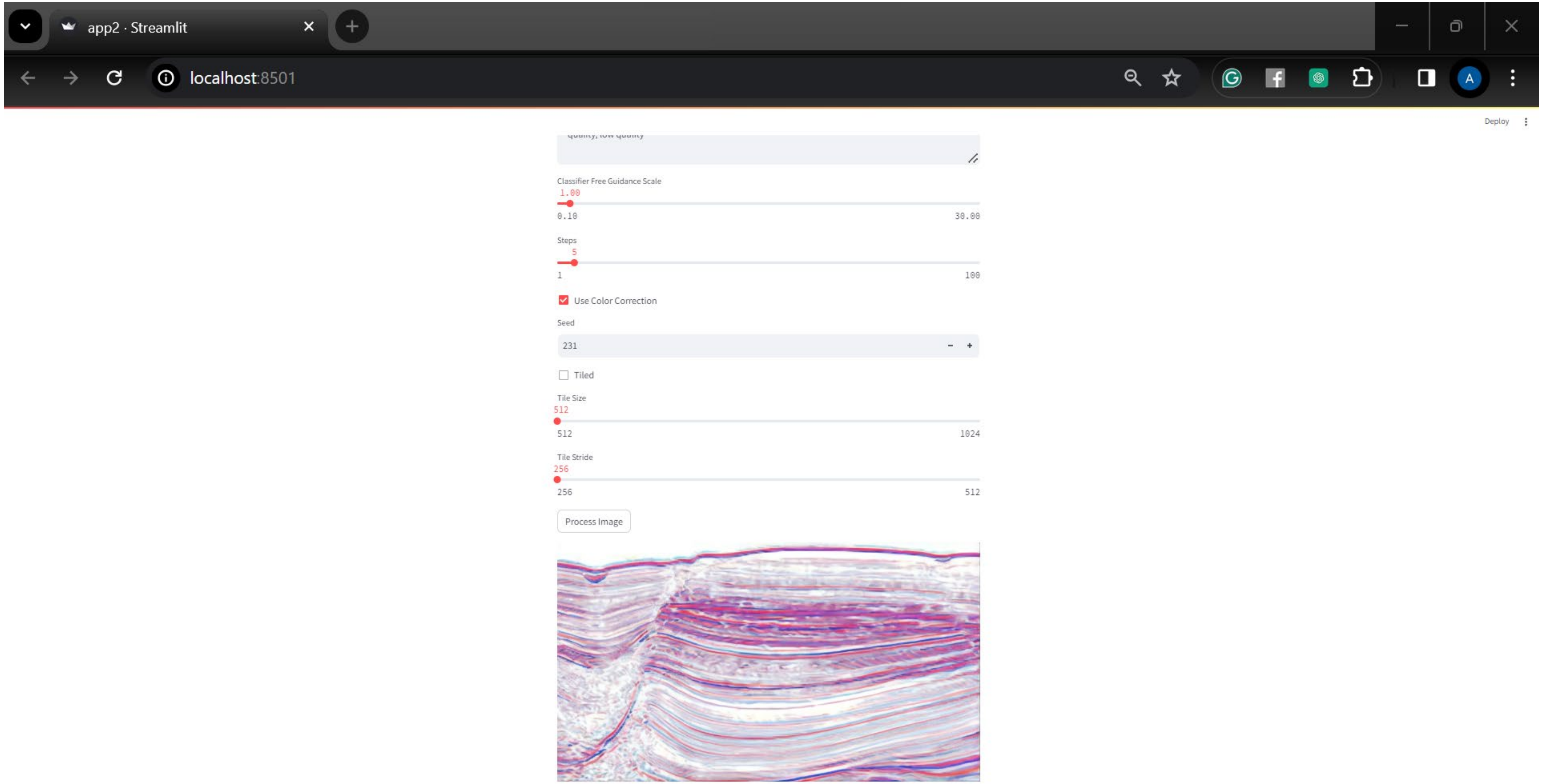

SeismoSynth AI: Results

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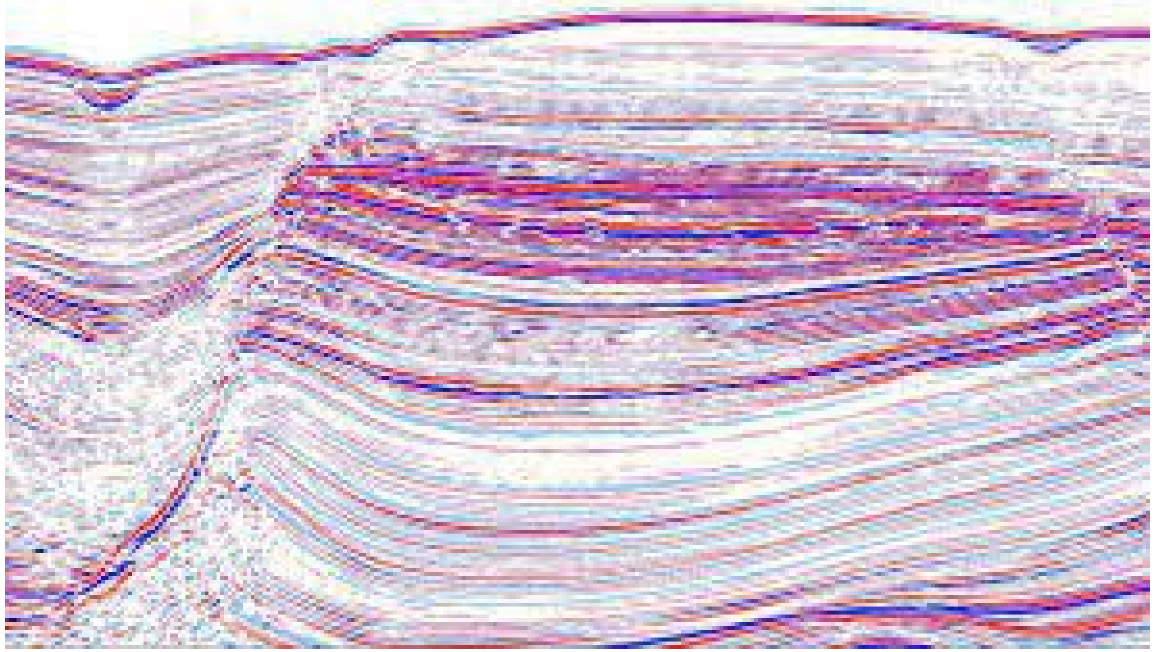
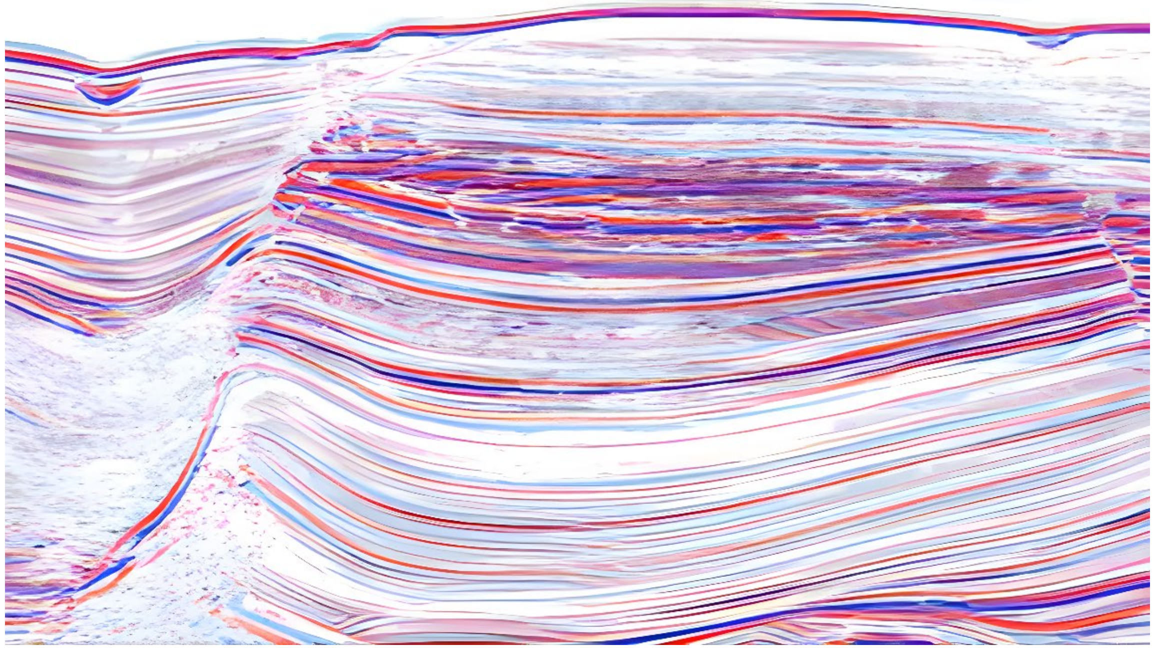
(Original) Test Image (16kB)



http://petroscan.co.uk/

(Generated) Upscaled Image (12.2MB)



Conclusions

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1. Refined the Velocity (Vp) predictions from well logs utilizing ML techniques
   - Random Forest Regression
2. Used Conditional Variational Autoencoders (CVAEs) to predict CO2 saturation levels in geological formations at the IBDP site
3. Facies lithology constrained full-waveform inversion (FWI) enhanced the estimation of elastic properties of subsurface rocks
4. Utilized Stable Diffusion to enhance the resolution and quality of seismic images

Future Steps

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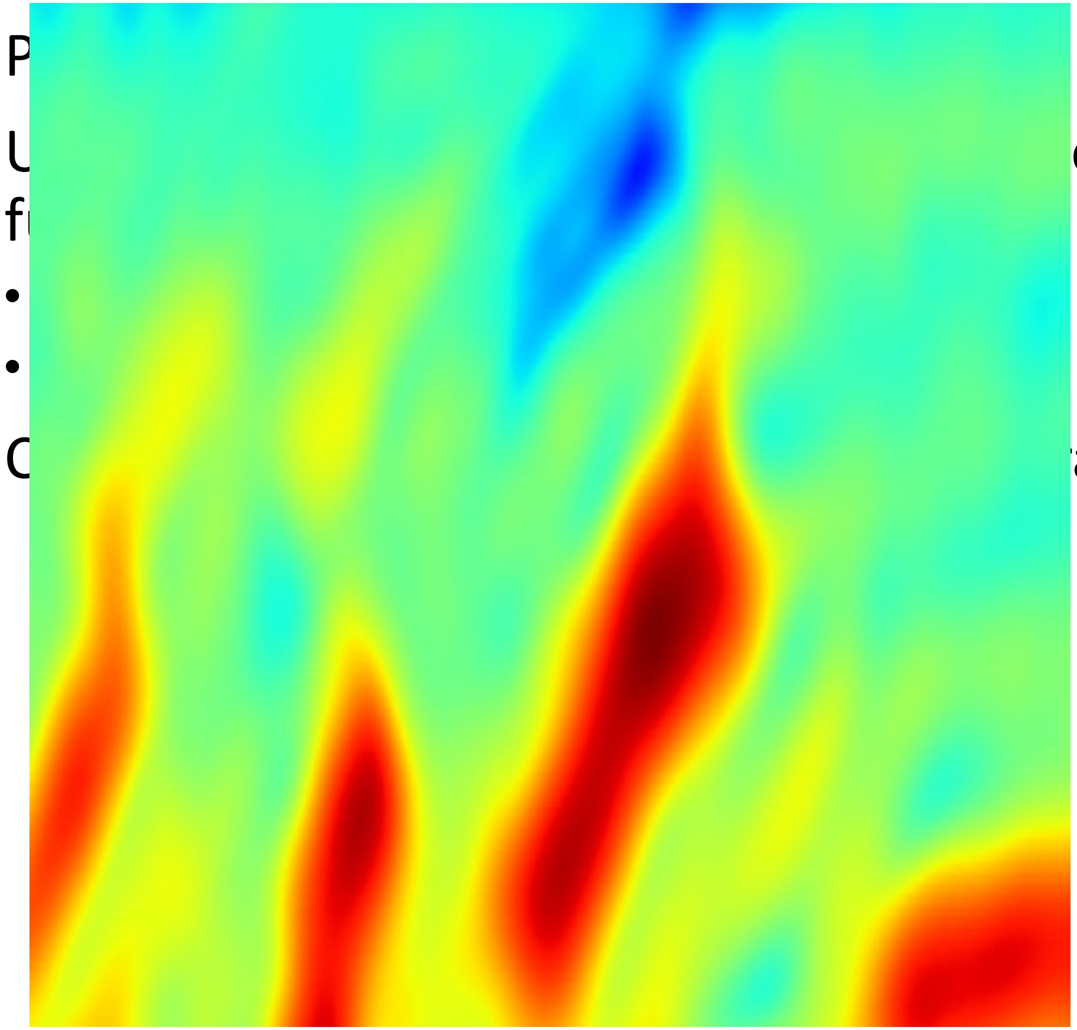
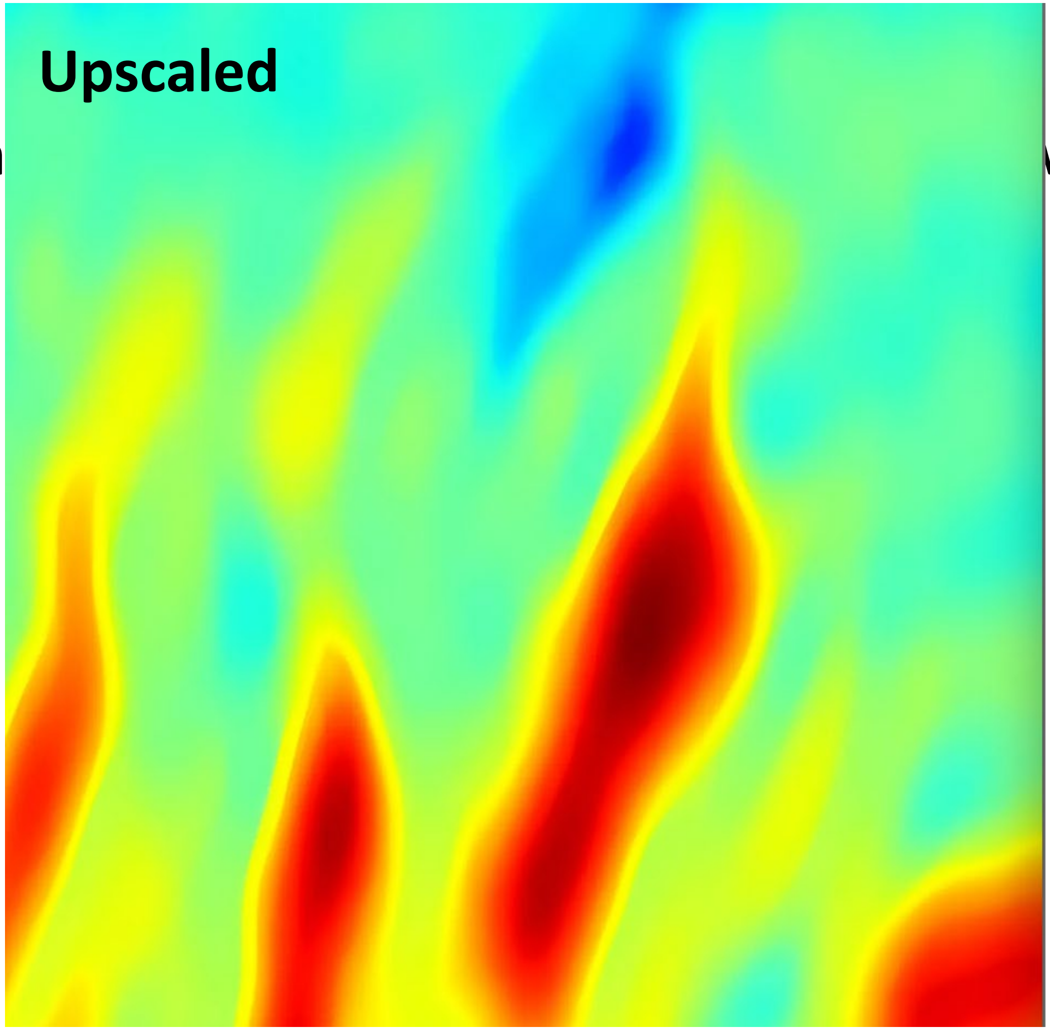
3. C ain





Thank you

Acknowledgments

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