Theory-based machine learning elastic full waveform inversion with various parameterizations

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University of Calgary ES 136

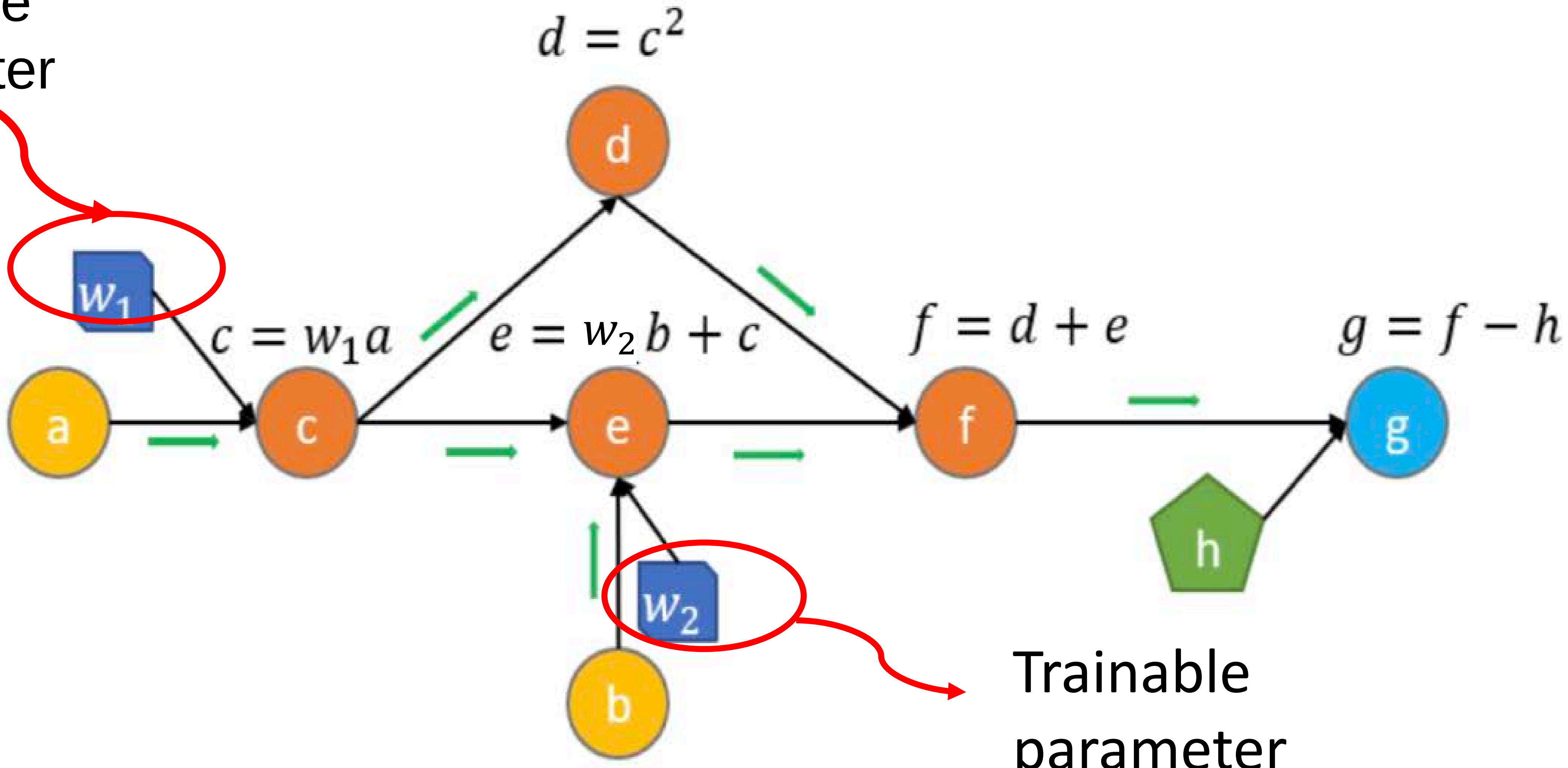
CREWES Teck Talk

Outline

- Introduction neural networks
- Recurrent neural networks (RNN)
- An RNN formulation of elastic full waveform inversion
- Noise stress test
- Conclusions

1. Feed forward network

Trainable parameter



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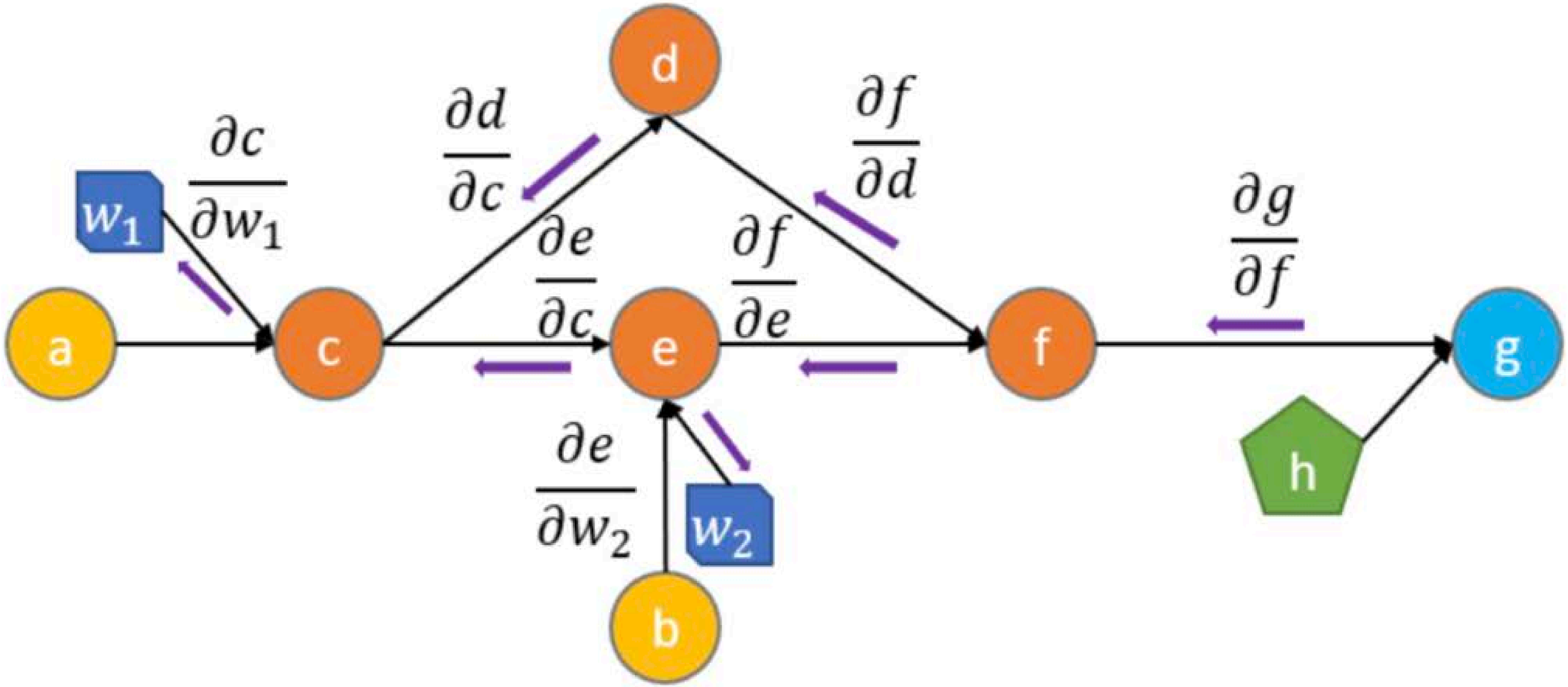
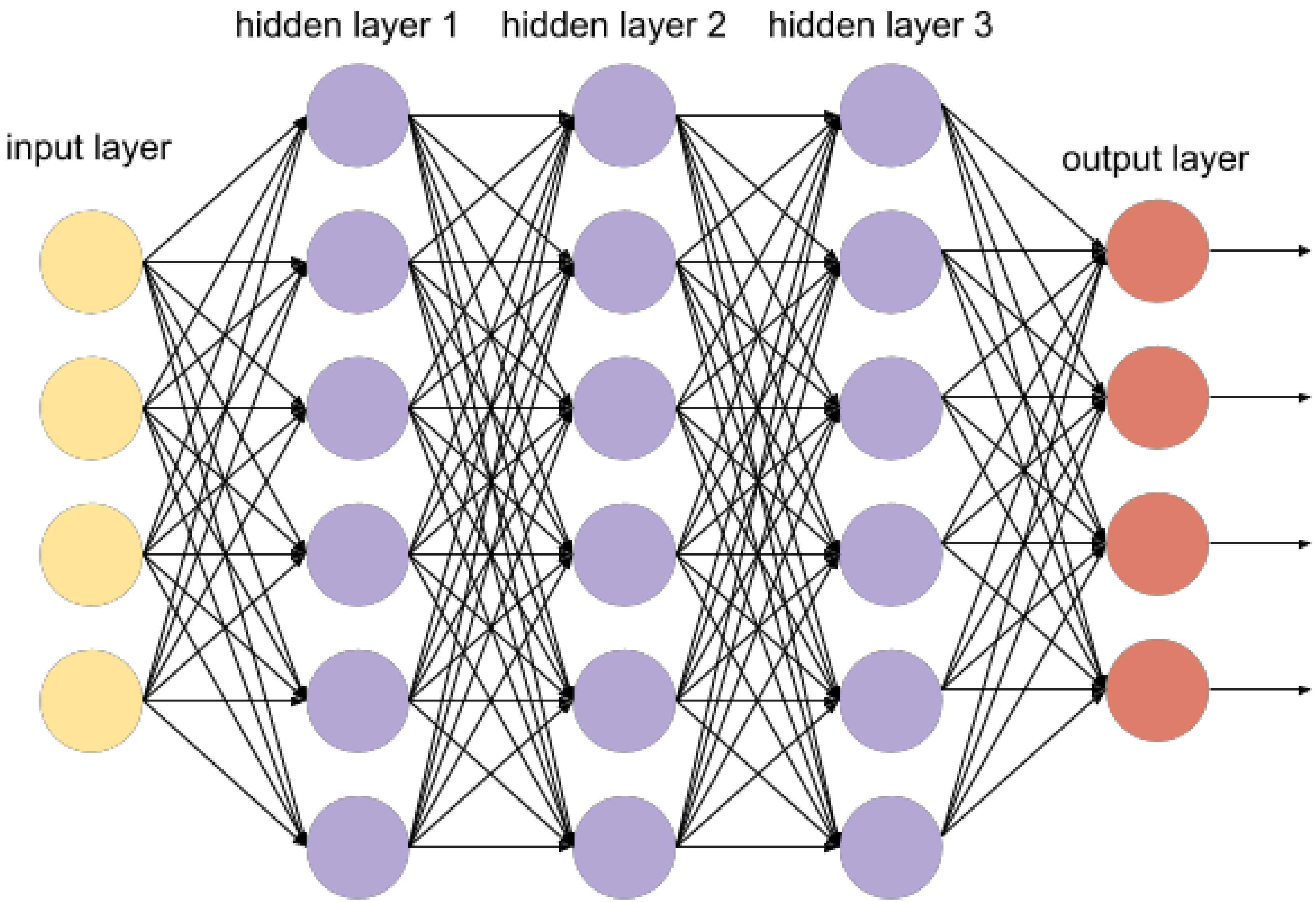
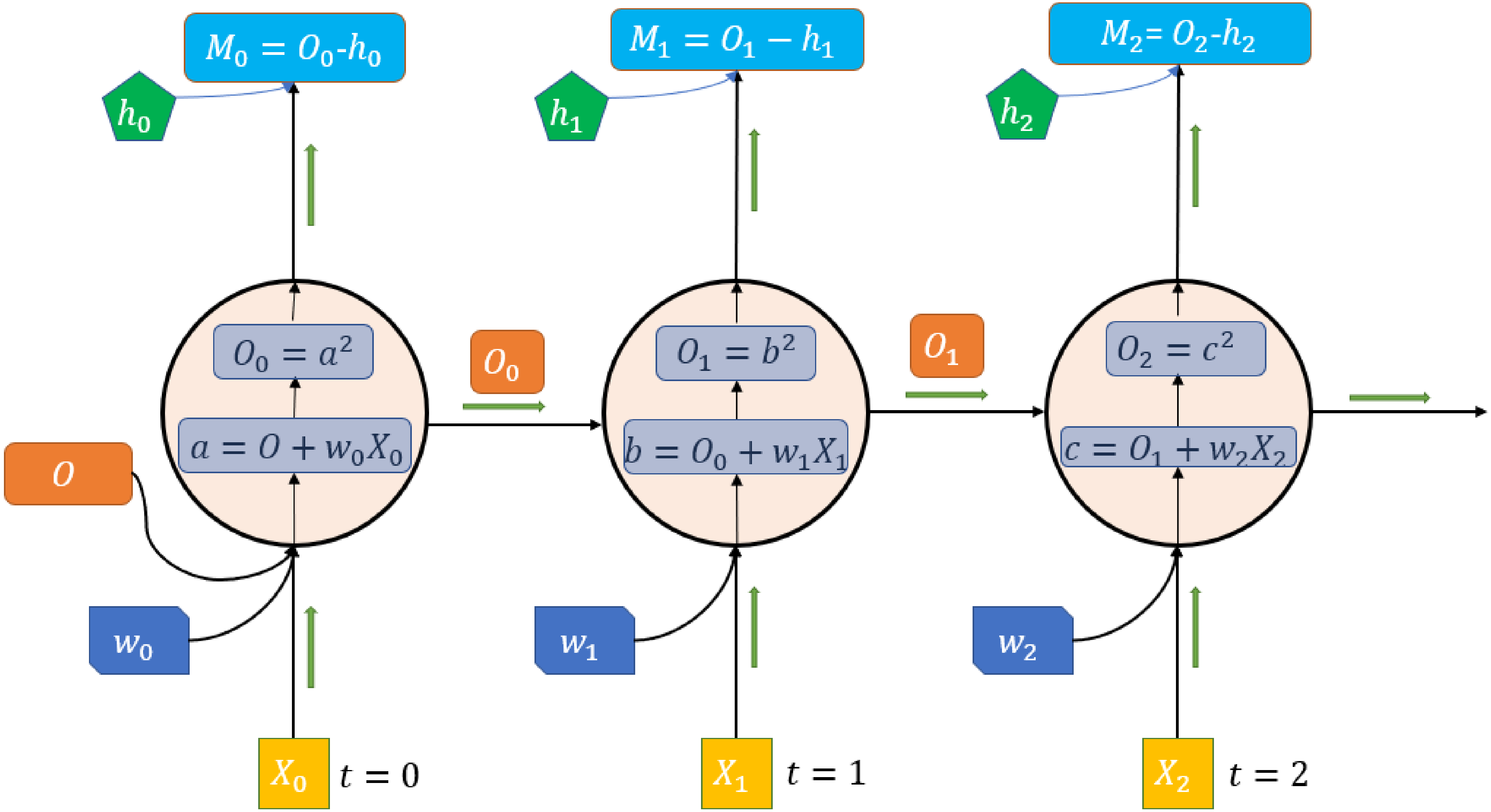
1. Feed forward network



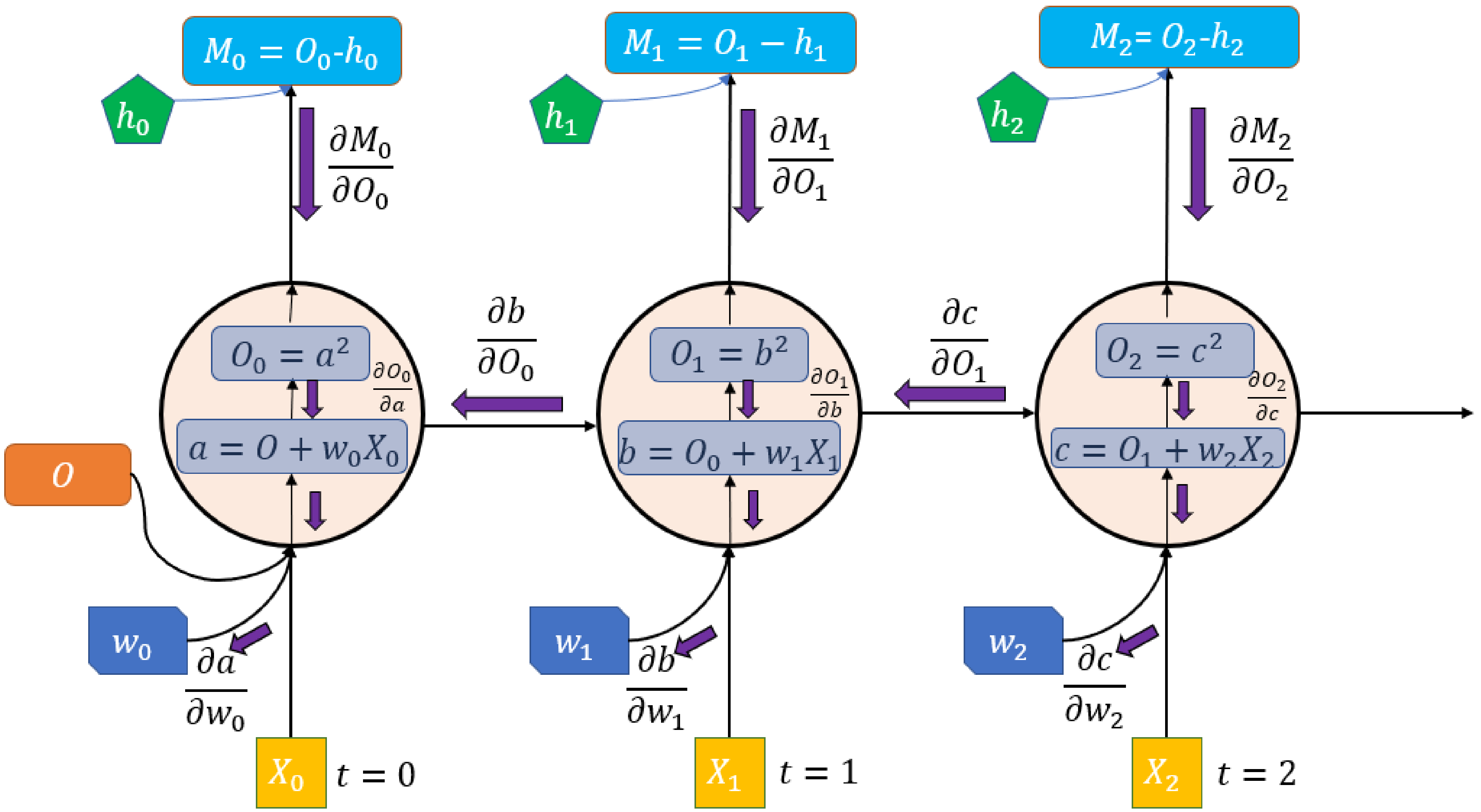
1. Fully connected network



2. Recurrent neural network (RNN) forward



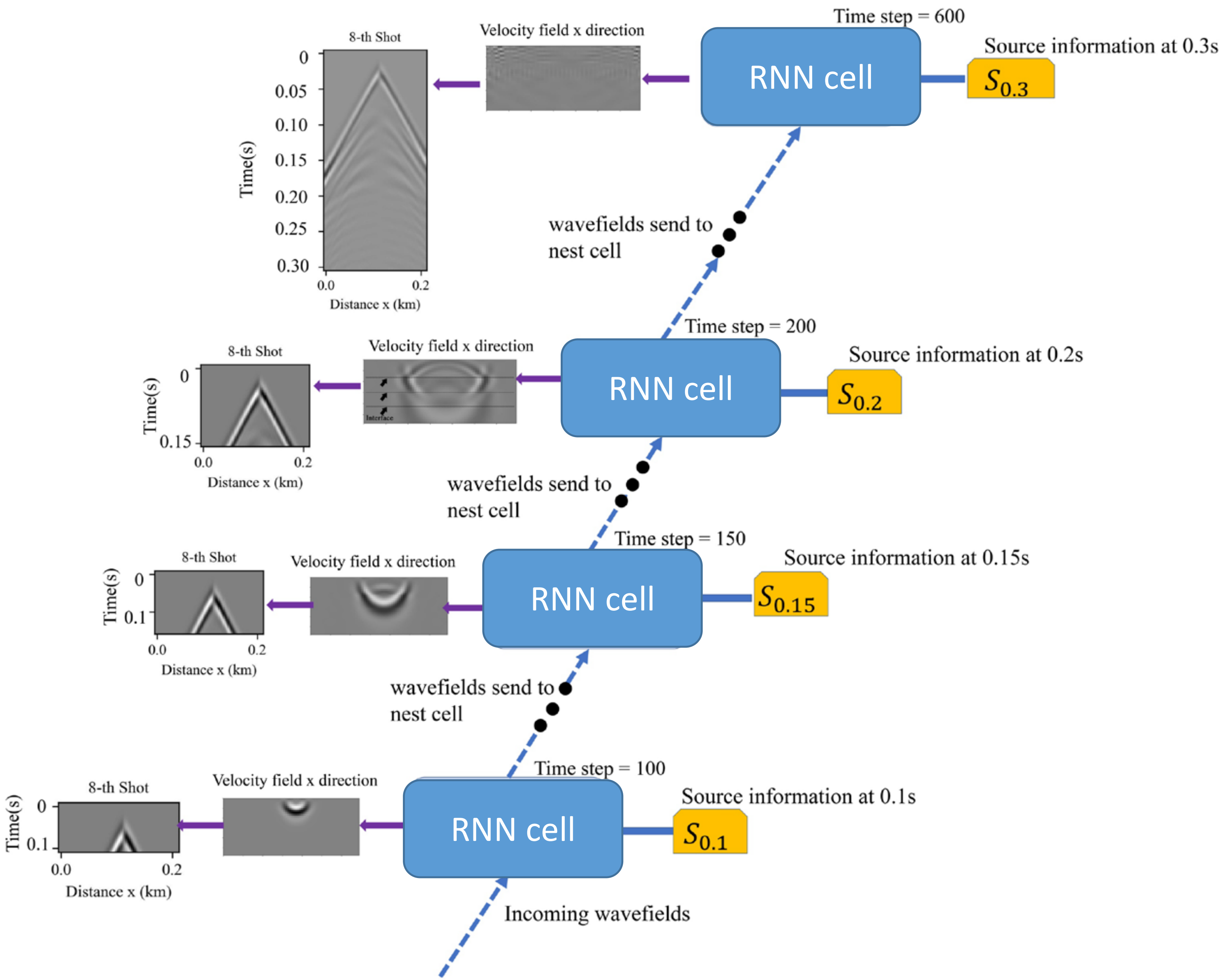
2. Recurrent neural network (RNN) backward



3.1 Isotropic elastic wave equation

$$
\begin{cases}
\dfrac{\partial \mathbf{v}_x}{\partial t} = \dfrac{1}{\rho}\left(\dfrac{\partial \boldsymbol{\sigma}_{xx}}{\partial x} + \dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial z}\right) \\
\dfrac{\partial \mathbf{v}_z}{\partial t} = \dfrac{1}{\rho}\left(\dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial x} + \dfrac{\partial \boldsymbol{\sigma}_{zz}}{\partial z}\right) \\
\dfrac{\partial \boldsymbol{\sigma}_{xx}}{\partial t} = (\lambda + 2\mu)\dfrac{\partial \mathbf{v}_x}{\partial x} + \lambda\dfrac{\partial \mathbf{v}_x}{\partial x} \\
\dfrac{\partial \boldsymbol{\sigma}_{zz}}{\partial t} = (\lambda + 2\mu)\dfrac{\partial \mathbf{v}_z}{\partial z} + \lambda\dfrac{\partial \mathbf{v}_x}{\partial x} \\
\dfrac{\partial \boldsymbol{\sigma}_{xz}}{\partial t} = \mu\left(\dfrac{\partial \mathbf{v}_x}{\partial z} + \dfrac{\partial \mathbf{v}_z}{\partial x}\right)
\end{cases}
$$

3.2 RNN cell designed according to elastic wave equation



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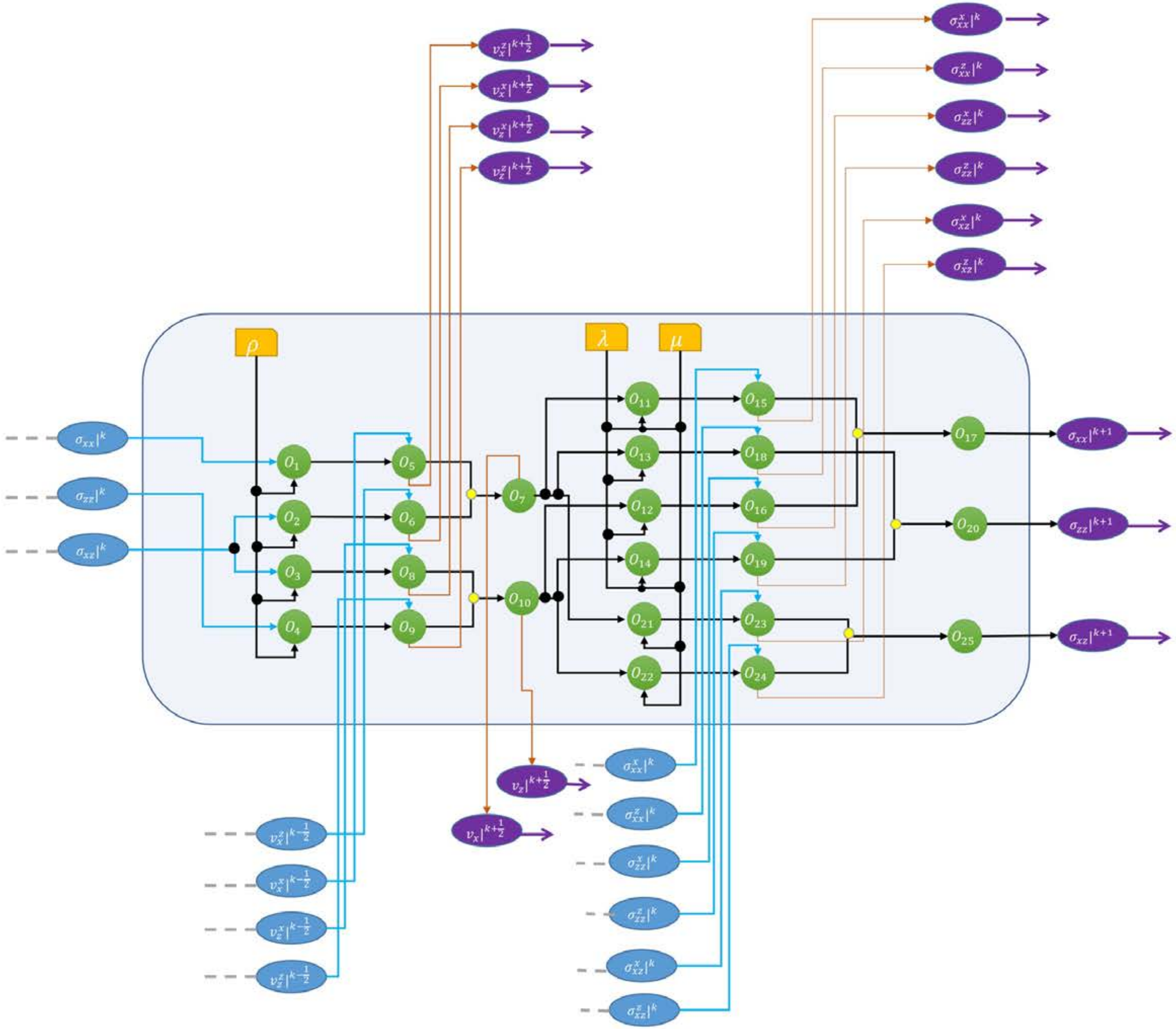
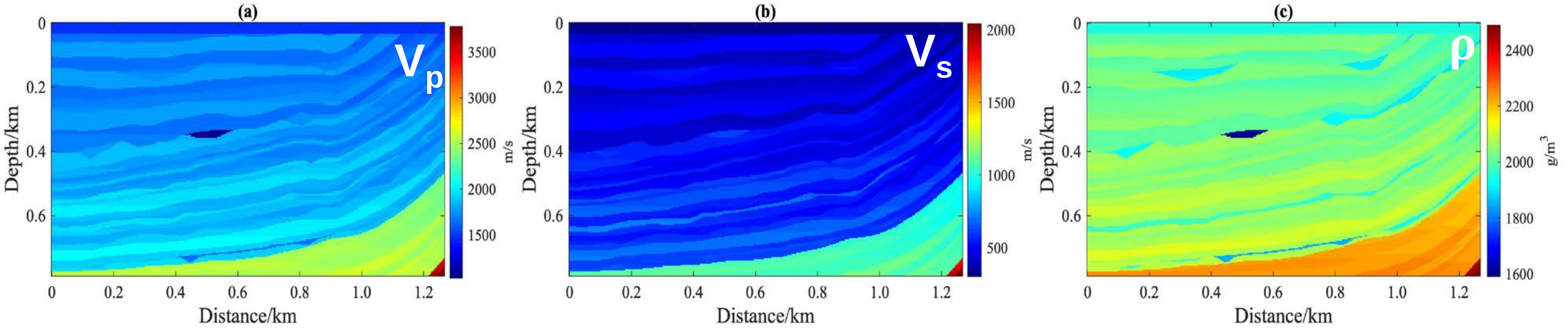
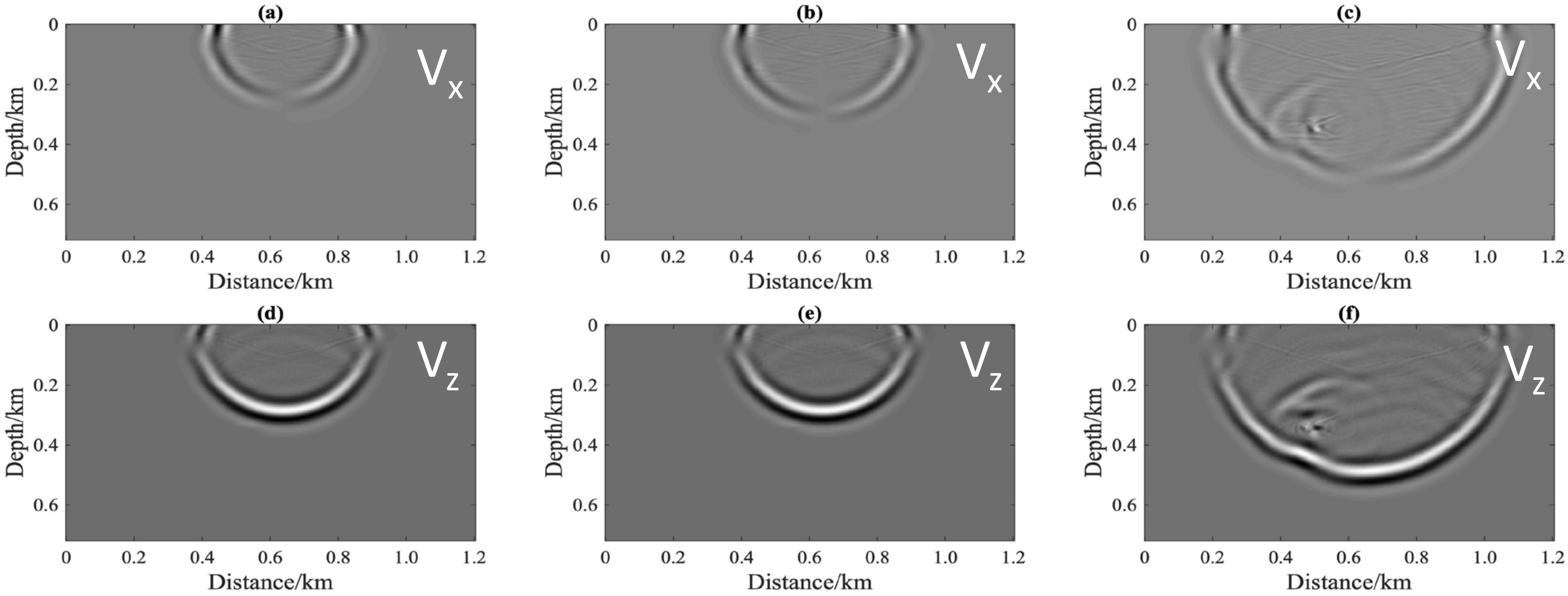


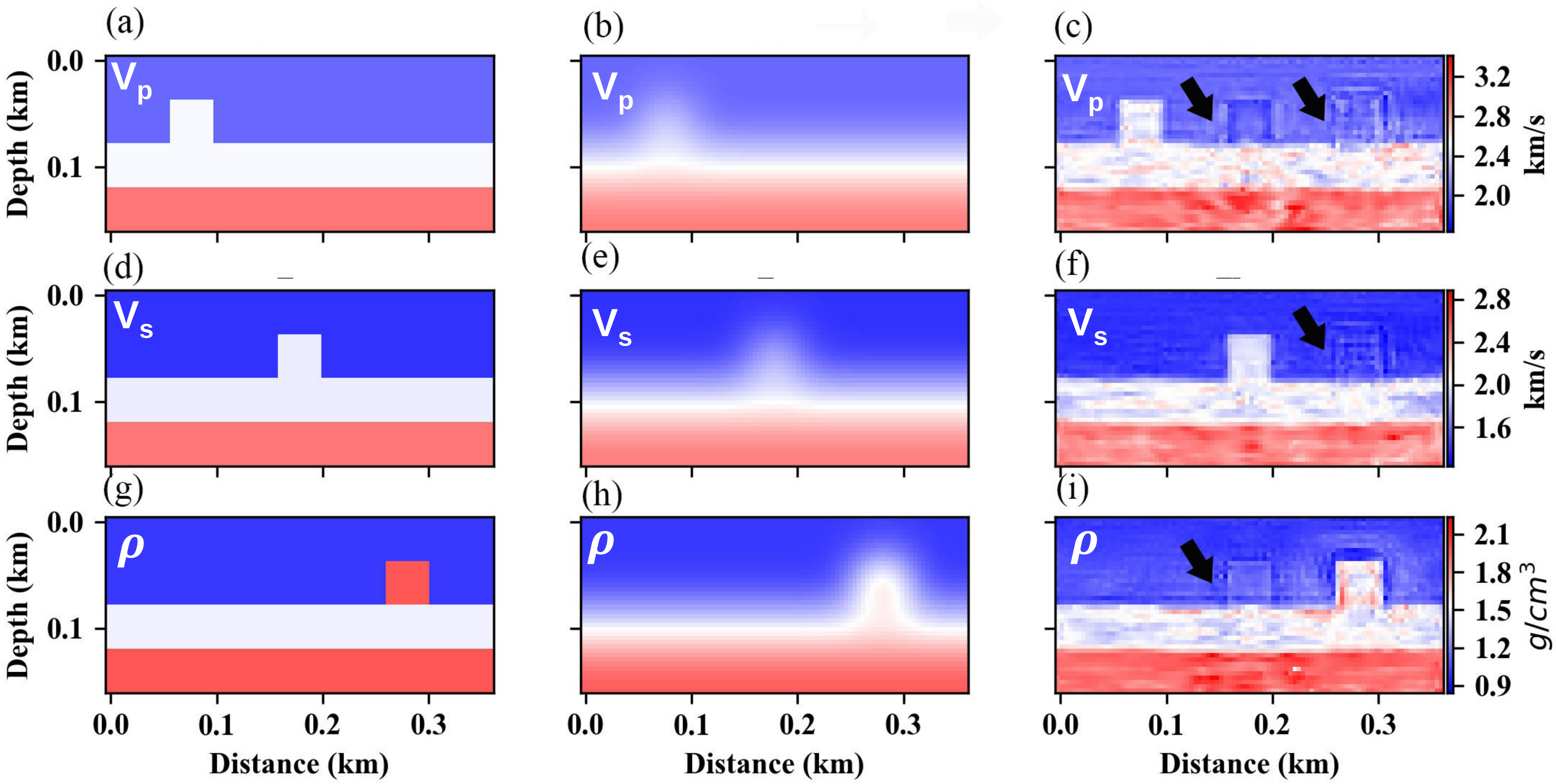
3.3 Elastic media to test forward modeling



3.4 Velocity fields generated by elastic RNN



3.5 Velocity parameterization-Toy model



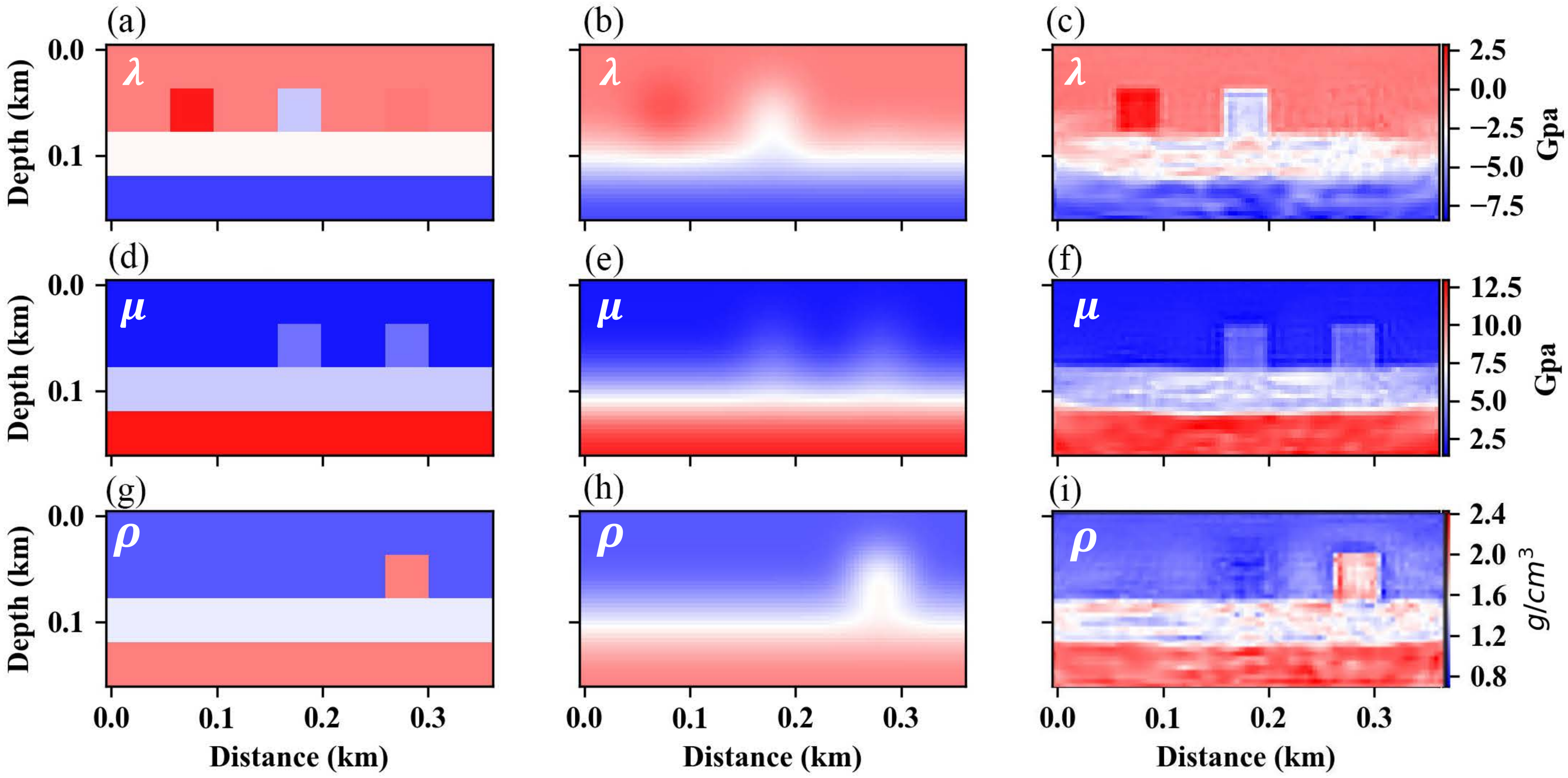
20 shots (top)

90 receivers (top)

f_{dom} 35Hz

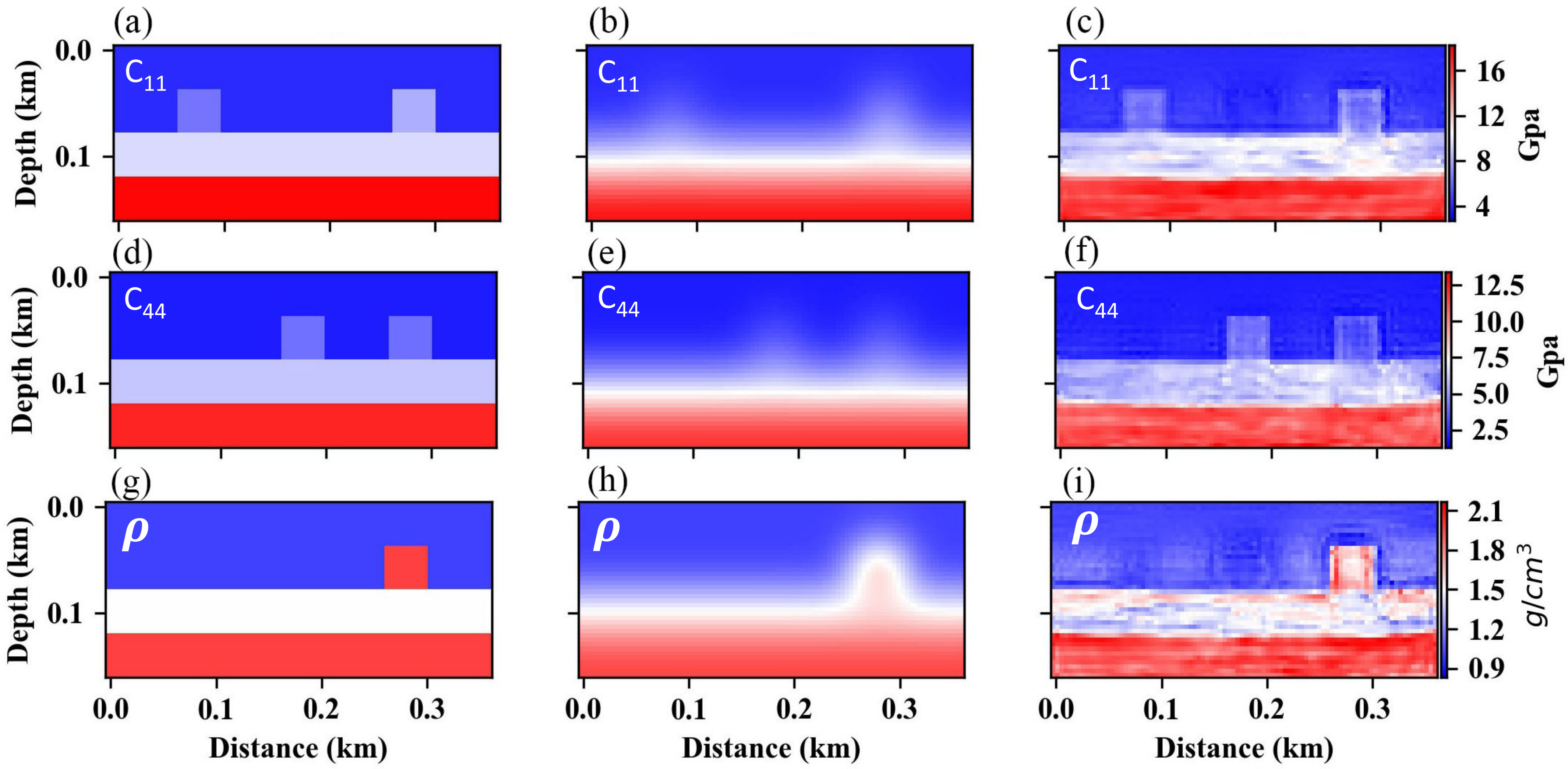
T_{max} 0.25s

3.6 Modulus parameterization-Toy model



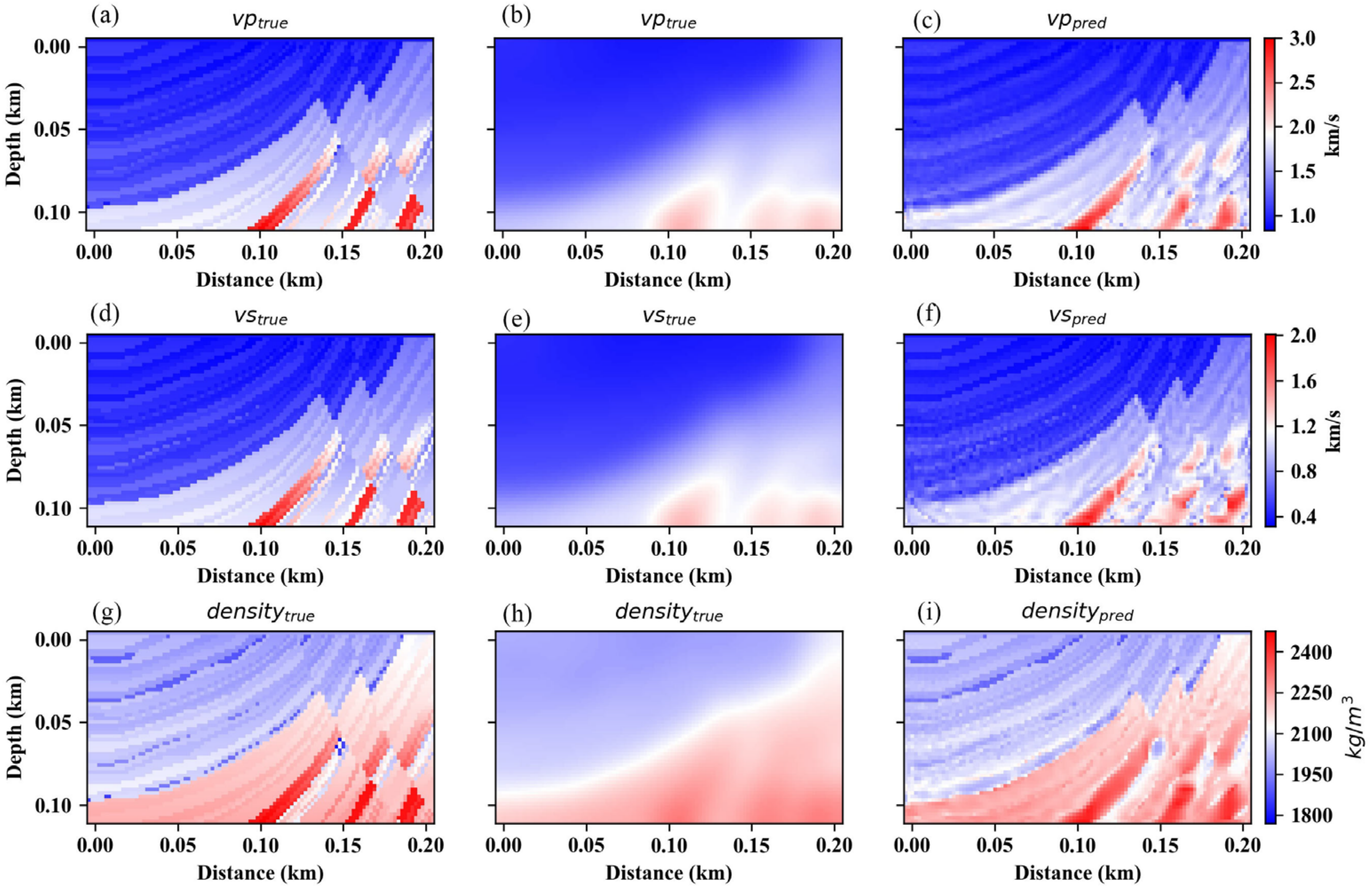
20 shots (top)
90 receivers (top)
f_{dom} 35Hz

3.7 Stiffness matrix parameterization-Toy model



20 shots (top)
90 receivers (top)
f_{dom} 35Hz
T_{max} 0.25s

3.8 Velocity parameterization:Part of Marmousi model



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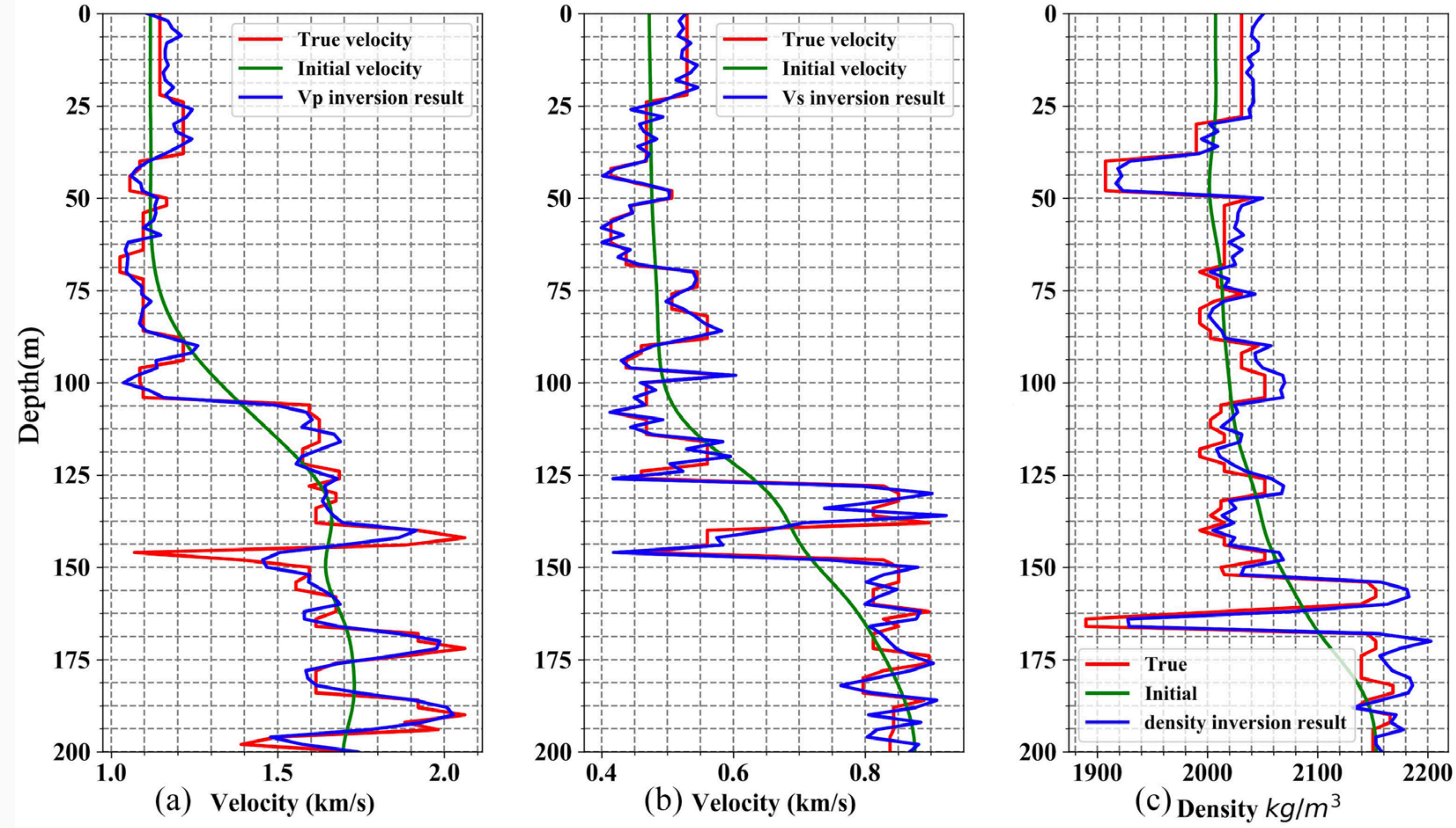
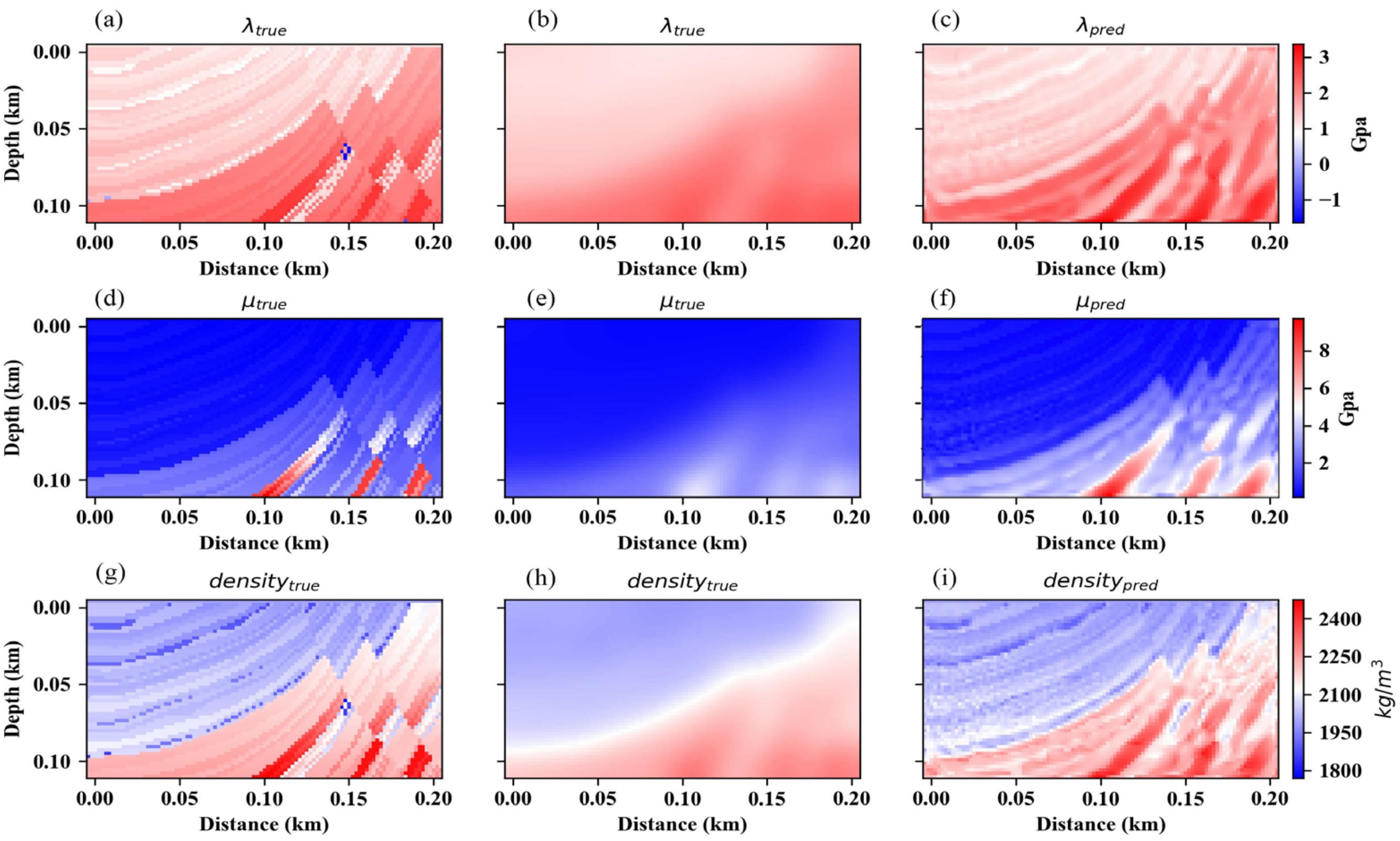


3.9 Modulus parameterization Part of Marmousi model



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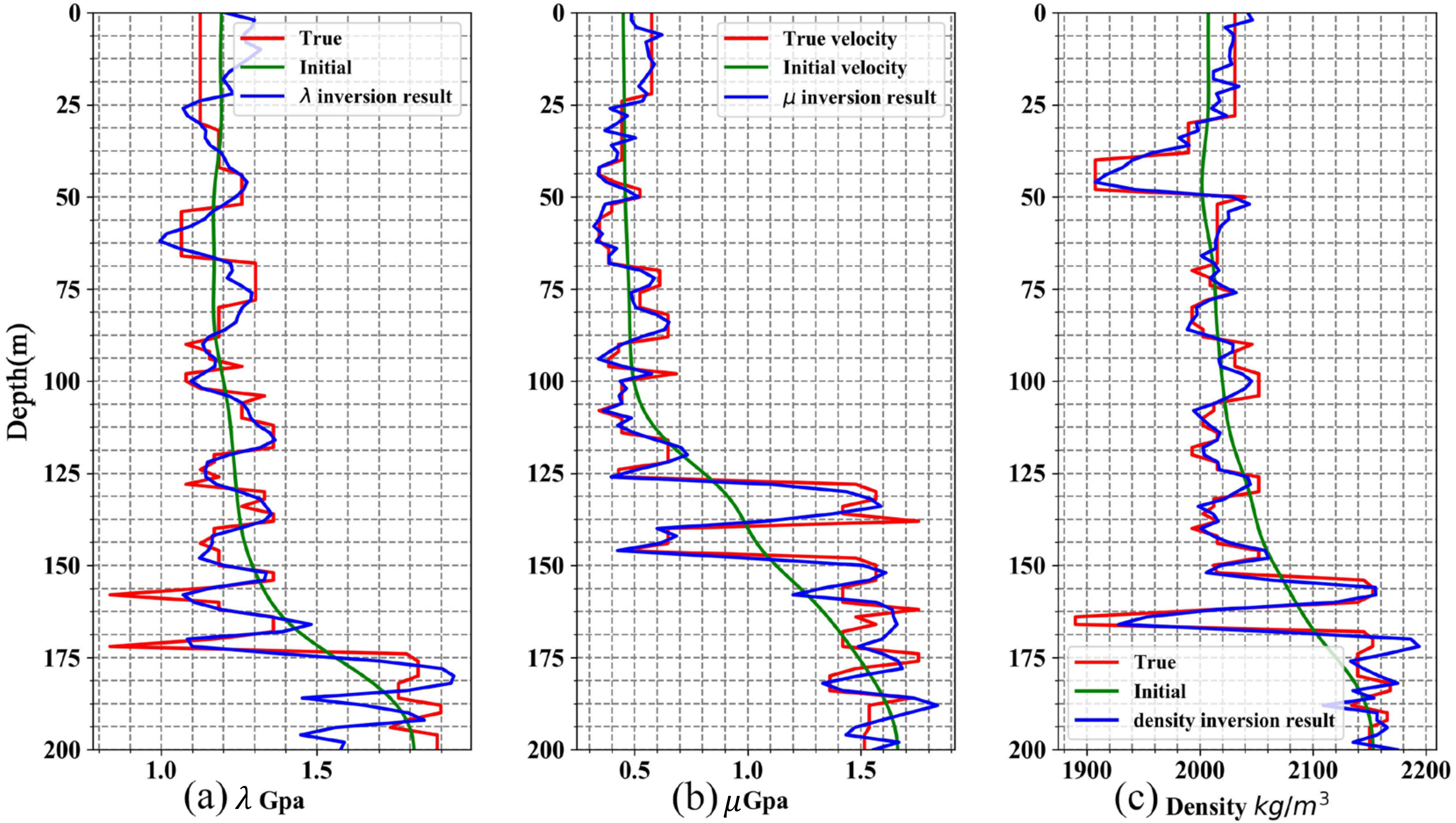
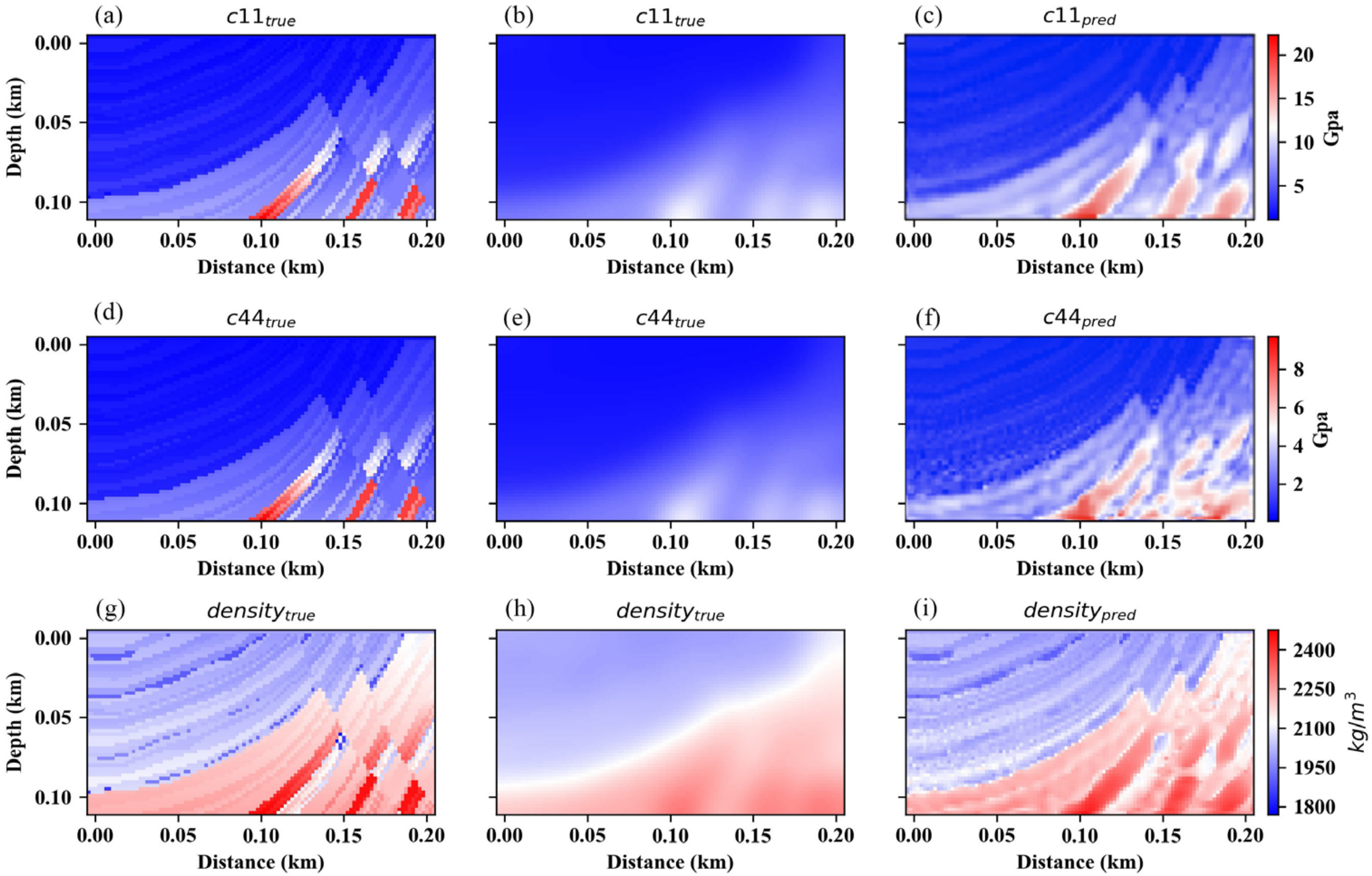


3.10 Stiffness matrix parameterization Part of Marmousi model



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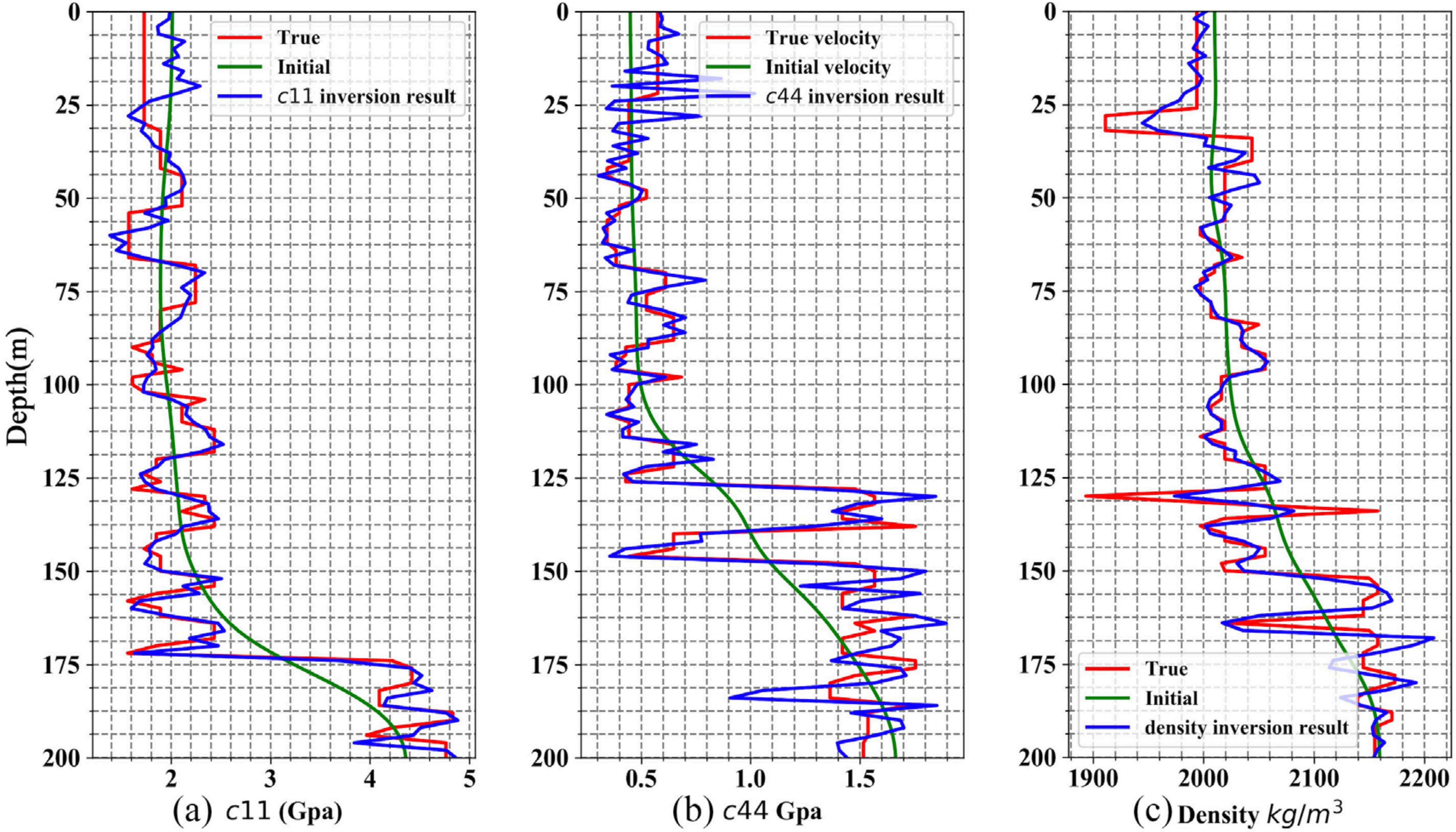
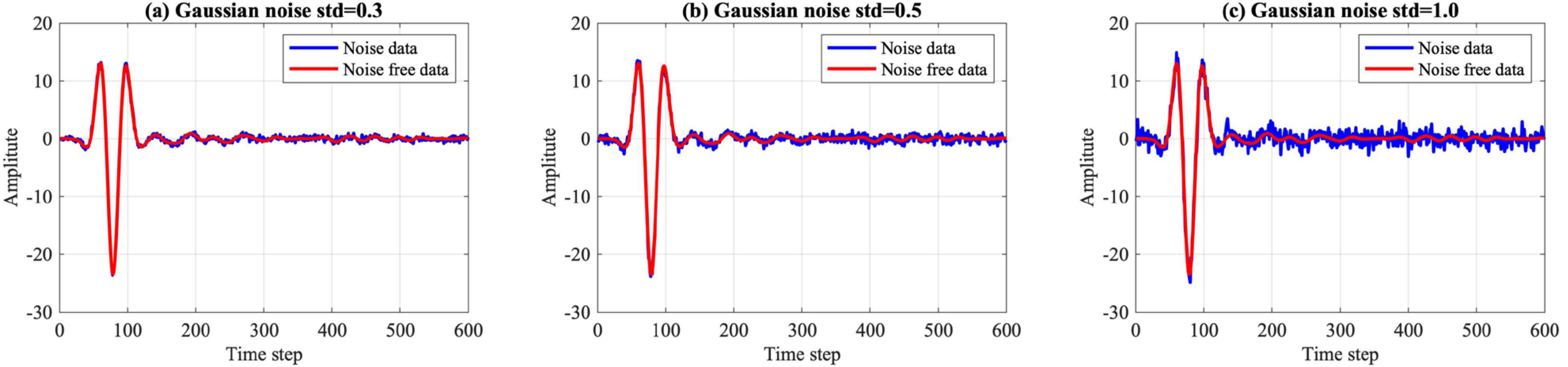


4. Noise stress test



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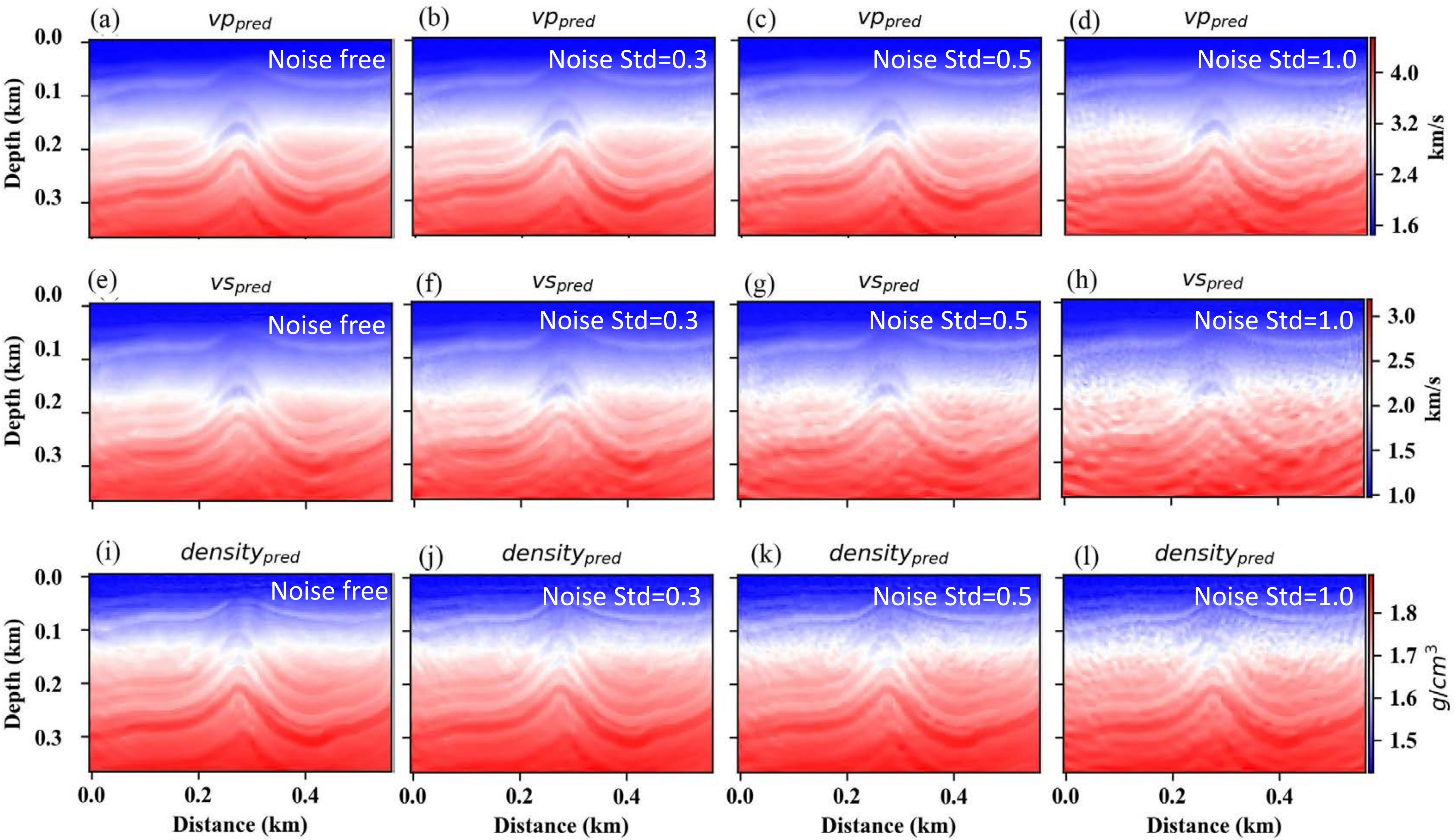

5 Conclusions

- RNN formulation of elastic FWI is robust and admits a range of optimization choices (e.g., Adam)
- These are gradient based; cross-talk is managed prior to inversion
- Modelling error:
  - Likely to cause issues for RNN/FWI
  - Can potentially be addressed through training
  - Can a deep learning FWI algorithm “teach itself” which physics rules to use?

Thanks

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Thanks Kris Innanen, Daniel Trad, Jian Sun and Zhan Niu for their discussion.