Improving the efficiency and quality of 3D seismic imaging applying ML algorithms

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Delphi Consortium

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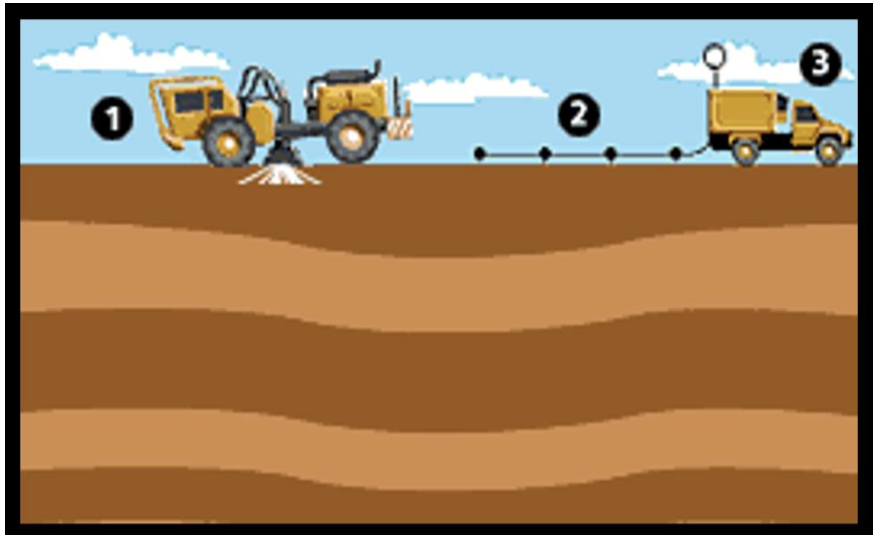
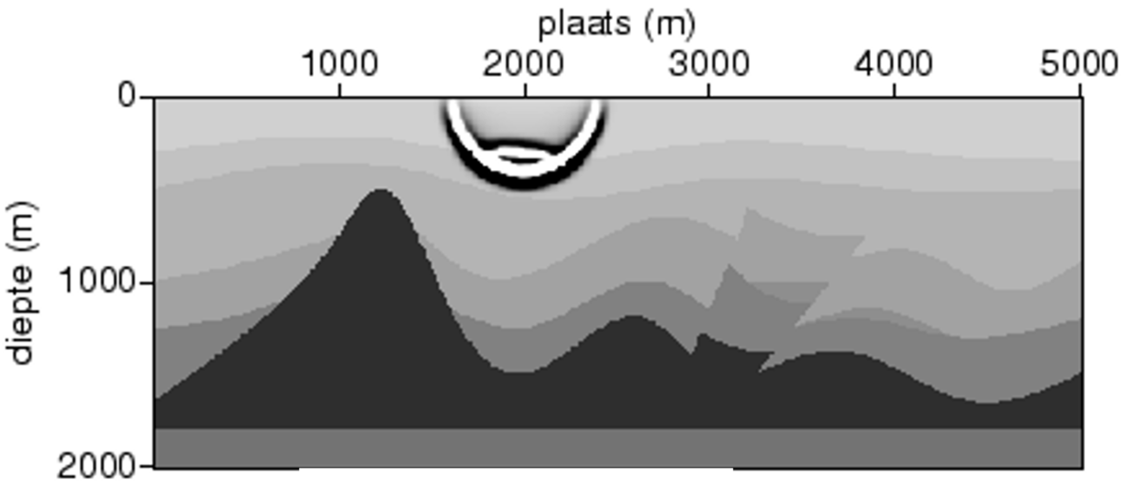
TU Delft

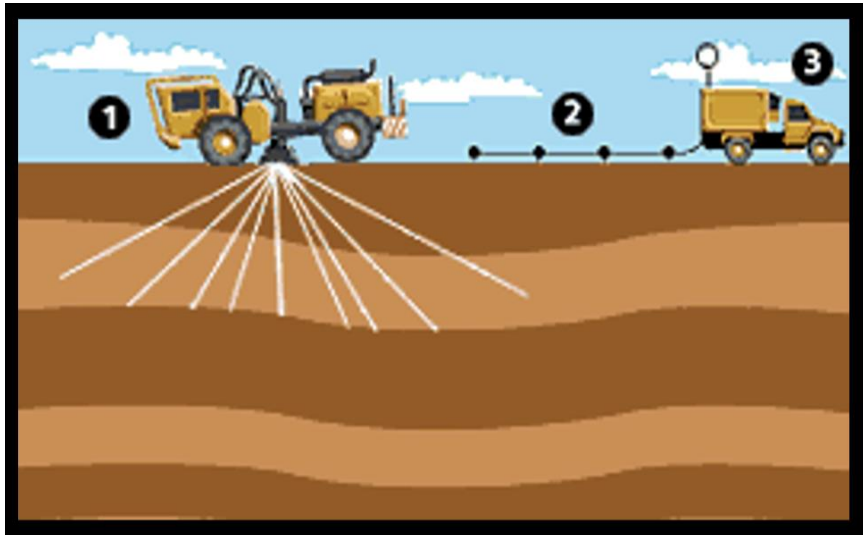
Seismic Imaging

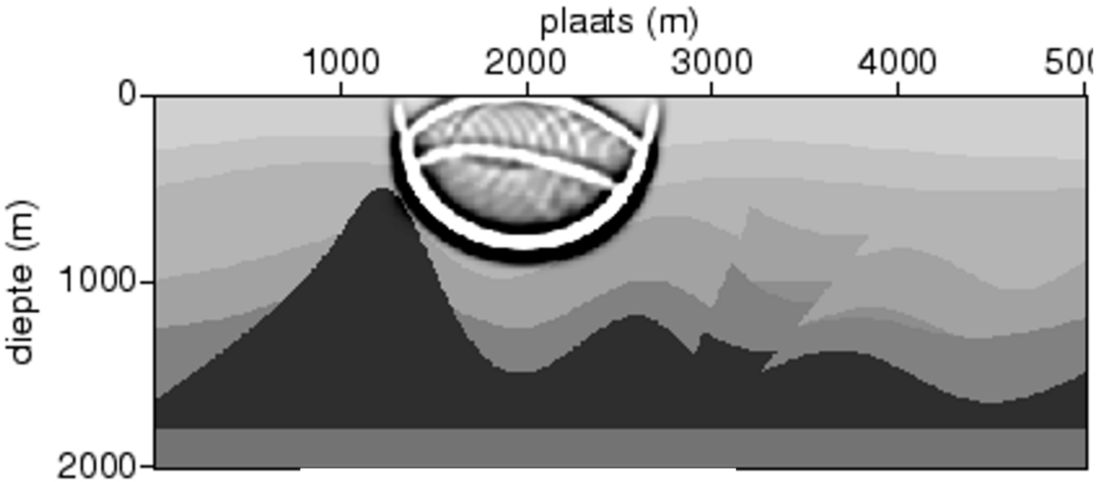




Wavefield at time 300 ms

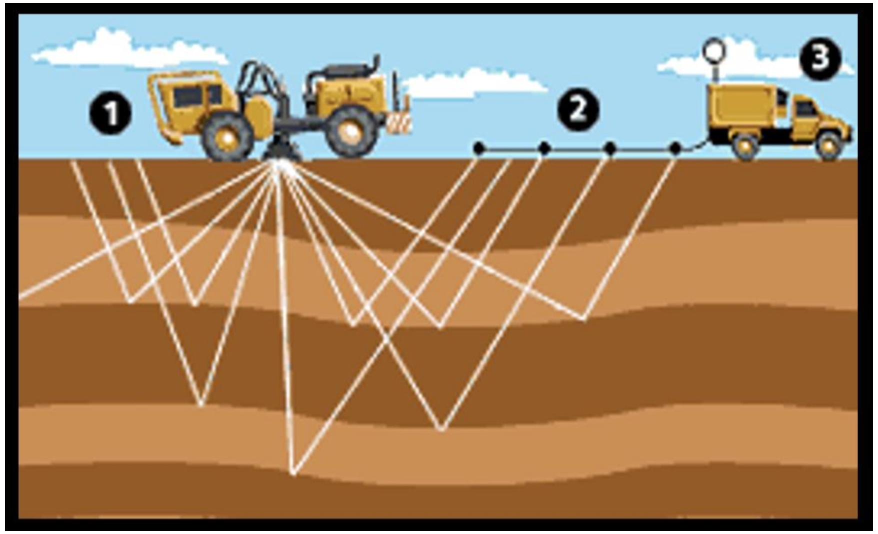
Seismic Imaging

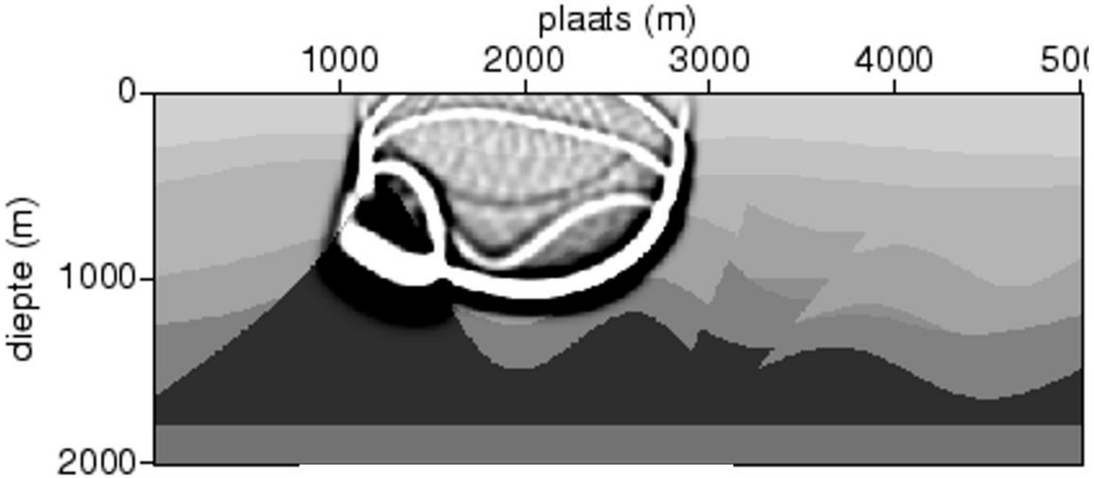




Wavefield at time 500 ms

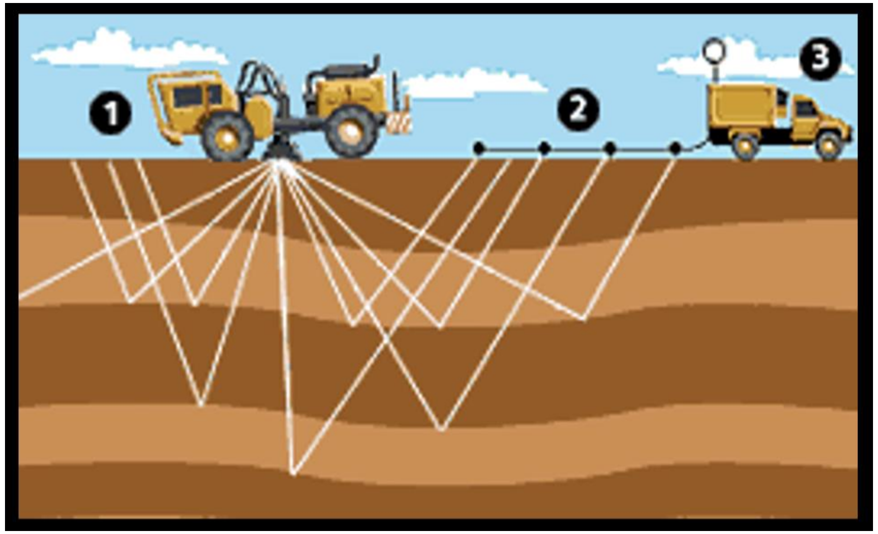
Seismic Imaging

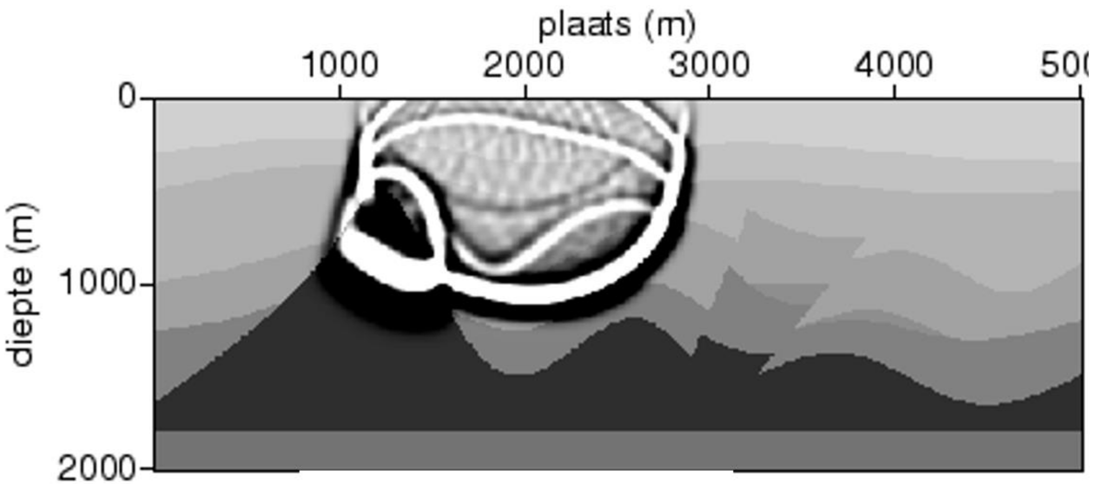




Wavefield at time 620 ms

Seismic Imaging





Wavefield at time 620 ms

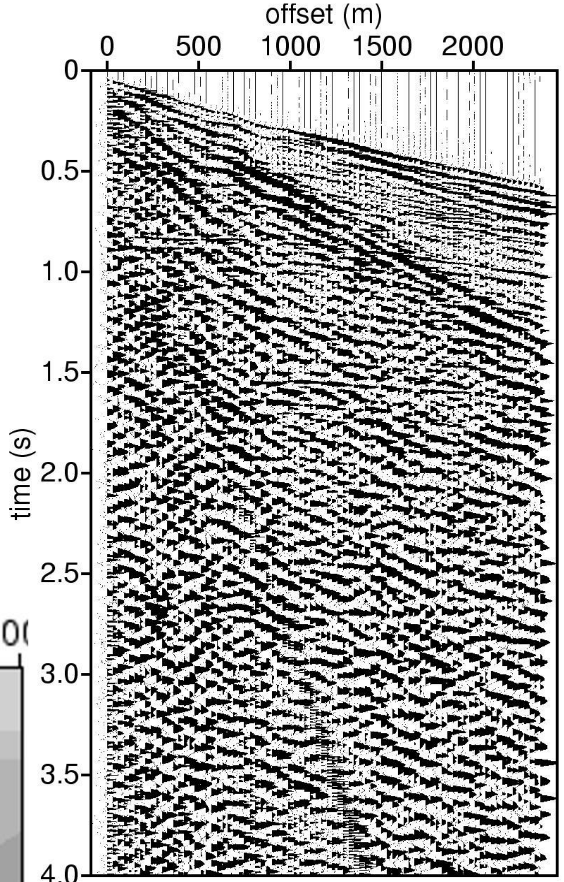
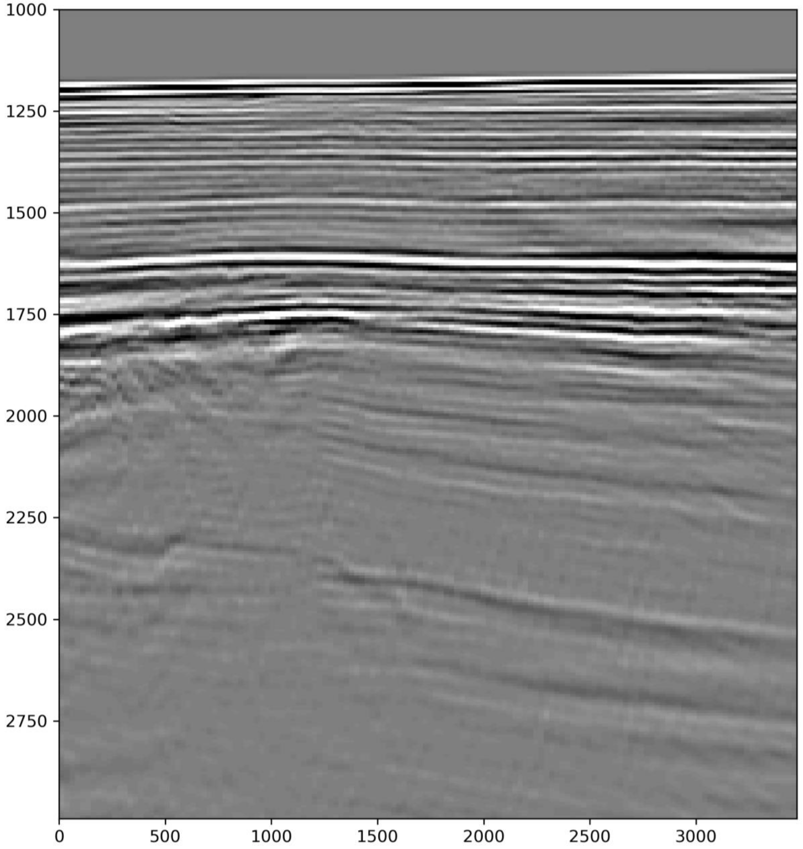


Image of the subsurface



Outline

- Attenuation effects
- Quality factor
- Including Q-compensation in FWM & JMI
- Including Q-estimation in FWM & JMI
- Conclusions

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Attenuation effects

Heterogeneous properties of the Earth

- geological structures
- soil properties
- fluid or gas distribution

Effects on the seismic wavefield

- wave scattering
- absorption
- transmission losses

Attenuation of seismic signals

Understanding and considering these variations is crucial for accurate modeling and interpretation of seismic data.

Types of attenuation effects

Attenuation Effects

- Geometric Spreading ✓
- Reflection and Transmission Effects ✓
- Residual Attenuation Effects

Anelastic Attenuation (Q): This type of attenuation is influenced by the presence of fluids within the rock and the degree of saturation it exhibits.

Elastic Attenuation: Elastic attenuation is determined by the scattering of energy at lithology boundaries and the effects of thin-layering.

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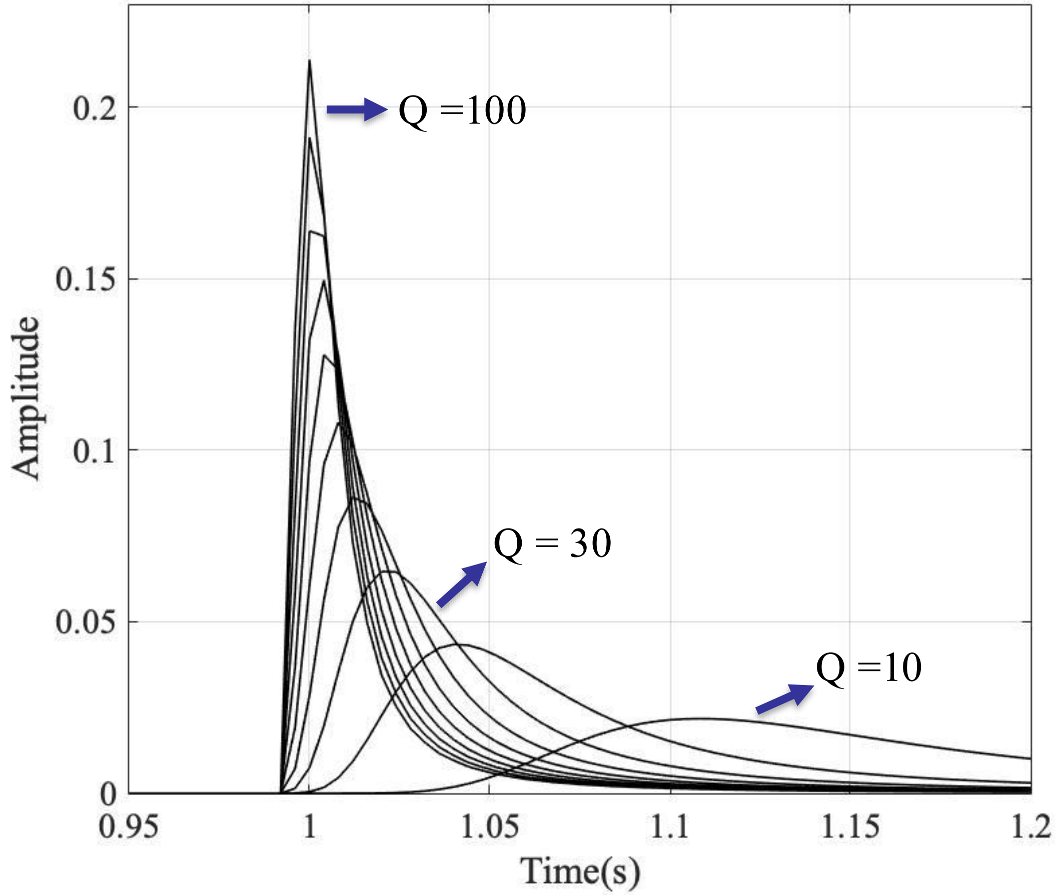
Quality factor

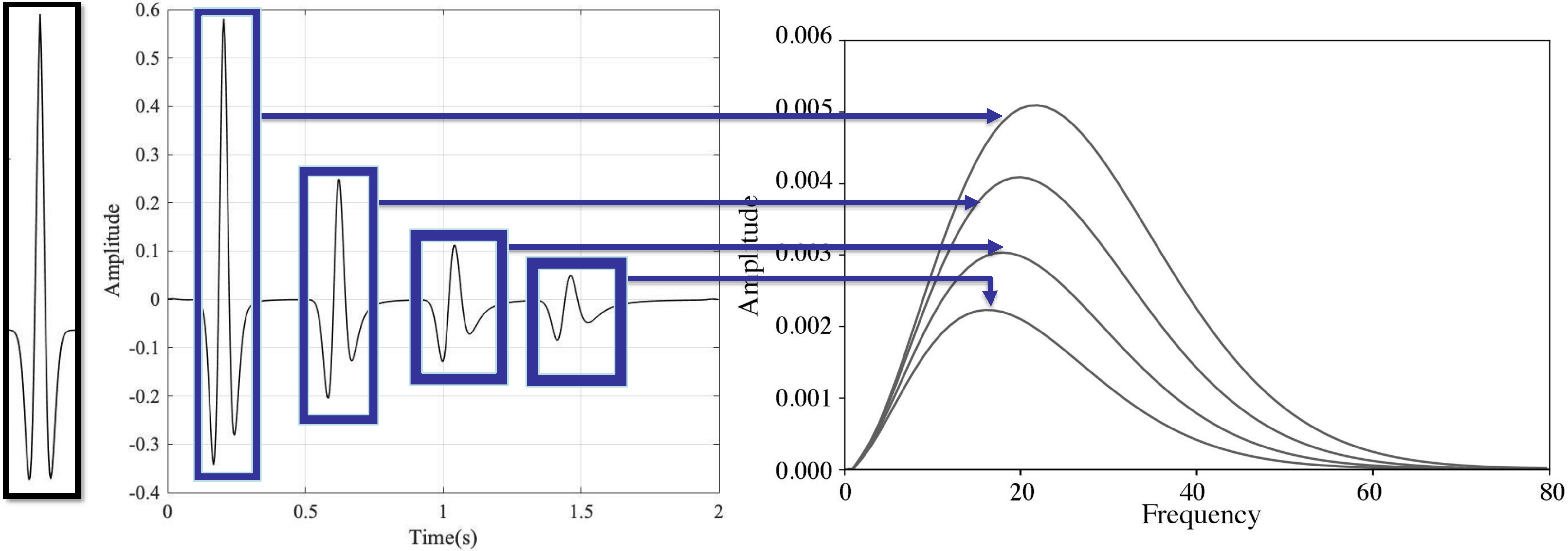
$$Q = 2\pi \frac{E}{\delta E}$$

E ⟷ Maximum energy per cycle

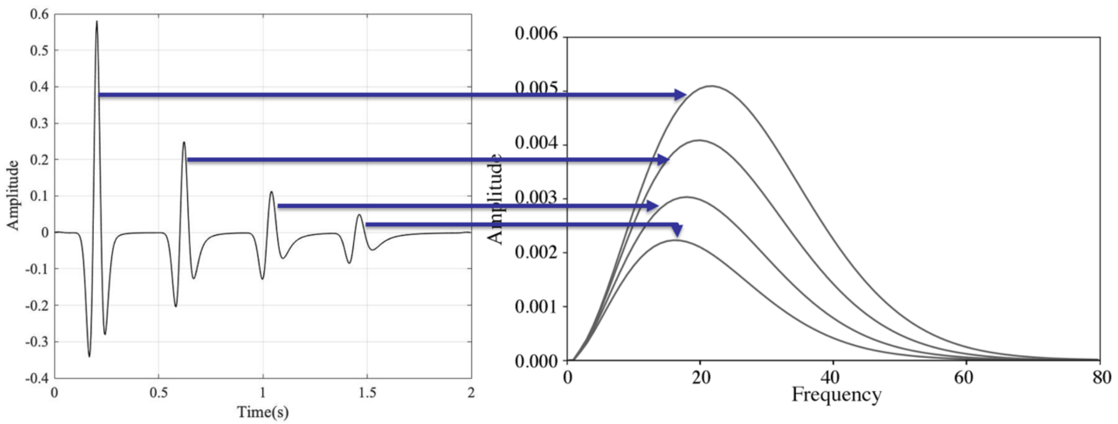
δE ⟷ Energy lost per cycle



Quality factor



Q-estimation Methods



- Complex spectral ratio (Kjartansson, 1971)
- Centroid frequency shift (CFS) method developed by (Quan and Harris, 1997)
- Peak frequency shift (PFS) method (Zhang and Ulrych, 2002)

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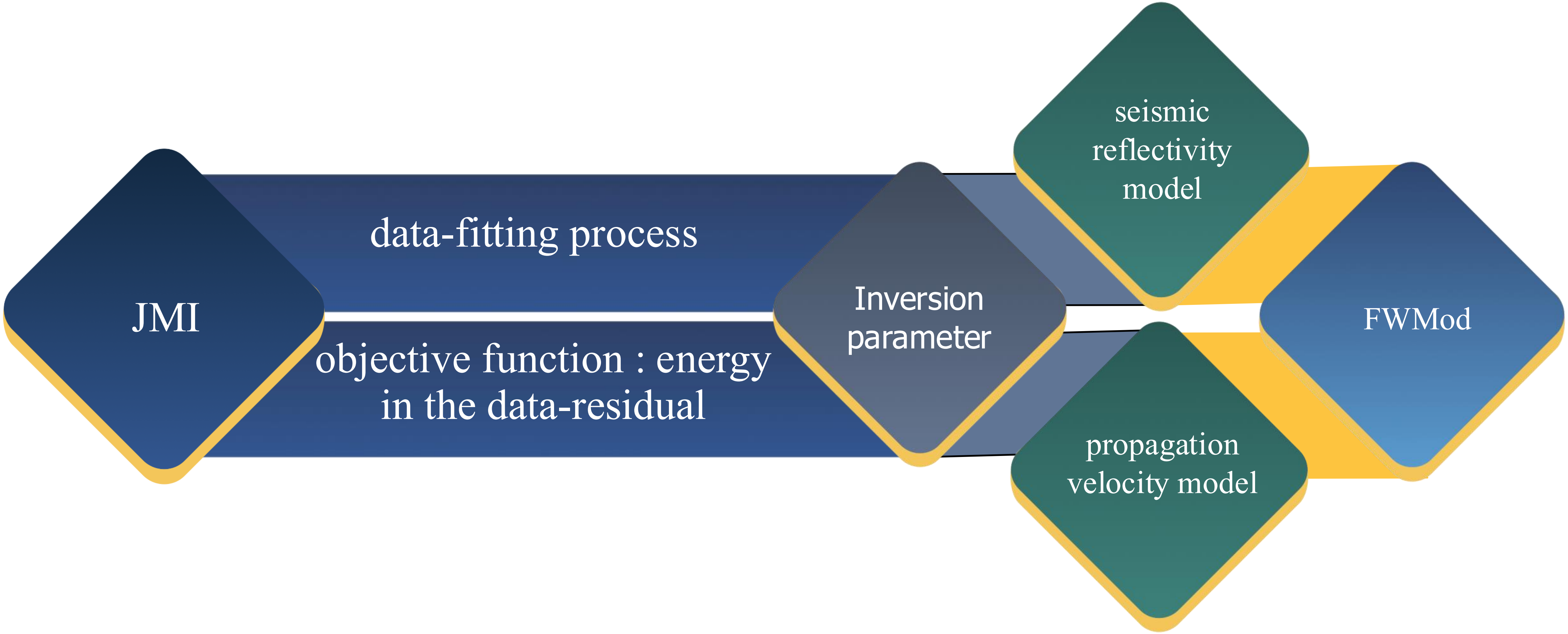
Joint Migration Inversion

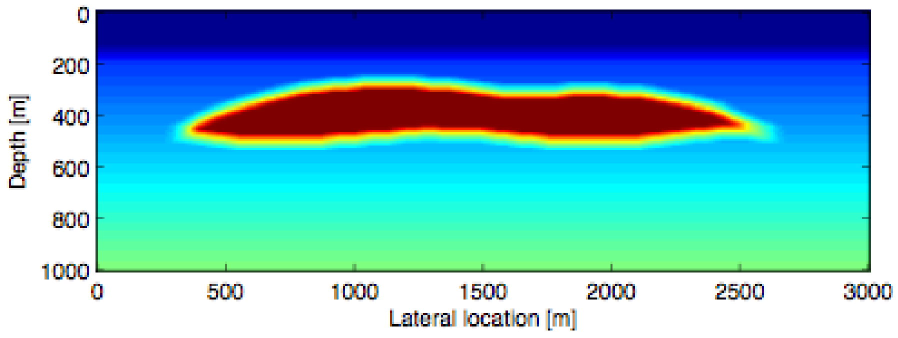


Full Wavefield Modeling

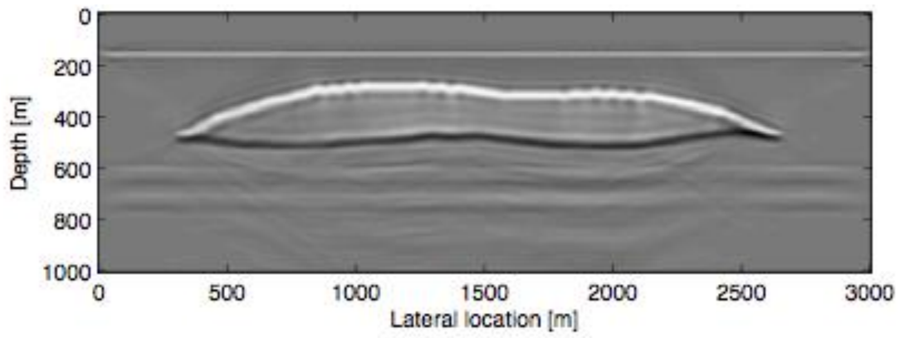
FWMod is an iterative solution of the wave equation by one-way steps:

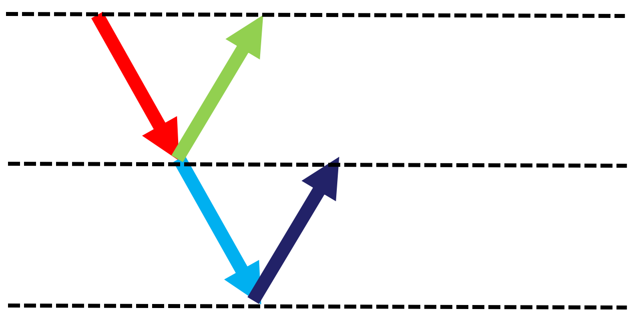
- up/downward propagation using the background velocity model
- up/down scattering of the wavefield using the image

Migration velocity model

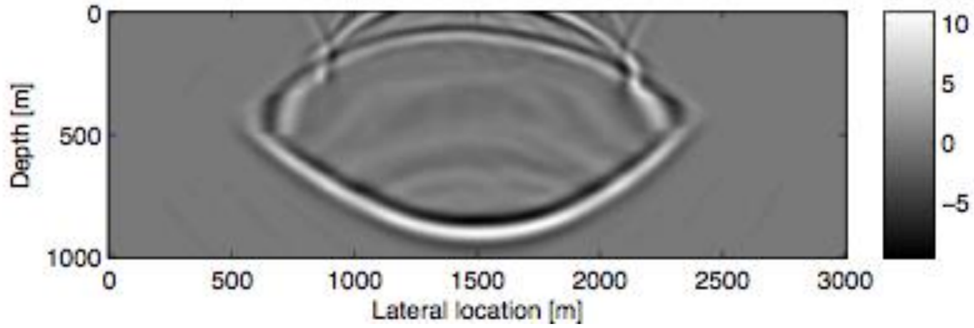


Reflectivity model





Iterative modelling (1st roundtrip)



Images from Mikhail Davydenko

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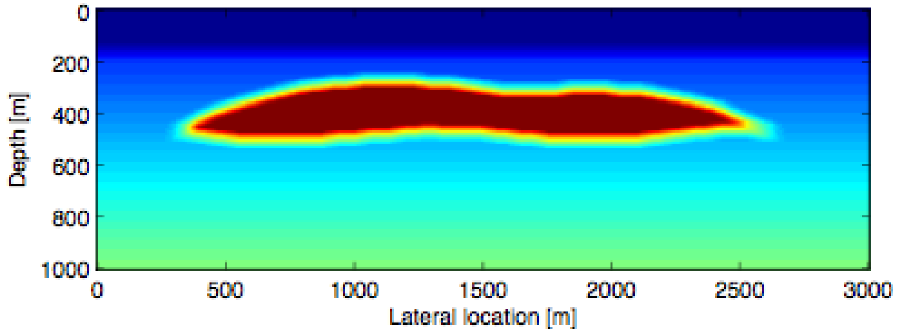
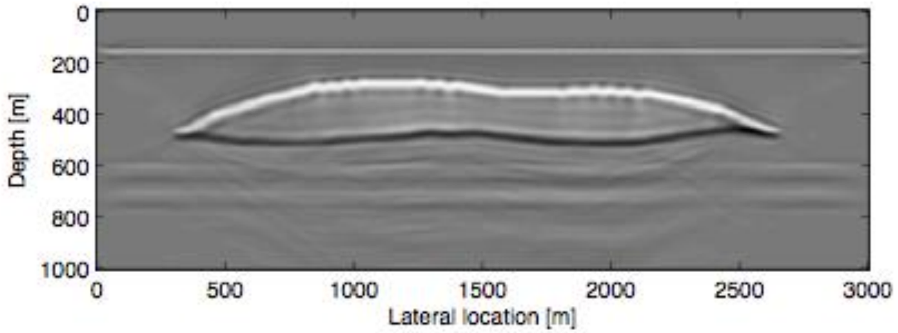
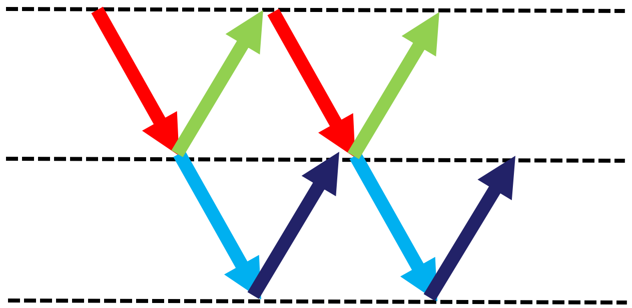
Migration velocity model

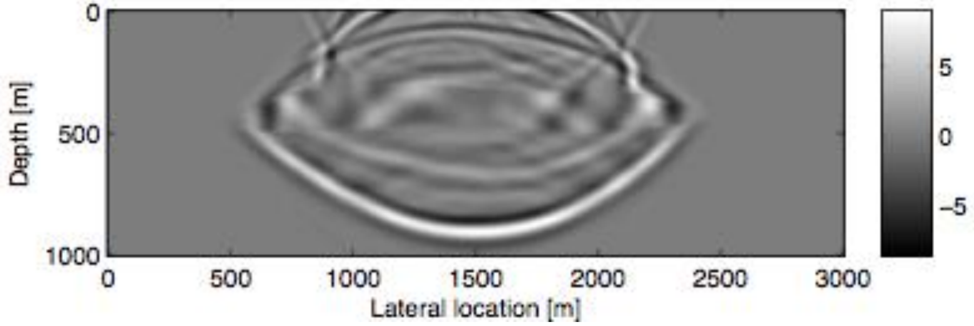


Reflectivity model





Iterative modelling (2nd roundtrip)



Images from Mikhail Davydenko

Including Q effects in FWM & JMI

- The Q-effects are part of the propagator
- Putting Q effects into the **W** operators

Forward propagation

$$W_Q = A_Q W$$

Inverse propagation

$$F_Q = [A_Q]^{-1} W^H$$

The Futterman Q model in 2D

Slowness

Angular Frequency

$$s_c = s\left(1 - \frac{1}{\pi Q}\ln\left(\frac{\omega}{\omega_0}\right)\right)\left(1 + \frac{i}{2Q}\right)$$

Complex Slowness

Reference Angular Frequency

$$s_c = s\left(1 - \frac{A}{\pi}\ln\left(\frac{\omega}{\omega_0}\right)\right)\left(1 + \frac{iA}{2}\right)$$

We can take the attenuation factor (A) as the inverse of the Q value where A is defined as Q^{-1}.

The Futterman model in FWMod

❖FWMod

- ➢ one-way propagators
- ➢ based on the phase shift operators

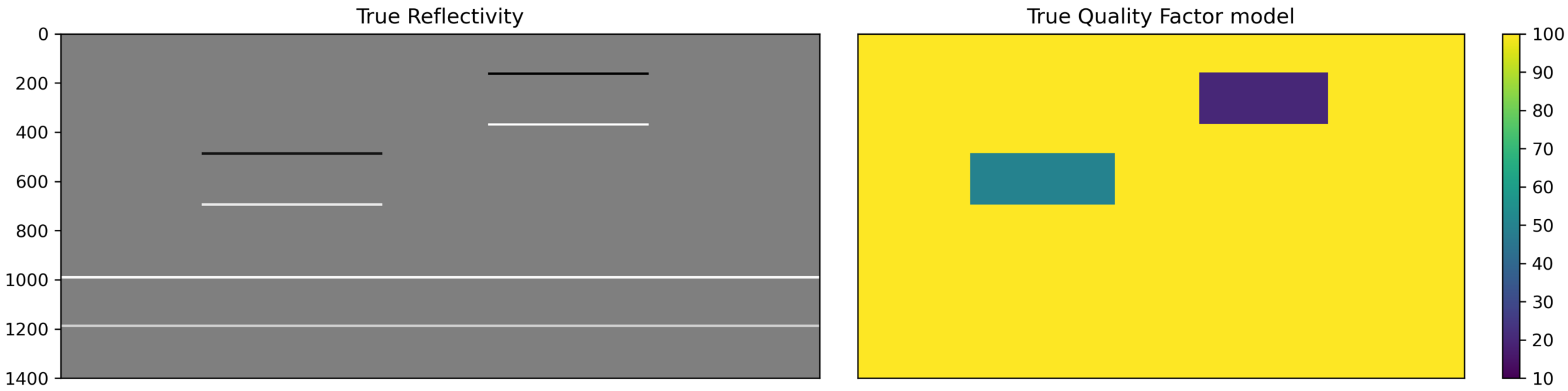
$$W(k_x,\omega) = e^{-jk_z\Delta z}$$

$$k_z = \sqrt{\omega^2 s^2 - k_x^2}$$

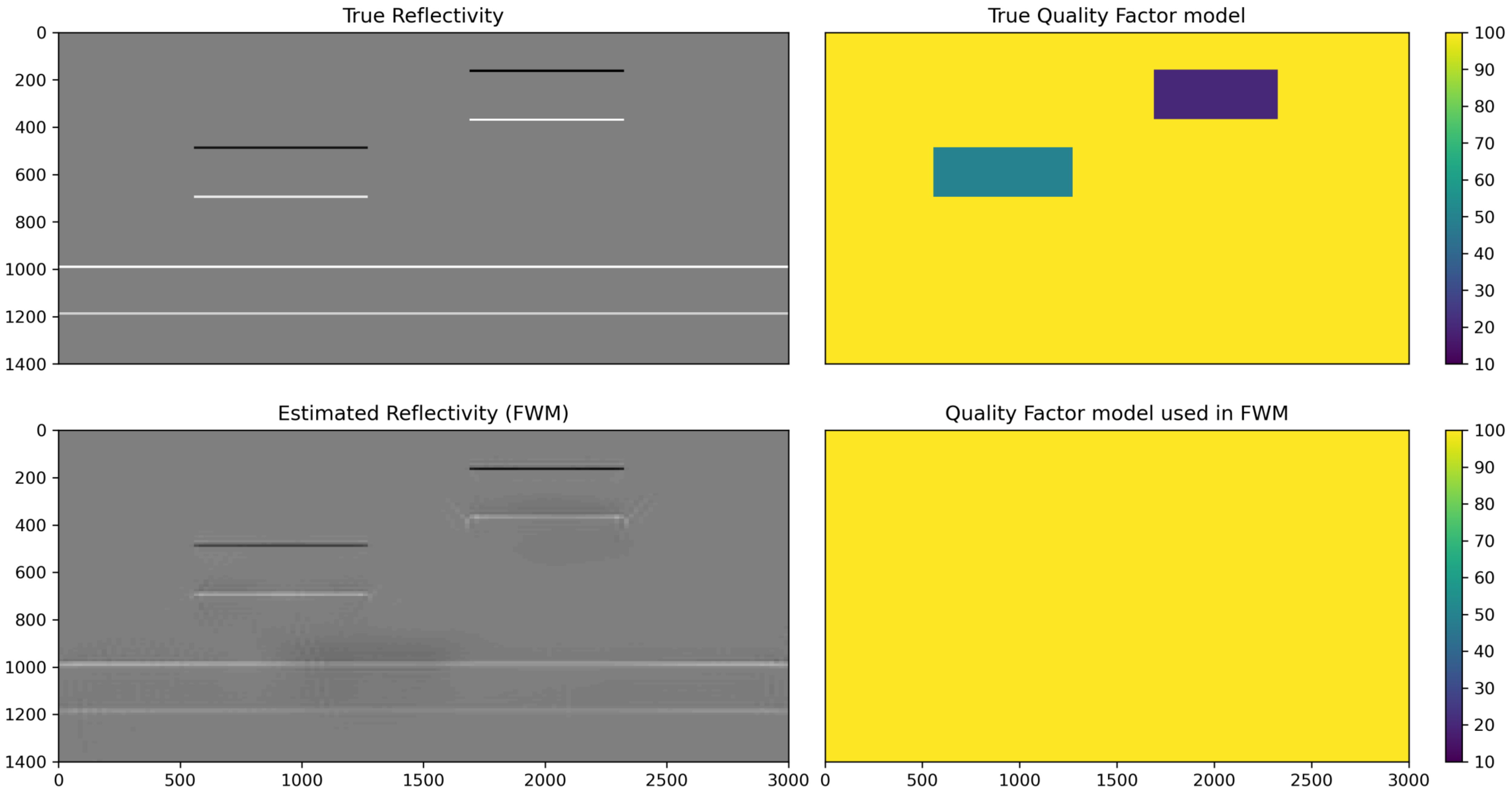
$$s_c = s\left(1-\frac{A}{\pi}\ln\left(\frac{\omega}{\omega_0}\right)\right)\left(1+\frac{iA}{2}\right)$$

$$W\left(k_x,\omega\right) = e^{-j\sqrt{\omega^2\left(s\left(1-\frac{A}{\pi}\ln\left(\frac{\omega}{\omega_0}\right)\right)\left(1+\frac{iA}{2}\right)\right)^2-k_x^2}\Delta z}$$

Synthetic model

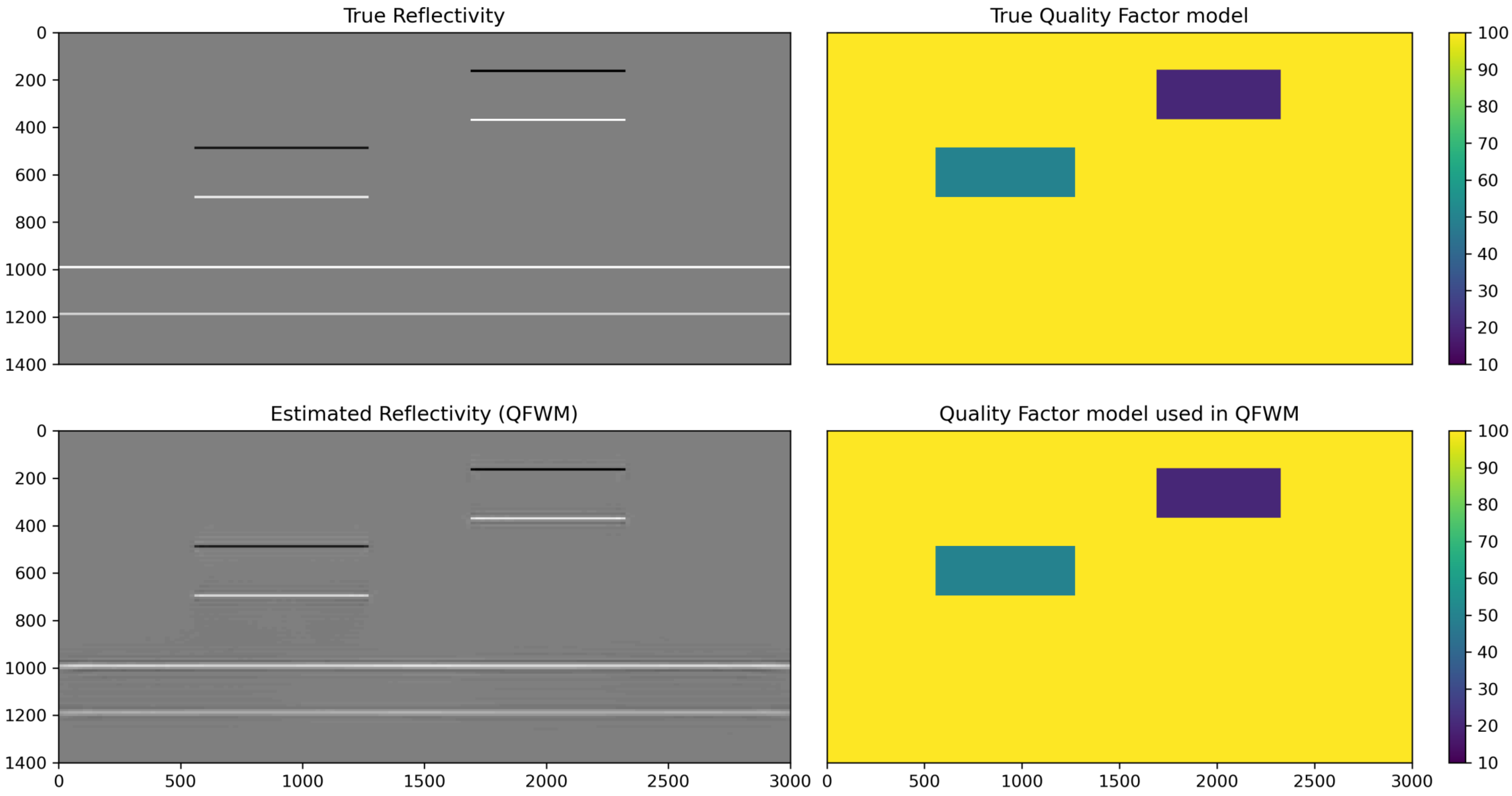


FWM results



True Reflectivity
True Quality Factor model
Estimated Reflectivity (FWM)
Quality Factor model used in FWM
0
200
400
600
800
1000
1200
1400
0
500
1000
1500
2000
2500
3000
100
90
80
70
60
50
40
30
20
10

Q-FWM results (given Q model)



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Including Q effects in FWM

Estimate Q-values

Tomographic assessment and updating

Perturbation Theory

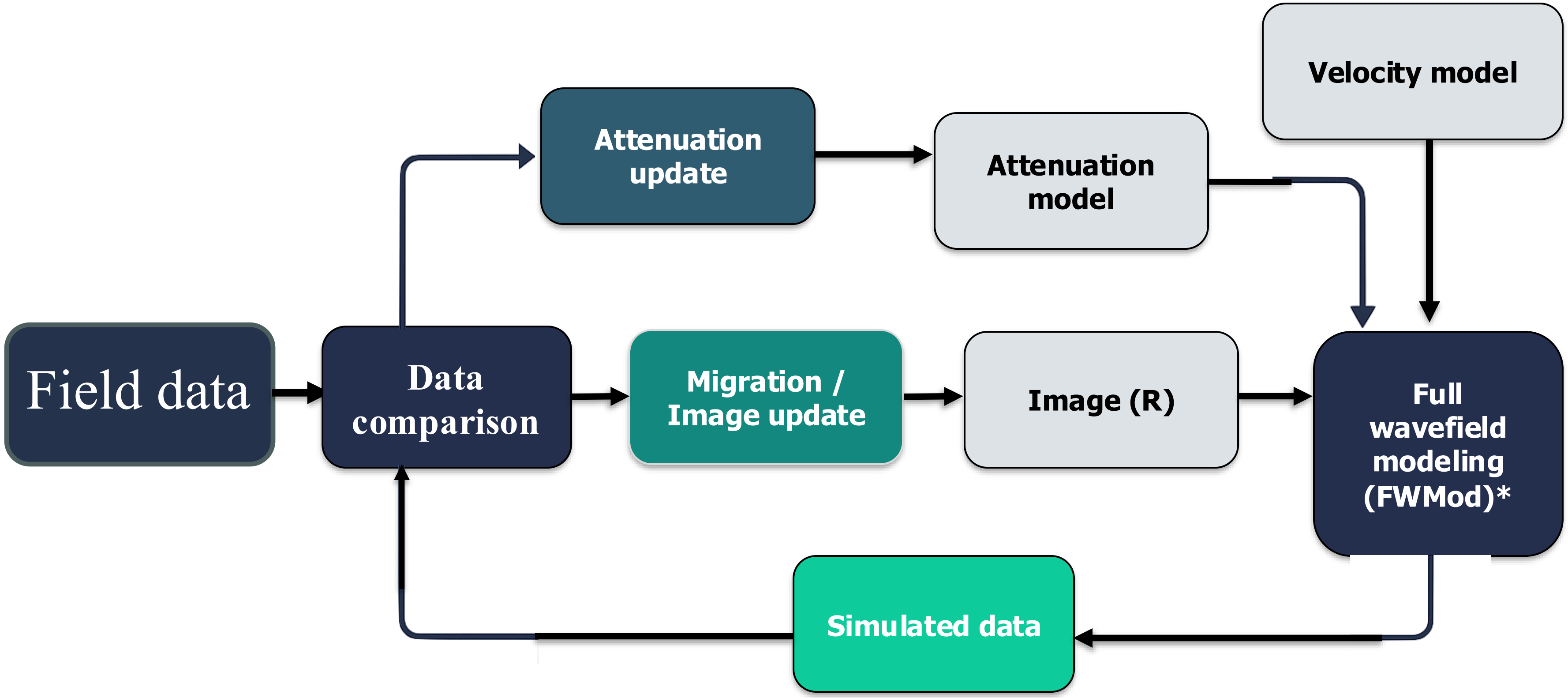
linear relationship between the propagation operators and the attenuation model

$$W(k_x, \omega) = e^{-j\sqrt{\omega^2\left(s\left(1-\frac{A}{\pi}\ln\left(\frac{\omega}{\omega_0}\right)\right)\left(1+\frac{iA}{2}\right)\right)^2 - k_x^2}\Delta z}$$

$$\Delta W_j^-(z_m, z_n) \approx \left[\frac{\partial \vec{W}^-}{\partial A}\right]_{A_{old}} \Delta A(x_j, z_n) = \vec{L}_{0j}^-(z_m, z_n)\Delta A(x_j, z_n),$$

$$\vec{L}_{0j}^-(z_m, z_n) \approx \mathcal{F}_x^{-1}\left[-j\Delta z\left[\frac{k_0^2}{k_z}\left(1-\frac{A}{\pi}\ln\frac{\omega}{\omega_0}\right)\left(1+\frac{iA}{2}\right)^2\left(\frac{\ln(\omega/\omega_0)}{\pi}\right)^2 + \left(\frac{i}{2}\right)\left(1+\frac{iA}{2}\right)\left(1-\frac{A}{\pi}\ln\frac{\omega}{\omega_0}\right)^2\right]_{A_{old}} e^{-jk_z\Delta z}e^{-jk_x x_j}\right]$$

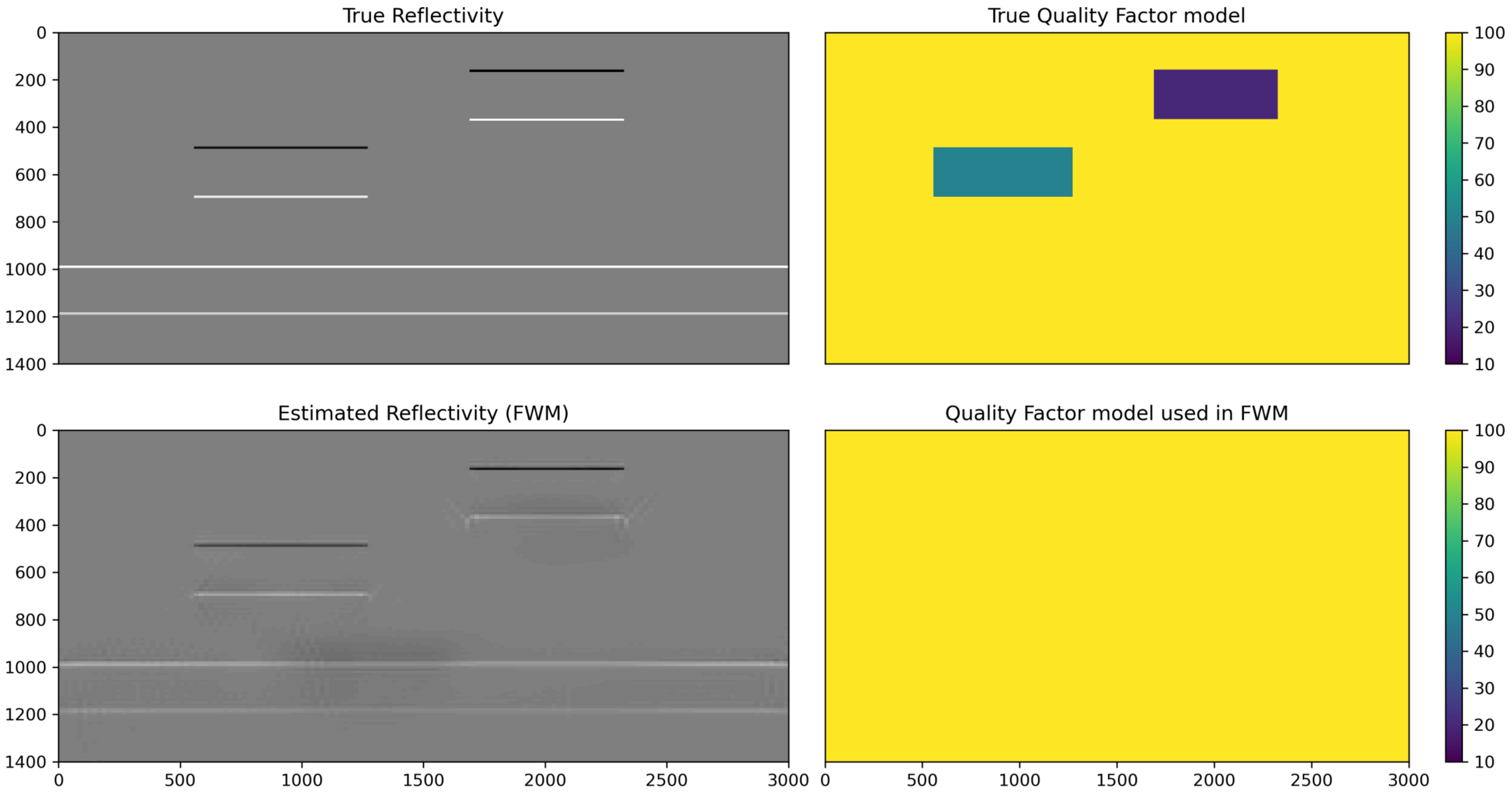
Q-FWM workflow



Closed-loop process:
iterate until modeled data fits the measurements

*=including multiples and transmission effects

FWM results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800
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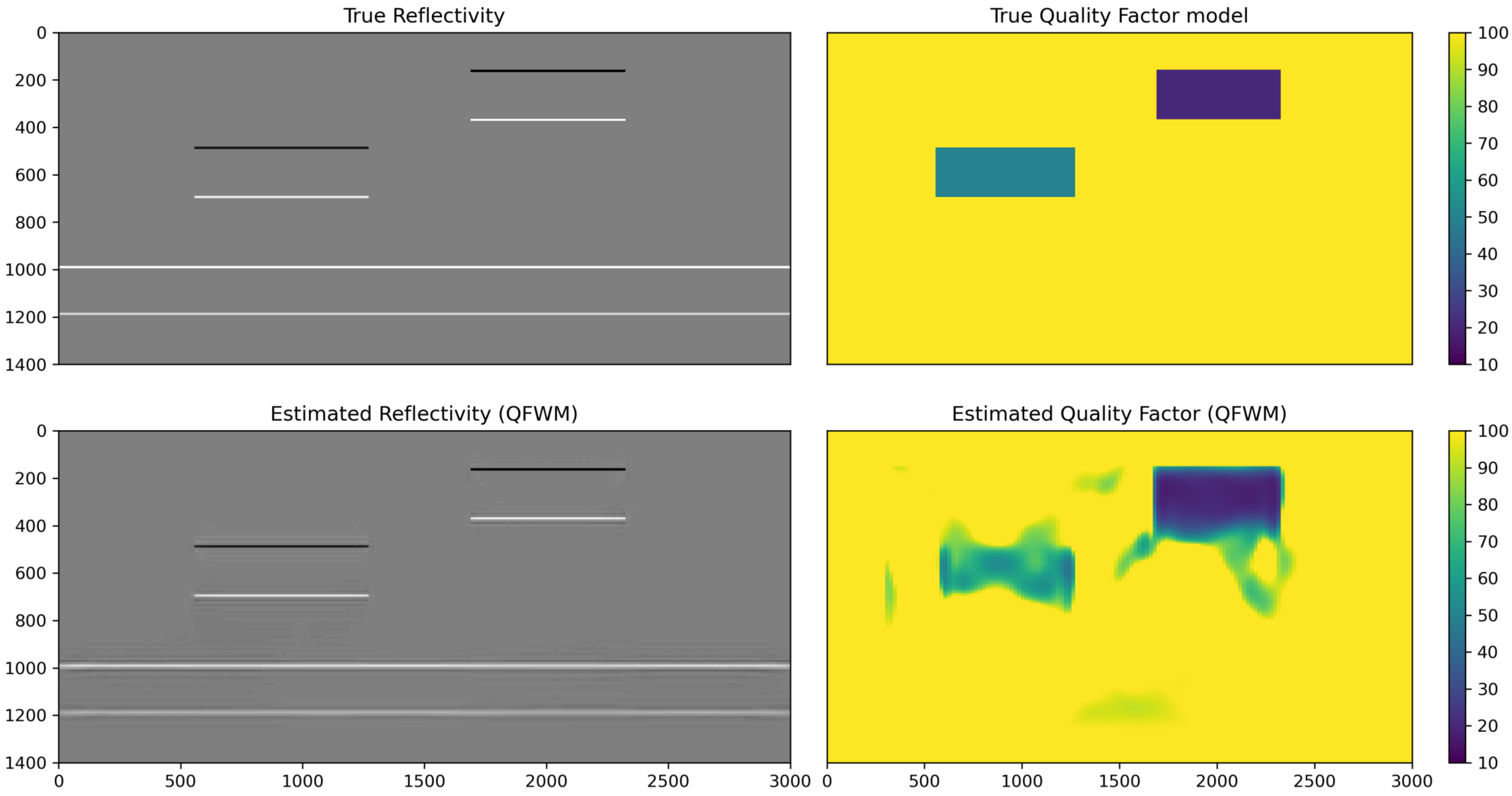
1200
1400
0
500
1000
1500
2000
2500
3000
100
90
80
70
60
50
40
30
20
10

Q-FWM results



Constraining Q-Estimation Using Random Forest Regression

Background Challenge

- Q-estimation is difficult due to crosstalk with reflectivity

- Traditional methods (Hessian, deep learning) are effective but computationally expensive

Why RF?

- Efficient and avoids overfitting
- Captures nonlinear relationships
- Links Q to physical parameters theory

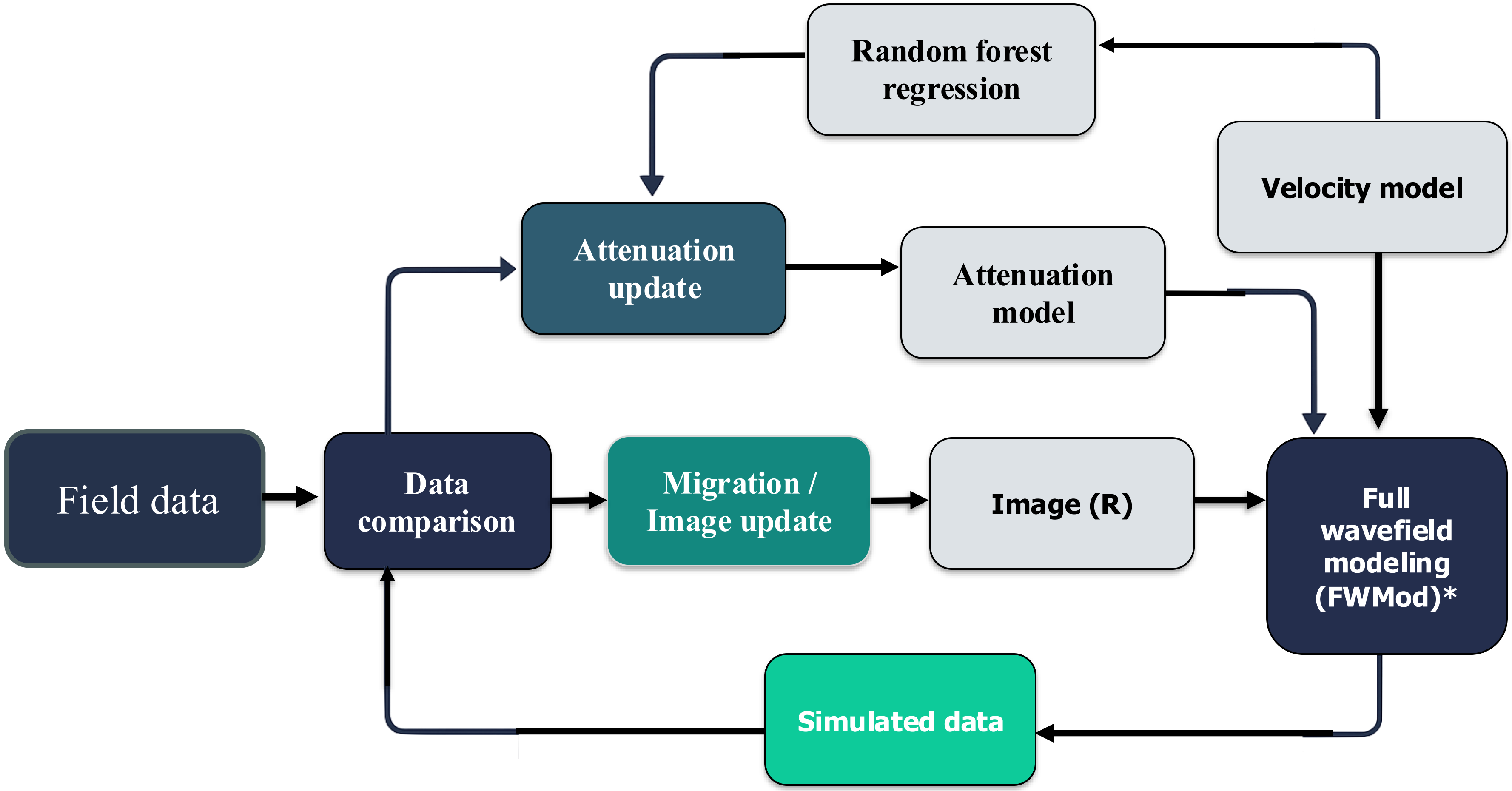
Our Approach

- Applied Random Forest Regression (RF) to constrain iterative Q-updates
- RF is an ensemble machine learning method using multiple decision trees

Velocity → Random Forest Regression

Depth → Random Forest Regression

Machin learning constarainted Q-FWM workflow



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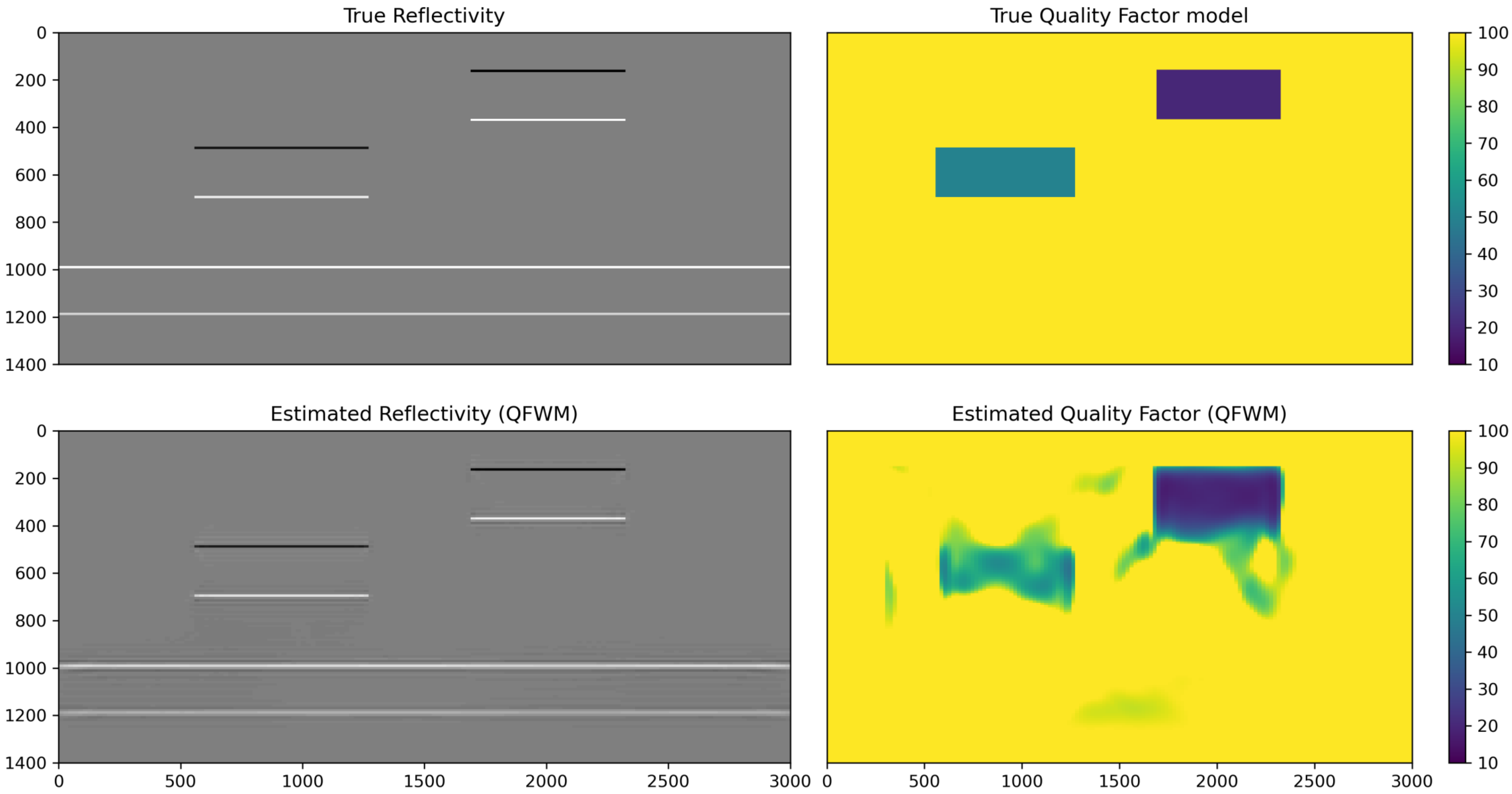
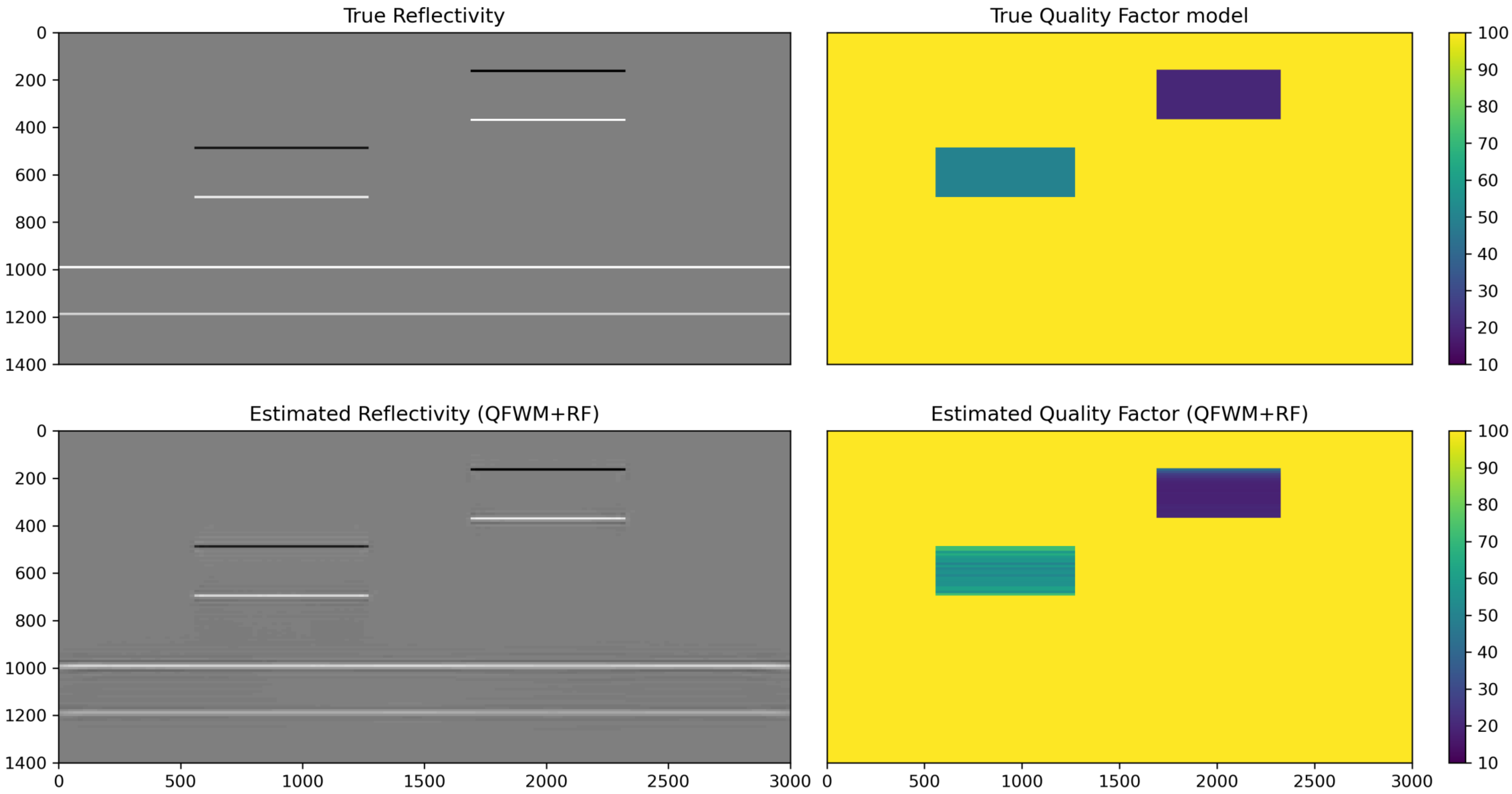
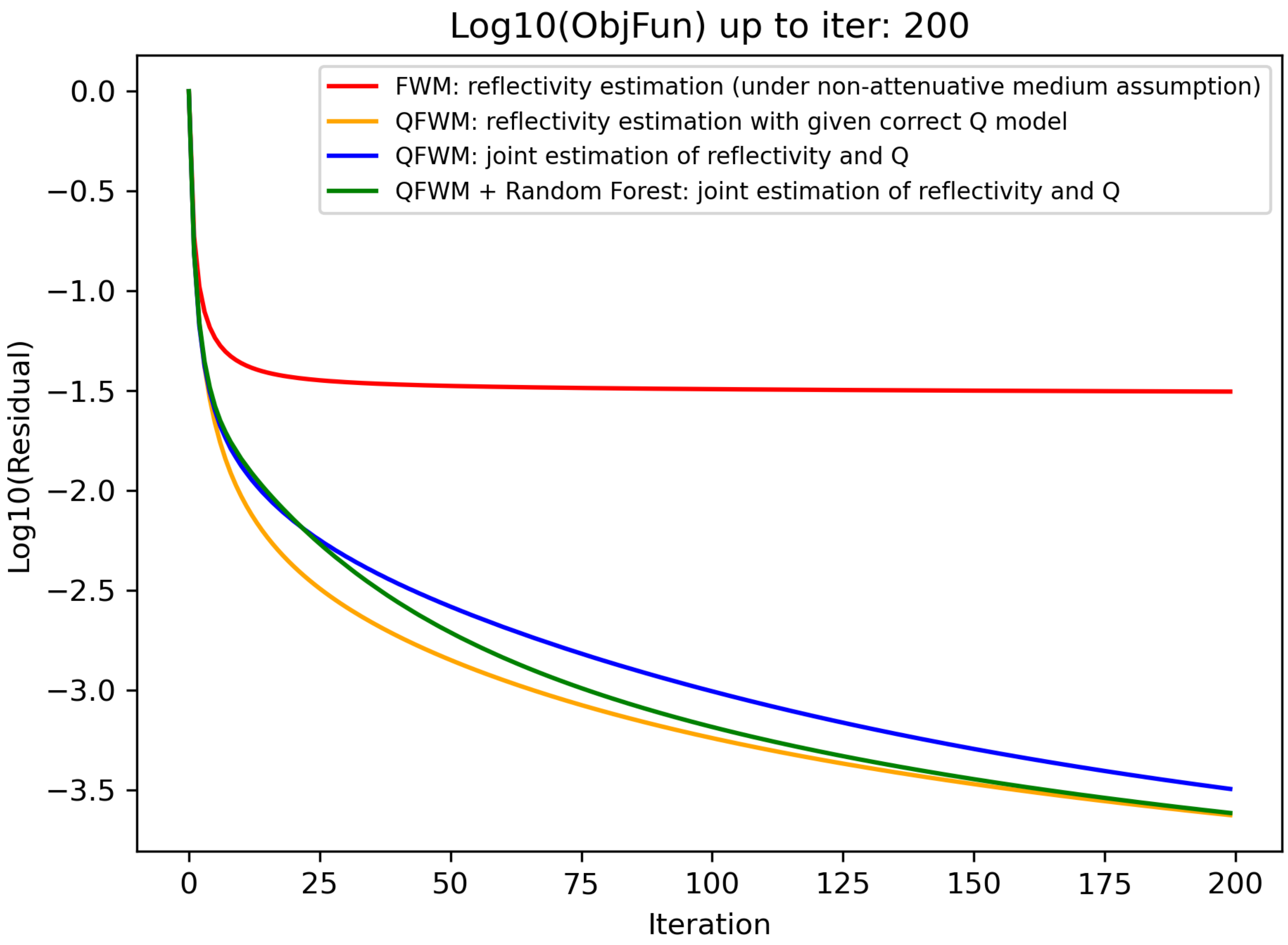
Q-FWM results



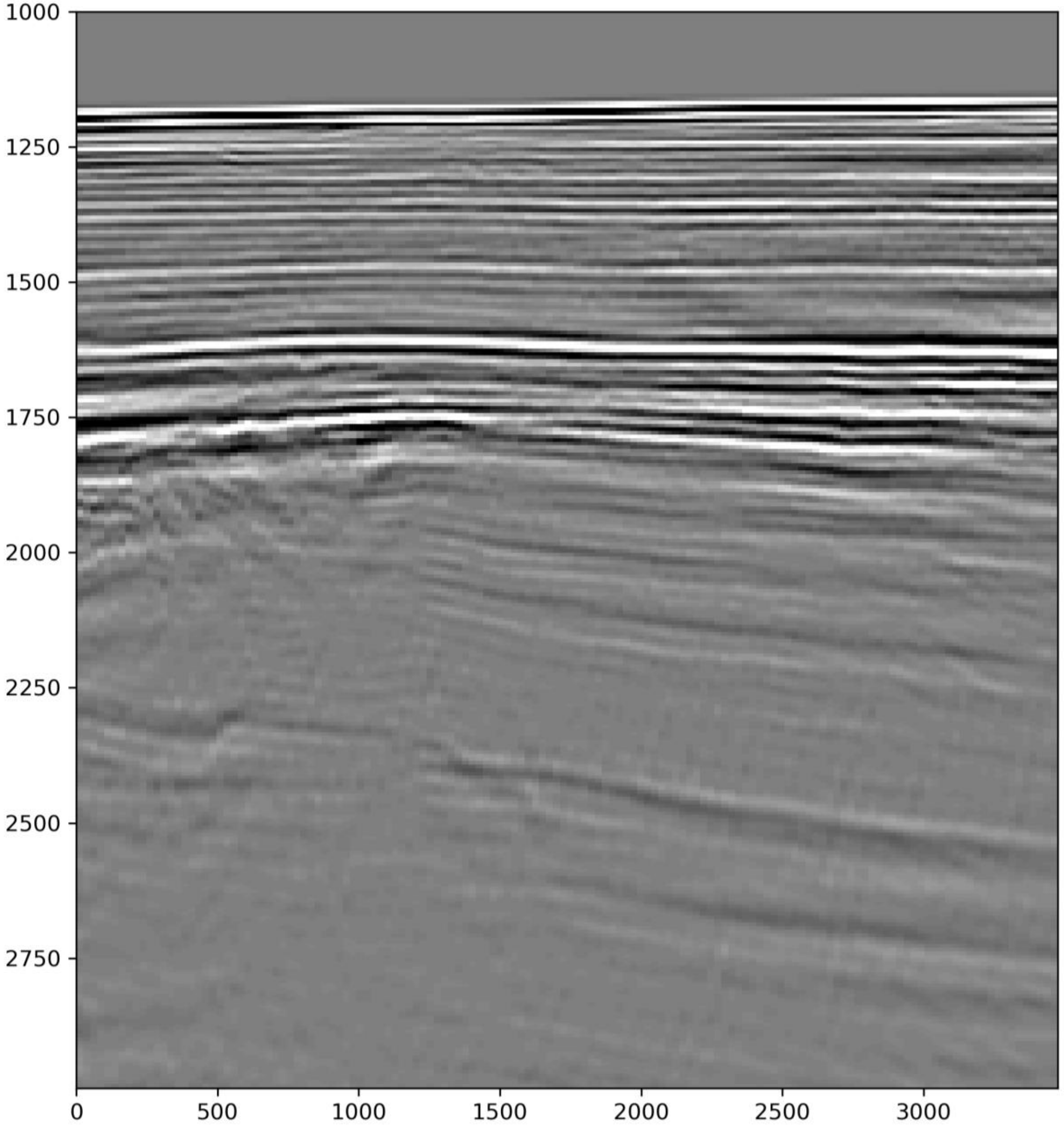
Constrained Q-FWM results



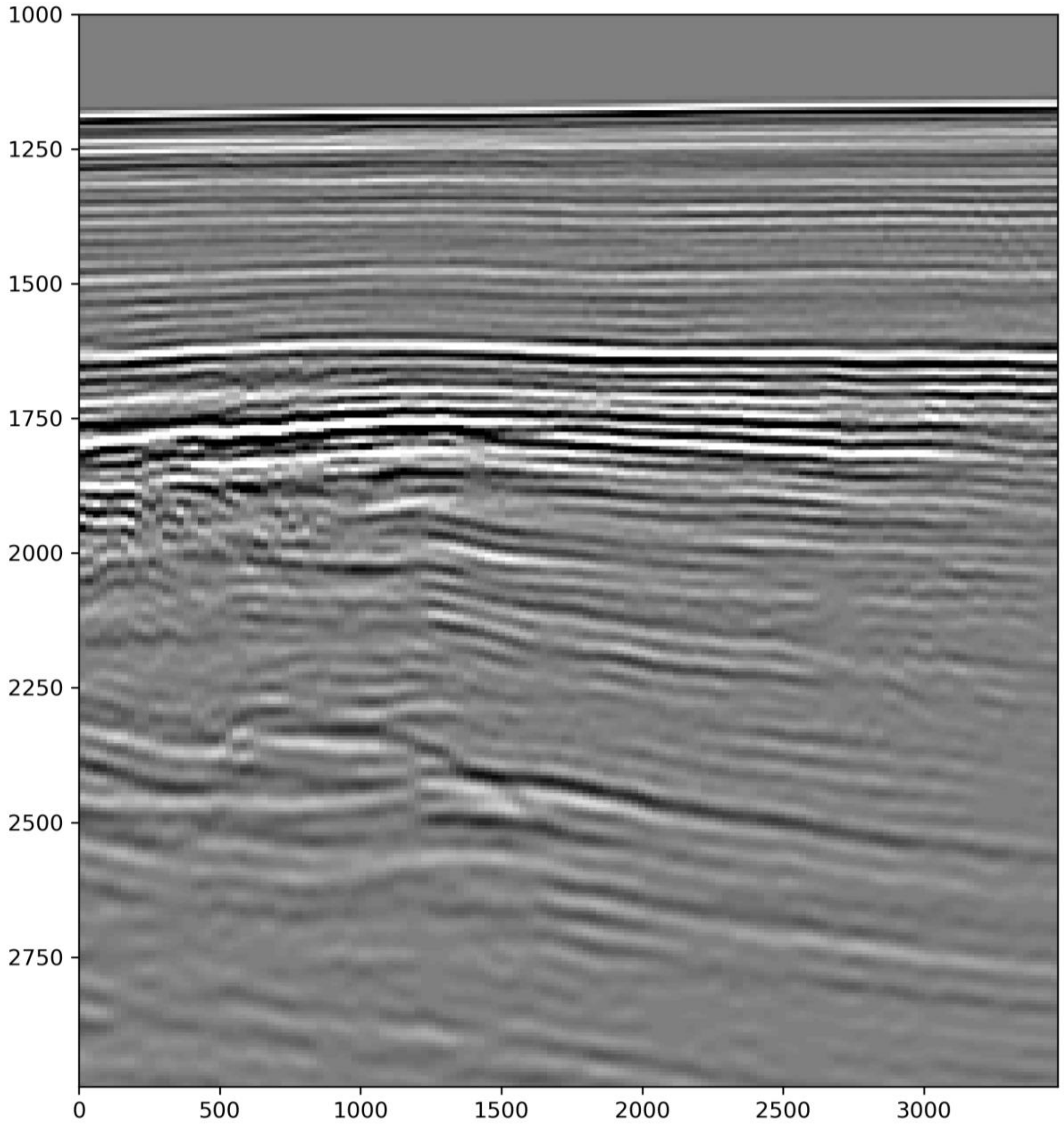
Synthetic test – Q-FWM+RF



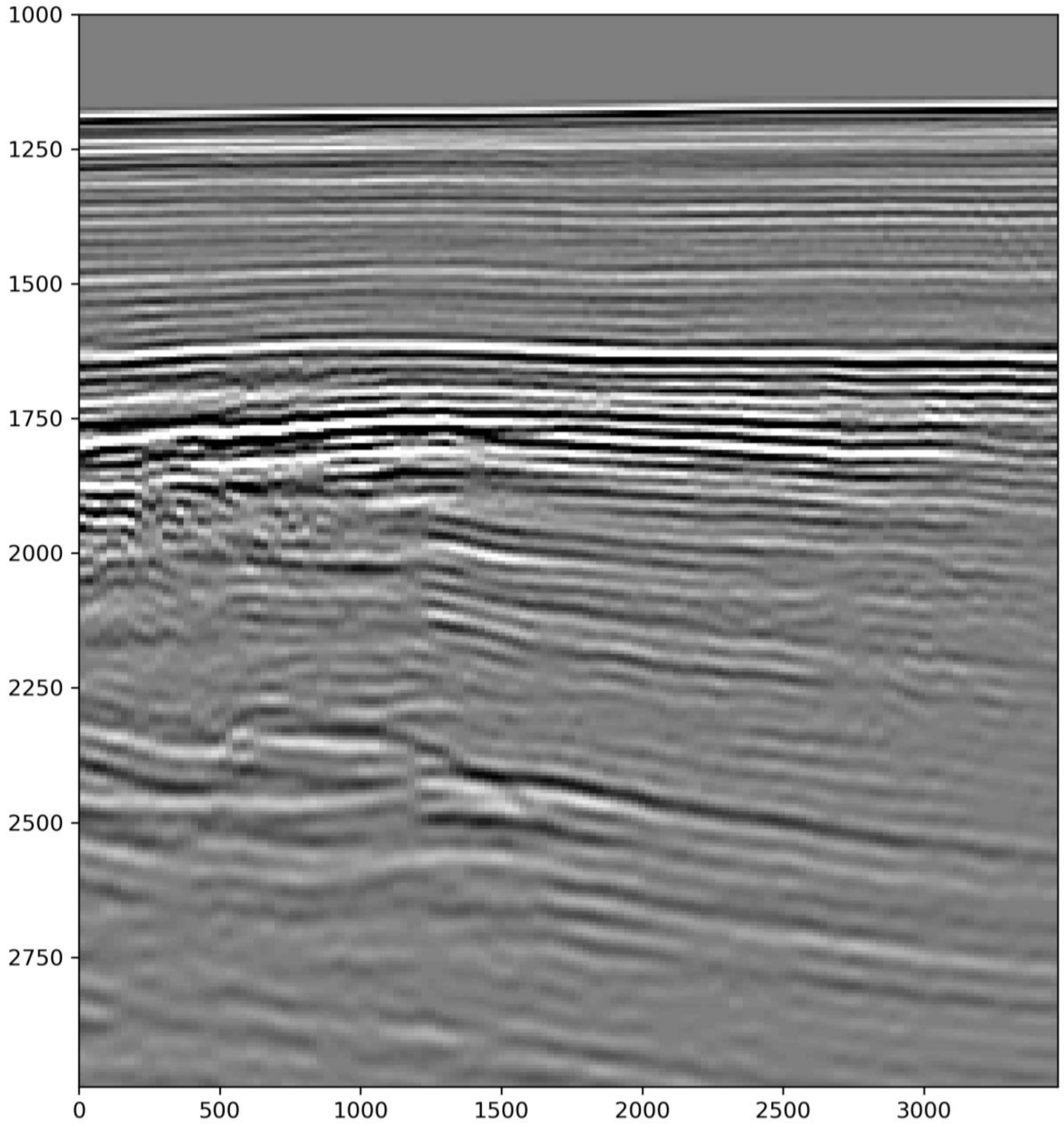
FWM Result


1000
1250
1500
1750
2000
2250
2500
2750
0
500
1000
1500
2000
2500
3000

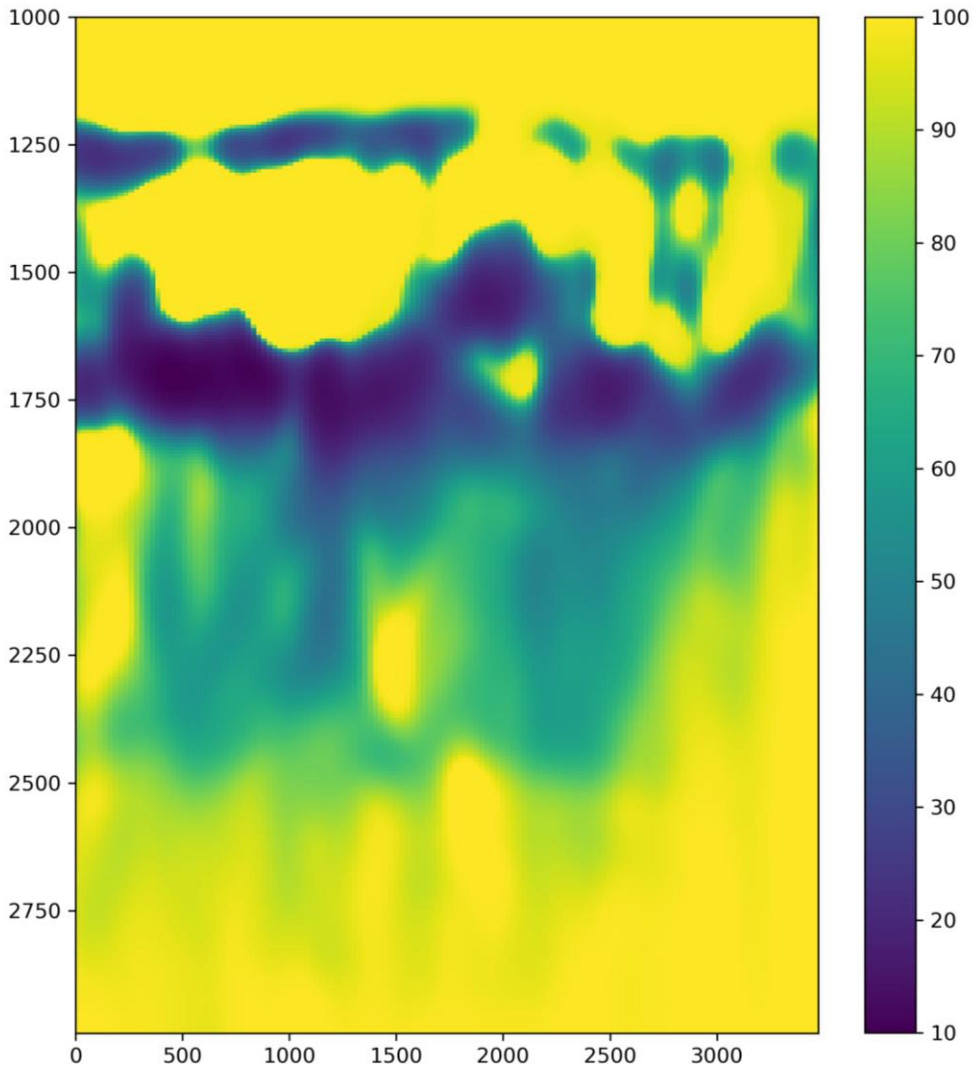
Q-FWM result – Primaries only



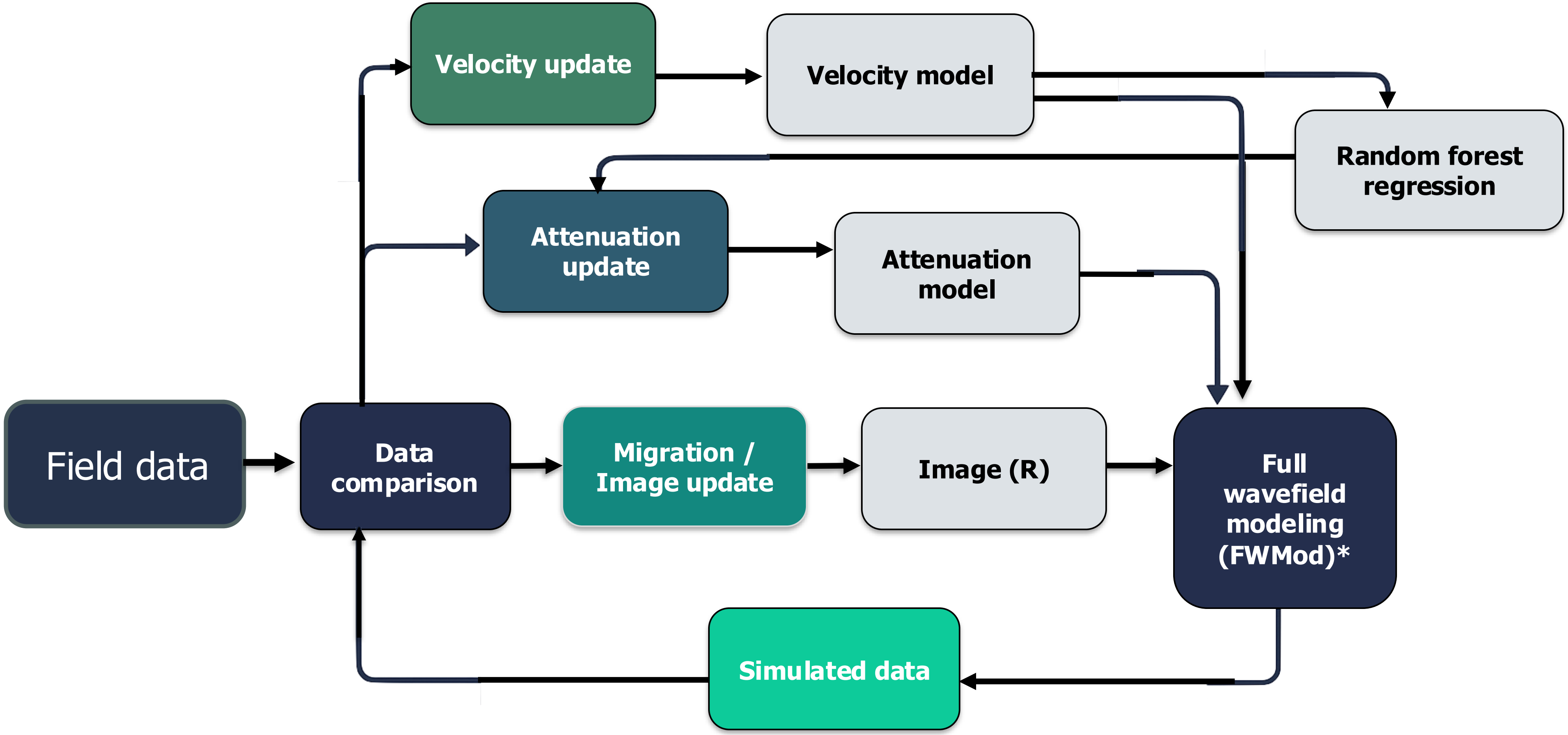
Q-FWM result – Total Wavefield



Q-FWM – field data test



Q-JMI workflow



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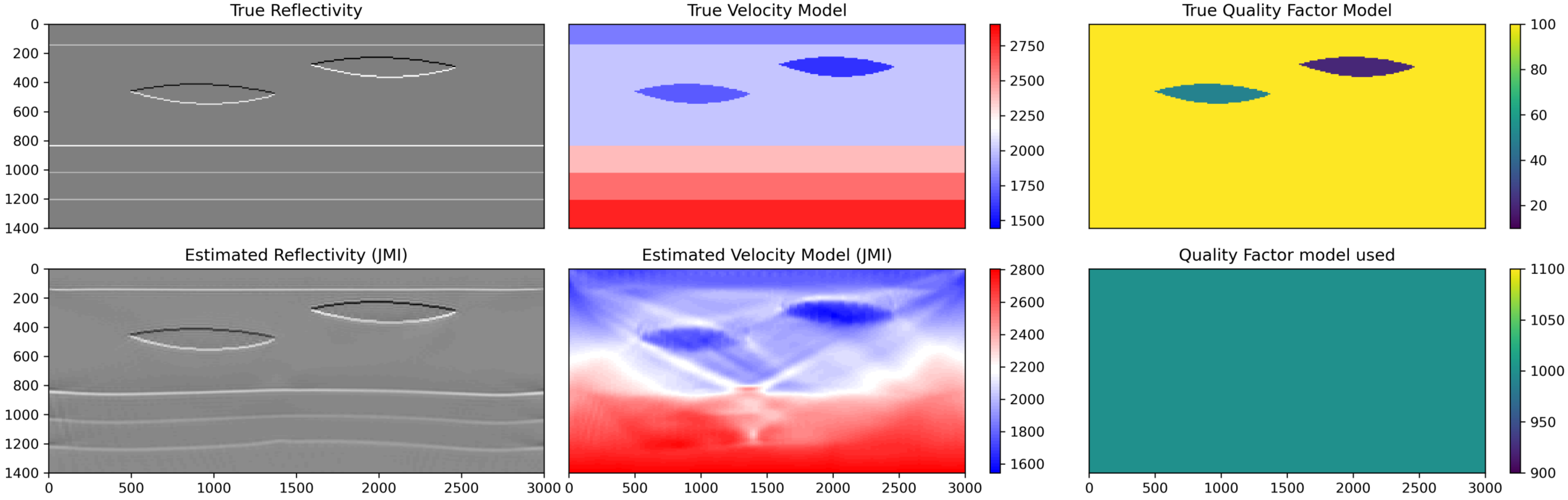
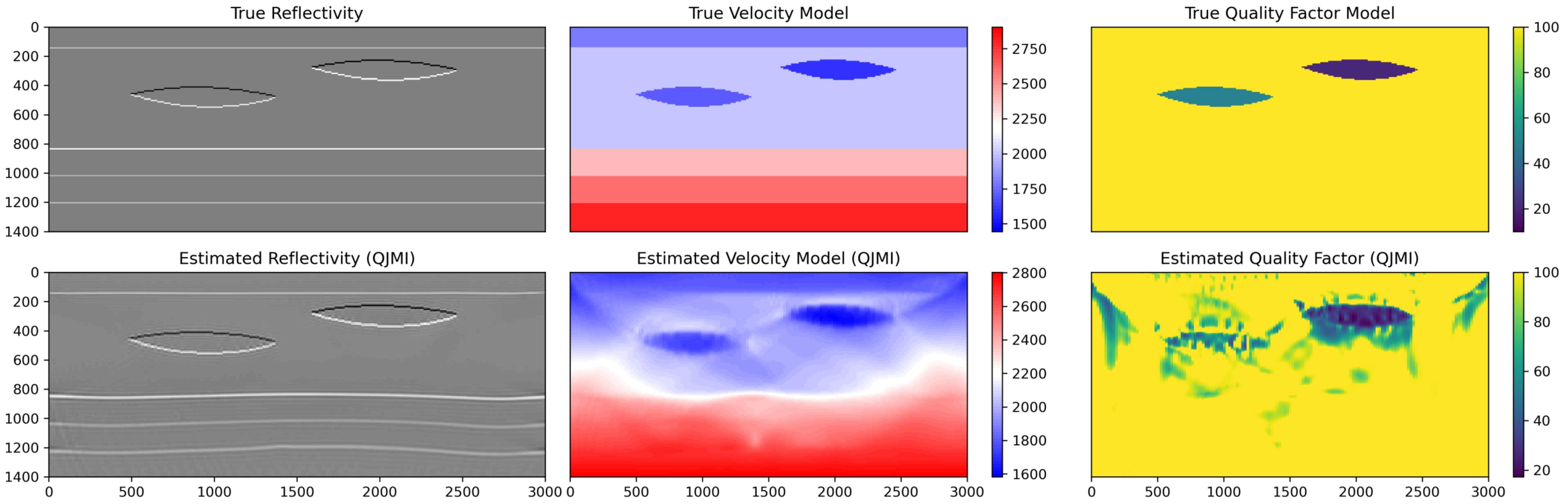
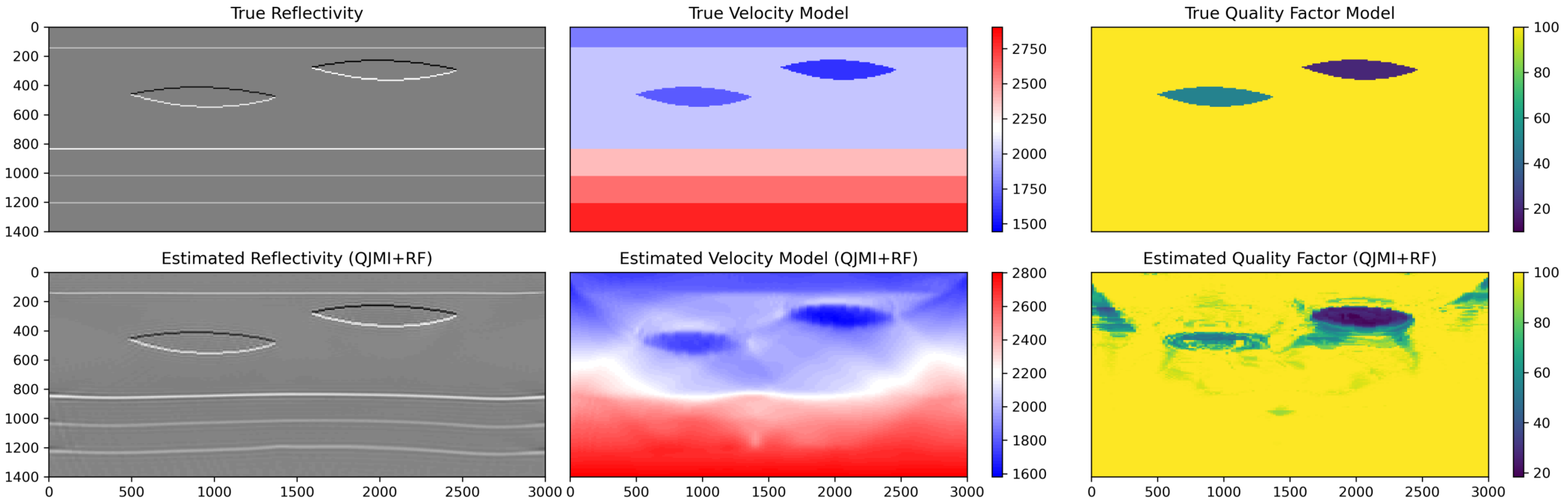
Synthetic test - JMI



Synthetic test – Q-JMI



Synthetic test – Q-JMI+RF



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Conclusions

- The JMI and the FWM methodologies are highly effective in accommodating Q simply by integrating the Q into the propagation operator.
- We presented a method for directly estimating the Q by utilizing full waveform matching in FWM and JMI.
- It was shown that Random Forest regression could be used as a constraint for mitigating cross-talk challenges.

Thank you for your attention!

Acknowledgement

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Delphi Consortium

Co-funded by the European Union

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