EGU General Assembly 2020

Online | 4–8 May 2020

Deep learning Q inversion from reflection seismic data with strong attenuation using an encoder-decoder convolutional neural network: an example from South China Sea

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Outline

- Introduction
- Method and theory
- Field data application
- Conclusion

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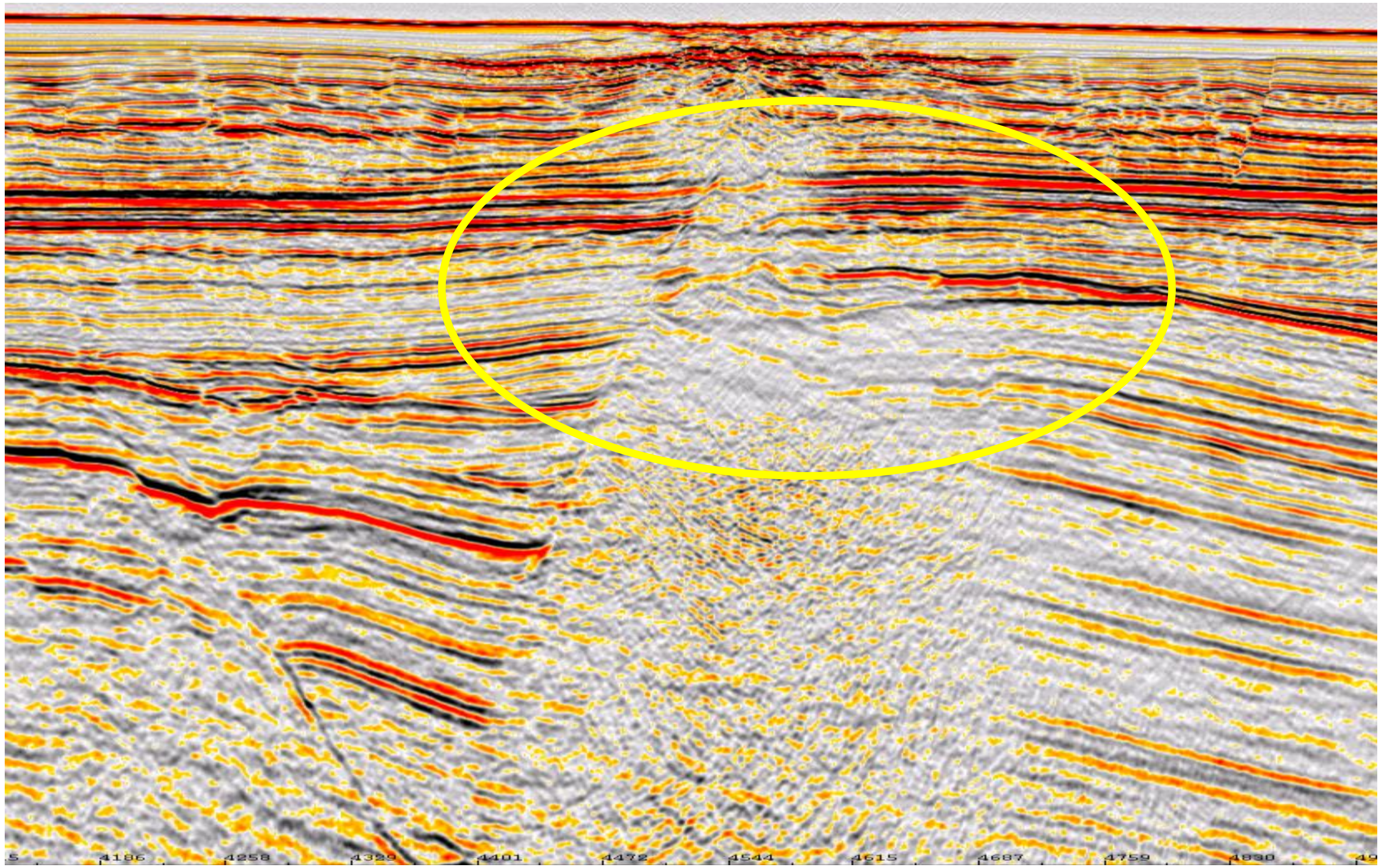
Problems of attenuation



A seismic image with strong Q effect

- ➢ Amplitude decay
- ➢ Poor illumination
- ➢ Unreliable AVO

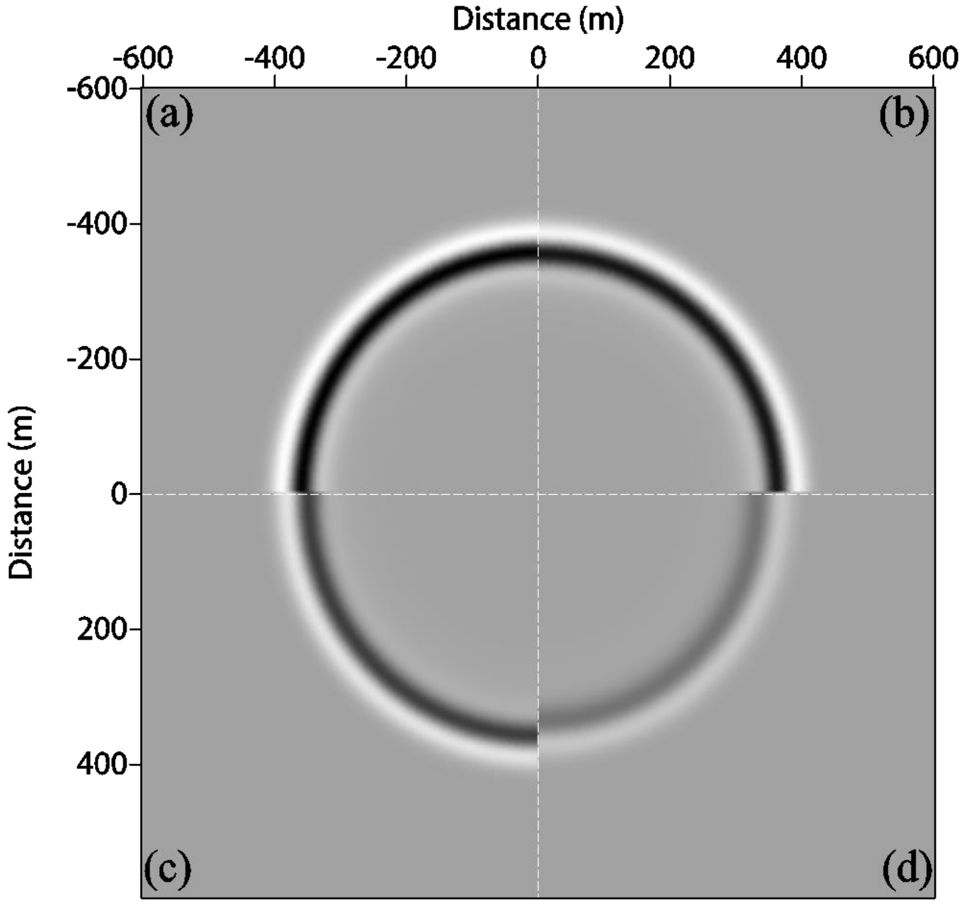
(Zhou ,2011)

The Q effect

Attenuation classification

Quality factor that quantifies **seismic attenuation**

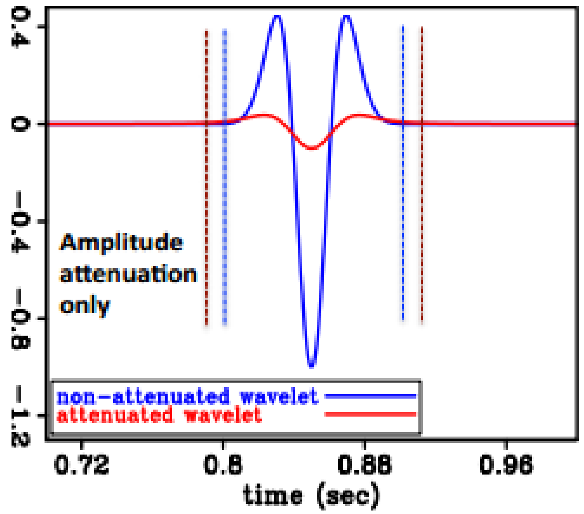
- Small Q means large attenuation
- Strong attenuation: Q ~ 10-50
- Mild attenuation: Q ~ 70-300
- Nearly no attenuation: Q >1000

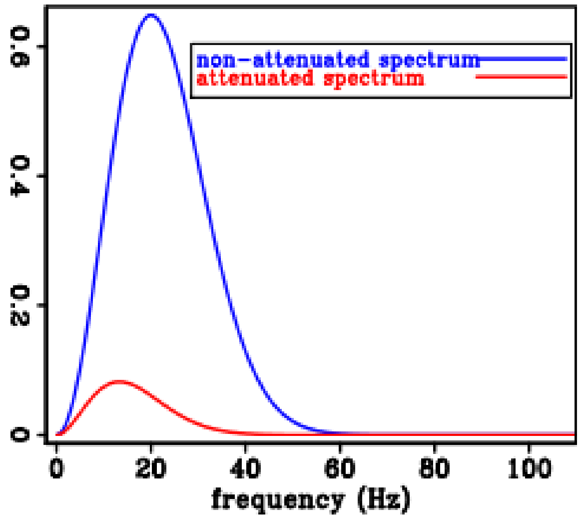


Effect of attenuation on amplitudes

Amplitudes

- The **higher** frequencies of a wave are attenuated more than its lower frequencies

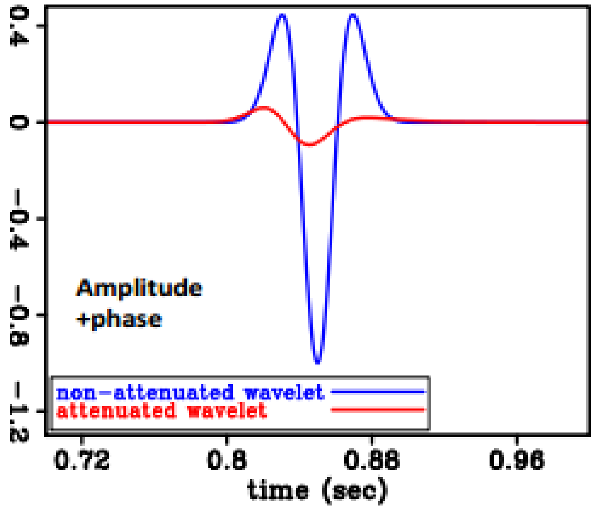


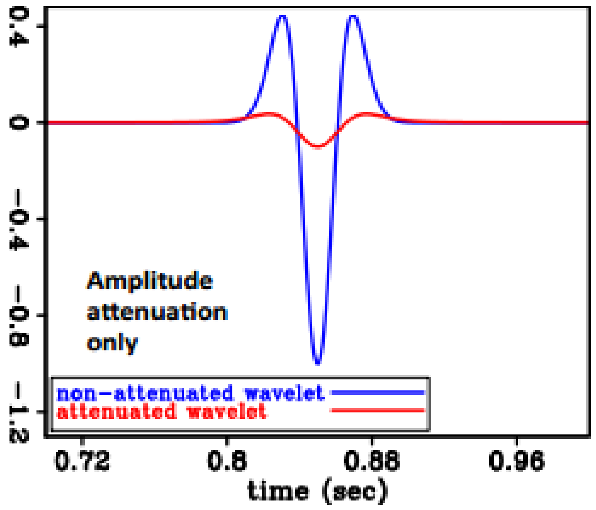


Effect of attenuation on phase

Phase

- The **higher** frequencies of a wave travel faster than its lower frequencies

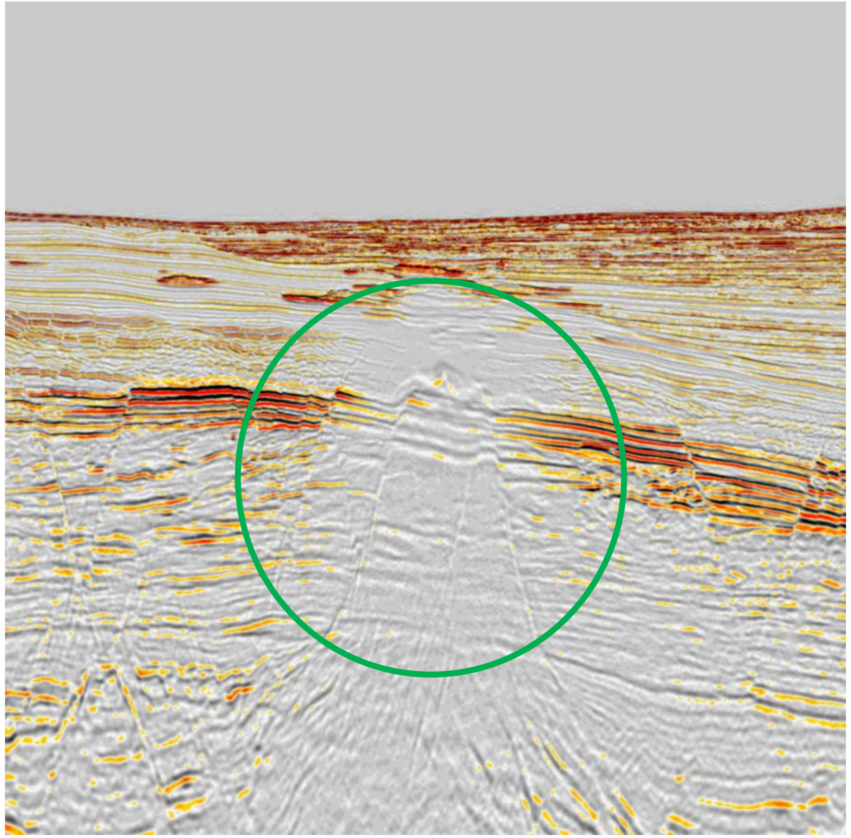




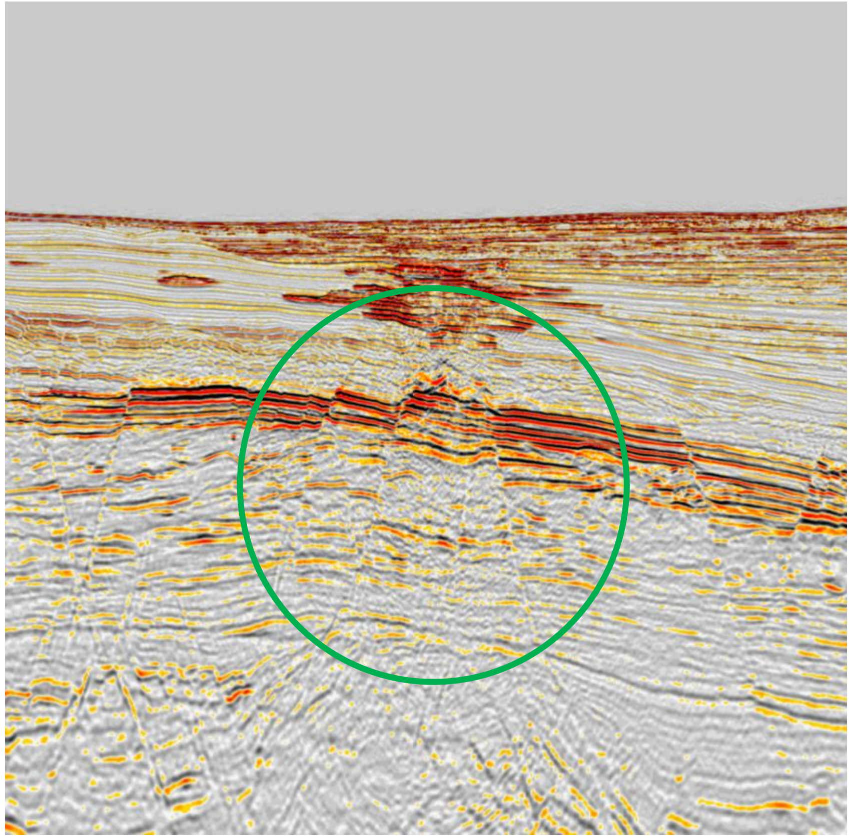
Effect of attenuation on imaging

Migration without Q compensation

- Damps amplitudes
- Lowers resolutions
- Disperses phases



Without Q compensation



With Q compensation

Courtesy of CNOOC

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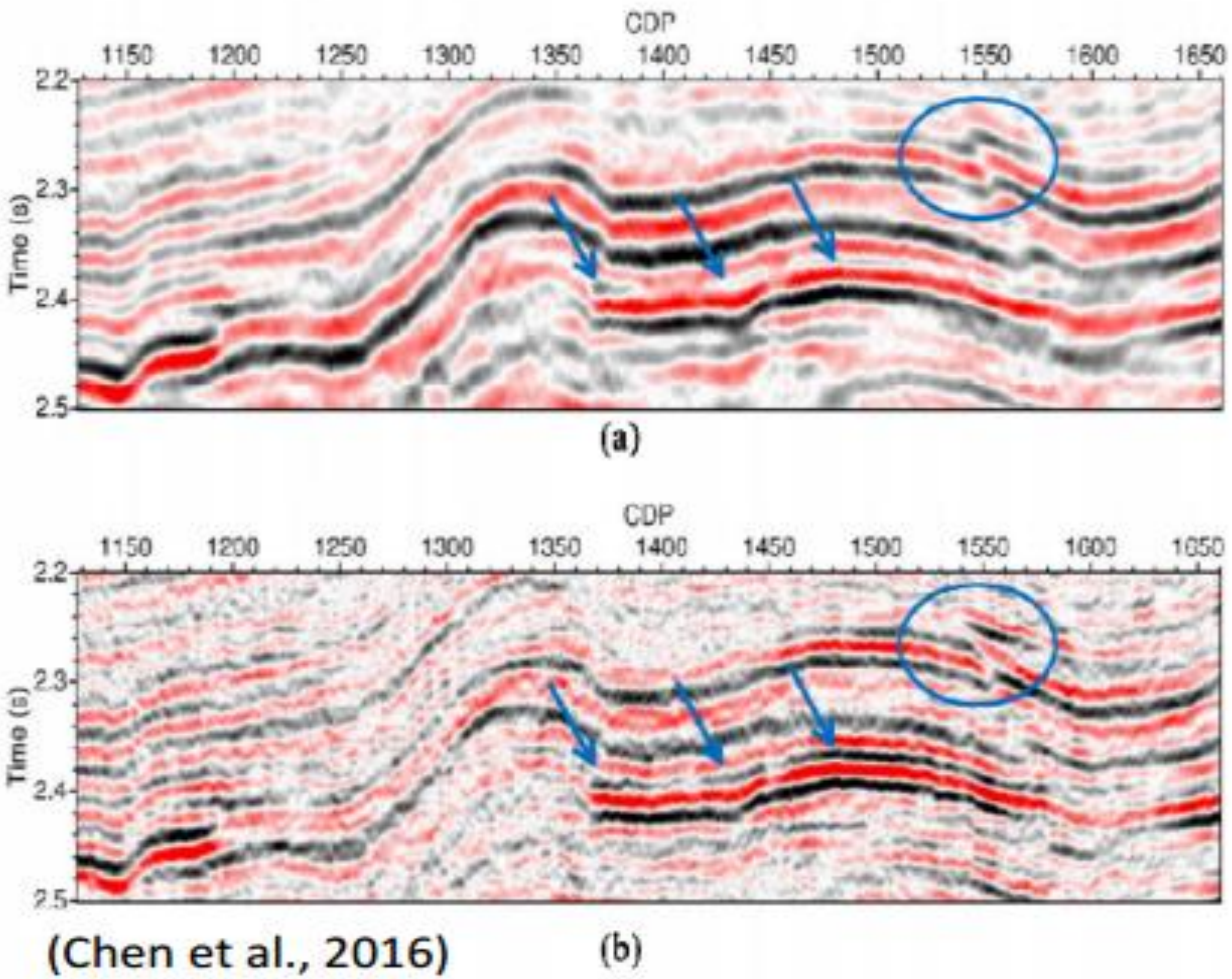
Effect of attenuation on reservoir characterization

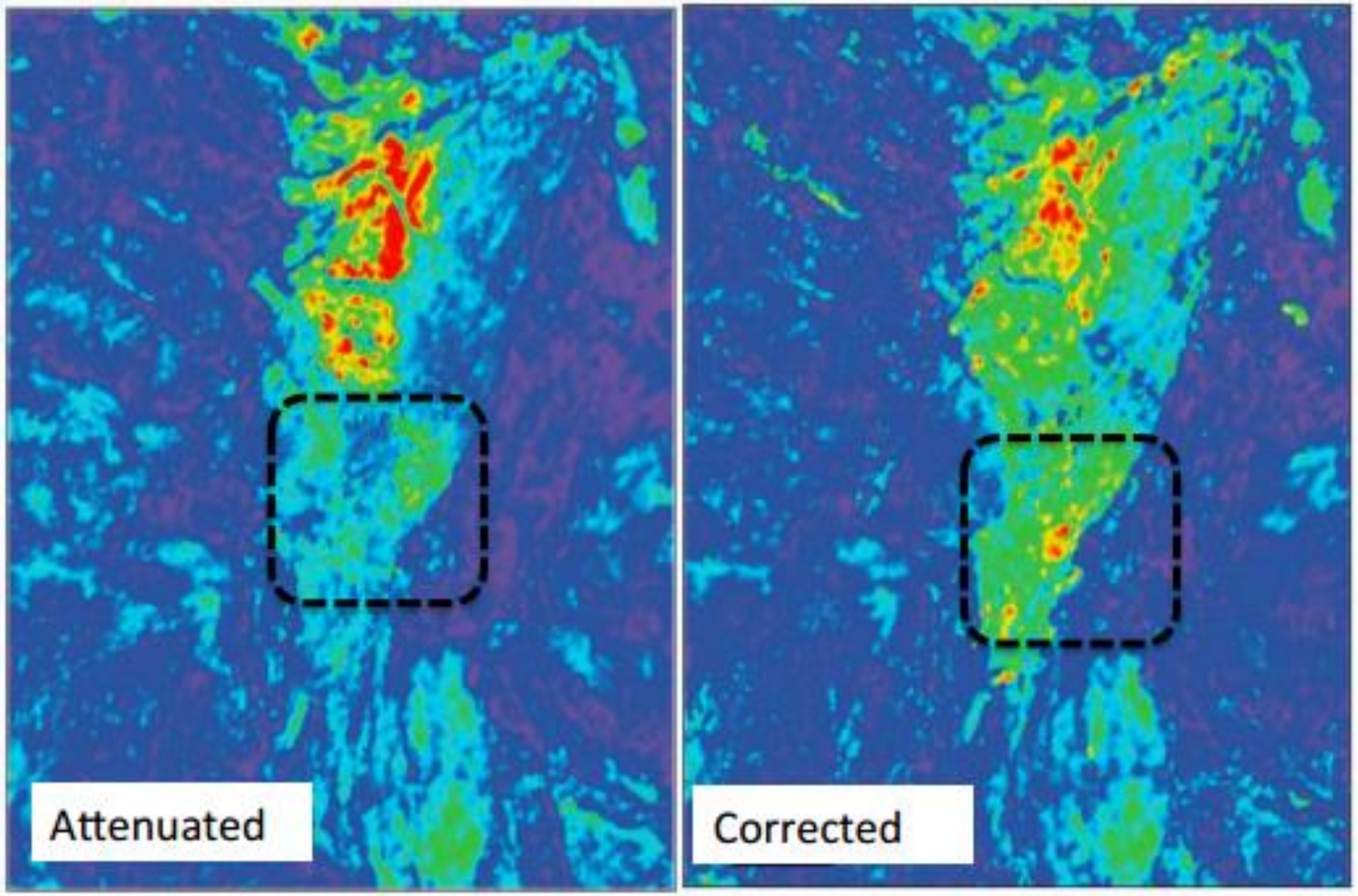


Attenuated

Corrected

(Chen et al., 2016)

Effect of attenuation on reservoir characterization



(Francis, 2016)

Approach to compensate Q effect

1. Filtering method

Nonstationary Deconvolution

（Dasgupta and Clark,1998;Margrave et al.,2003， 2011;van der Baan, 2012）

Poststack inverse Q filtering

（Bickel and Natarajan,1985;Hargreaves and Calvert,1991;Wang,2002）

Prestack inverse Q filtering (Wang,2006; Cavalca et al.,2011)

Q inversion and compensation

（Causse et al.,1999;Reine et al., 2012; Chen et al.,2013;Wang and Chen,2014; Li and Liu ,2015; Chai et al.,2016 ）

Limitation : Simple Q model used, can not handle heterogeneous Q model well.

Approach to compensate Q effect

2. Q compensation through Pre-stack migration

Ray-based（Ribodetti et al.,1998），

One way wave equation

（Dai and West,1994; Mittet et al.,1995; Yu et al.,2002; Mittet.,2007; Zhang et al,.2013;   Shen et al,.2014）

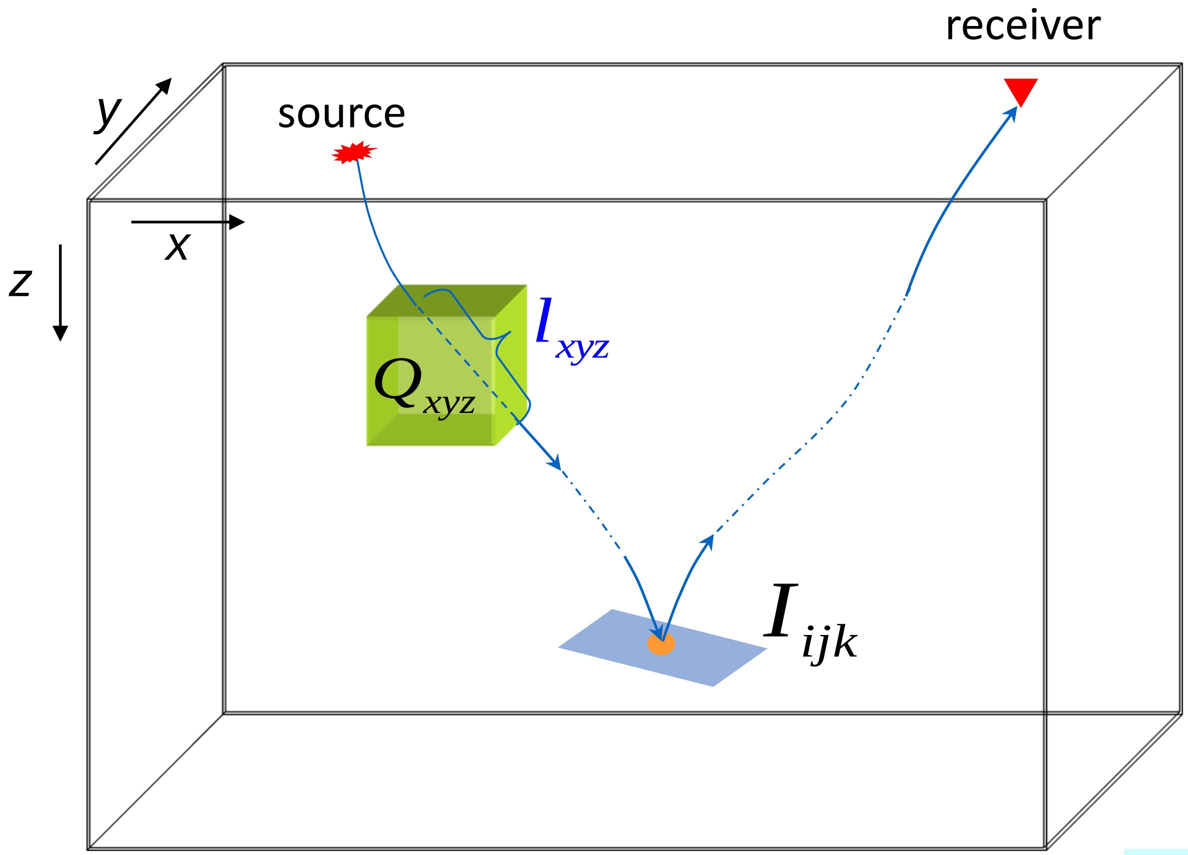
Two way wave equation

（ Causse and Usin,2000; Deng and McMechan,2007,2008; Zhang et al.,2010; Yan and   Liu,2013; Zhu et al,.2014）

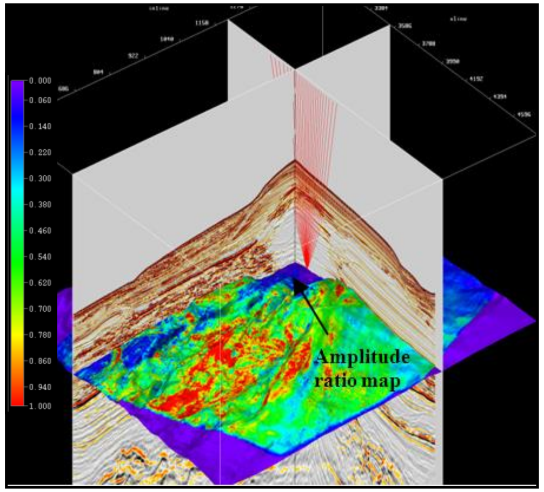
Challenge : Needs a fine heterogeneous Q model in depth domain

Q-PSDM: accumulated Q effect along raypath

Back-project the amplitude variations along raypaths

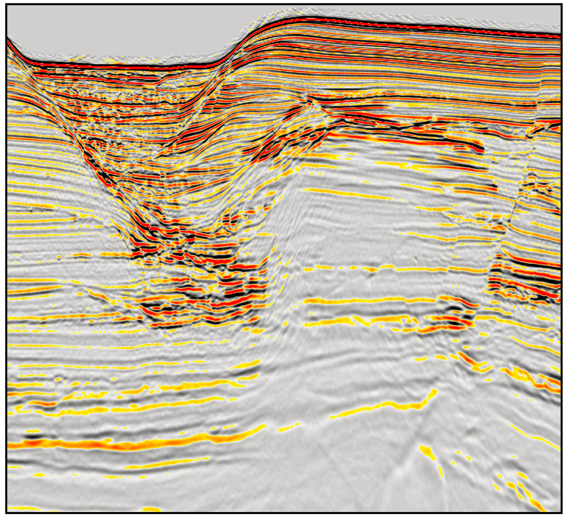


$$A(l) = A_0 \exp\left(-\frac{\omega l}{2vQ}\right)\exp\left(i\frac{\omega l}{\pi v Q}\ln\frac{\omega}{\omega_0}\right)$$

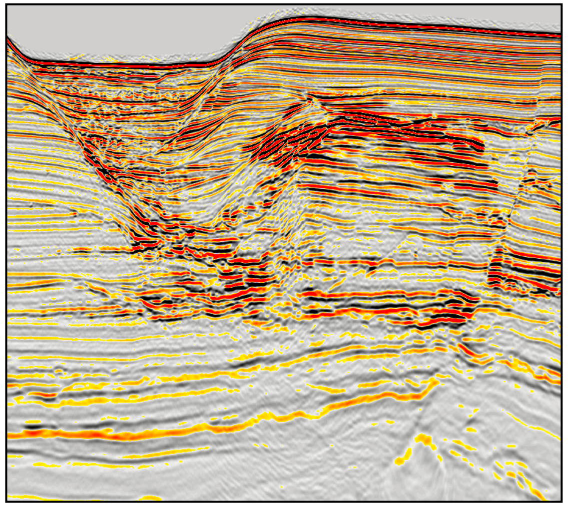


$$\text{Amp\_attenuation} = \exp\left(-\frac{\omega}{2}\sum_{raypath}\frac{l}{vQ}\right)$$

PSDM



Q-PSDM



(Zhou,2011)

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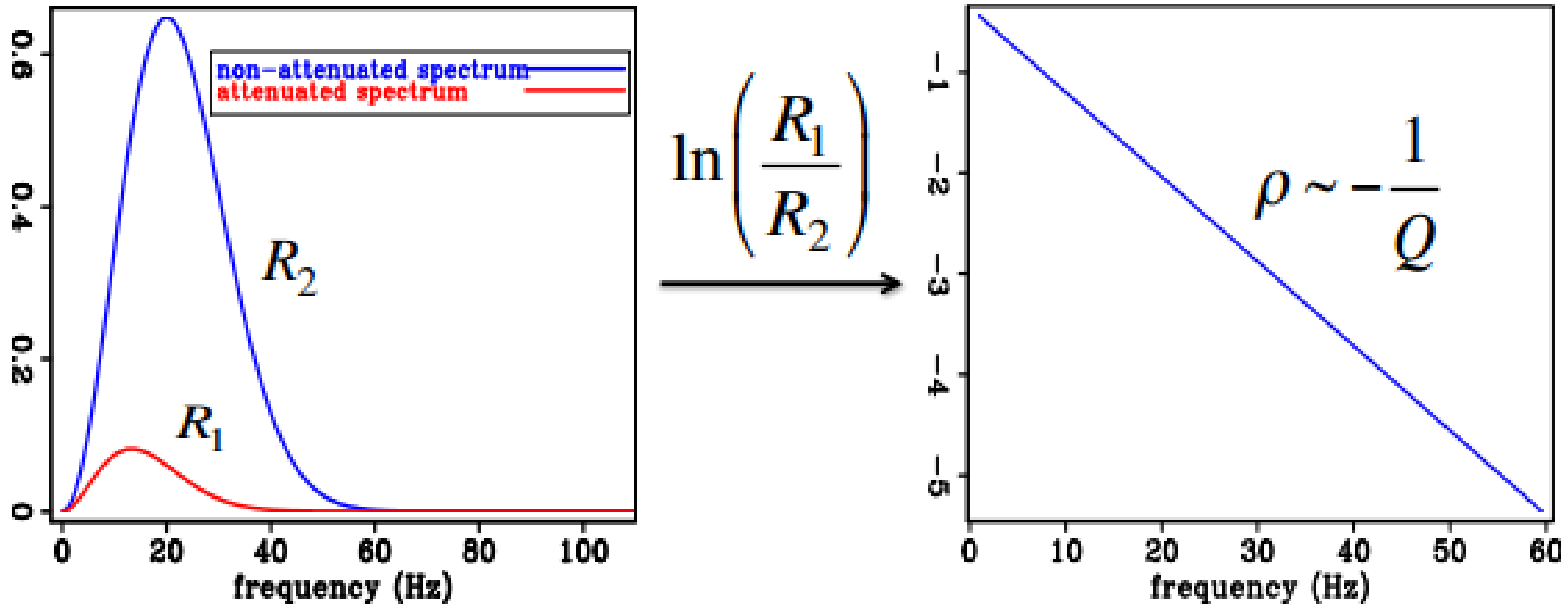
Traditional Q estimation approach
-- Spectral ratio method



(Tonn, 1991)

Traditional Q estimation approach -- Centroid frequency shift method

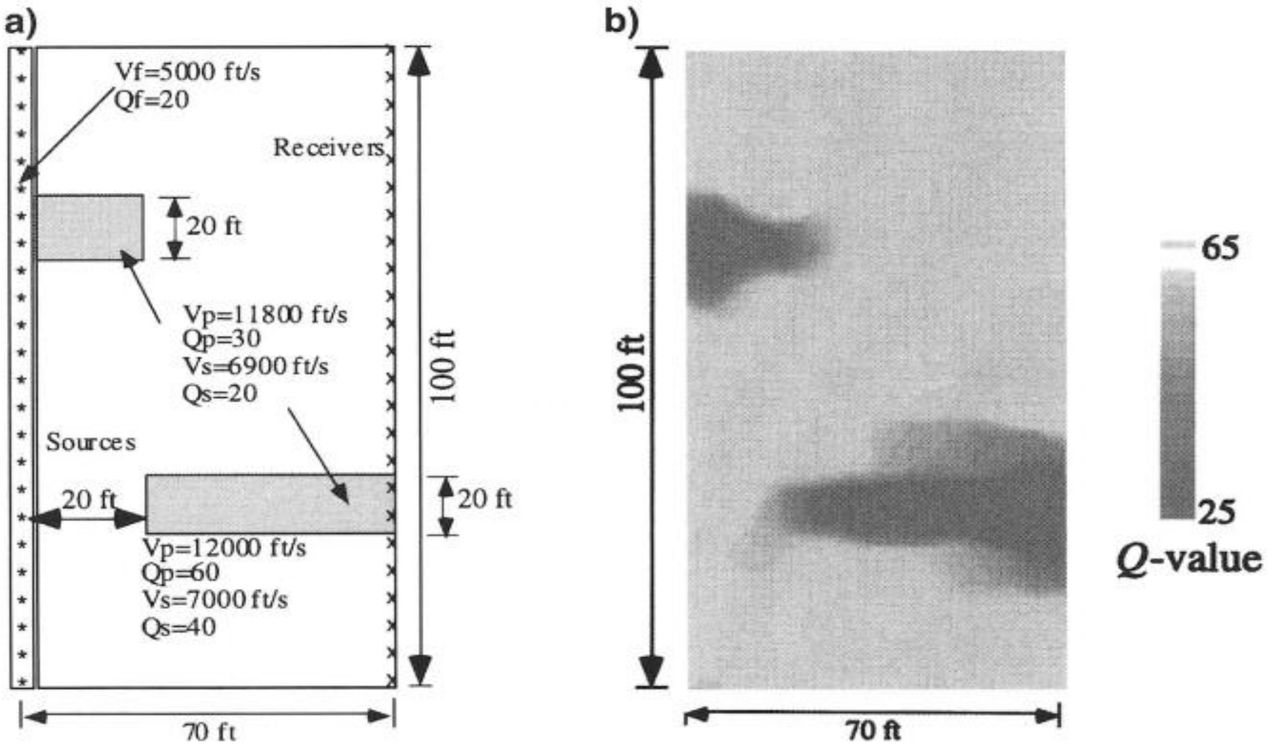


FIG. 10. A synthetic test on 2-D attenuation tomography. (a) is the original model. There are two low Q-value areas in this model, and (b) is the reconstructed Q-value distribution.

$$Q = \frac{\sigma_S^2 \pi \Delta t}{f_S - f_R}. \qquad (2)$$

Where f_S and σ_S^2 are the centroid frequency and variance of source wavelet, respectively. f_R is the centroid frequency of received amplitude spectrum. The expressions

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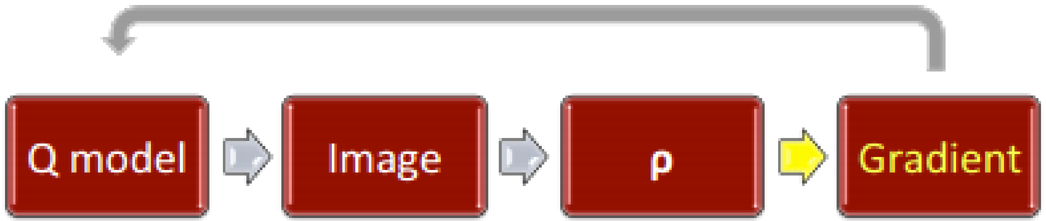
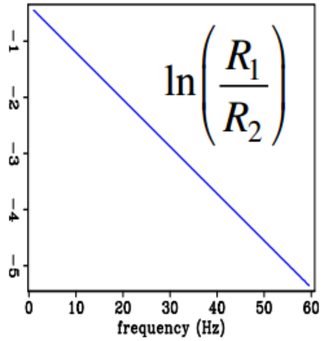
(Quan and Harris., 1997; Li et.al.,2015)

Recent Q estimation approach
-- Image domain WE migration Q analysis

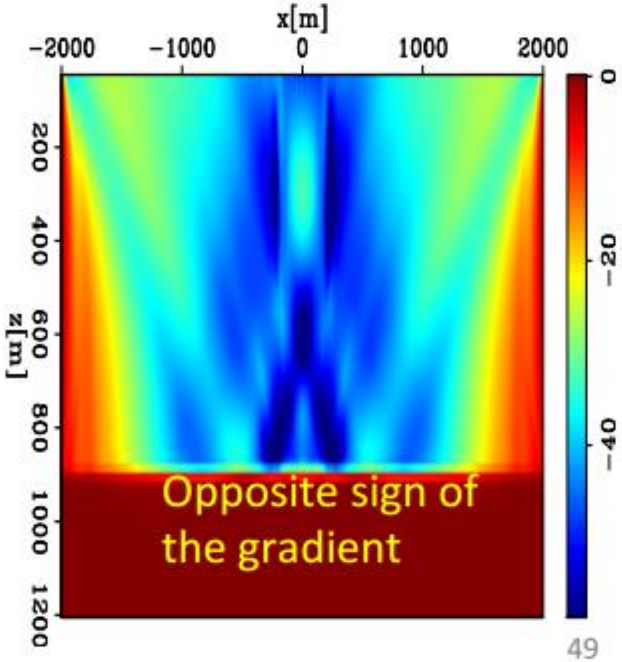


Define ρ as the effect of attenuation (**effect of Q**) on seismic **migrated images**

$$J = \frac{1}{2}\sum_{\mathbf{x}} \left|\rho(\mathbf{x};Q)\right|^2$$

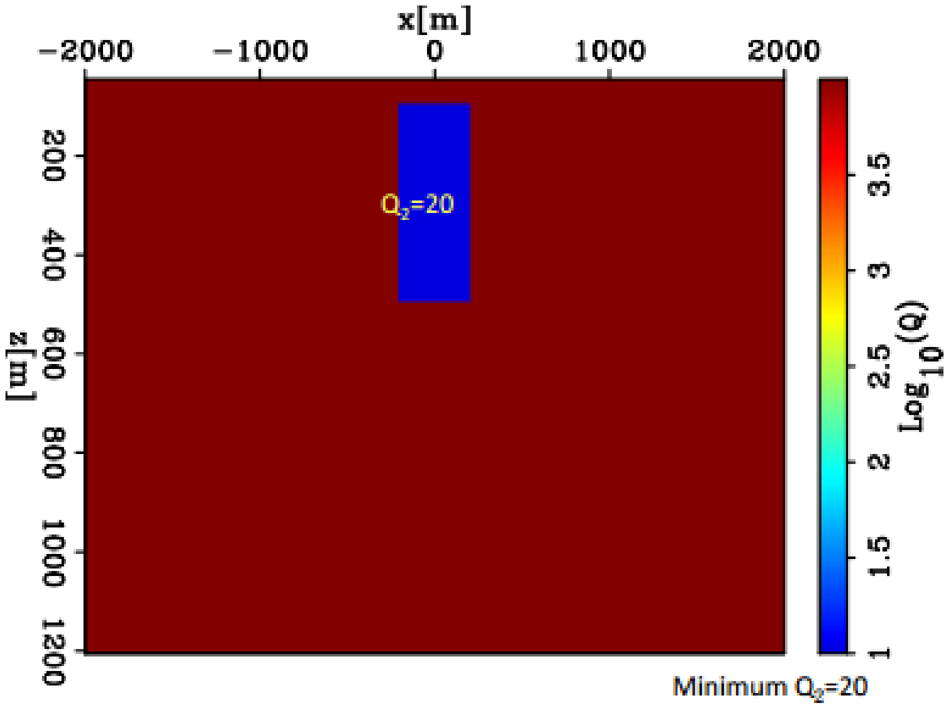


x is each a spatial location in the image space
Q is the current model for quality factor

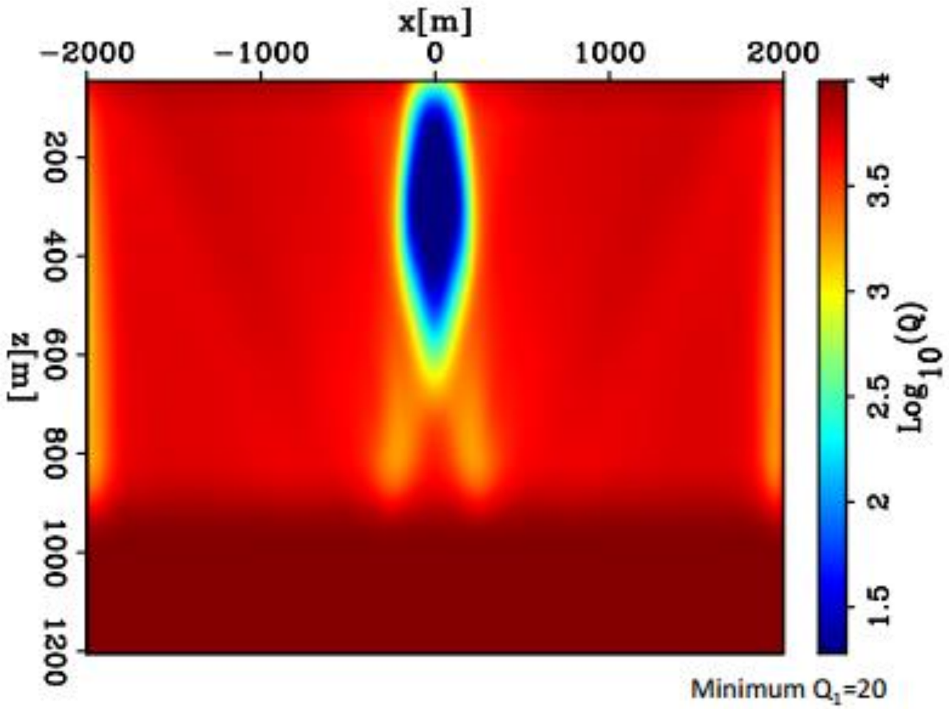


(Shen et al., 2018)

Recent Q estimation approach
-- image domain WE migration Q analysis



Ground truth



Inversion result

- Large scale industry problem
- Sensitive to noise

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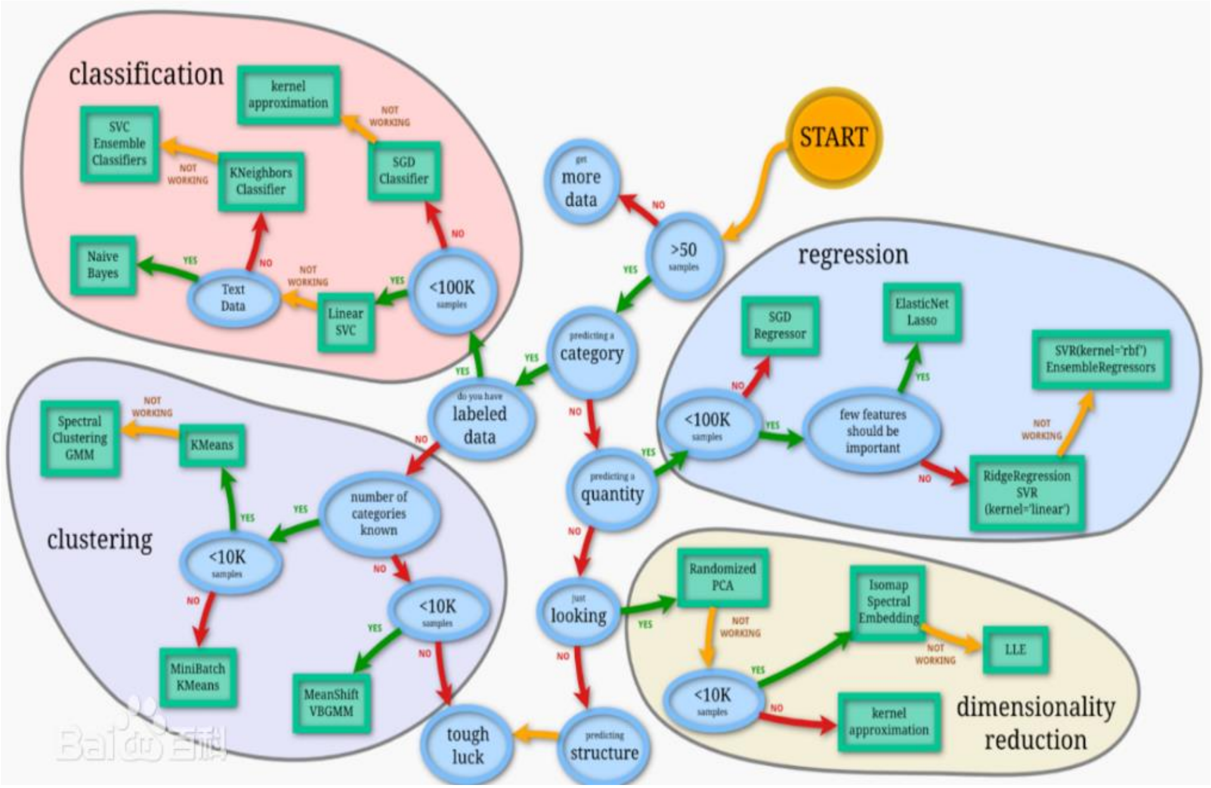
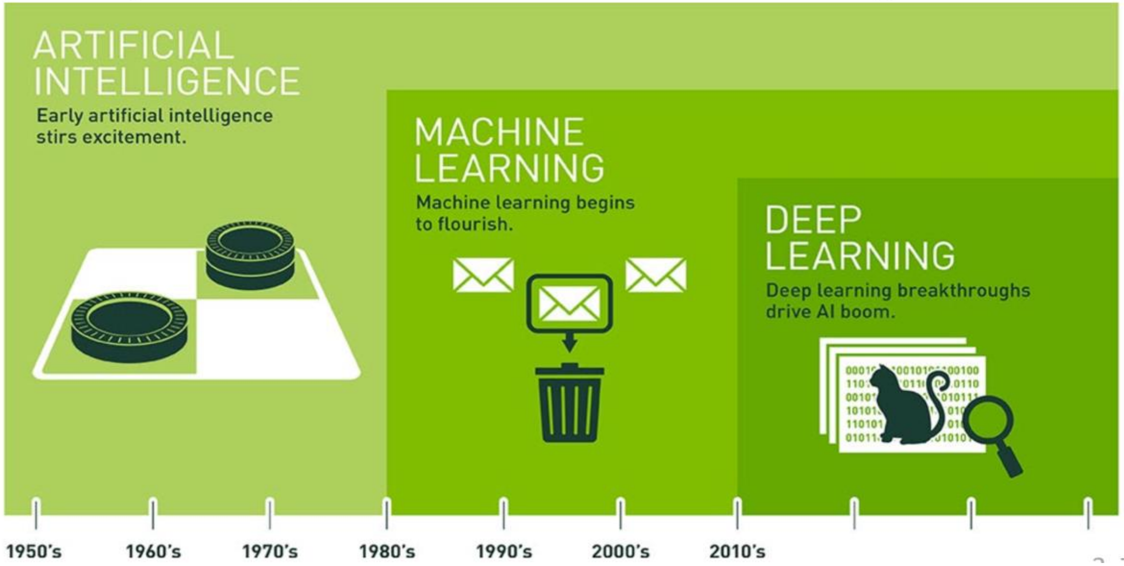
(Shen et al., 2018)

ML and DL in Geophysics





Good at solving the problems of **classification**, **clustering, regression** and **dimensionality reduction** of high-dimensional data

First break picking

VA and FWI

Fault, horizon and salt dome identification

Classification of phases

...

Yuan et al，2018， Araya-Polo et al, 2018,Lewis and Vigh，2017, Wu et al, 2016

Work Flow

Data and Network preparation

Migration to output seismic image

Dividing datasets to training, testing, Validation set.

Labelling the data by hand picking

Constructing the structure of neural network, choosing number of network layers, input neurons, the activation function, loss function and optimization method.

Network training and data validation

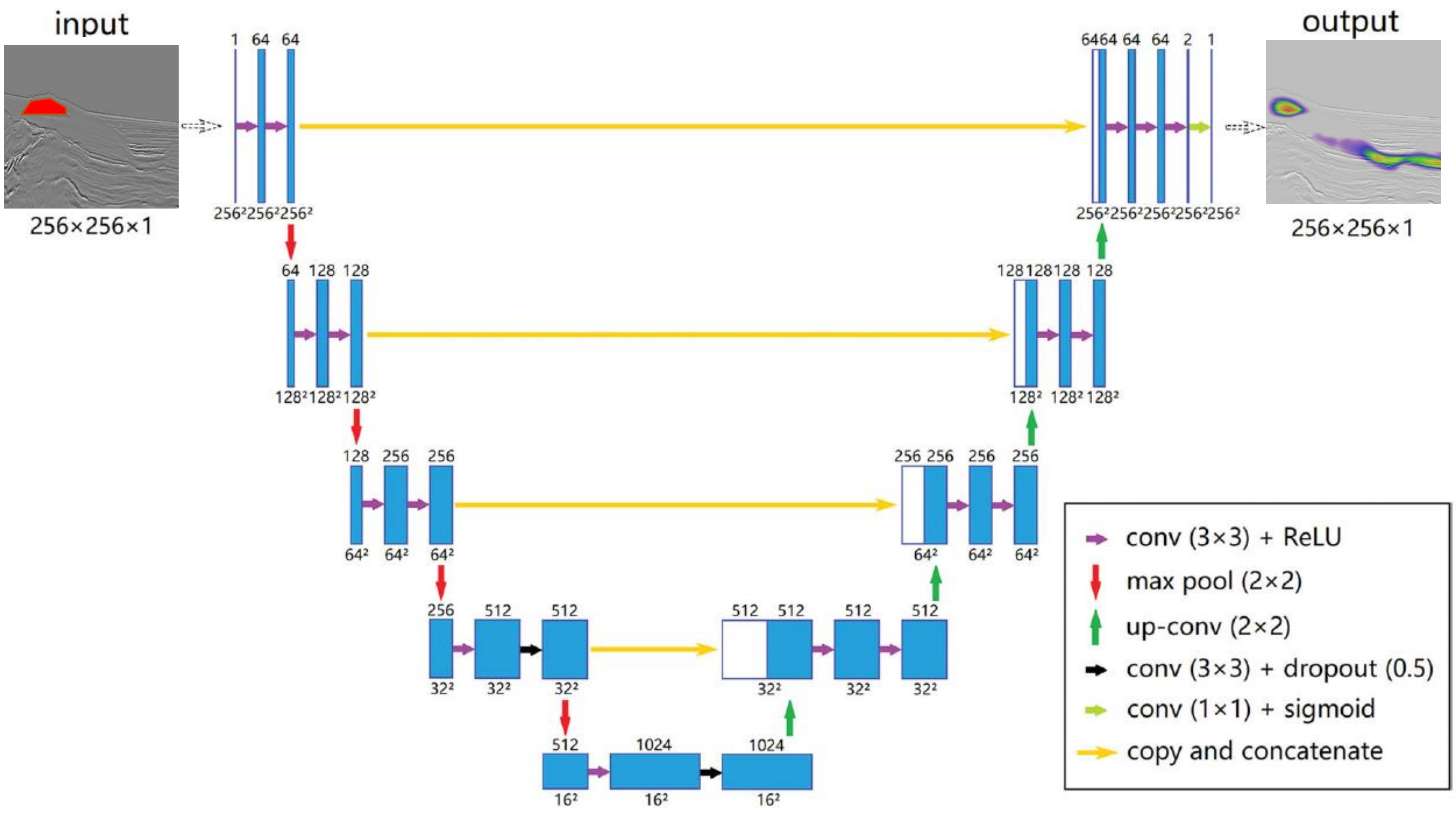
Training the network using the training set with labels, adjust the network structure based on the performance of the cost function.

Verify network parameters, complete network training, using test data to check generalization effect.

Input the whole dataset, finish automatic Q inversion and imaging with the Q field.

Network training is most time-consuming

CNN architecture for Q inversion

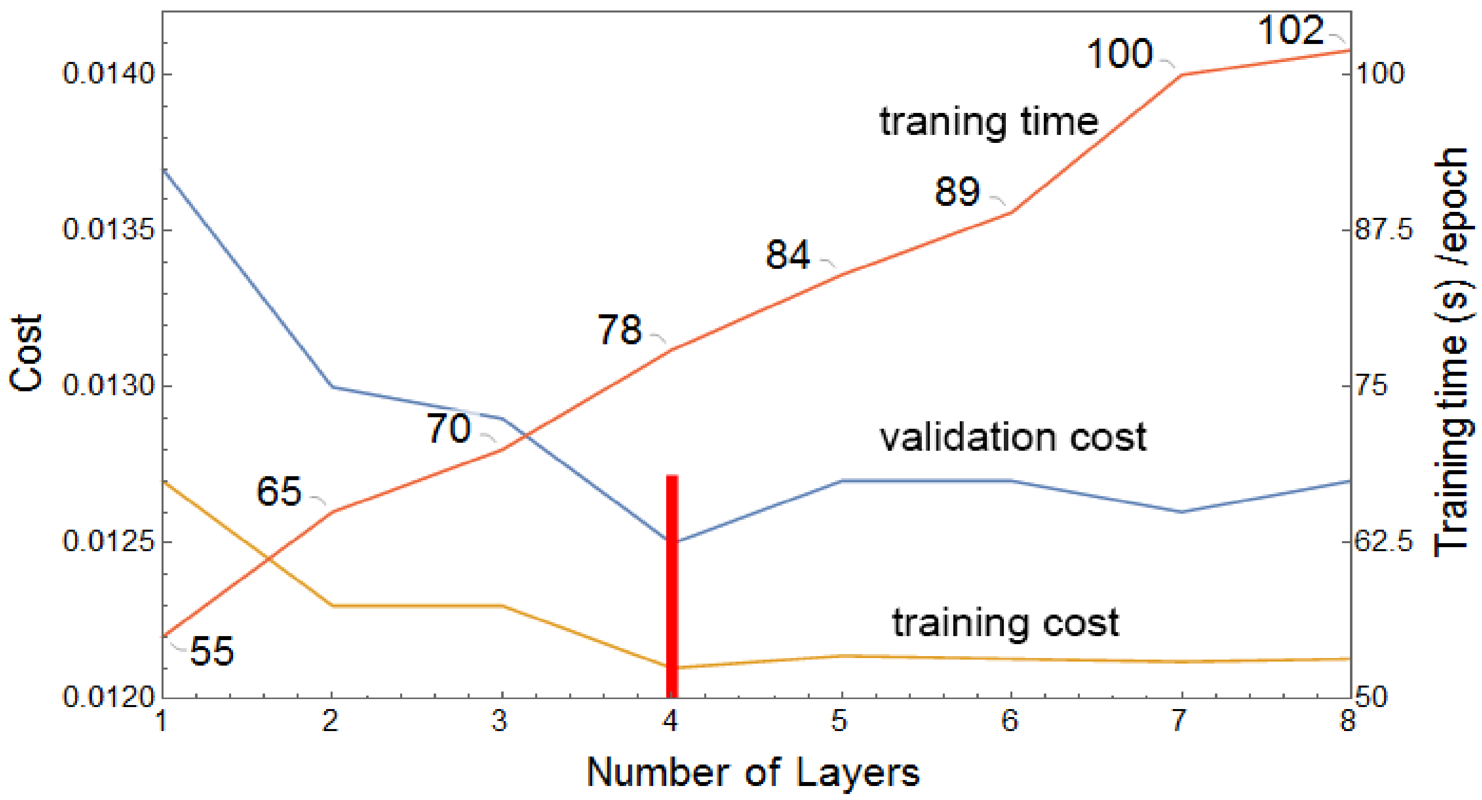


Training evaluation

Compare the training error and the validation error with training time

Too simple NN causes underfitting.

Over complicated NN causes overfitting.



Through testing, we choose the number of layers at 4

The depth and width of hidden layers decide the learning ability of a NN

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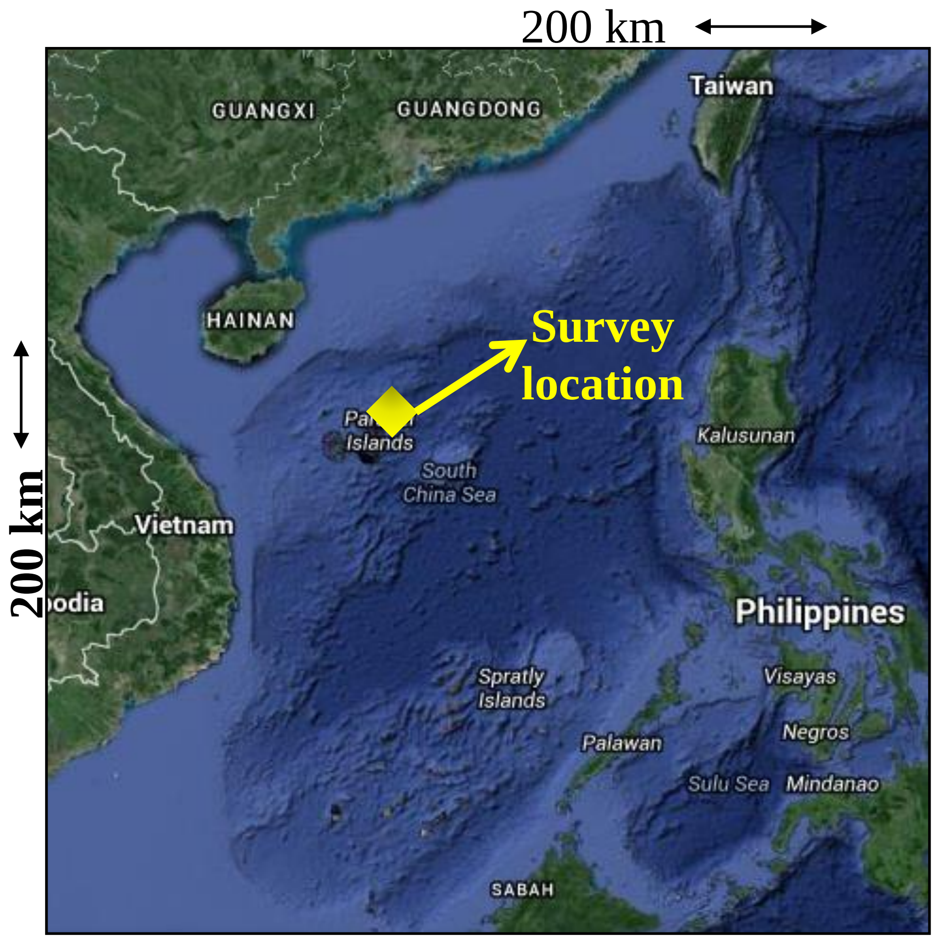
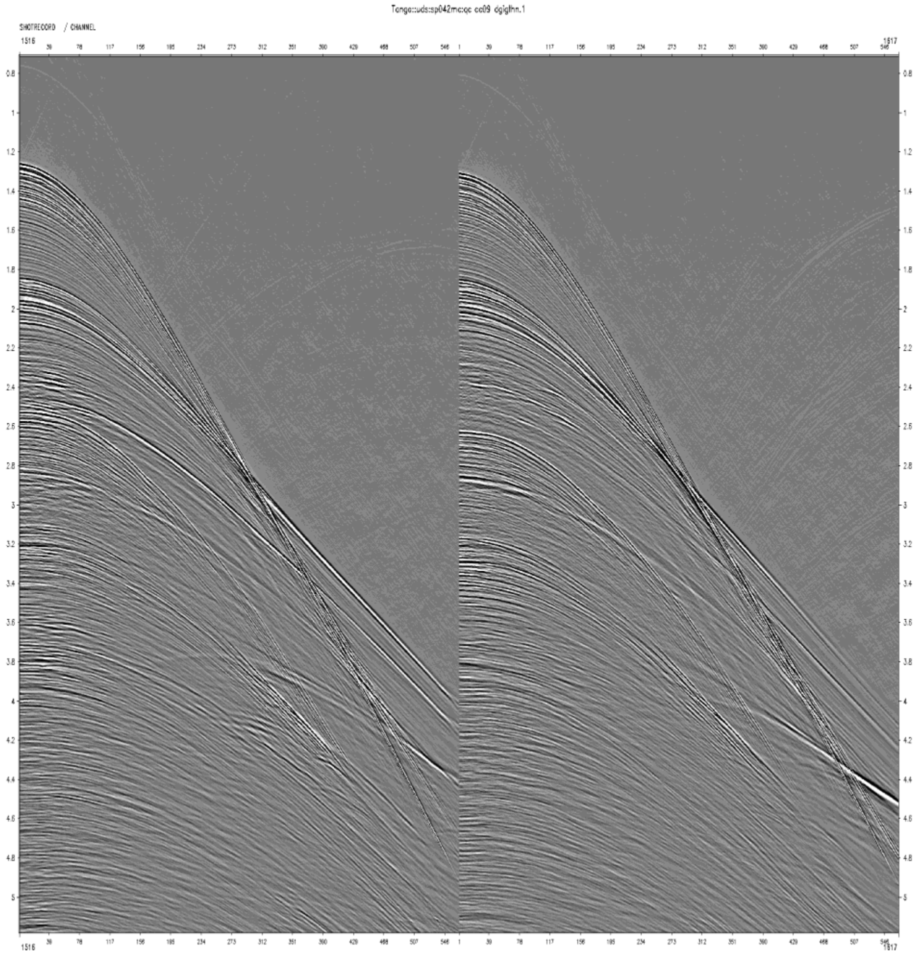
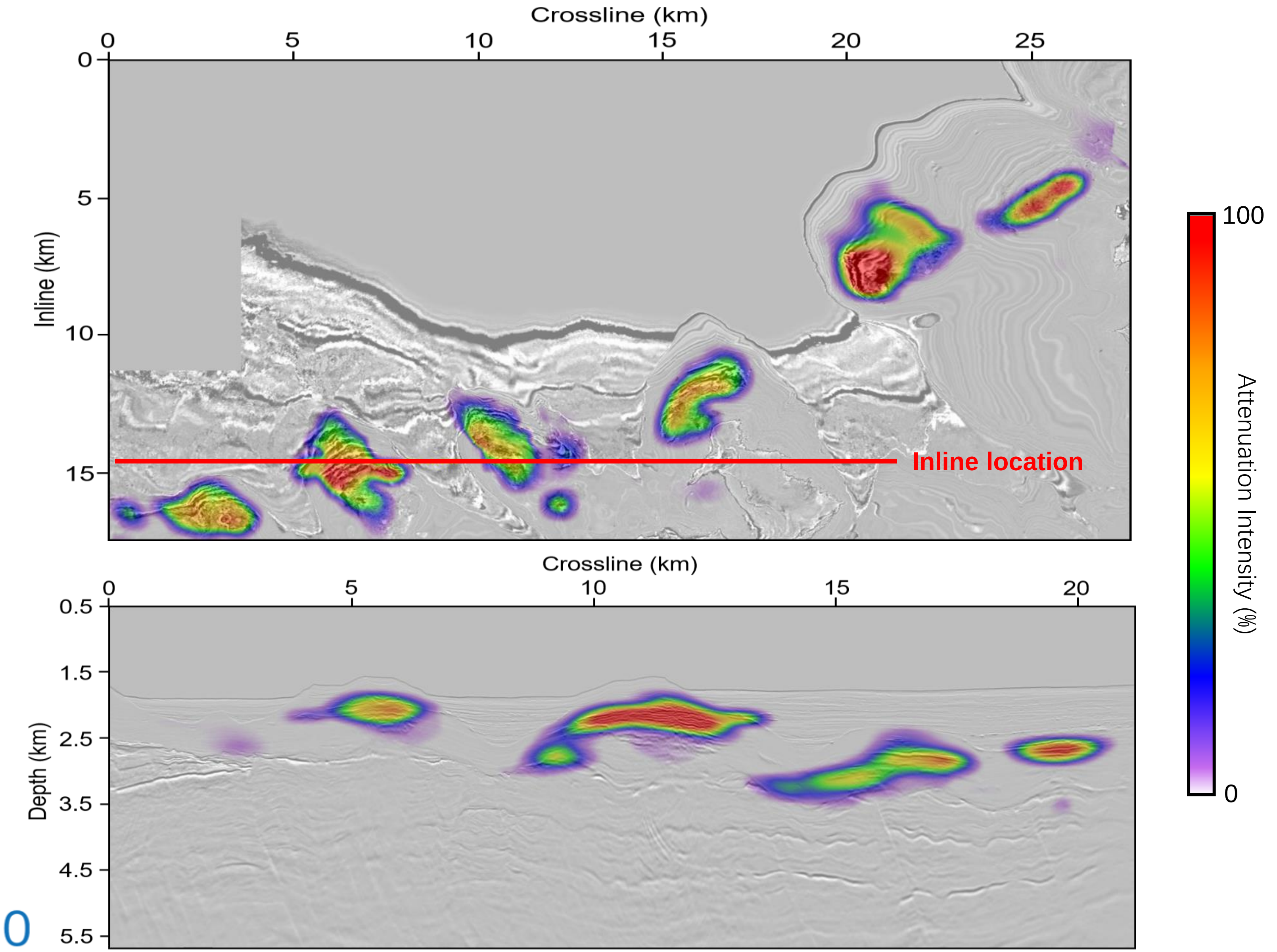
The 3D seismic data





The Q inversion result



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The Q-PSDM method to verify

Imaging result

$$I(x,y,d)=\left(\frac{A_s}{A_g}\right)^2\int F(\omega)\omega\exp\left(-j\frac{\pi}{2}\right)\exp\left[j\omega\left((\tau_s+\tau_g)-\frac{\ln(\omega/\omega_0)}{\pi}\left(\frac{\tau_s}{Q_s}+\frac{\tau_g}{Q_g}\right)\right)\right]\exp\left\{\frac{\omega}{2}\left(\tau_s/Q_s+\tau_g/Q_g\right)\right\}d\omega$$

Weights

3D effect

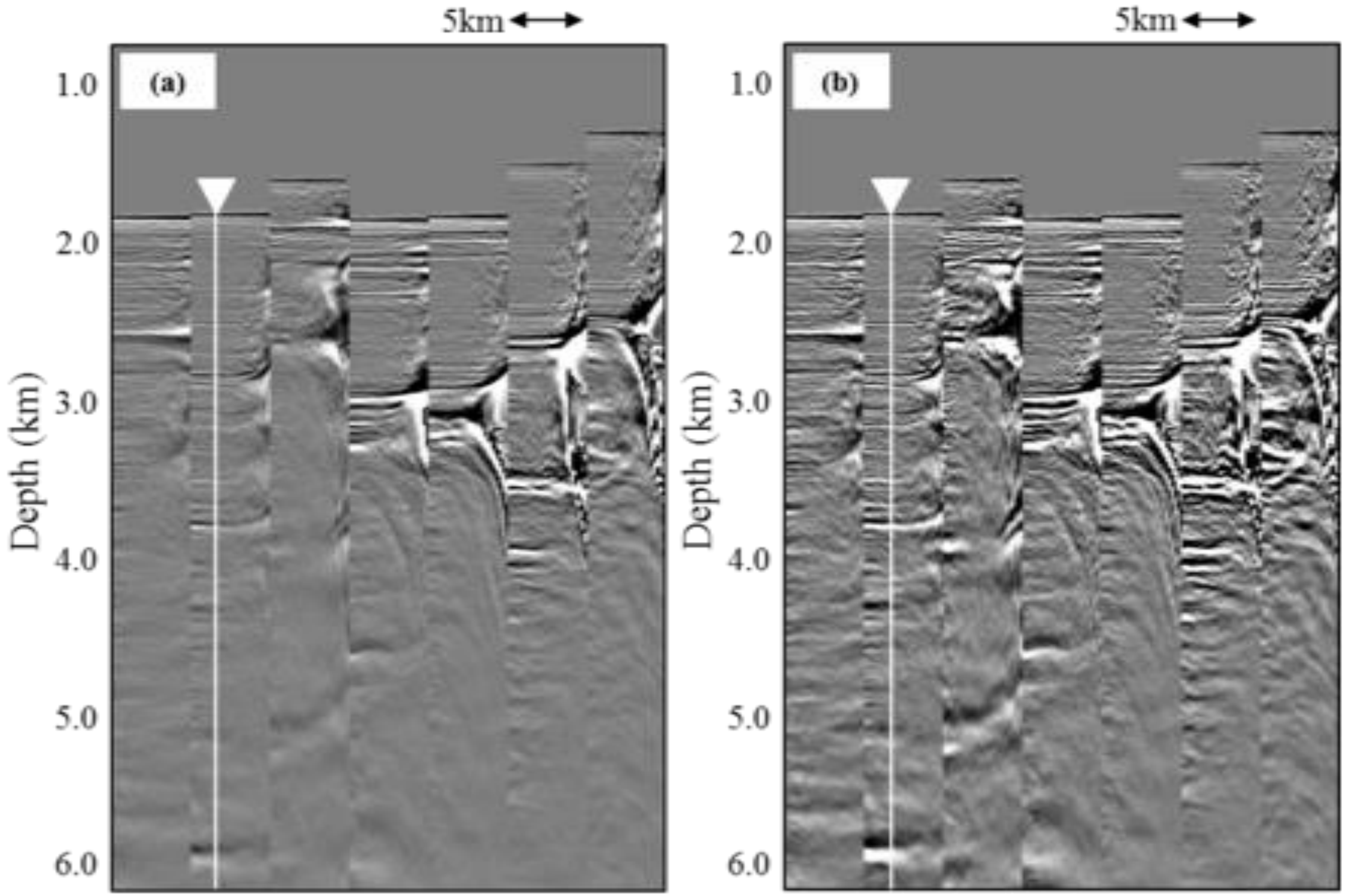
Traveltime

Phase correction

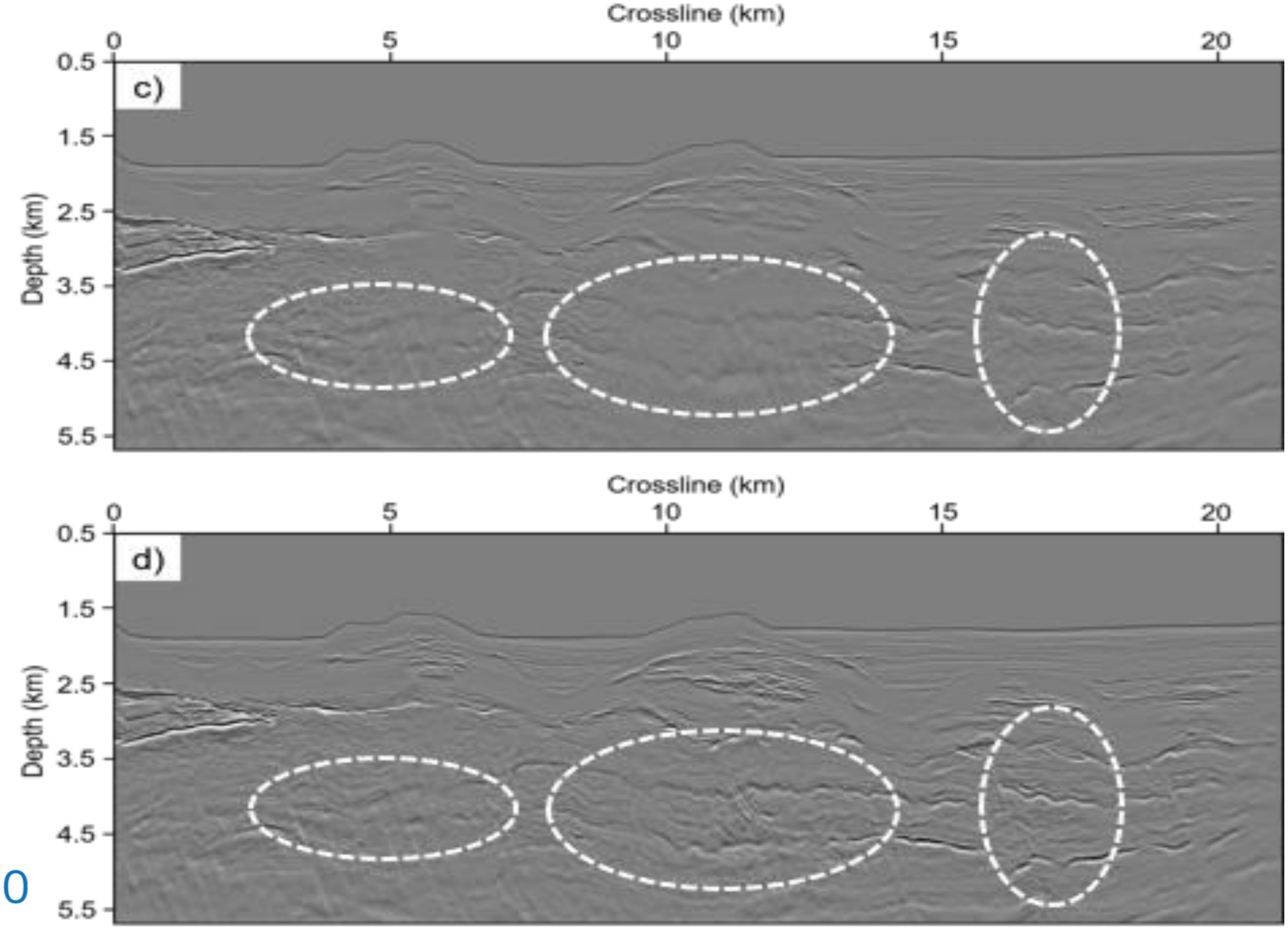
Amplitude compensation

Compensating Q effect

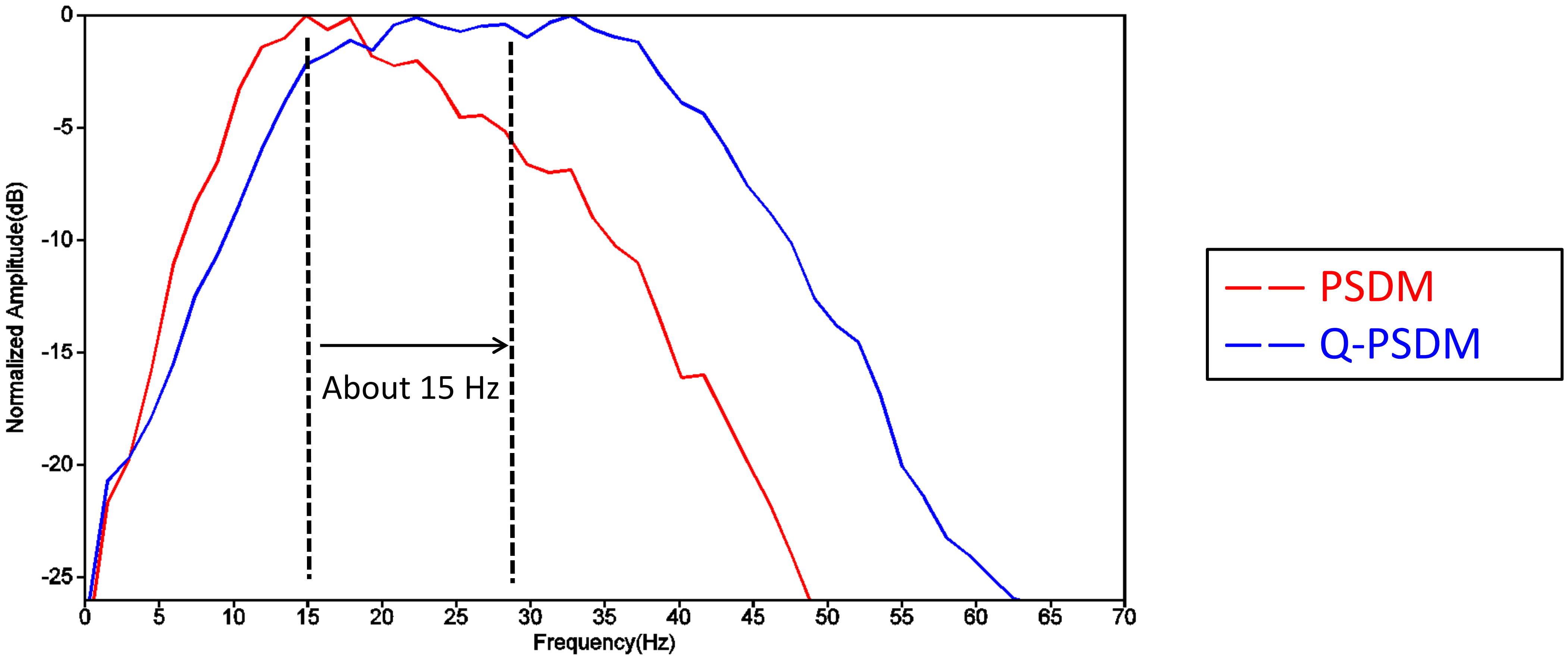
The migration gather w/o Q compensation



The imaging result w/o Q compensation



Result comparison : Spectrum



About 15 Hz main frequency lifting

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Conclusions

- The DL method can help to capture the Q anomaly automatically after network training.
- The proposed Q model building workflow is less affective by the noise and suitable for large-scale industrial problems.
- Automatic labeling is the topic that needs further study.

THANK YOU!