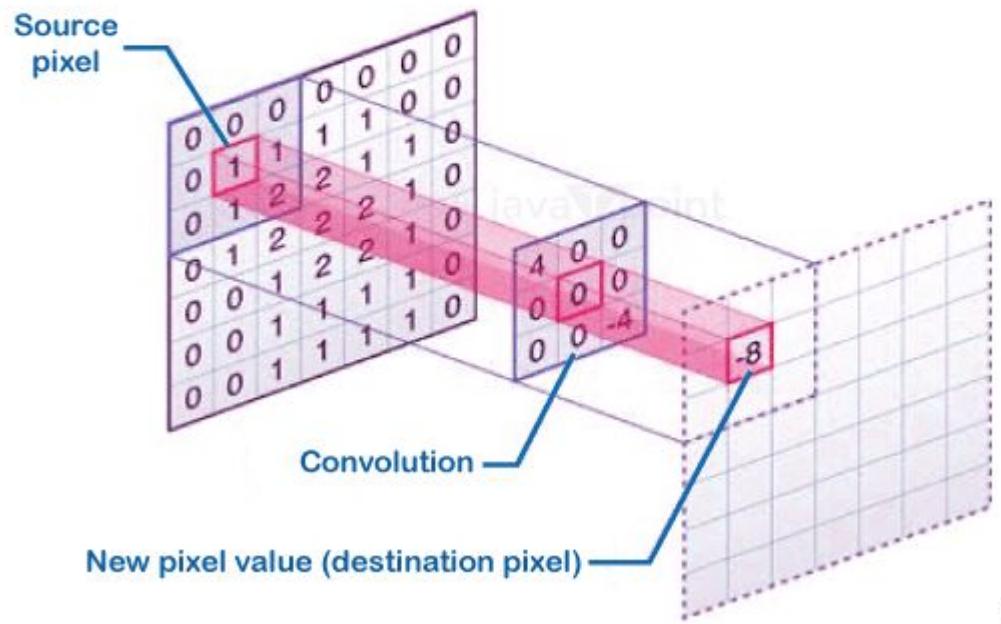


Machine Learning and Inversion

Vitaliy Ogarko and Mark Jessell

Convolution in a nutshell

Center element of the kernel is placed over the source pixel. The source pixel is then replaced with a weighted sum of itself and nearby pixels.



Convolution is a mathematical operation used in **convolutional neural networks (CNNs)** to extract important features from input images.

Feature Extraction: As the filter slides it produces a new image (feature map) that highlights certain features, like edges, textures, or patterns.

Automatic Feature Detection: CNNs automatically learn to detect features such as edges, shapes, or textures from raw data.

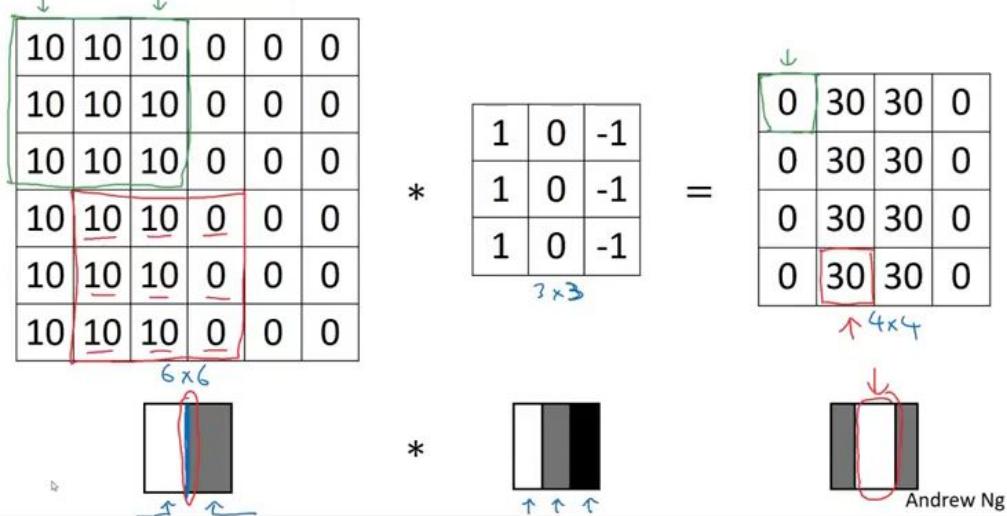
Convolution: edge detection example

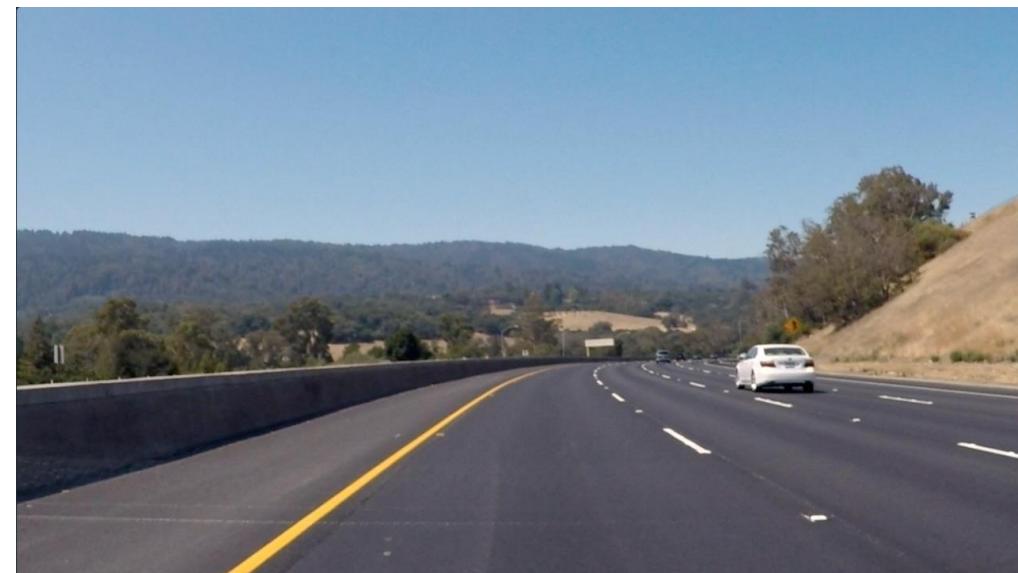
Vertical edge detection

$$\begin{array}{|c|c|c|c|c|c|} \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline 10 & 10 & 10 & 0 & 0 & 0 \\ \hline \end{array} \quad * \quad \begin{array}{|c|c|c|} \hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline 1 & 0 & -1 \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline 0 & 30 & 30 & 0 \\ \hline \end{array}$$

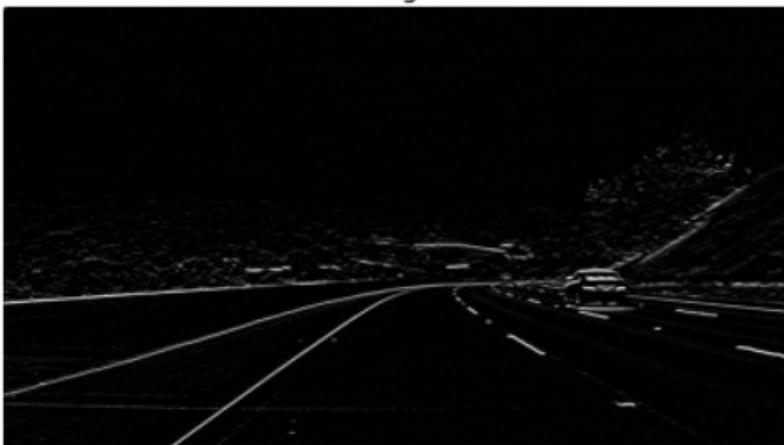
3×3 4×4

\downarrow \downarrow
 6×6 4×4





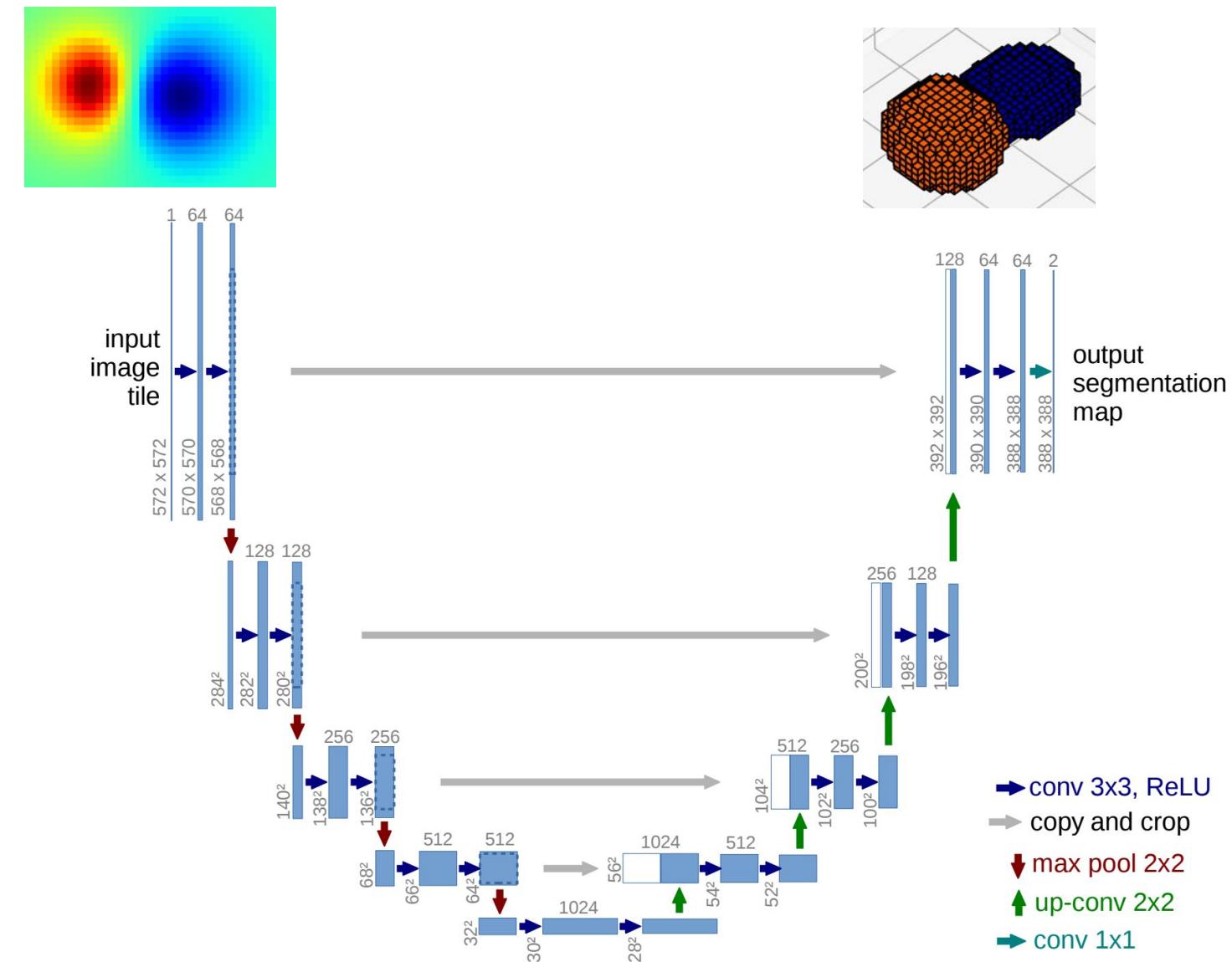
horizontal edge detection



vertical edge detection



U-Net architecture



Encoder (Contracting Path):

Extracts key features from gravity data, like regions with high or low density anomalies.

Decoder (Expanding Path):

Reconstructs the segmented output, highlighting important geological structures.

Skip Connections:

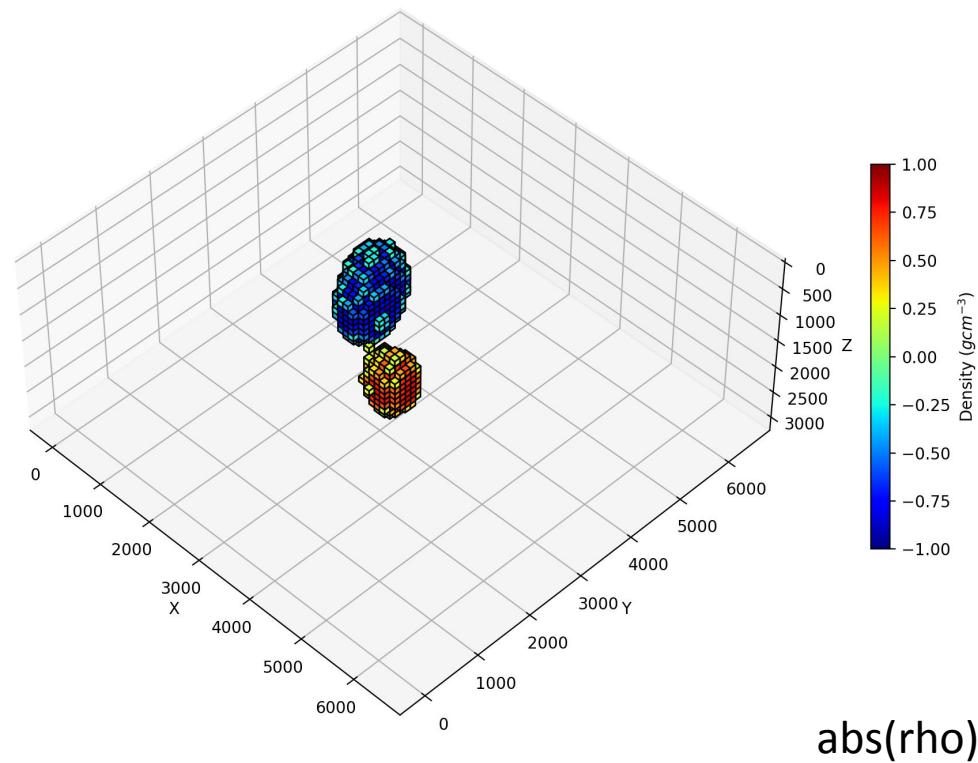
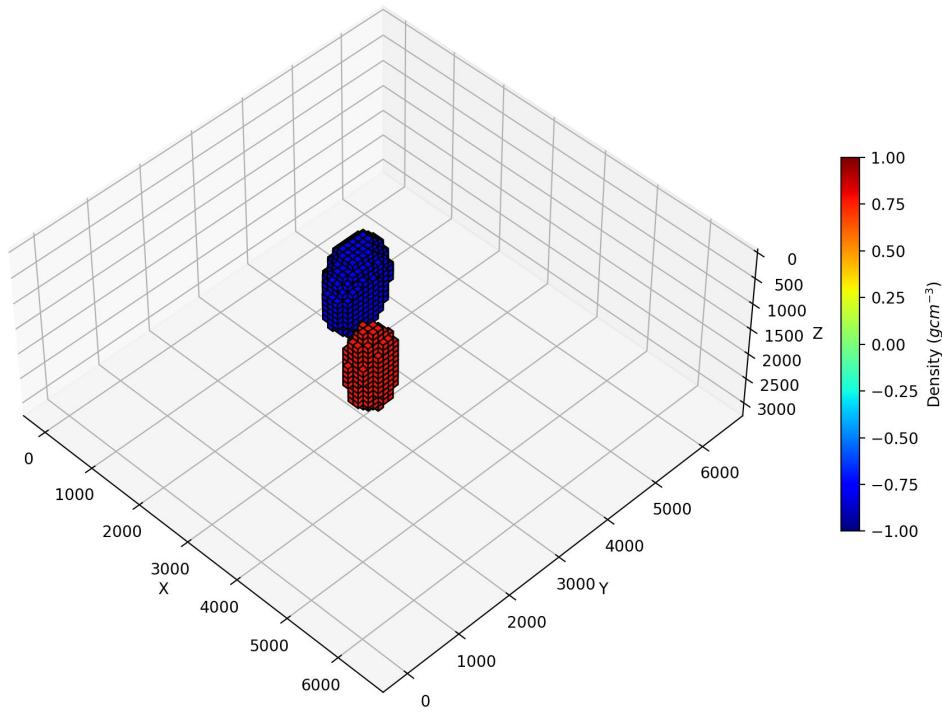
Retain spatial information from the encoder, preserving the resolution needed to precisely identify geological boundaries.

Machine Learning based gravity inversion

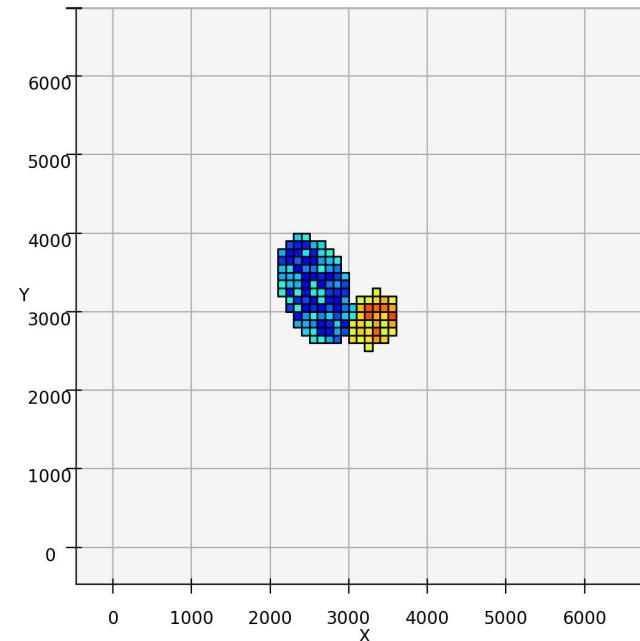
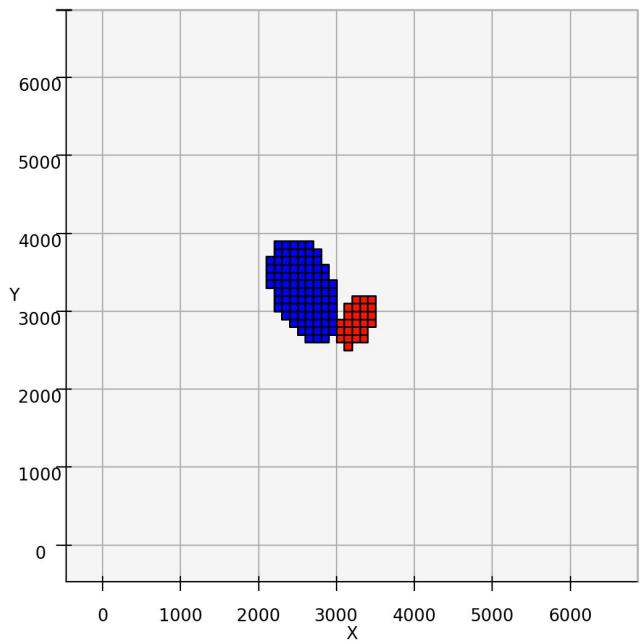
- Geology and petrophysical constraints are embedded into training set.
- Training set generated by Noddy 3D geological modelling platform.
- PyTorch library used.

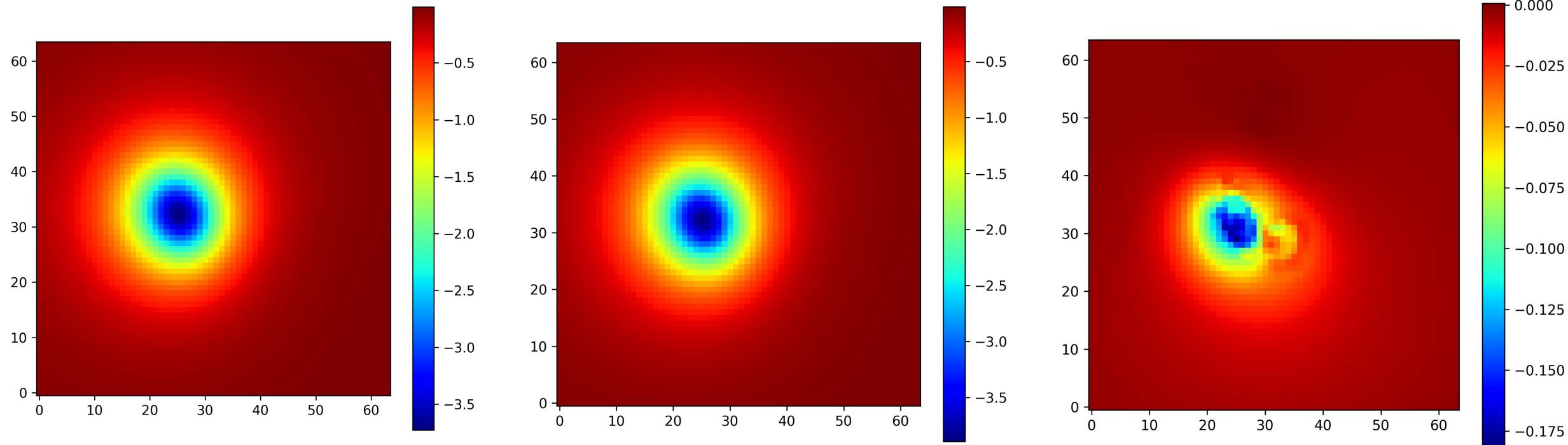
Machine Learning based gravity inversion

- Geology and petrophysical constraints are embedded into training set.
 - Training set generated by Noddy 3D geological modelling platform.
 - PyTorch library used.
-
- Ellipsoidal intrusions with different density, orientation and size.
 - Model size 6.4x6.4x3.2km, cell size = 100m.
 - Number of data $64 \times 64 = 4096$, spacing = 100m.
 - Training set size = 38400.
 - Training time: ~ 4.5h using NVIDIA 3900.
 - Inversion time: under 1 second.

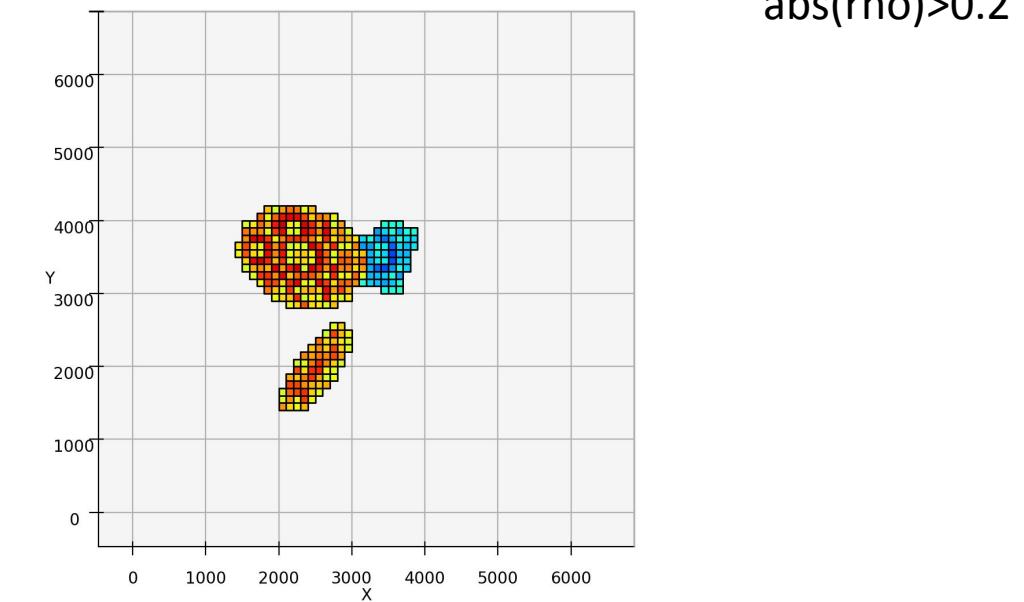
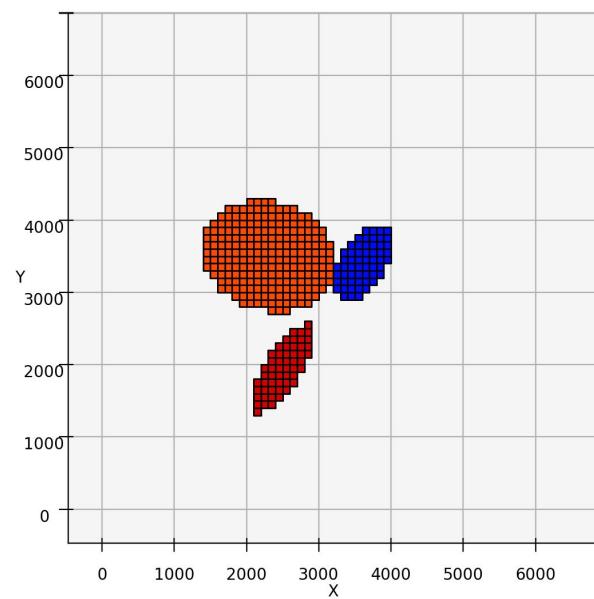
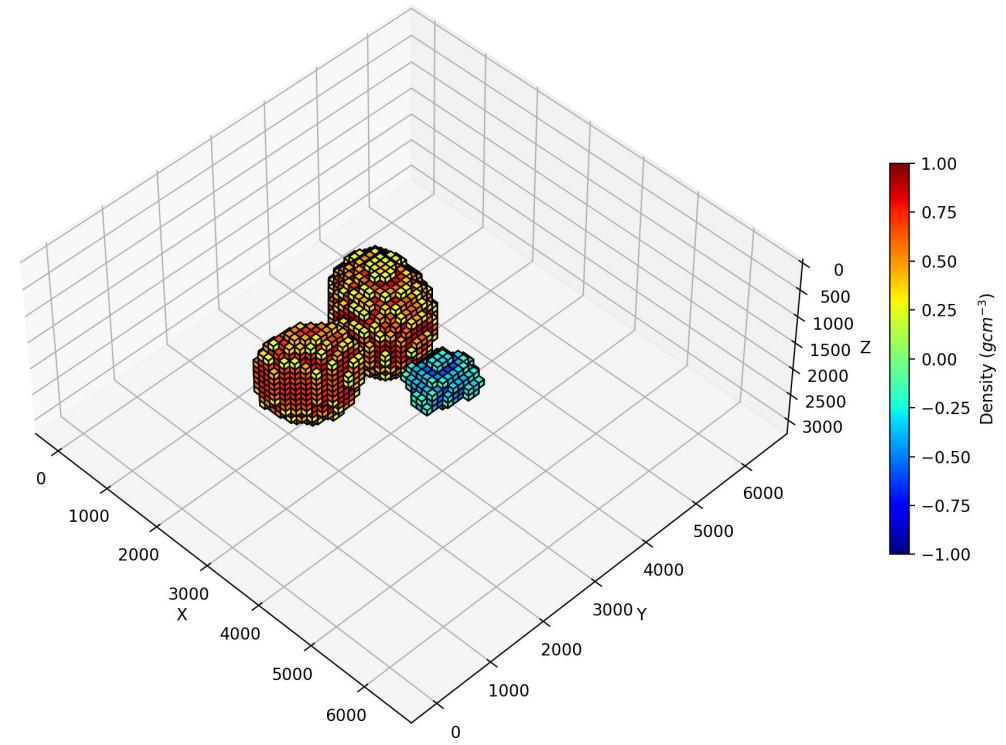
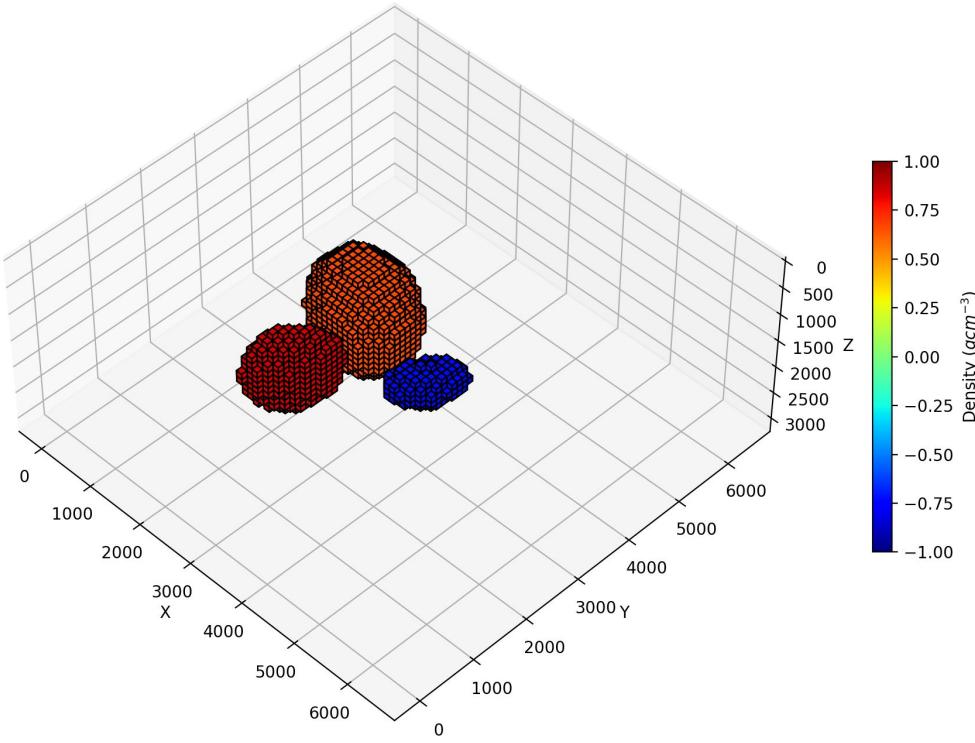


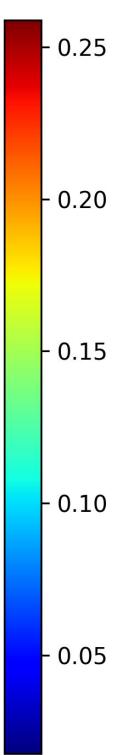
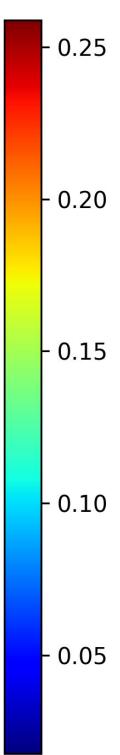
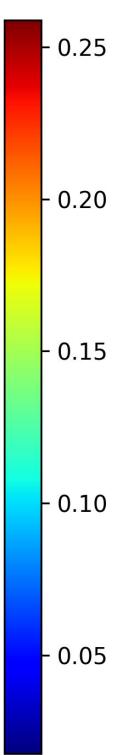
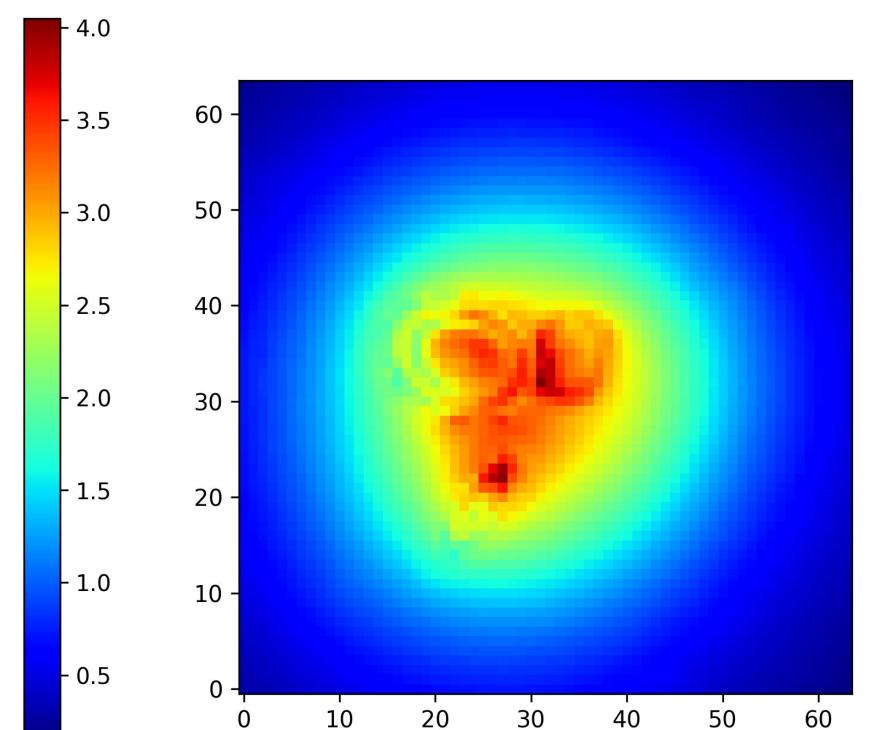
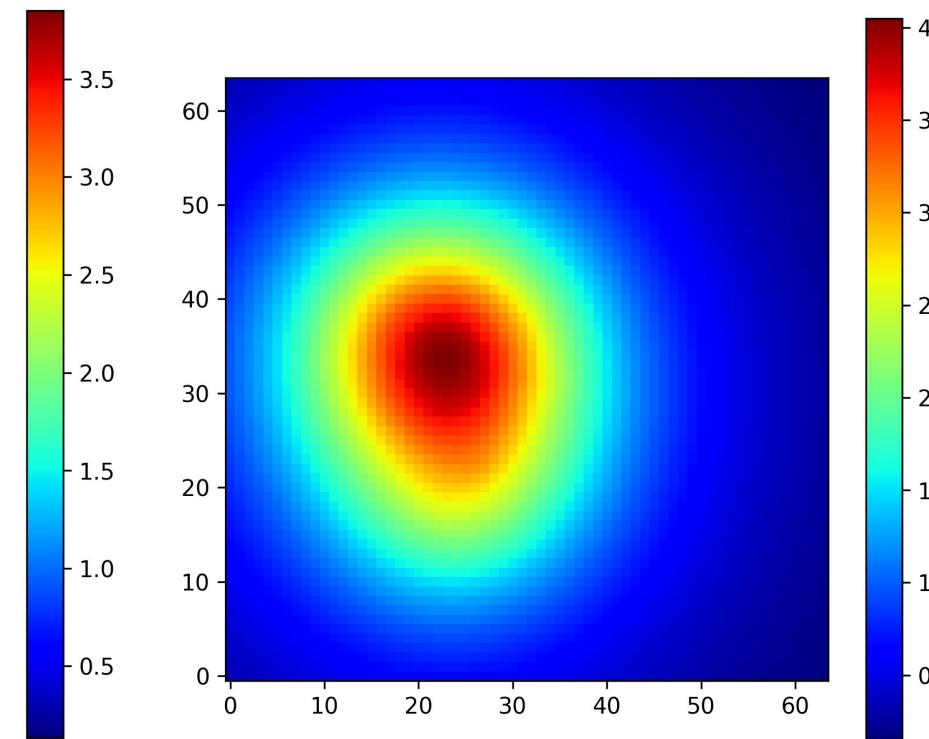
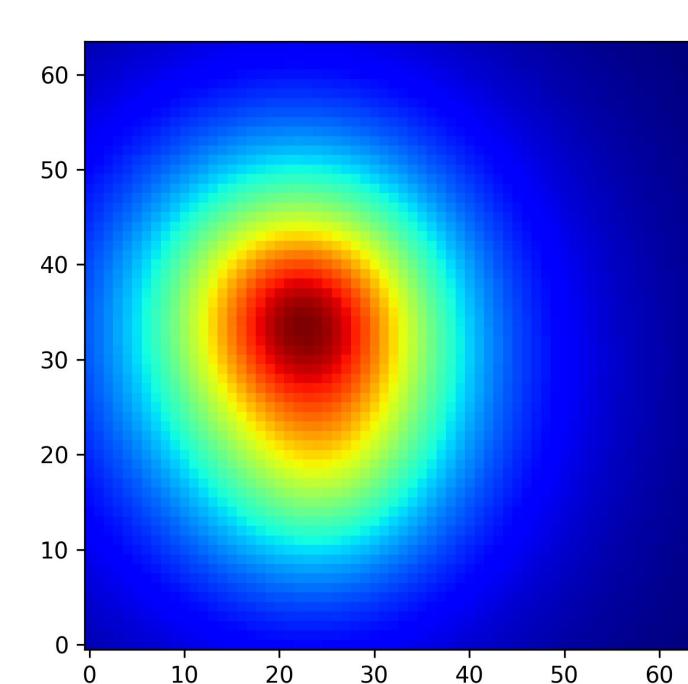
$\text{abs}(\rho) > 0.2$



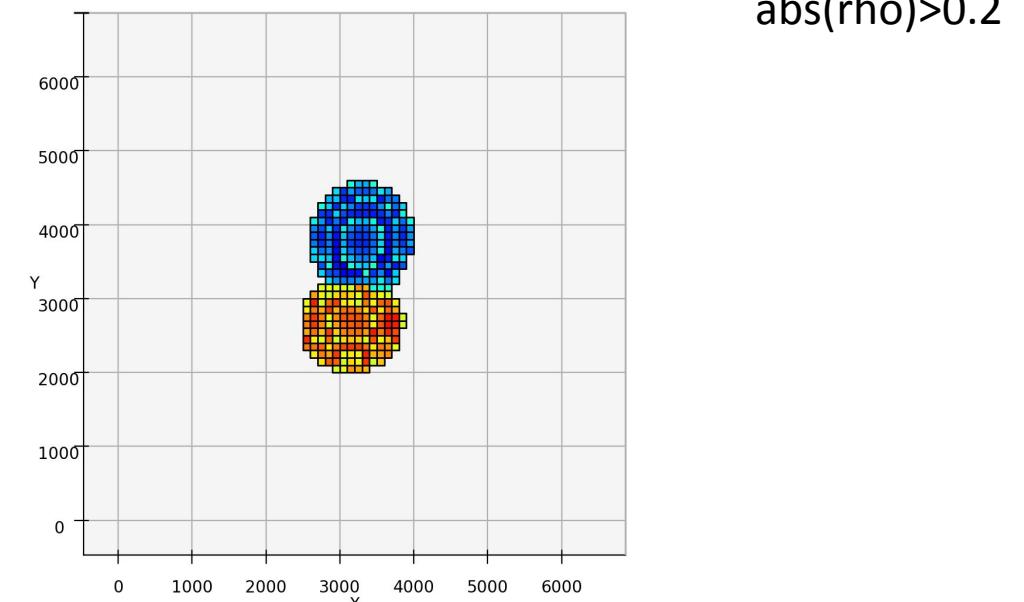
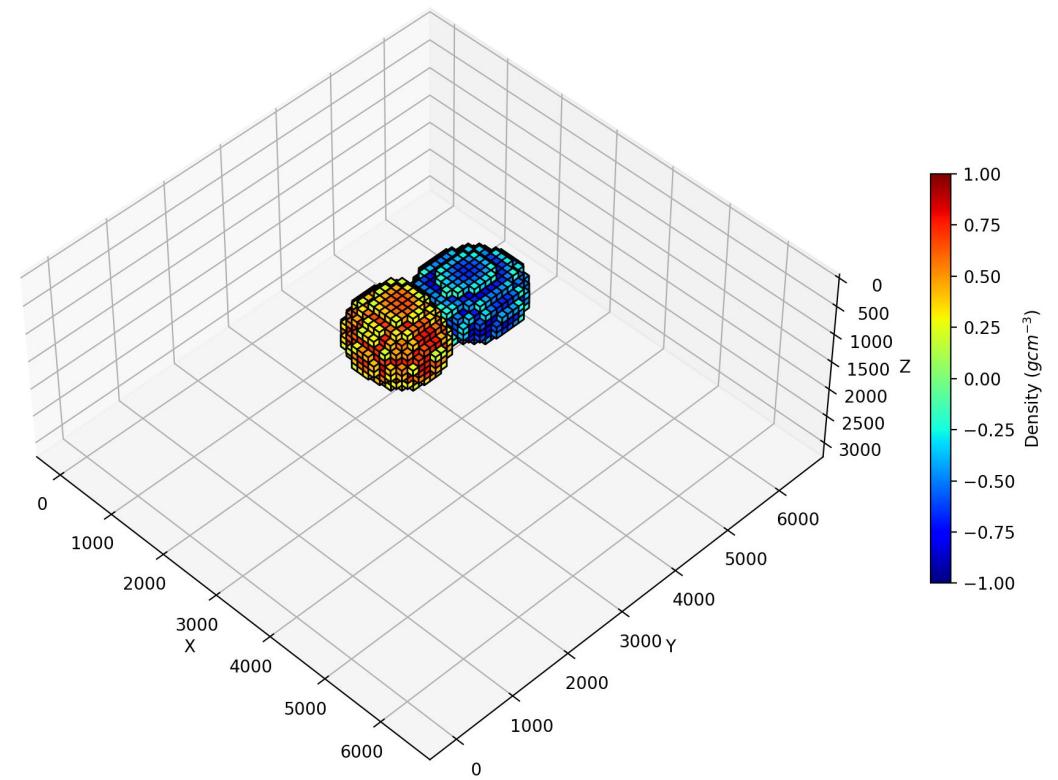
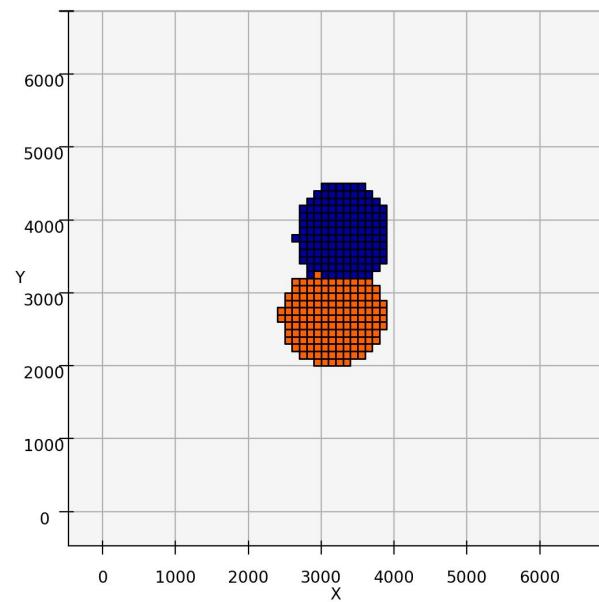
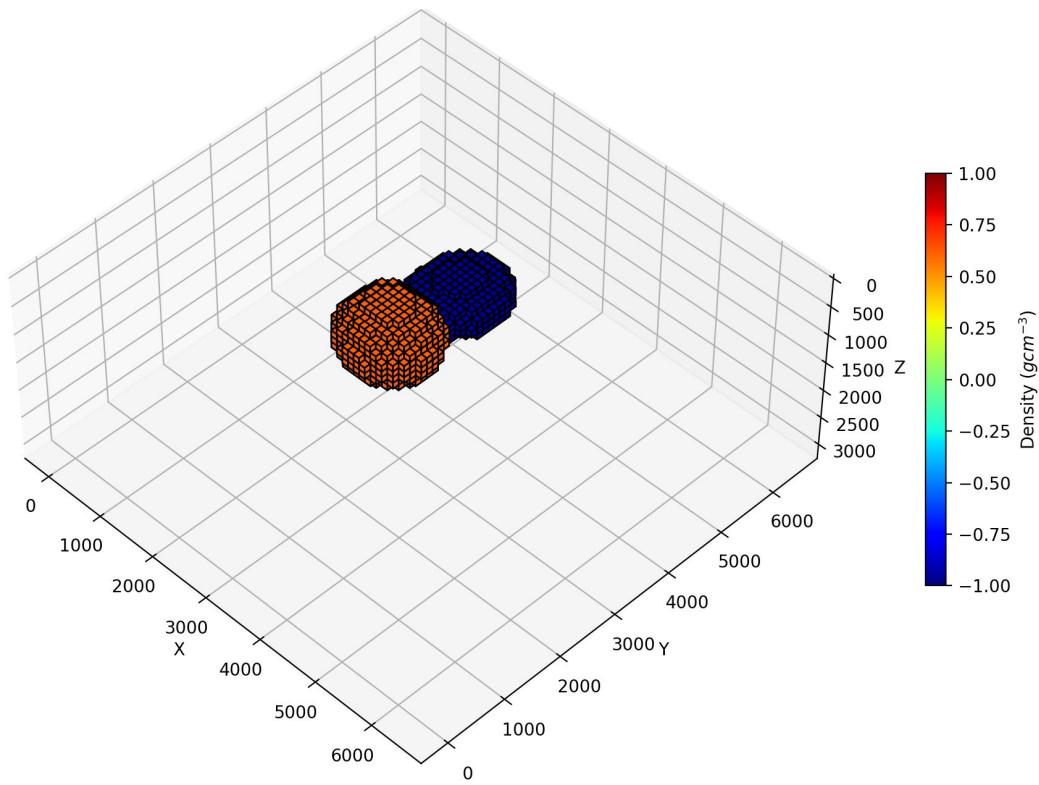


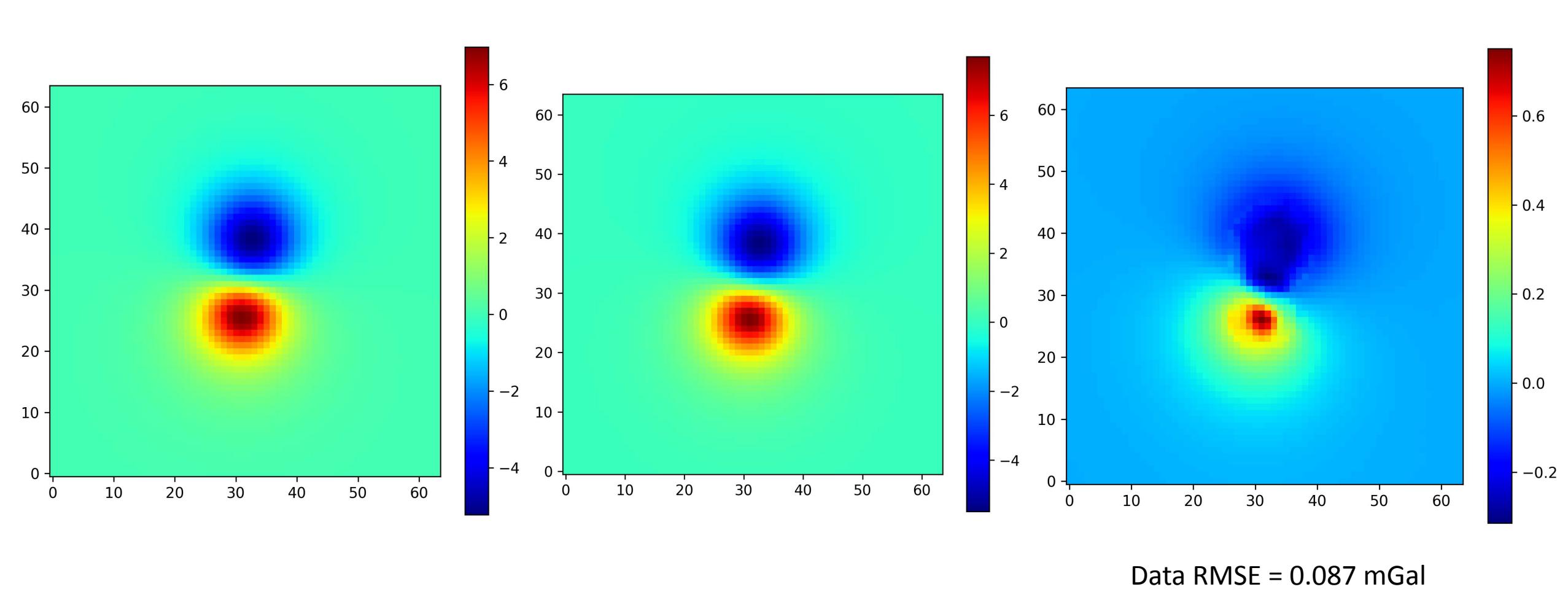
Data RMSE = 0.0239 mGal





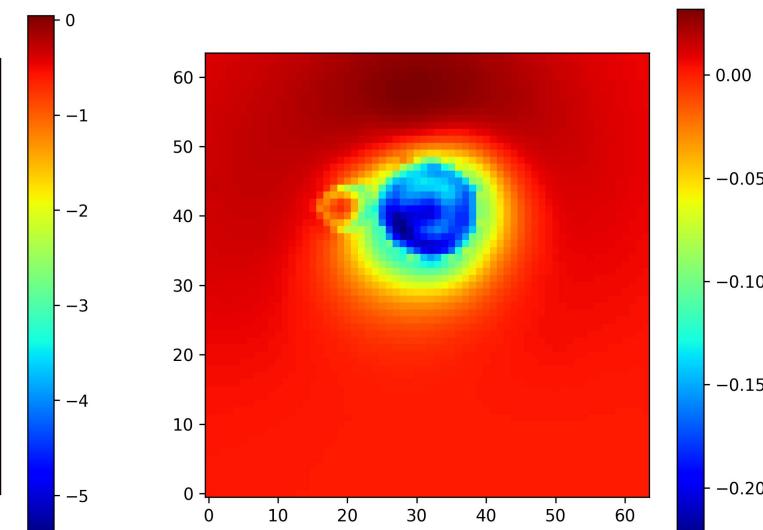
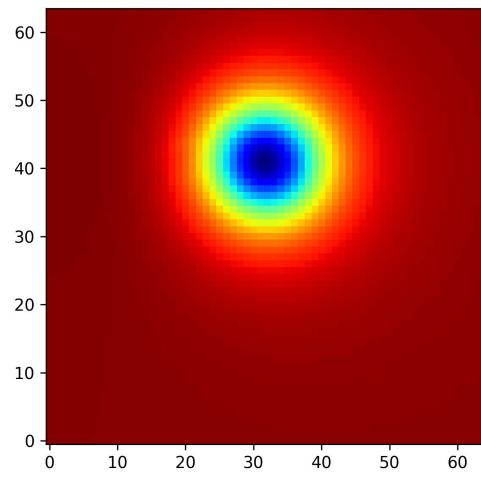
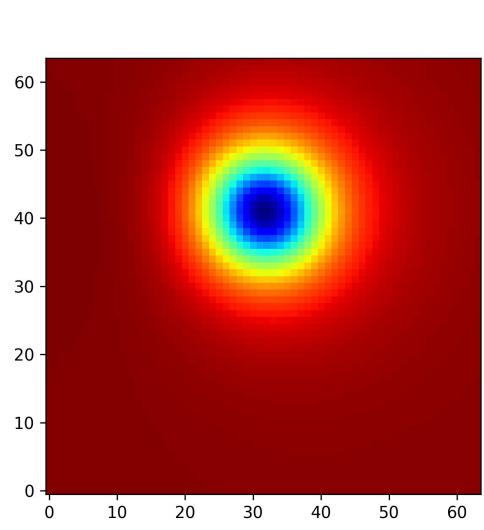
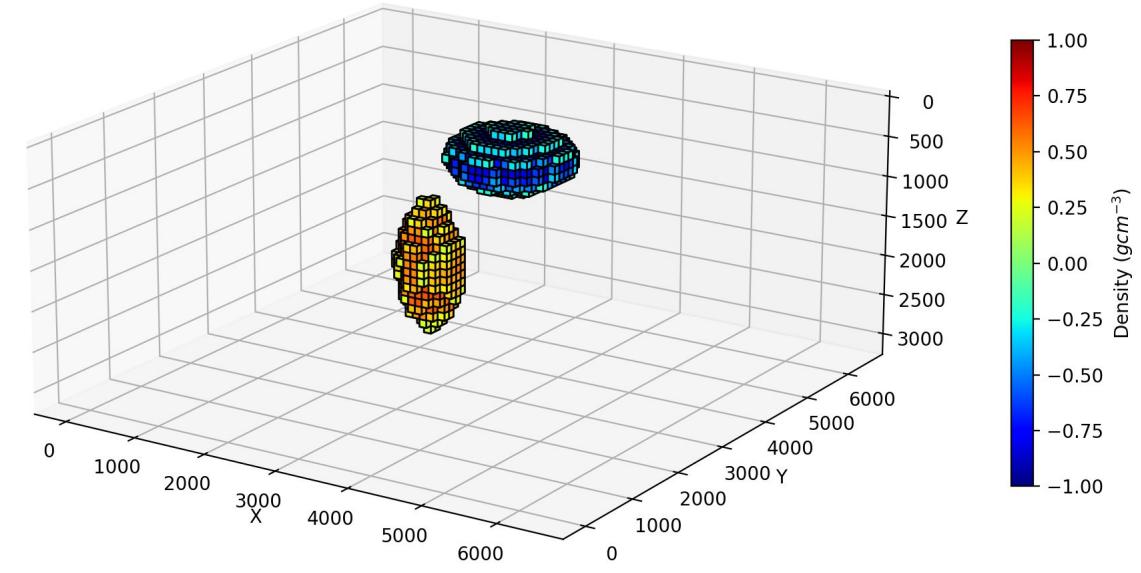
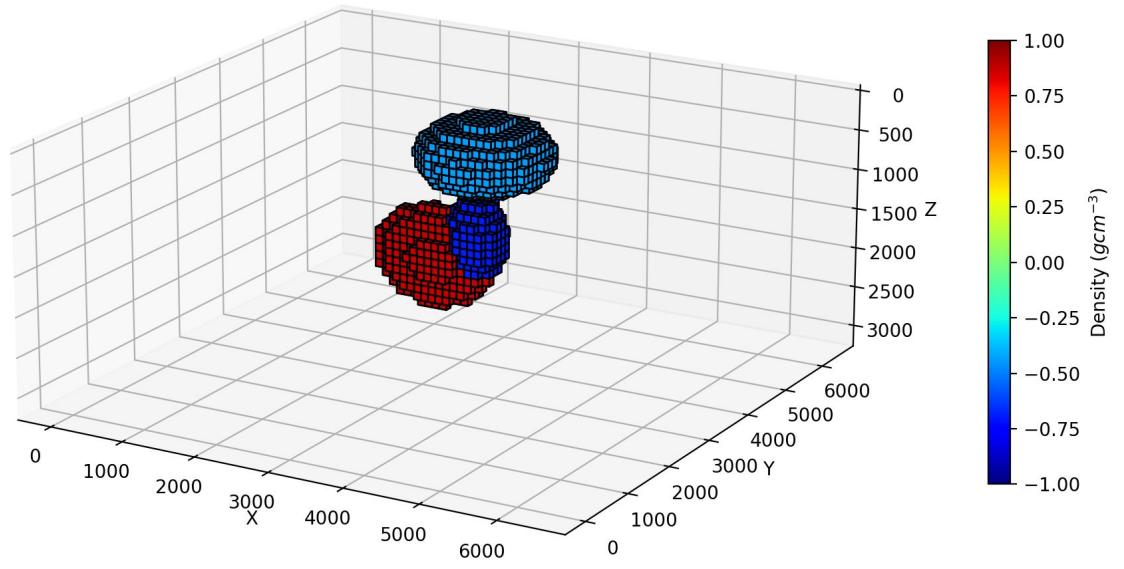
Data RMSE = 0.099 mGal



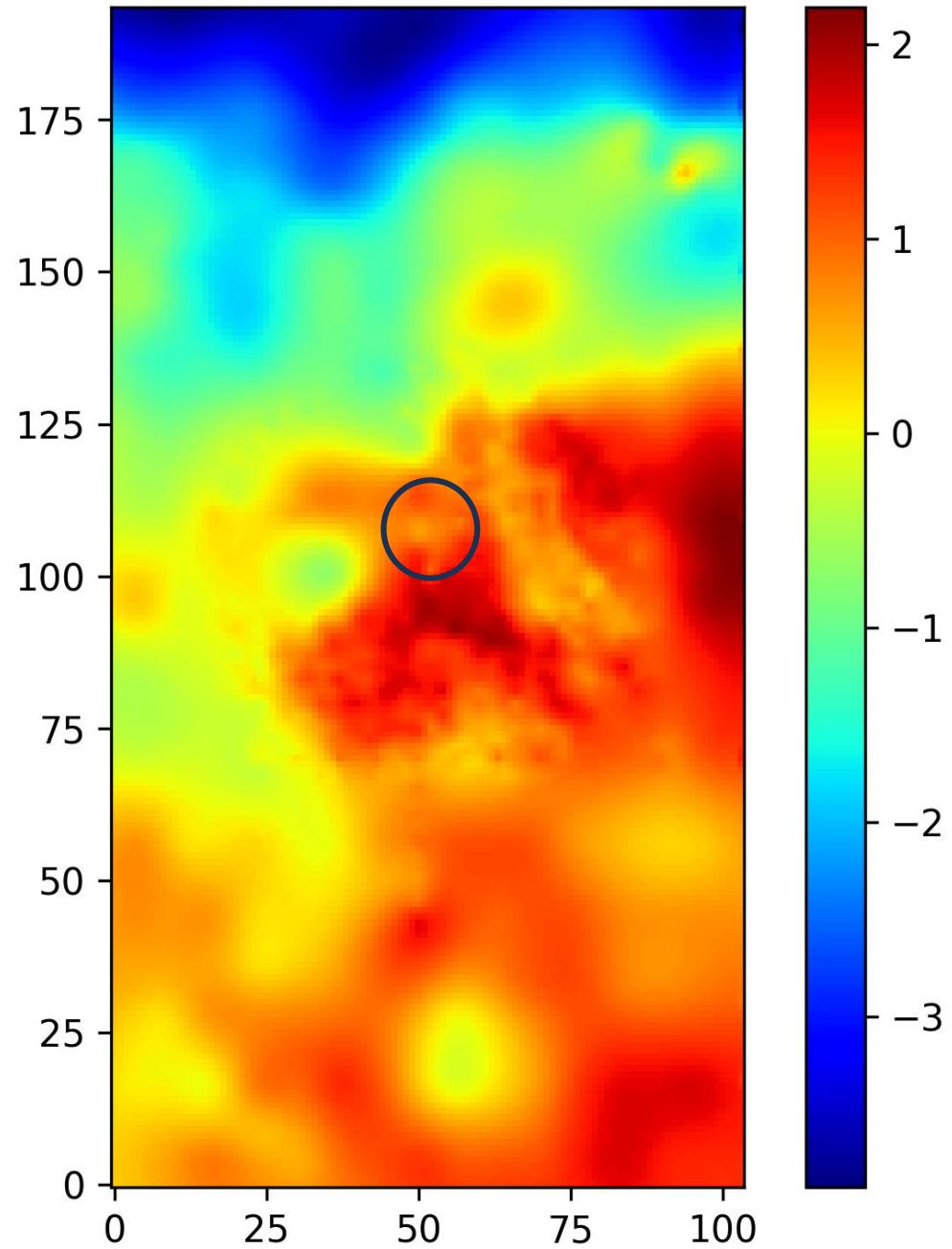


Data RMSE = 0.087 mGal

Very complex case: deeper object signal is fully swamped



Data RMSE = 0.040 mGal



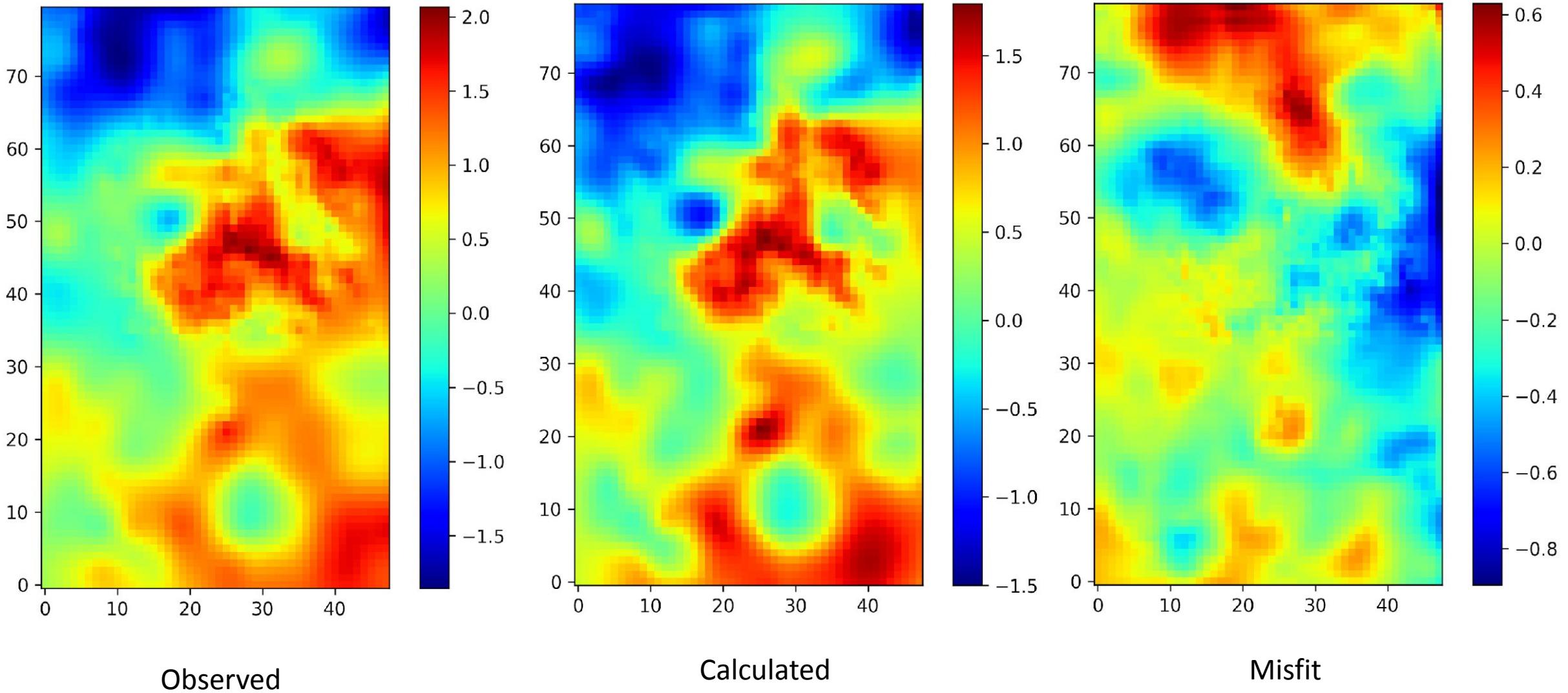
Field Data example (data provided by ExploreGeo)

Data spacing: 30m

Area: 3km x 6km

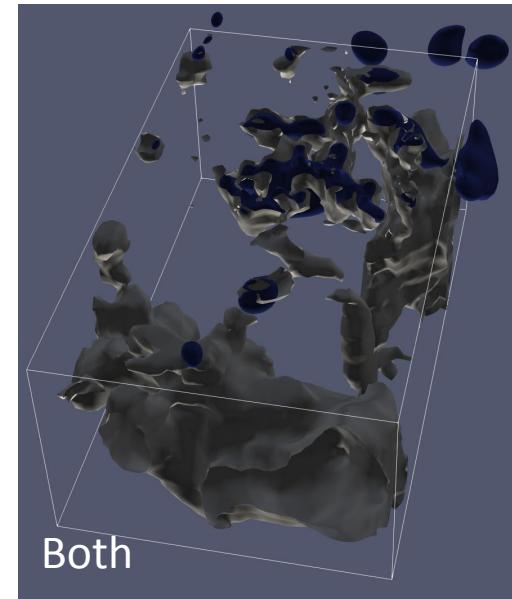
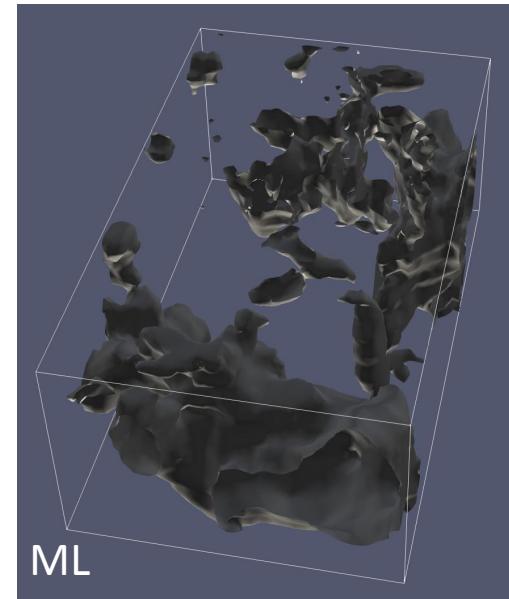
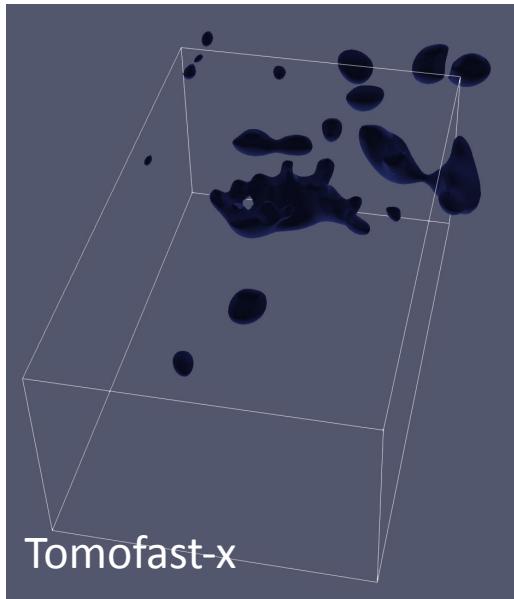
Interested in Syenite intrusions inside Mafic.

First inversion attempt using decimated data (60m) and clipped the northern part

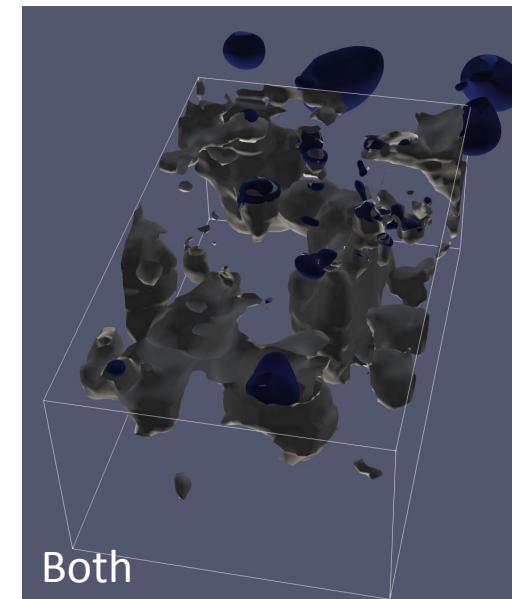
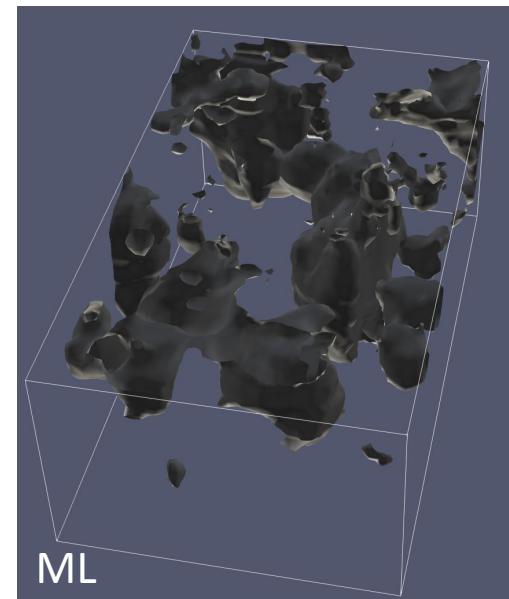
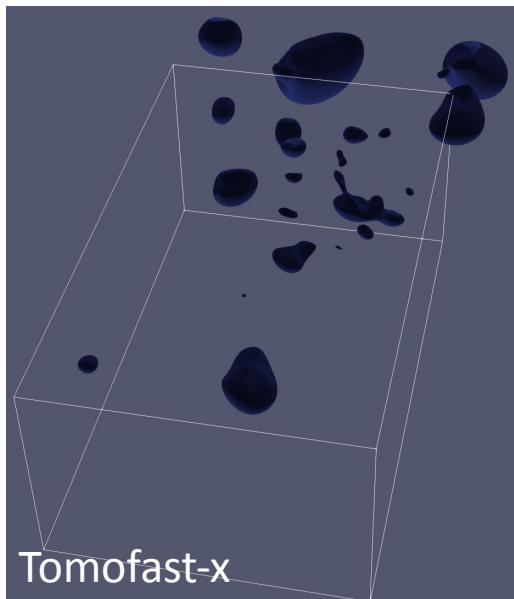


Comparison of inverted model with Tomofast-x

$\rho=+100$



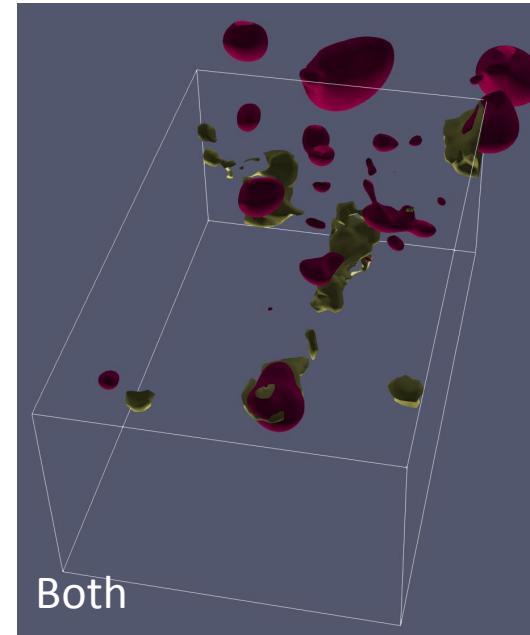
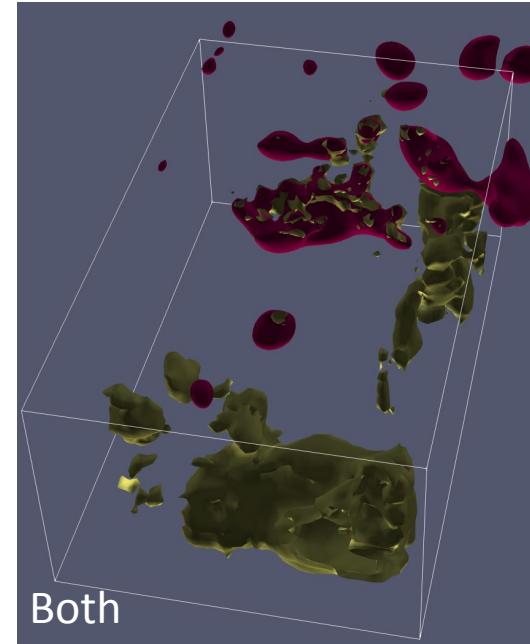
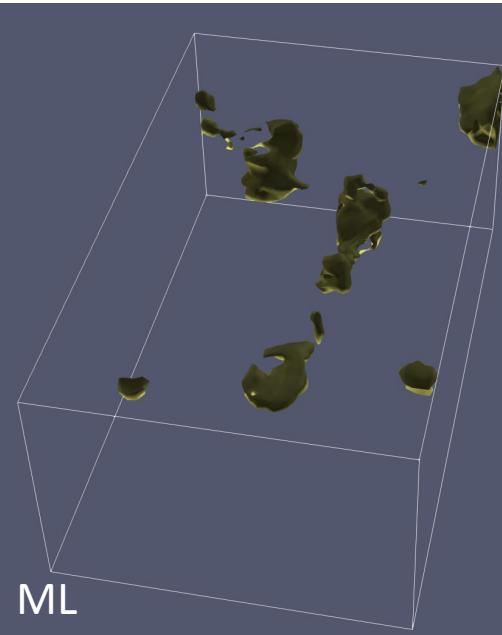
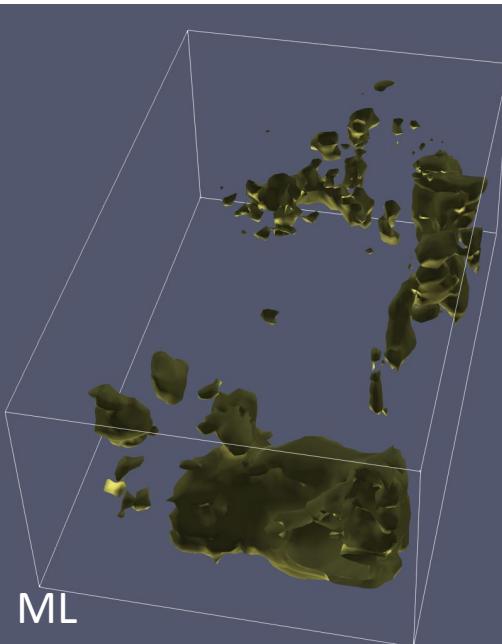
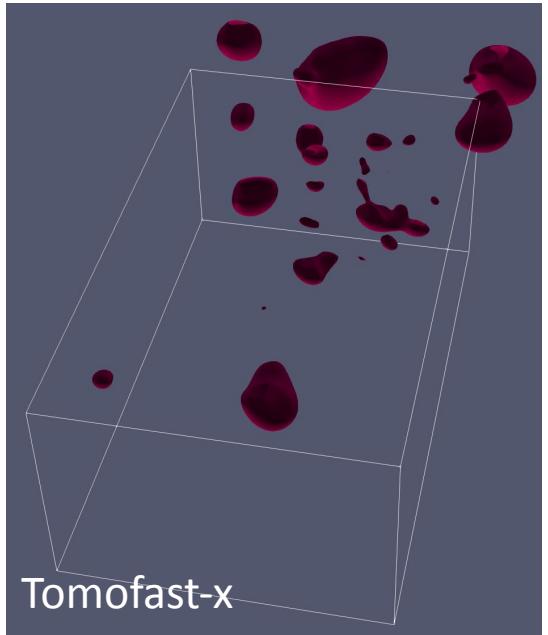
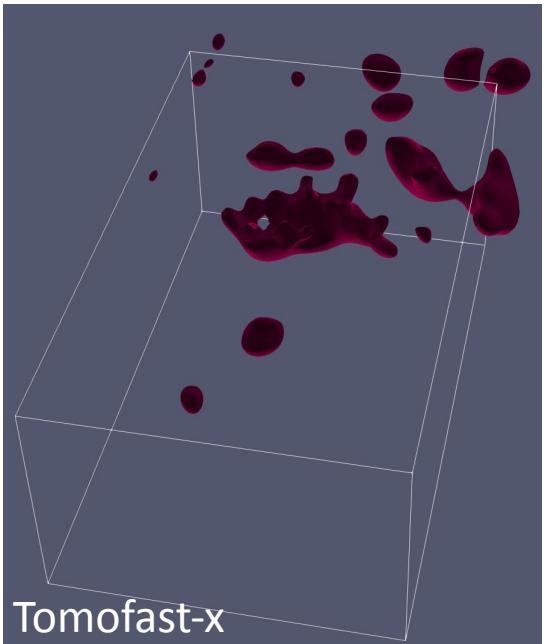
$\rho=-100$



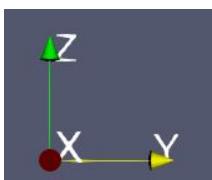
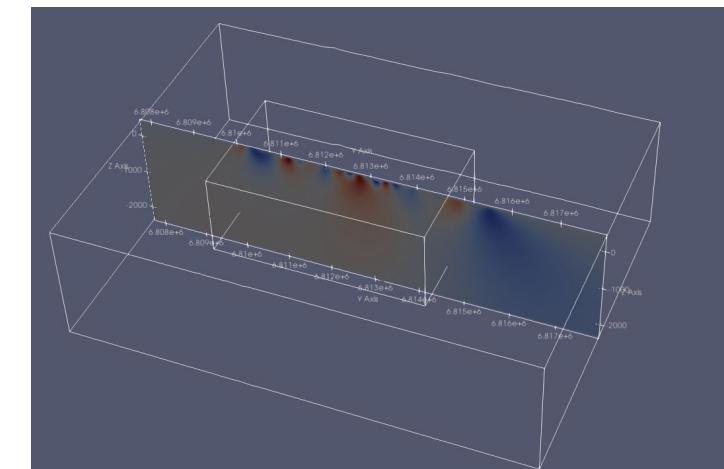
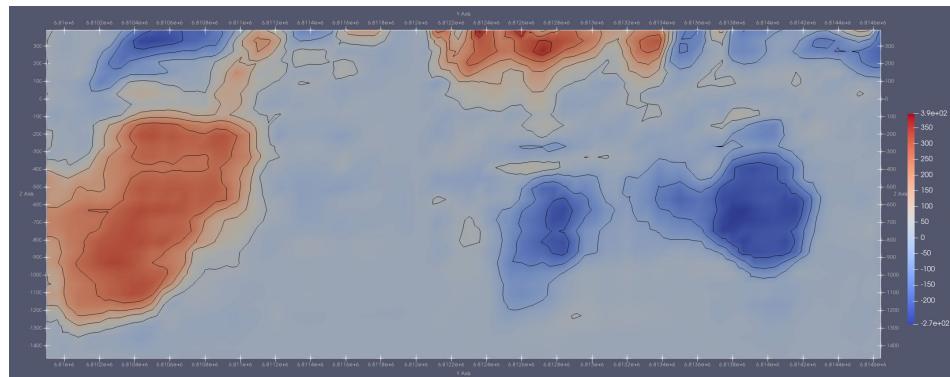
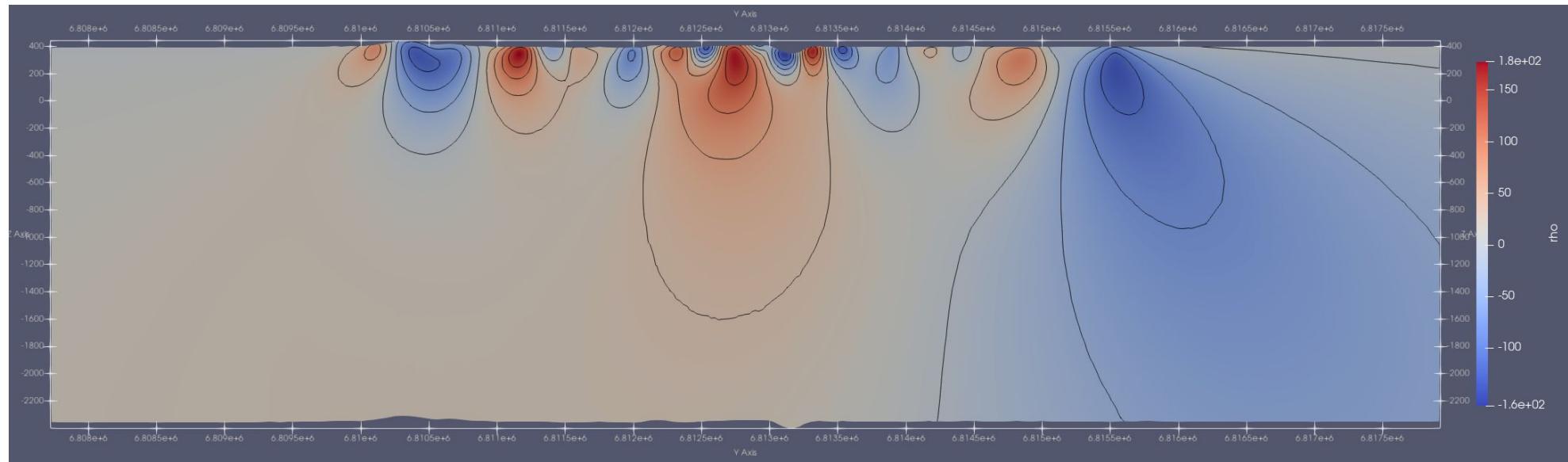
Comparison of inverted model with Tomofast-x

$\rho_{\text{tomo}} = +100$

$\rho_{\text{ML}} = +250$



Comparison of inverted model with Tomofast-x



Next steps

- Address noise in data
- Extend code to *physics informed neural network*
- Other geological structures for ML training (fault, fold etc)