Building 3D quasi-geology models and predicting mineral resources using joint inversion and open-source code

Xiaolong Wei[1,2] & Jiajia Sun[1]

[1]University of Houston, USA. [2] Stanford University, USA

July 29th, 2023

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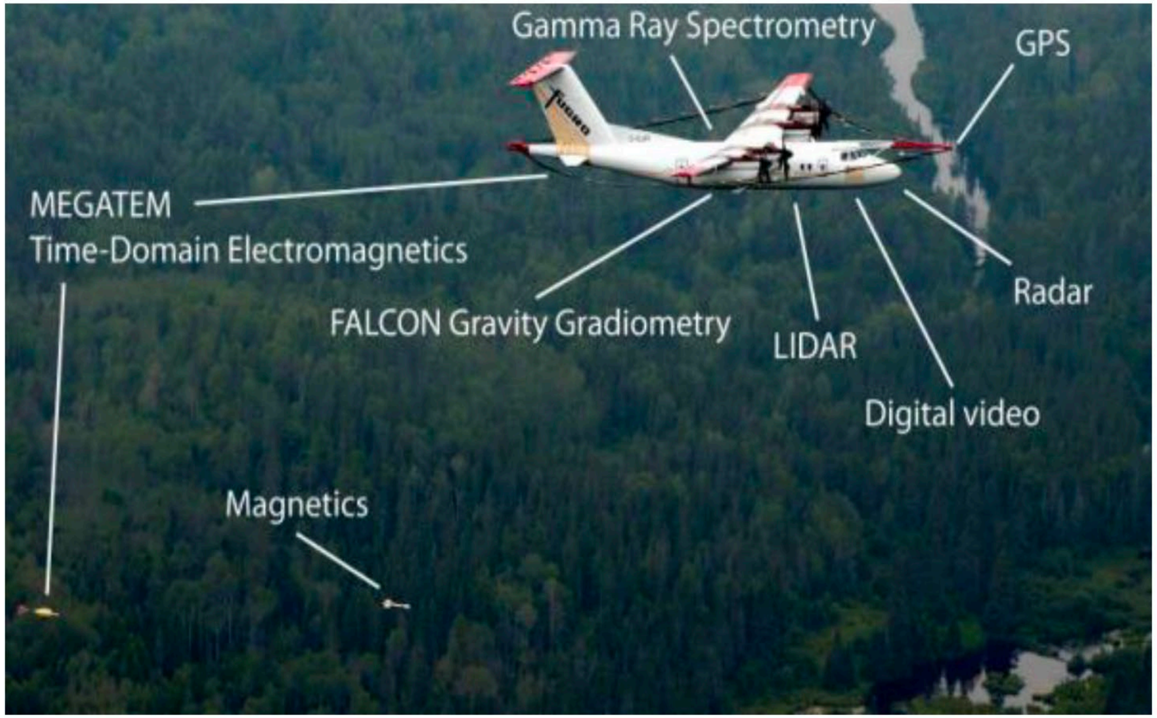
- Introduction
- Part I: Building probabilistic quasi-geology model
- Part II: Predicting mineral resources
- Discussions
- Conclusions

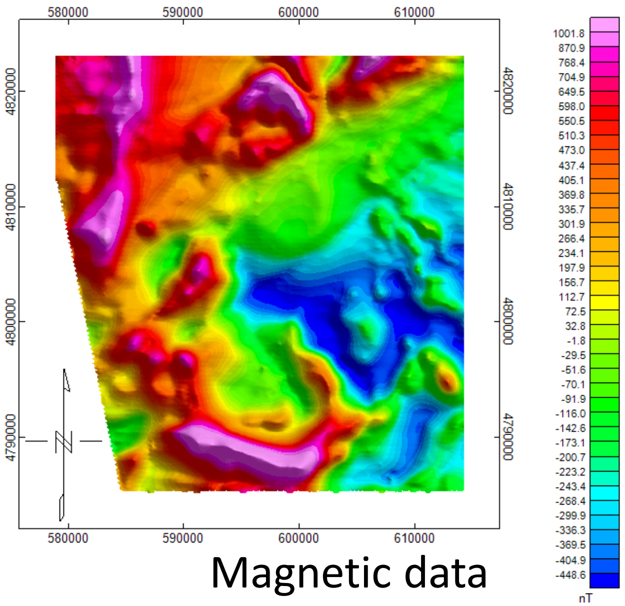
Introduction

- Widely use airborne geophysical survey
- Collect multiple data sets
- Construct reliable subsurface models

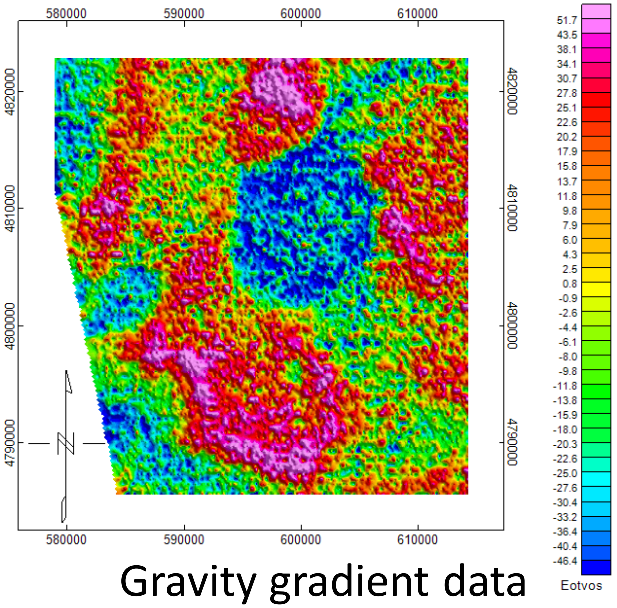


Multi-sensor airborne platform (Wilson et al., 2011)

Introduction



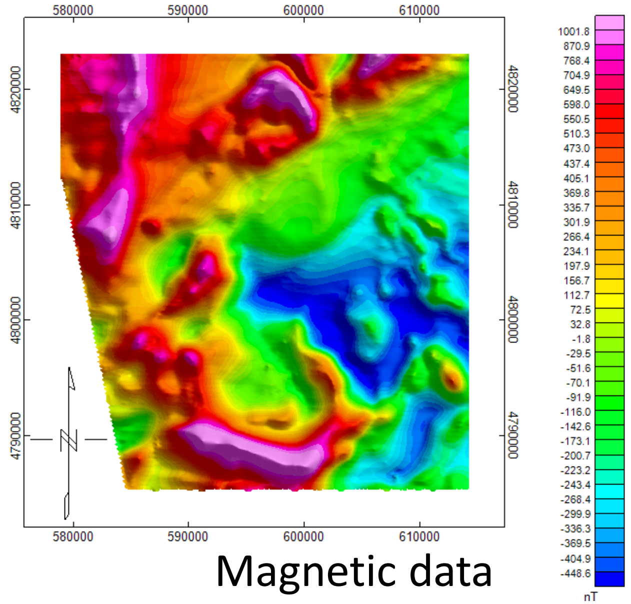
Magnetic data



Gravity gradient data

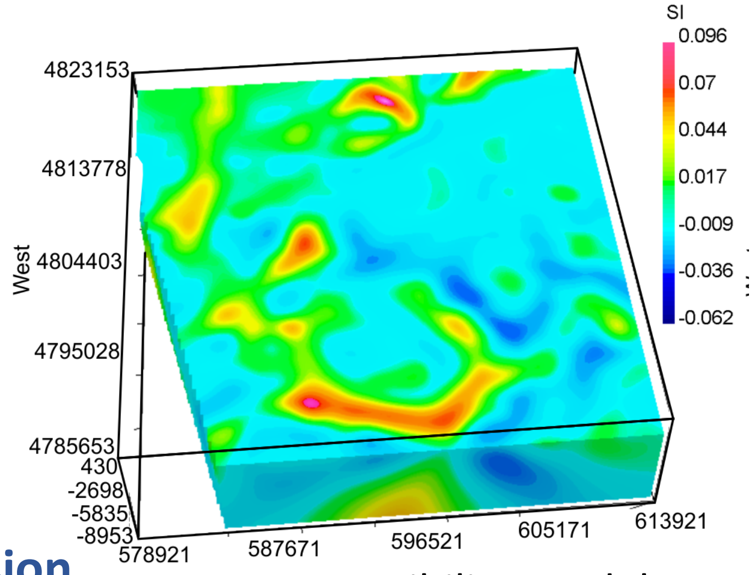
Sun et al. (2020, Interpretation)

Introduction

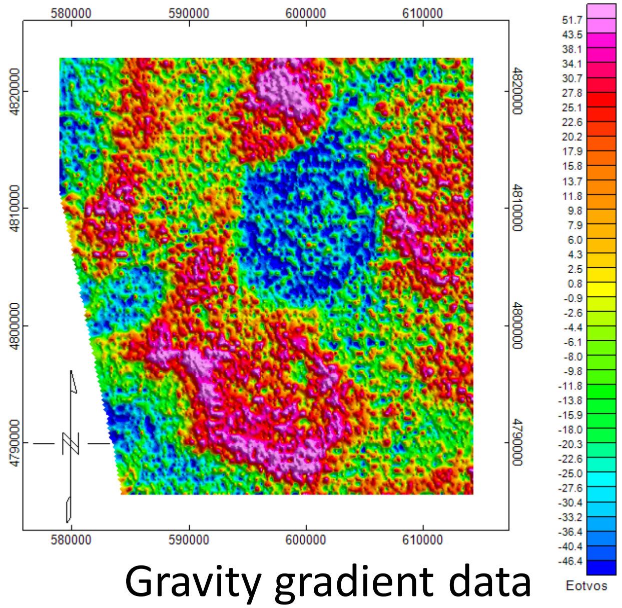


Magnetic data

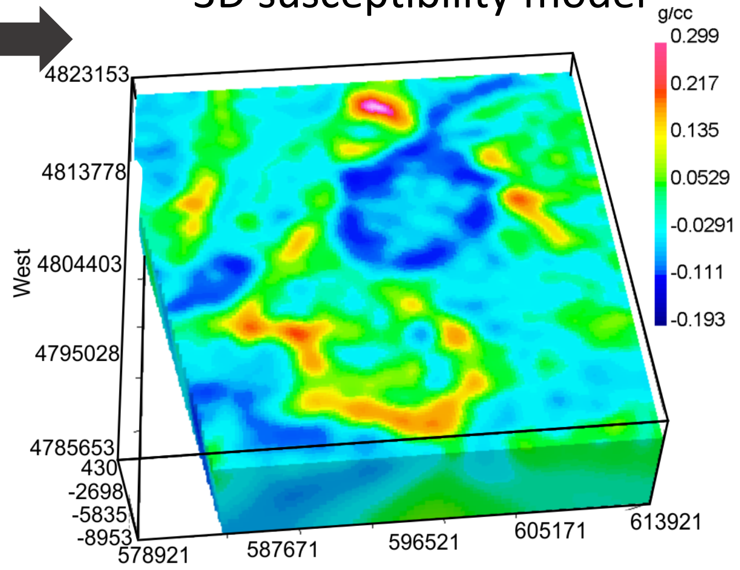
Inversion



3D susceptibility model



Gravity gradient data



3D density contrast model

Sun et al. (2020, Interpretation)

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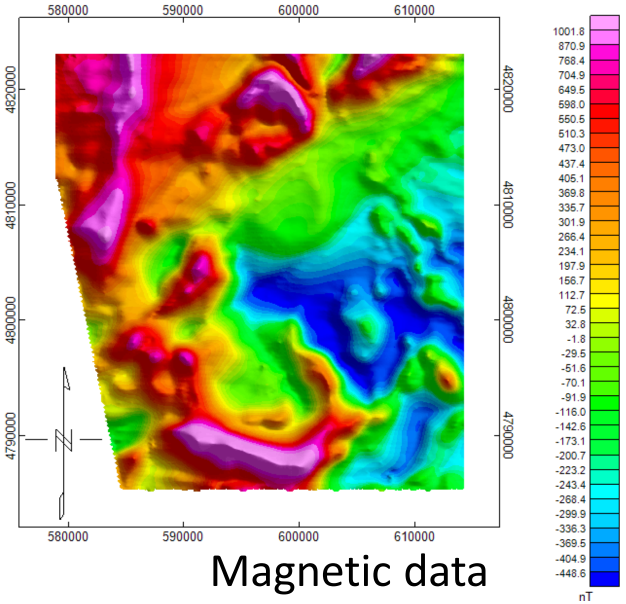
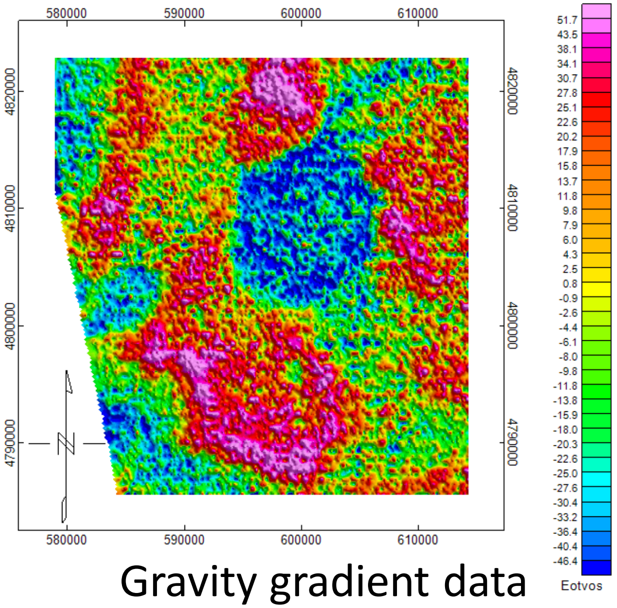
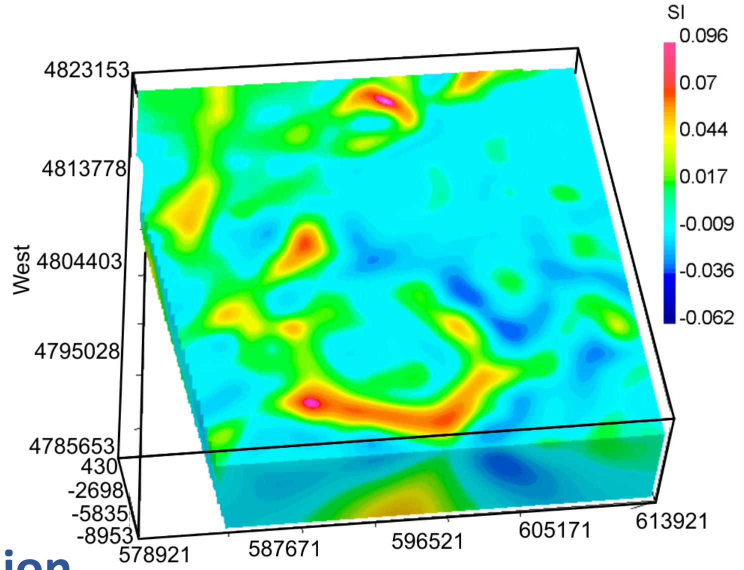


Magnetic data

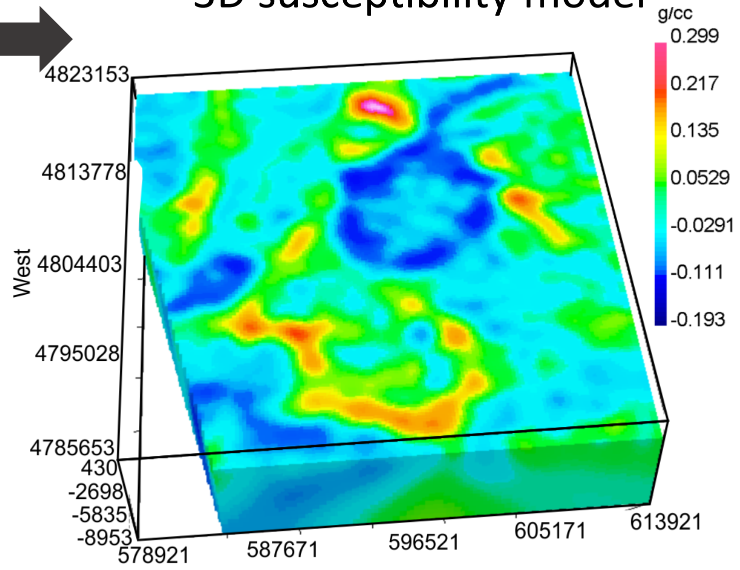


Gravity gradient data

Inversion



3D susceptibility model



3D density contrast model

Differentiation

Sun et al. (2020, Interpretation)

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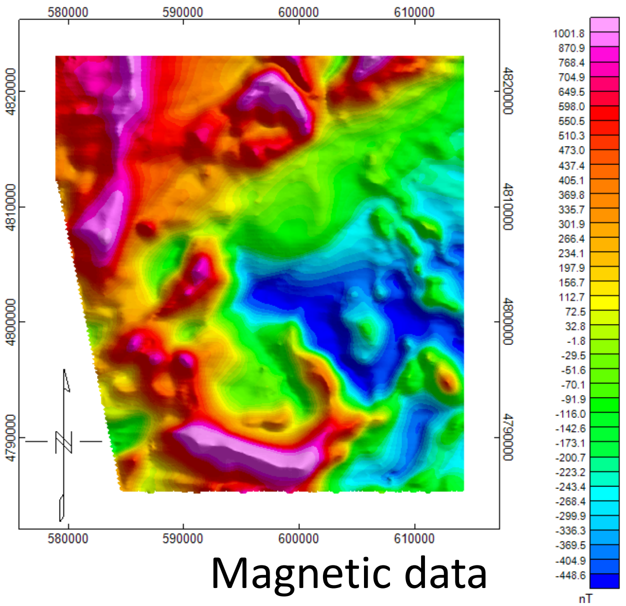

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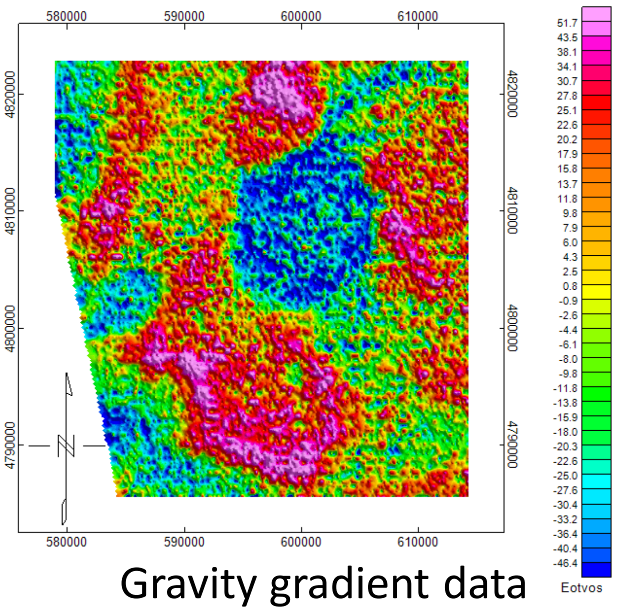
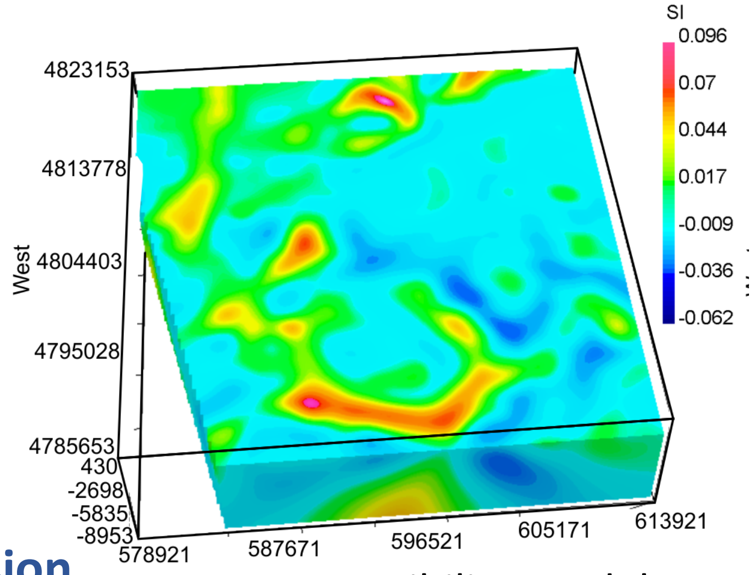
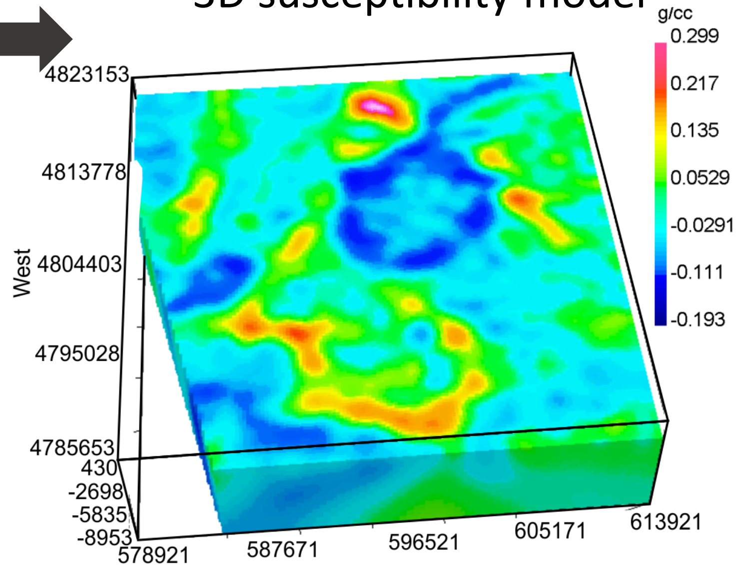


Gravity gradient data

Inversion

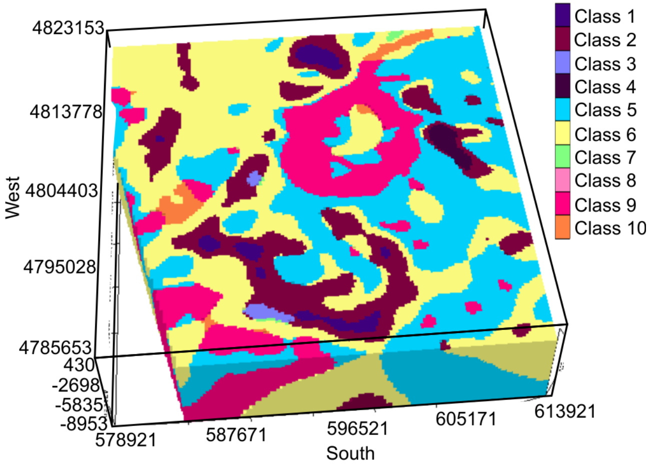


3D susceptibility model



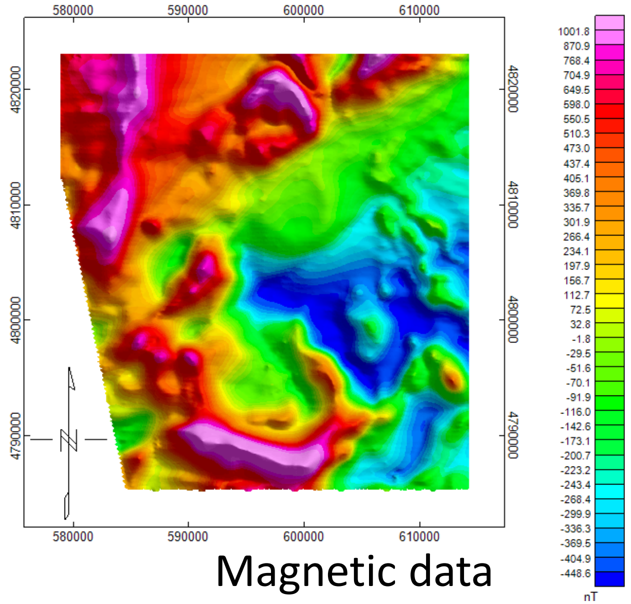
3D density contrast model

Differentiation



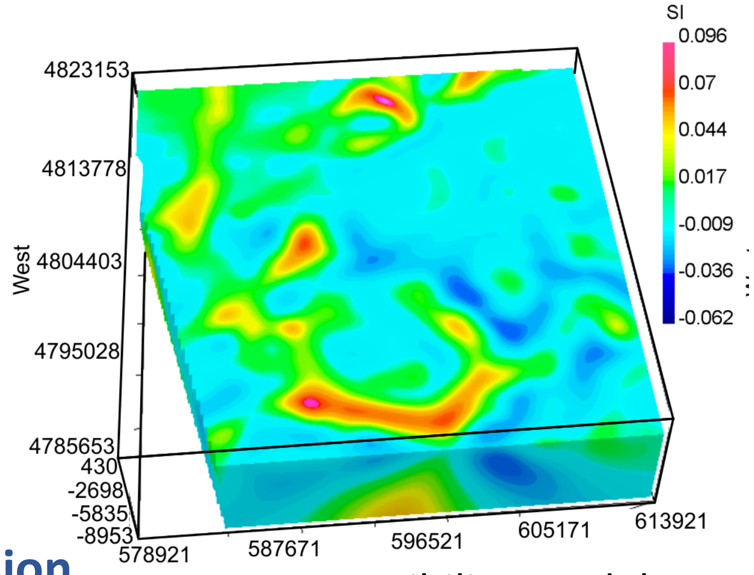
Sun et al. (2020, Interpretation)

Introduction



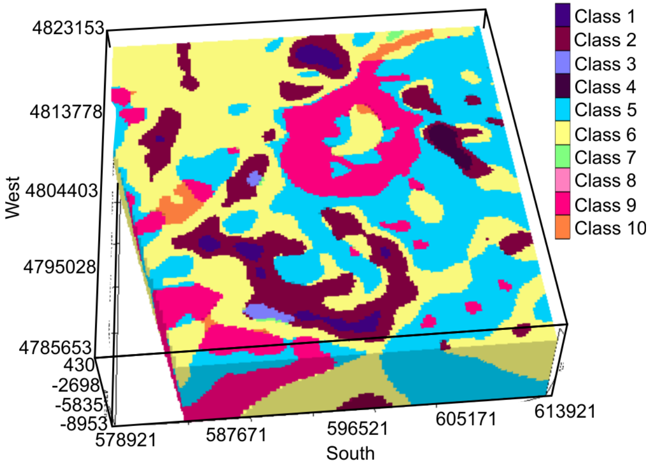
Magnetic data

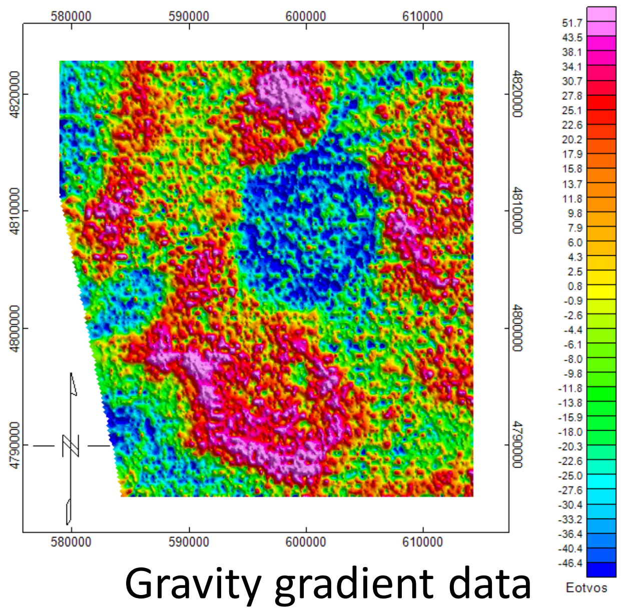
Inversion



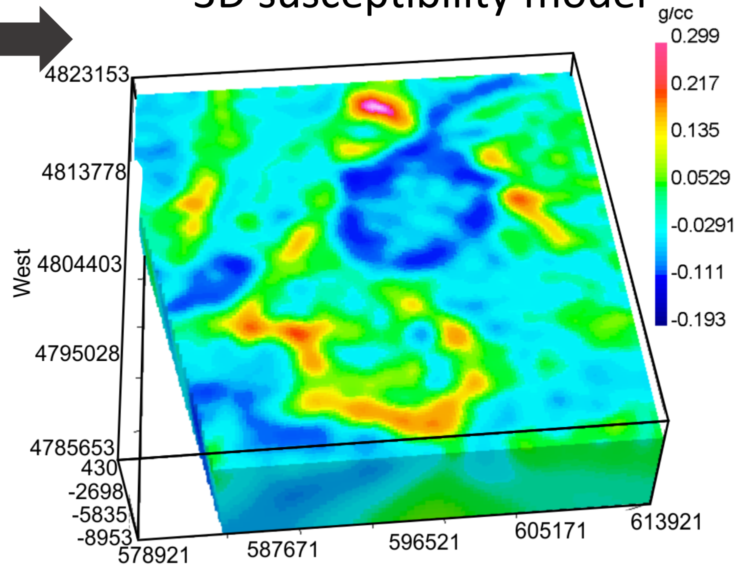
3D susceptibility model

Differentiation



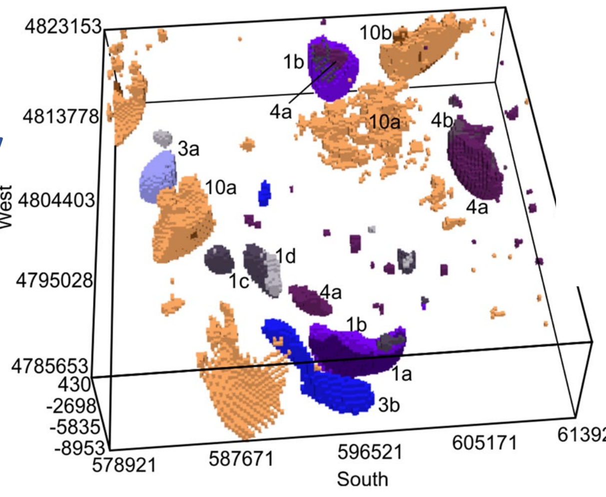


Gravity gradient data



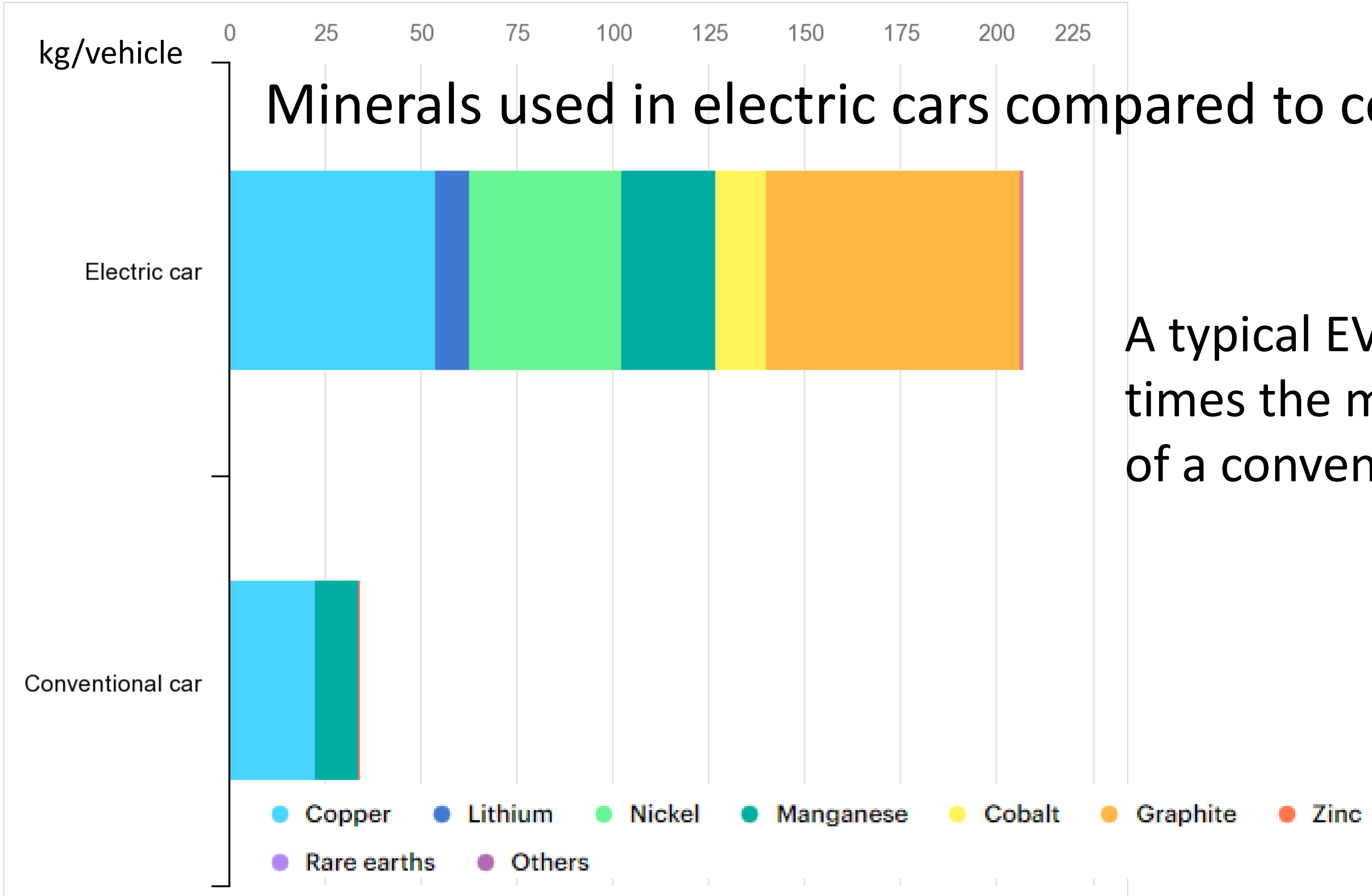
3D density contrast model

Mineral prospectivity



Sun et al. (2020, Interpretation)

Minerals used in electric cars compared to conventional cars



A typical EV requires six times the mineral inputs of a conventional car.

https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary

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Methodology: mixed Lp norm inversion

(Fournier and Oldenburg, 2019)

Objective function: $$\Phi = \Phi_d + \beta\Phi_m$$

p and q could be same or different values between 0 to 2

Data misfit term: $$\Phi_d = \sum_{i=1}^{N}\left(\frac{d_i^{pre} - d_i^{obs}}{\sigma_i}\right)^2$$

Regularization term: $$\Phi_m^{pq} = \alpha_s \int \left| f_s(m) \right|^p dv + \sum_{j=x,y,z} \alpha_j \int \left| f_j(m) \right|^q dv$$

$$f_s = m,\ f_x = \frac{dm}{dx},\ f_y = \frac{dm}{dy},\ f_z = \frac{dm}{dz}$$

Methodology: mixed Lp norm joint inversion

(Wei and Sun, 2020)

$$\Phi(m_1,m_2)=\Phi_{d1}(m_1)+\beta_1\Phi_{m1}(m_1)+\Phi_{d2}(m_2)+\beta_2\Phi_{m2}(m_2)+\lambda\Phi_c(m_1,m_2)$$

$$\begin{aligned}\Phi^{pq}(\mathbf{m}_1,\mathbf{m}_2) &= \left\|\mathbf{W}_{d1}(\mathbf{d}_1^{obs}-\mathbf{d}_1^{pre})\right\|_2^2+\beta_1\left\|\mathbf{W}_{m1}\mathbf{R}_1^{\boxed{pq}}\mathbf{m}_1\right\|_2^2\\ &+\left\|\mathbf{W}_{d2}(\mathbf{d}_2^{obs}-\mathbf{d}_2^{pre})\right\|_2^2+\beta_2\left\|\mathbf{W}_{m2}\mathbf{R}_2^{\boxed{pq}}\mathbf{m}_2\right\|_2^2\\ &+\lambda\Phi_c(\mathbf{m}_1,\mathbf{m}_2)\end{aligned}$$

Different norm values

$$\Phi_c(\mathbf{m}_1,\mathbf{m}_2)=\sum_i^m\|\nabla m_{1i}\times\nabla m_{2i}\|_2^2.$$

(Gallardo and Meju, 2003, 2004)

Understanding mixed Lp norm joint inversion

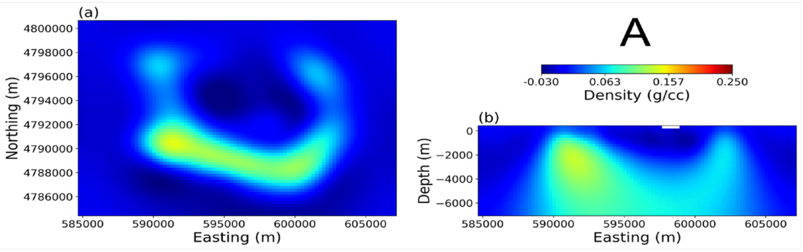
(Wei and Sun, 2021)

$$\Phi_m^{pq} = \alpha_s \int \left| f_s(m) \right|^{p} dv + \sum_{j=x,y,z} \alpha_j \int \left| f_j(m) \right|^{q_j} dv$$

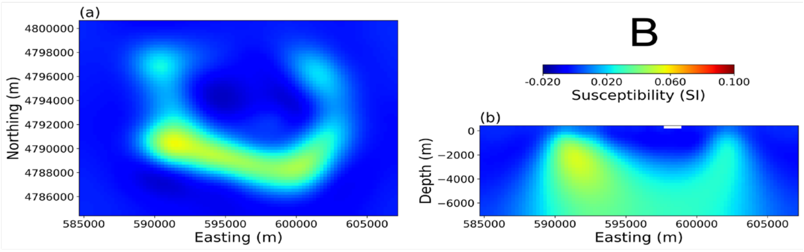
Different tuning parameters result in different model characteristics.

p=q=2

Density models



Susceptibility models

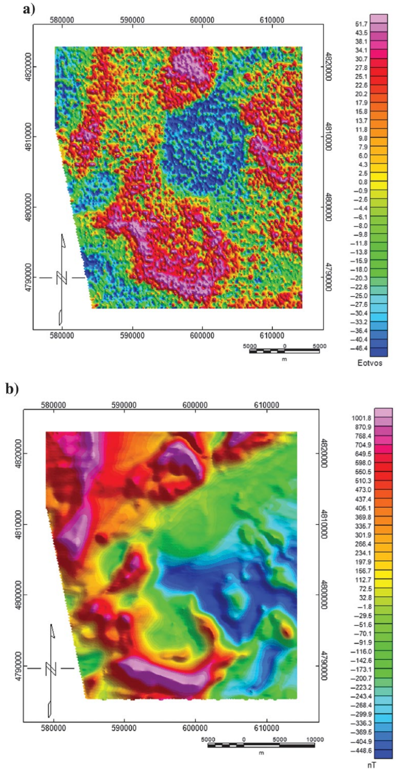


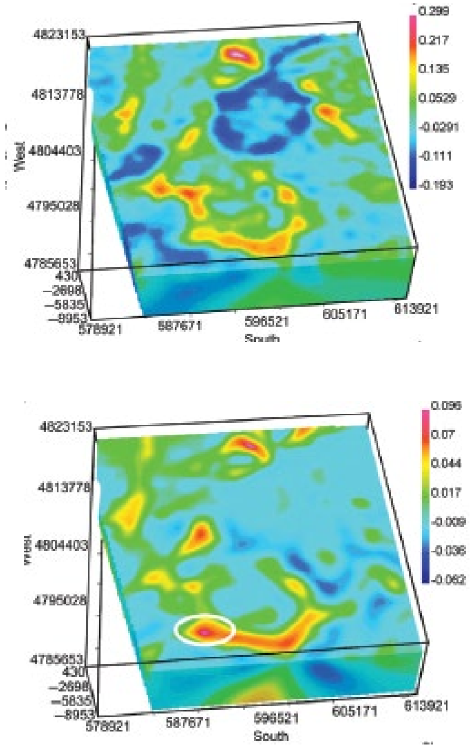
Methodology: geology differentiation

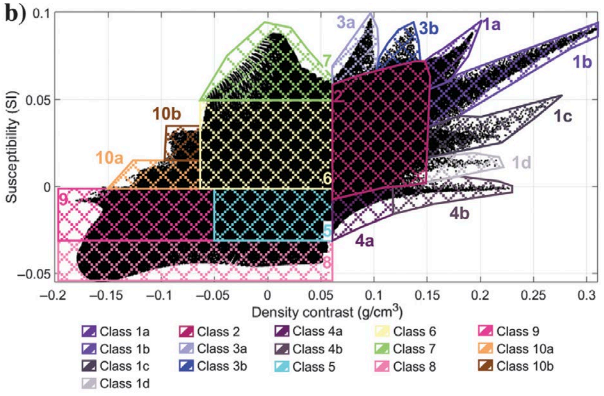
(Li et al., 2019; Sun et al., 2020)

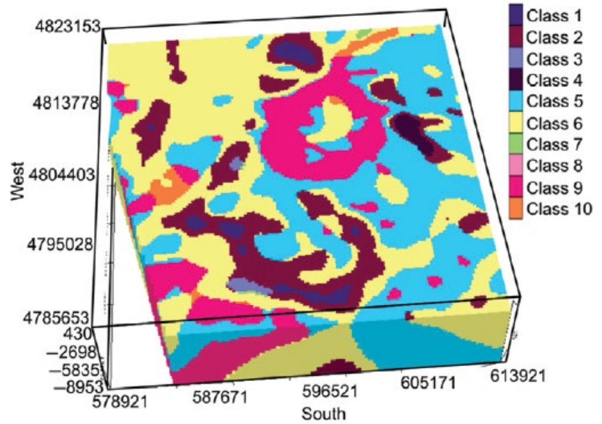
Identifying and delineating geologic units based on multiple physical property models obtained from geophysical inversions.

Data → **3D Inversion** → Models → **Visualization** → Scatter plot → **Differentiation** → Quasi-geology model



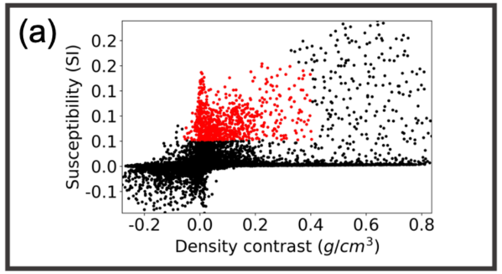




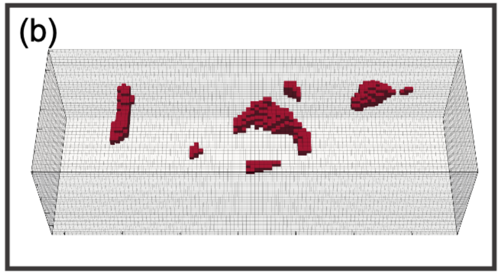


Geology differentiation

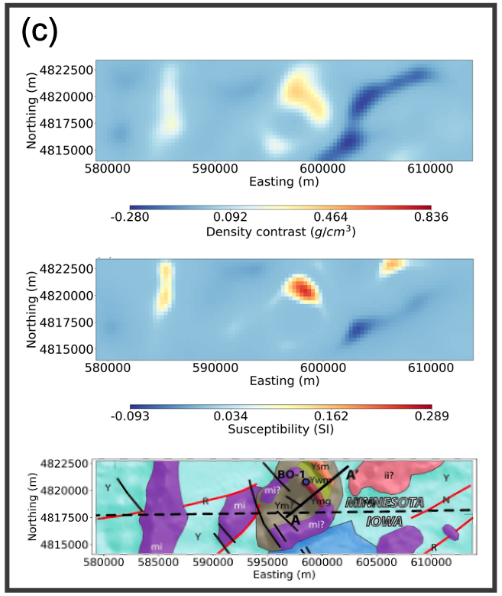
Geology differentiation



3D quasi-geology model



Compare with inverted density and susceptibility models, existing geological information and previous work



Are the identified anomalous bodies in (b) consistent with (c) ?

No

Adjust the bounds of classification

YES

Accept the classification in (a)

Wei and Sun (2022, GEOPHYSICS)

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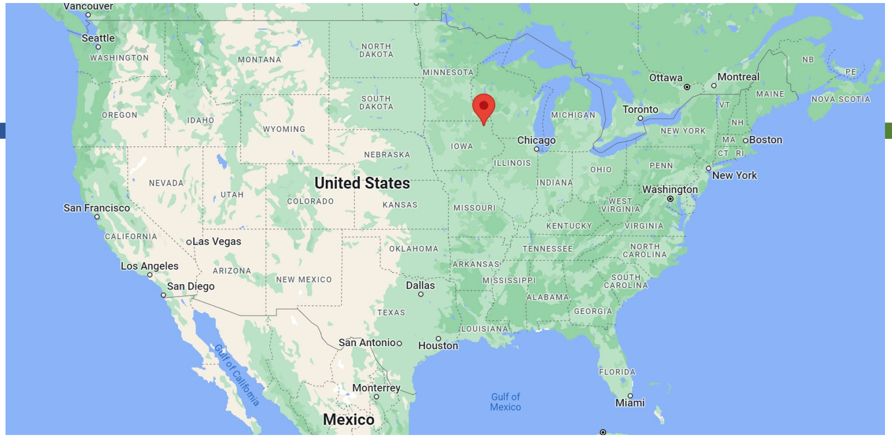
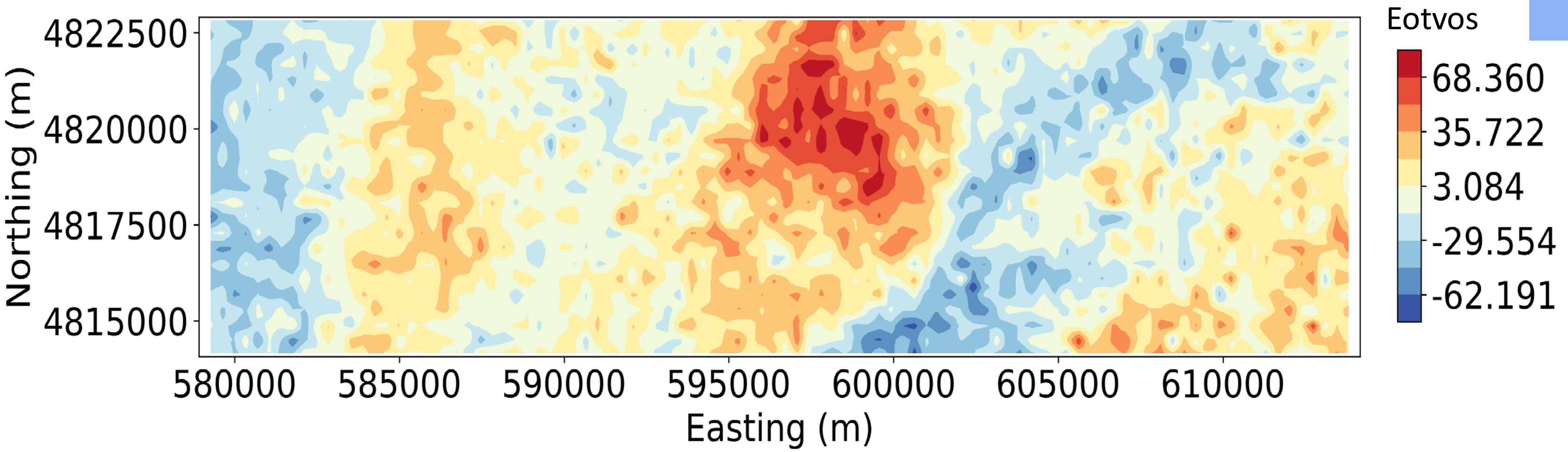
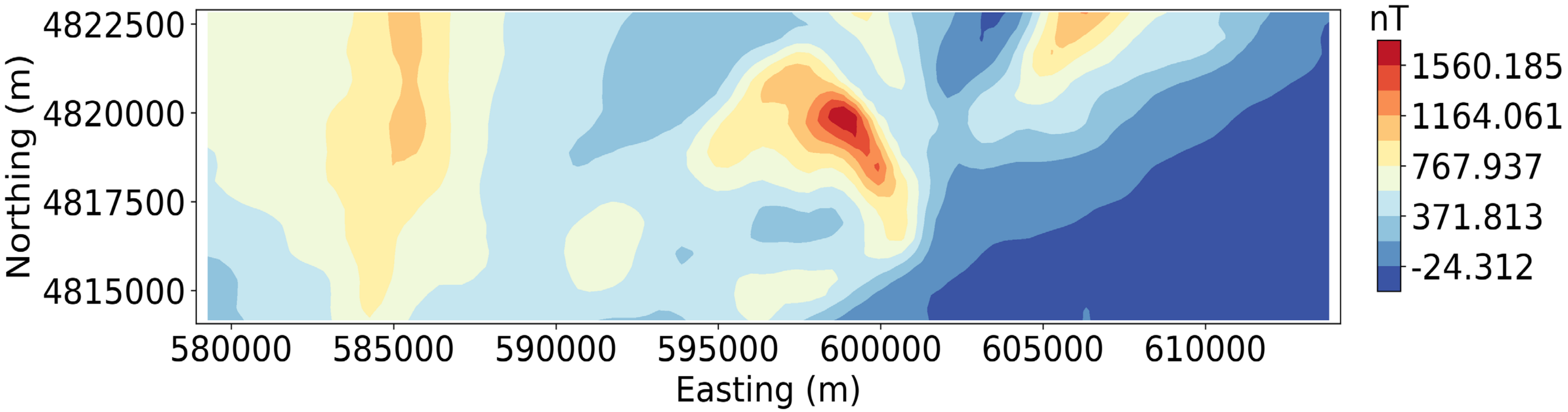
Geologic setting and geophysical data



North Decorah area located in the northeast Iowa.

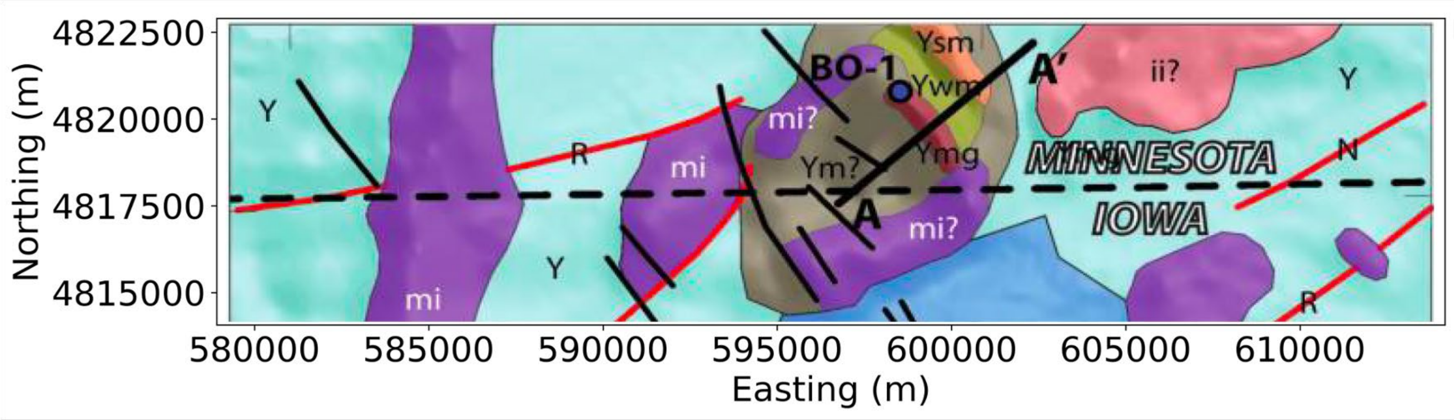


Observed gravity gradient data



Observed magnetic data

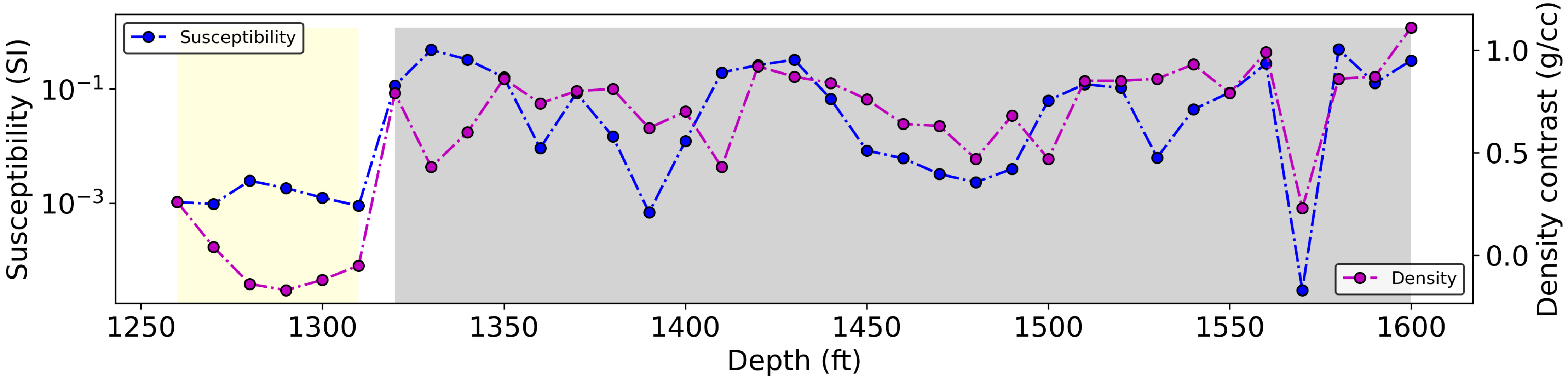
Geologic setting and geophysical data



2D geologic model (Drenth et al., 2015)

Sedimentary and weathered basement

Precambrian basement



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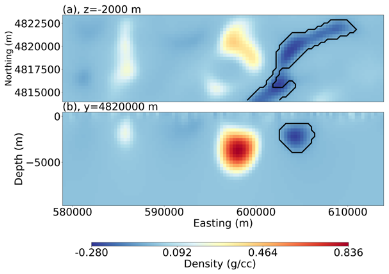
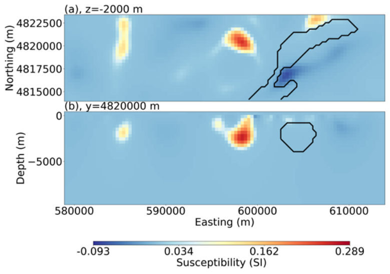
Geology differentiation in the north Decorah area

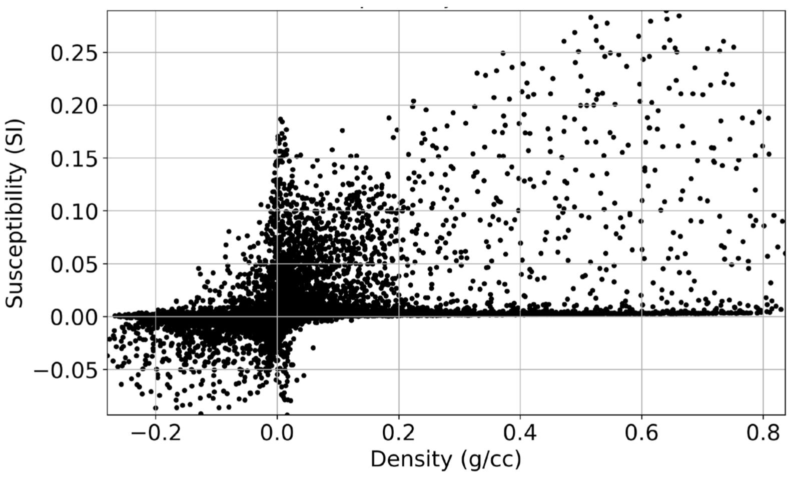
p=0.25, α_s=0.03

Density model

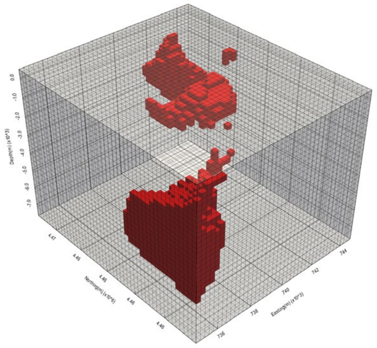


Susceptibility model

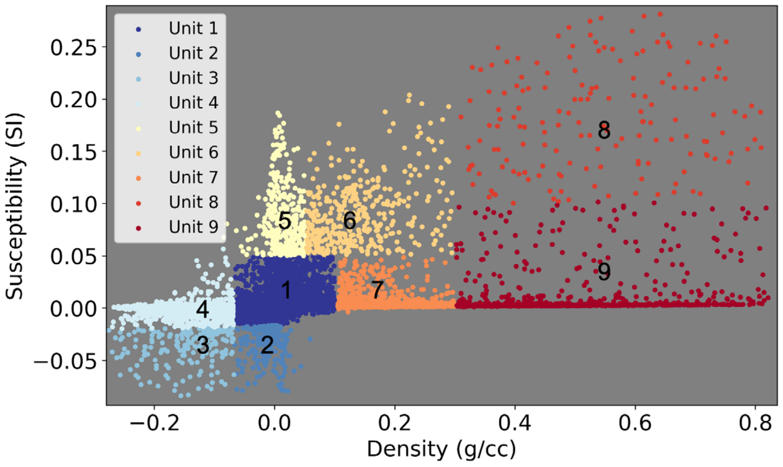




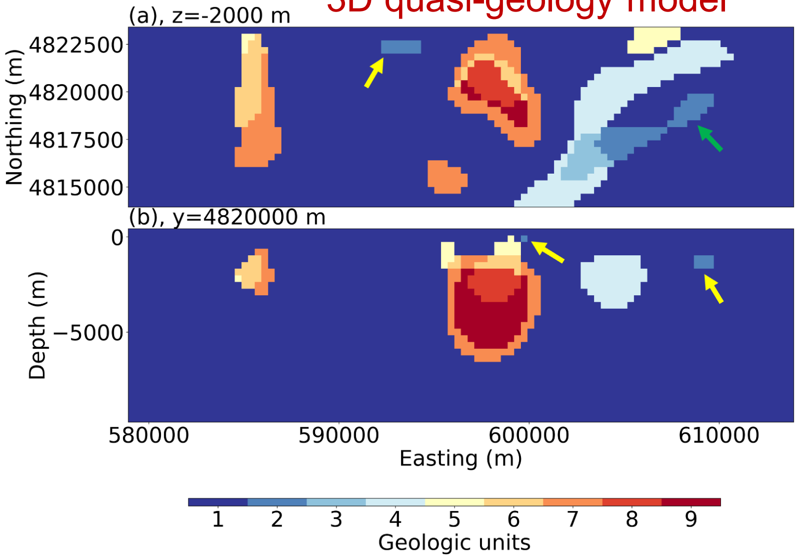
3D geological units



Geology differentiation

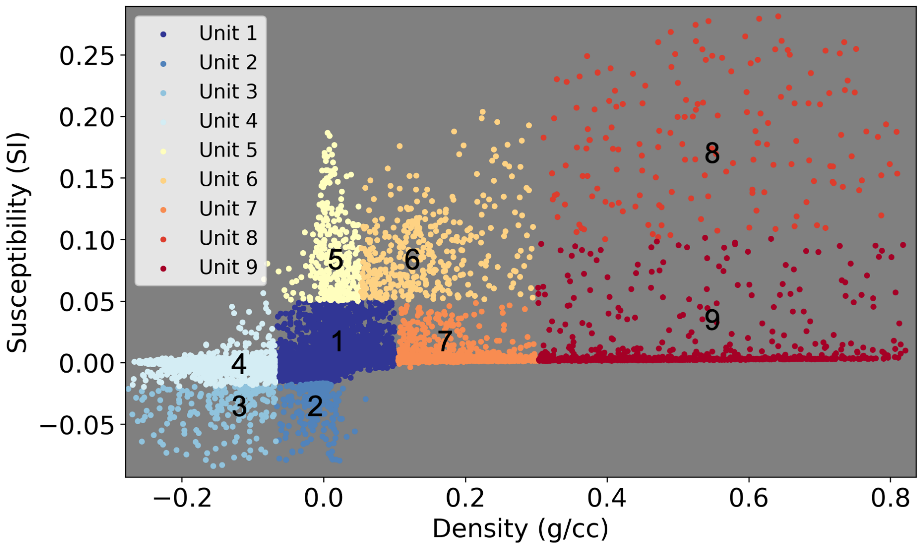


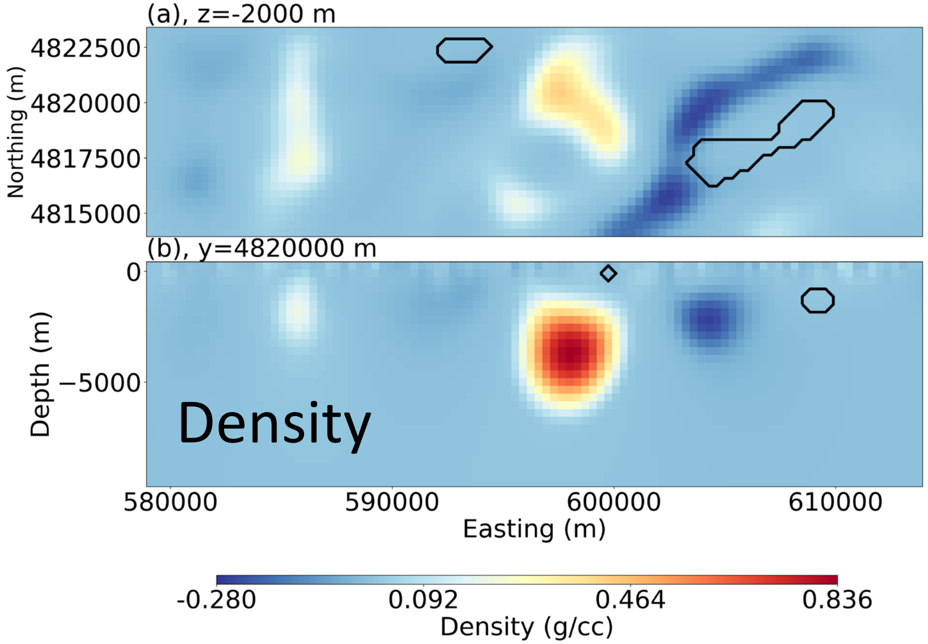
3D quasi-geology model

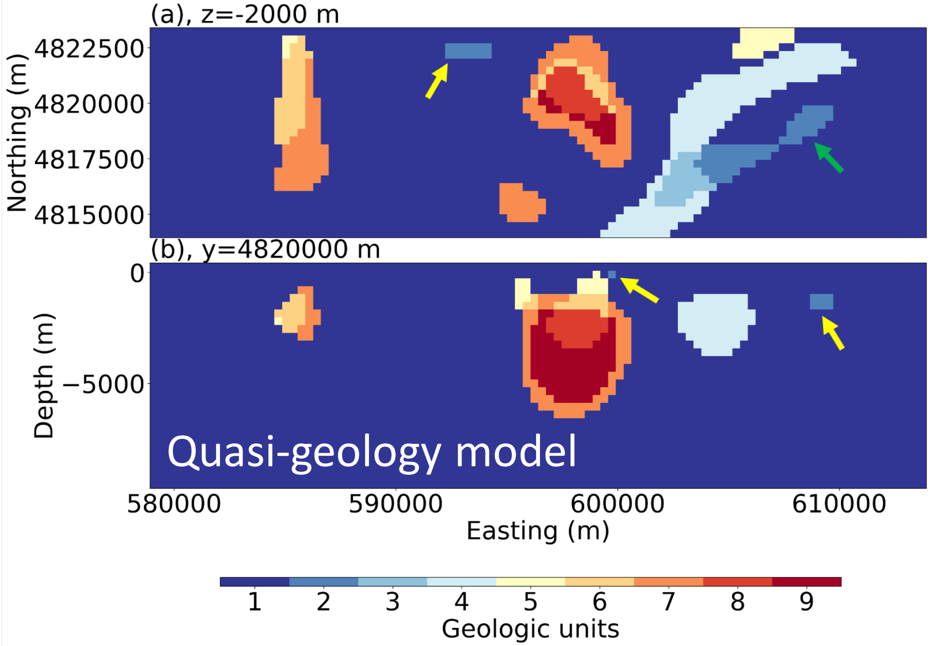


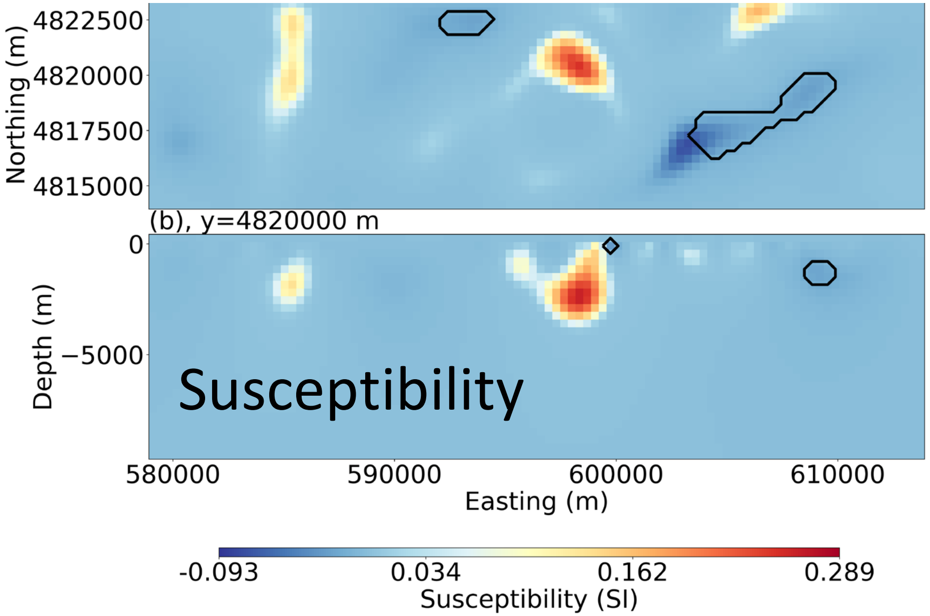
Wei and Sun (2022, GEOPHYSICS)

Geology differentiation: Unit 2

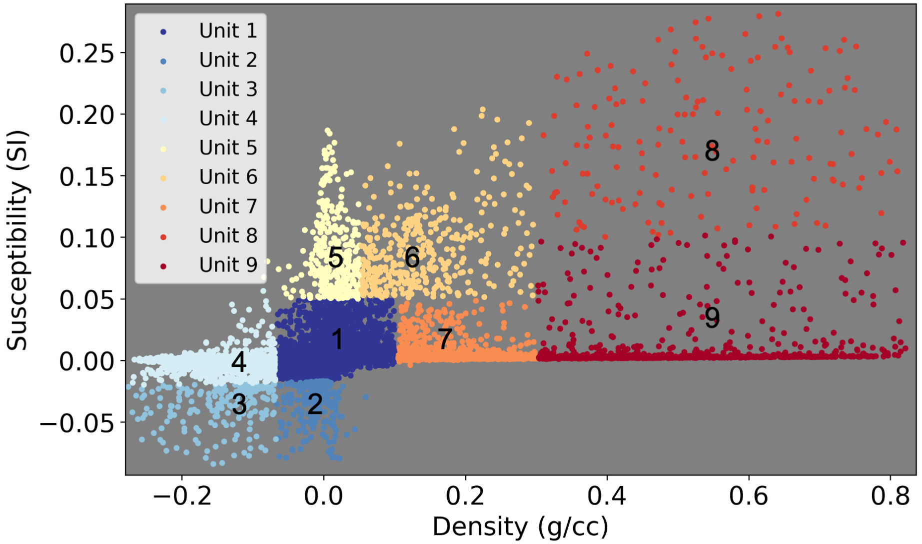


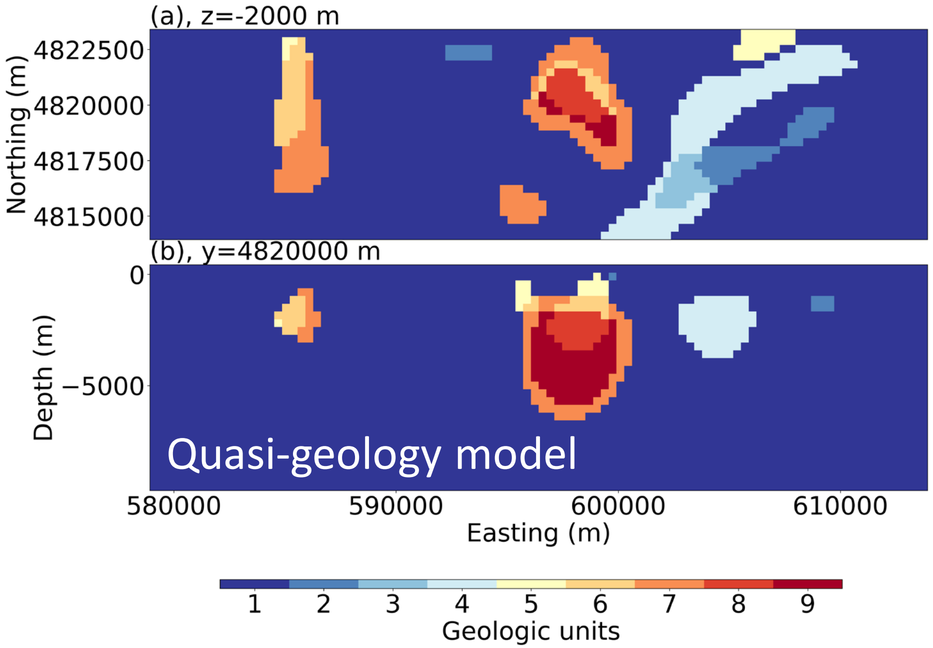


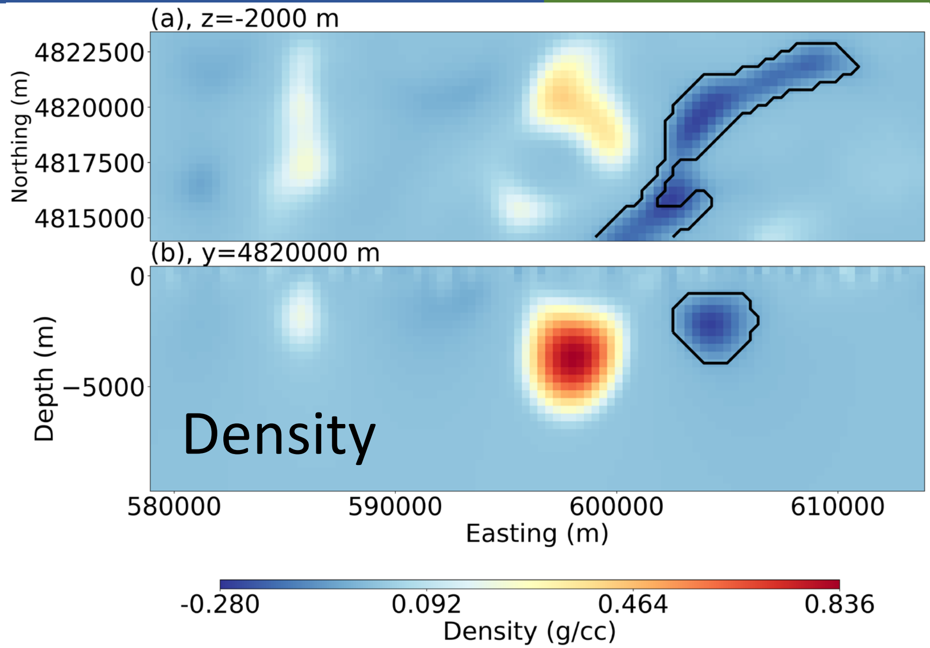


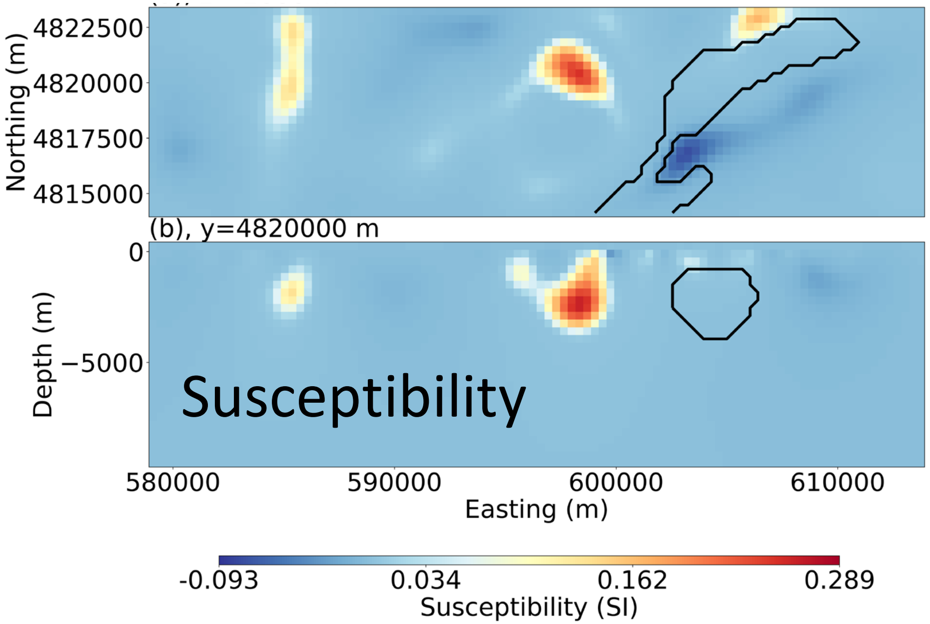


Geology differentiation: Unit 4

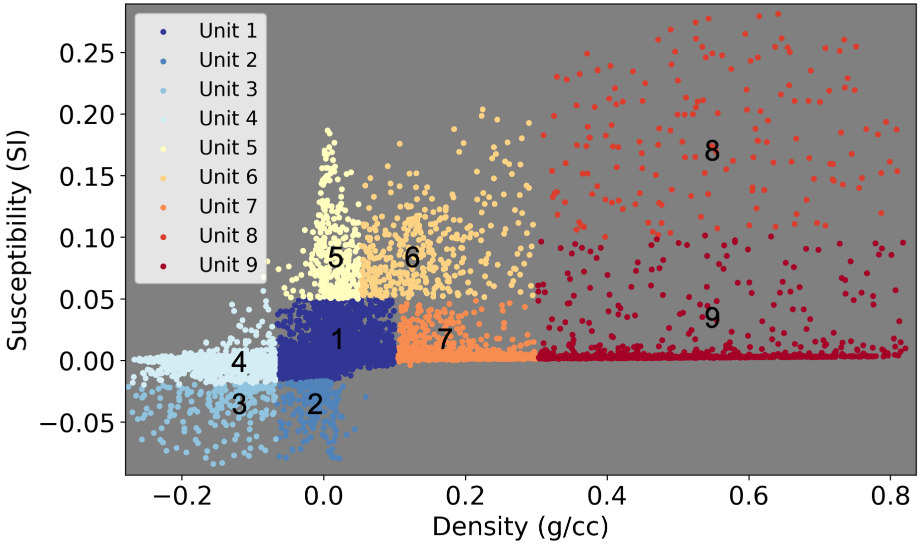


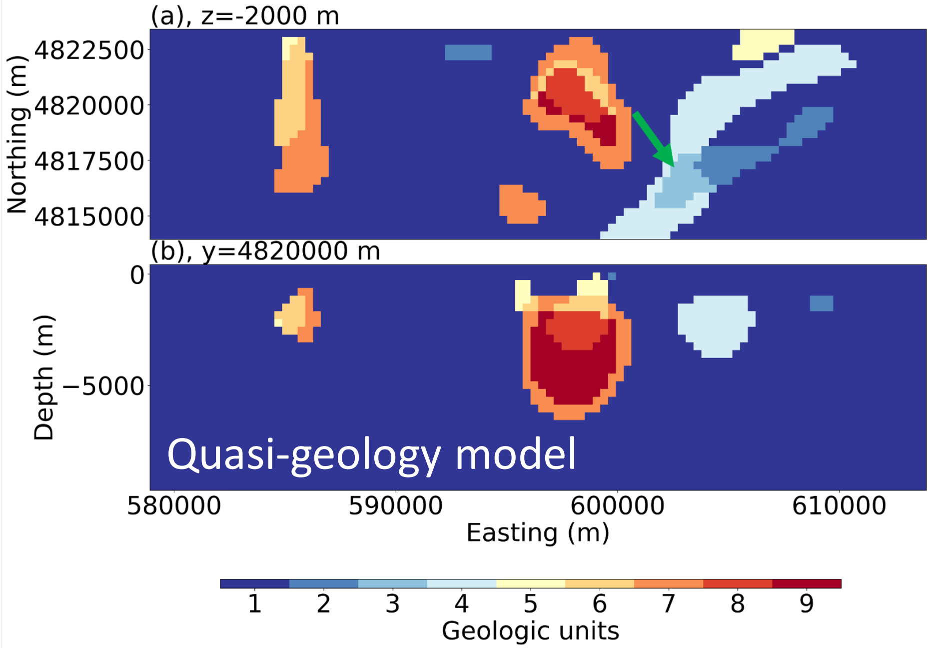


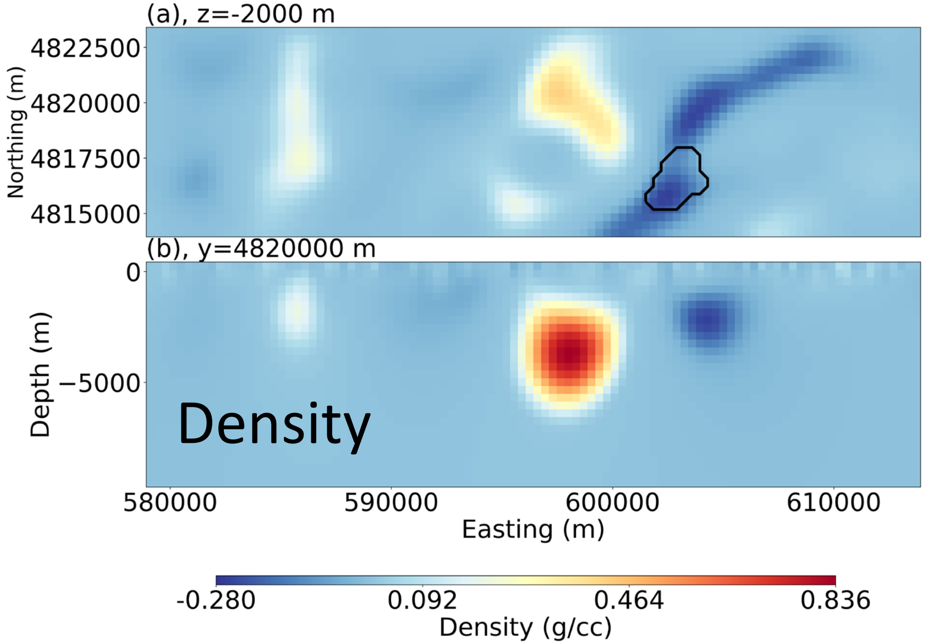


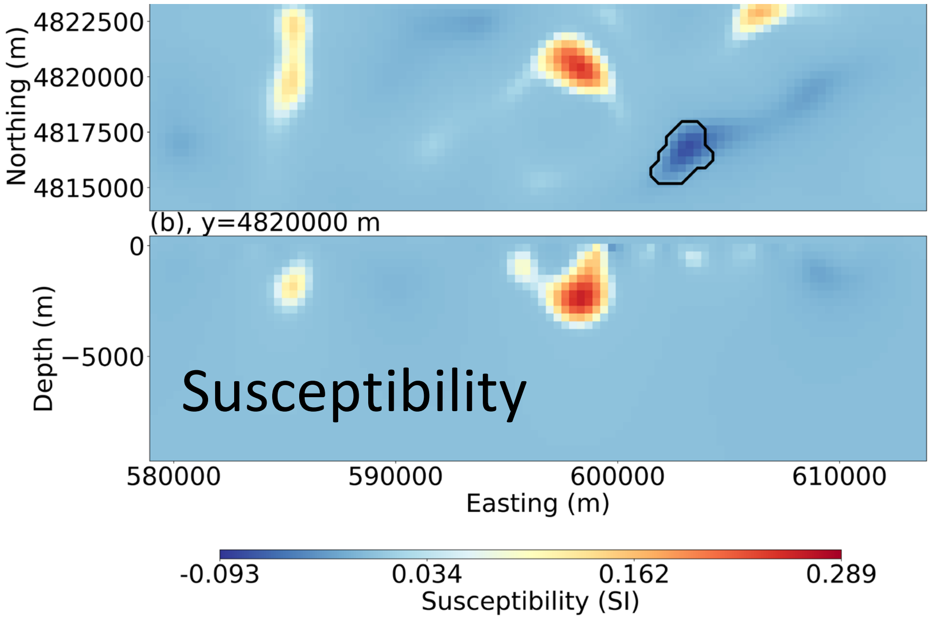


Geology differentiation: Unit 3

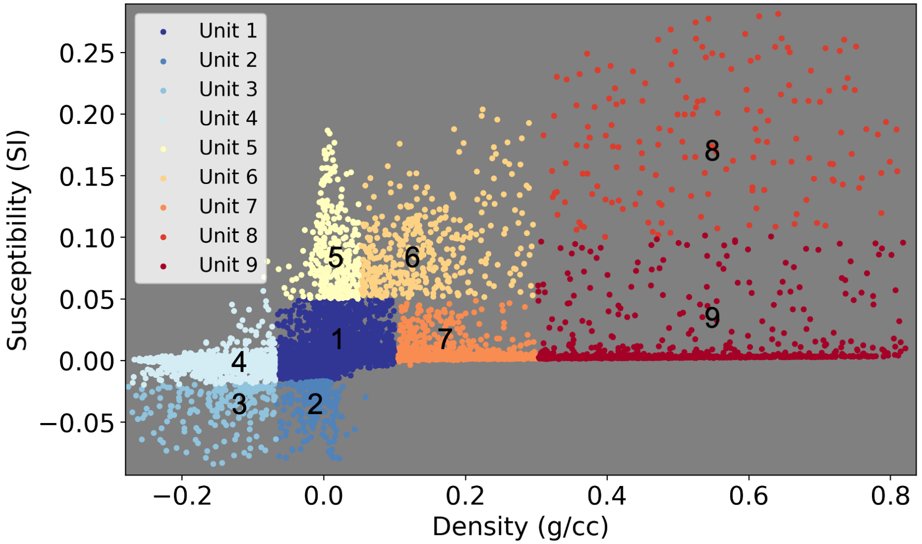


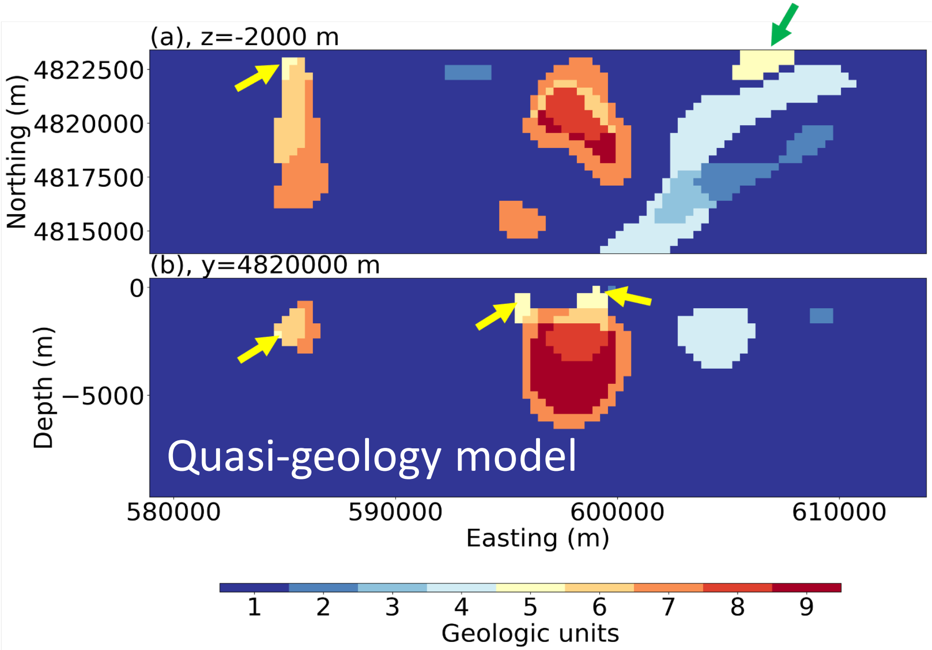


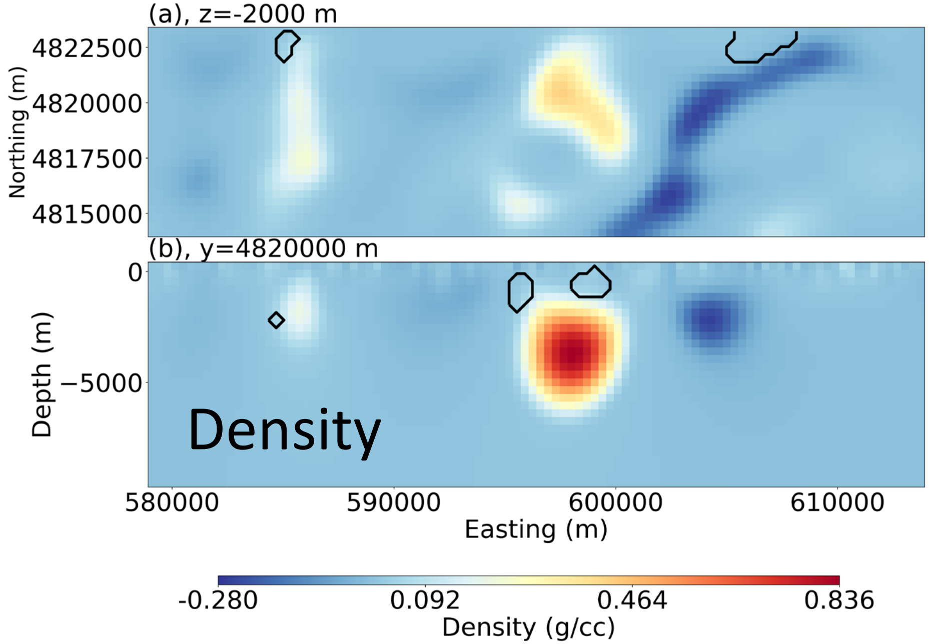


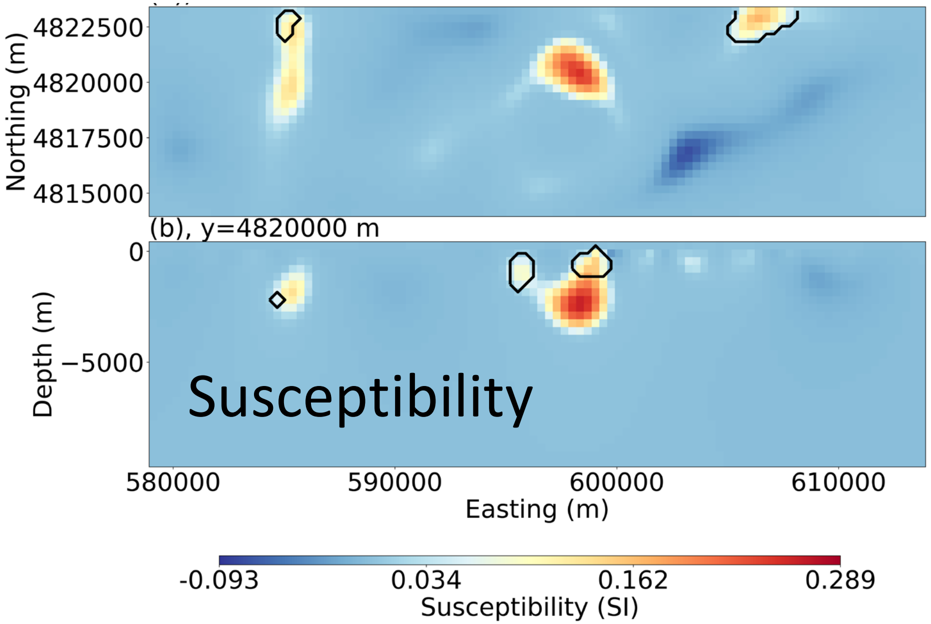


Geology differentiation: Unit 5

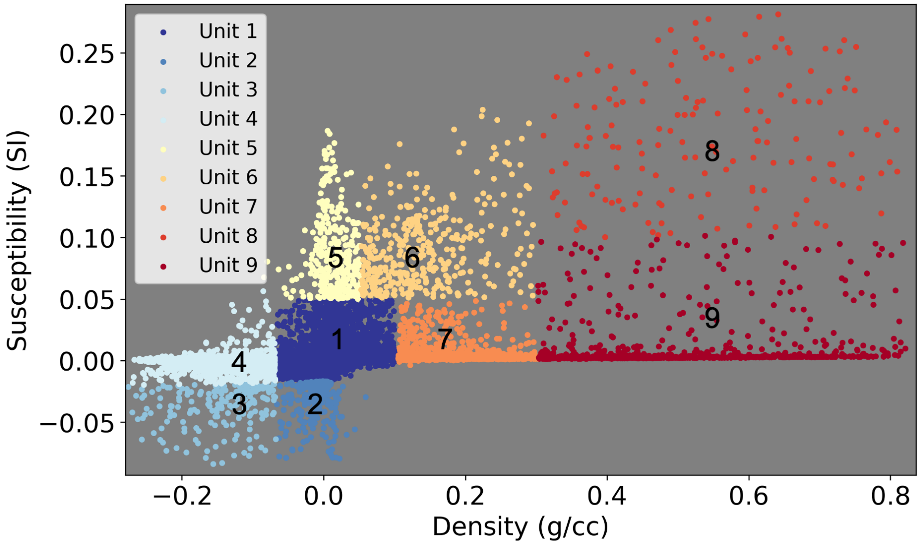


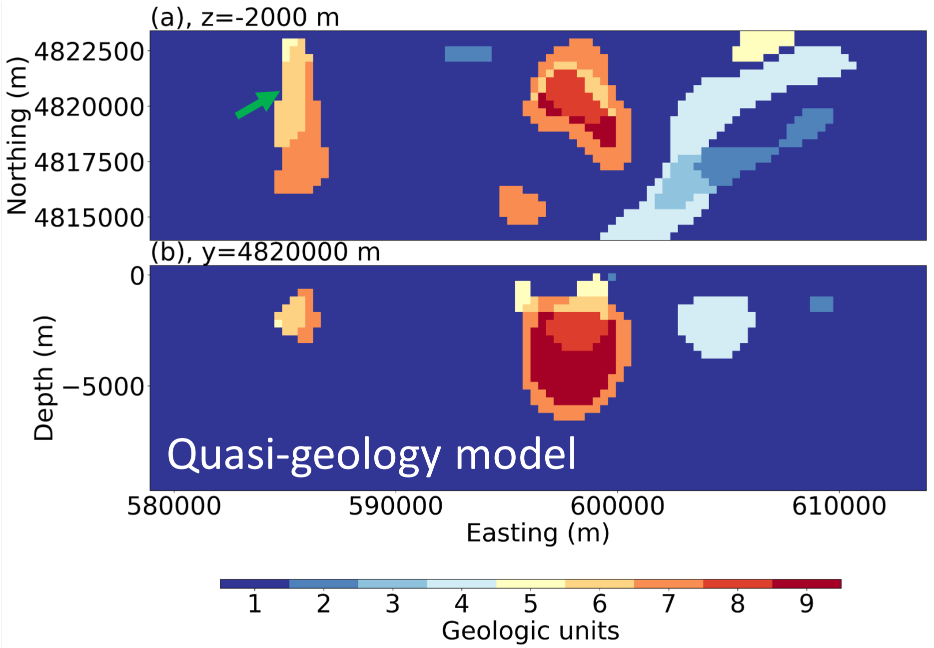


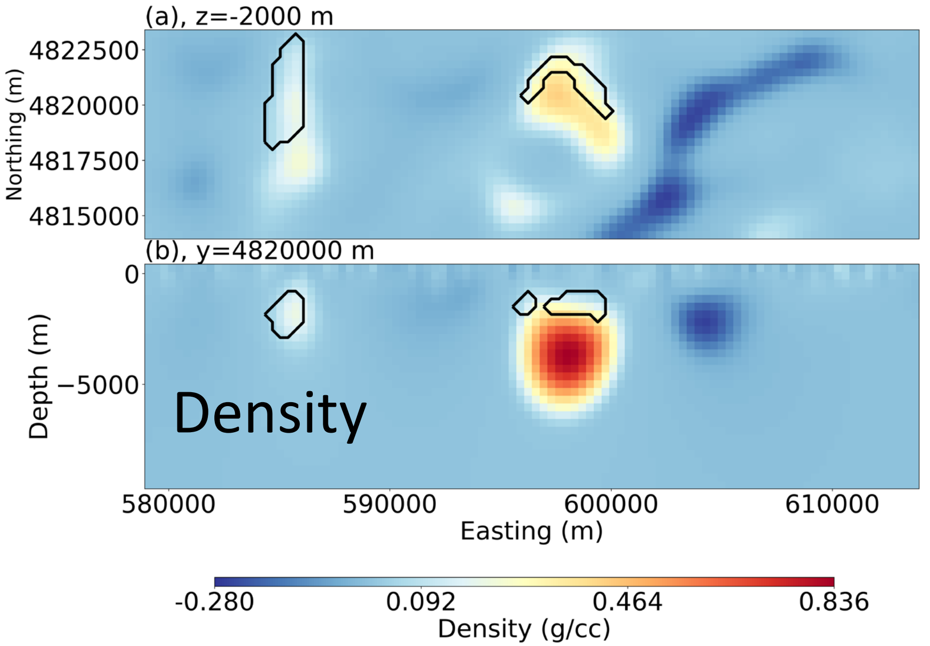


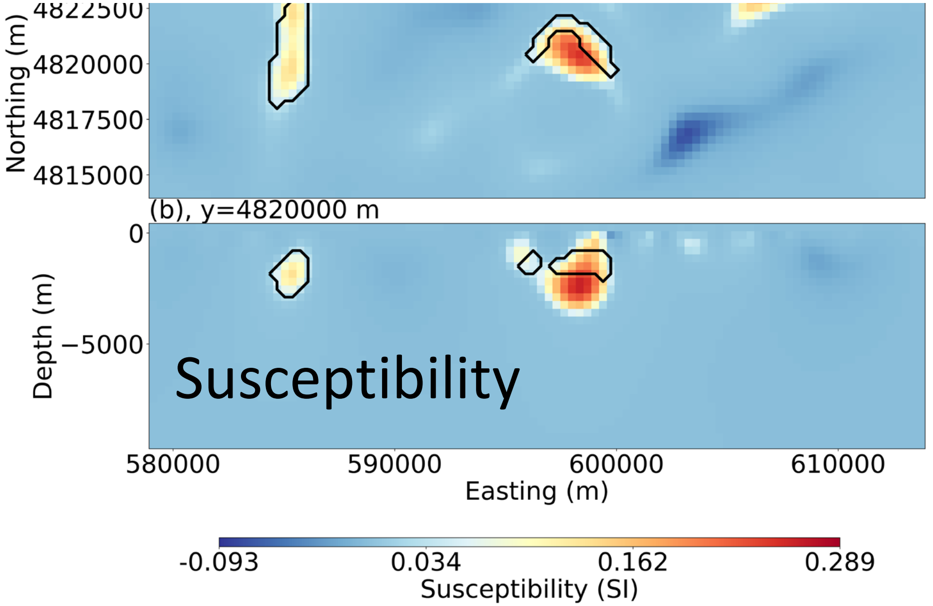


Geology differentiation: Unit 6

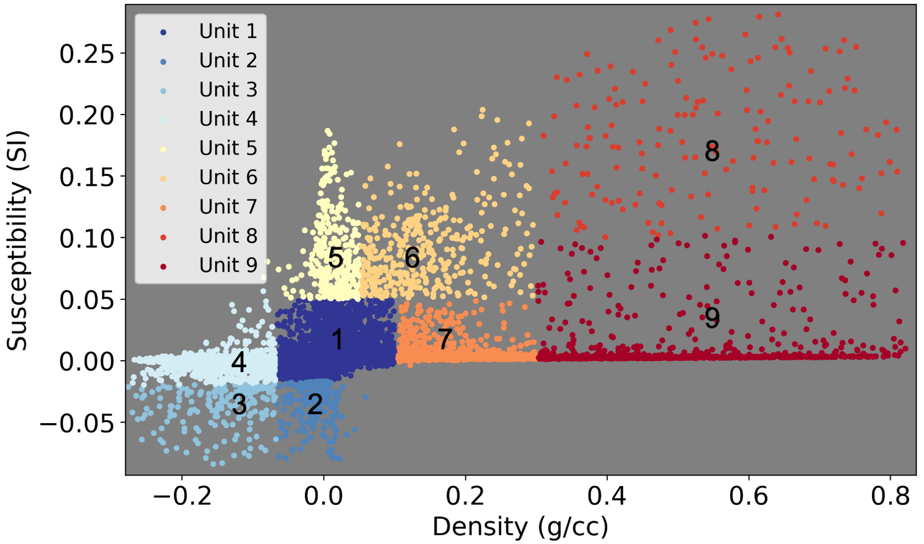


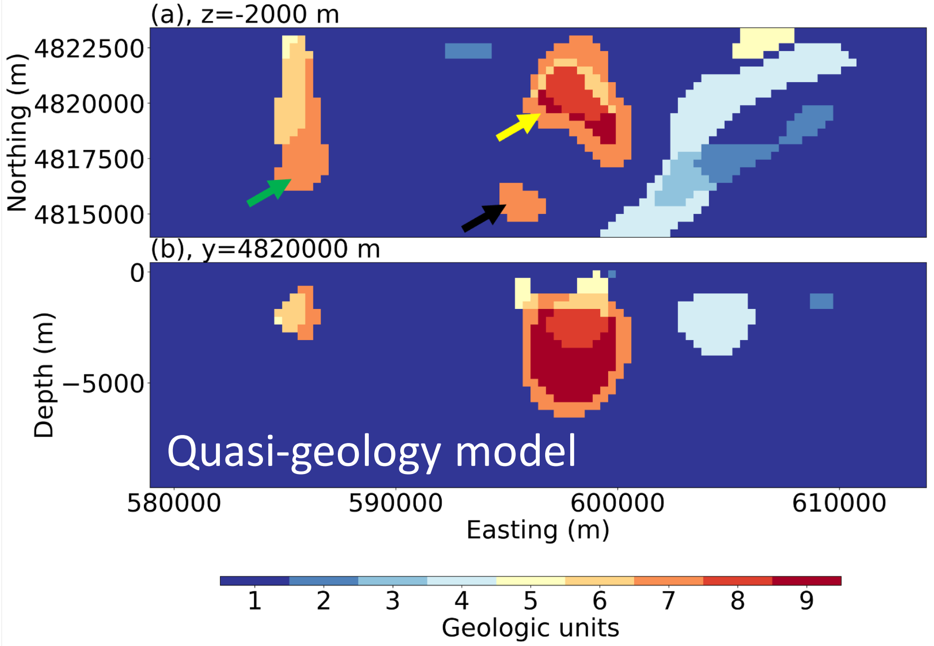


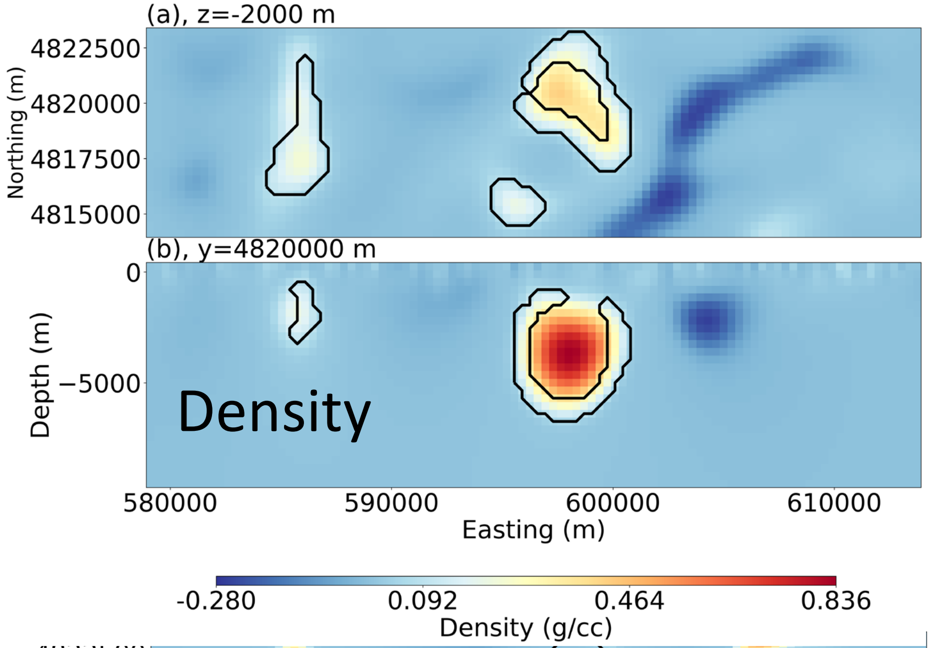


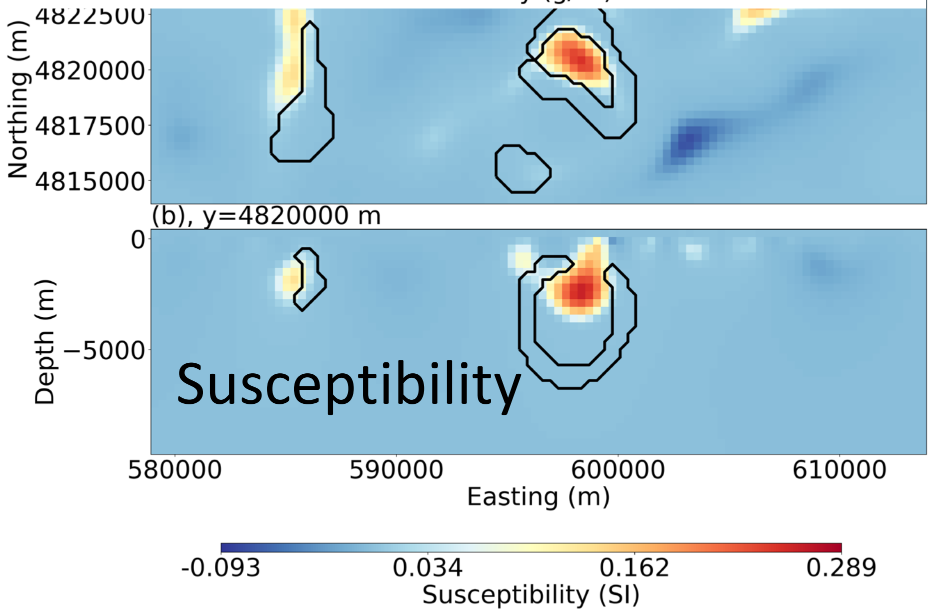


Geology differentiation: Unit 7

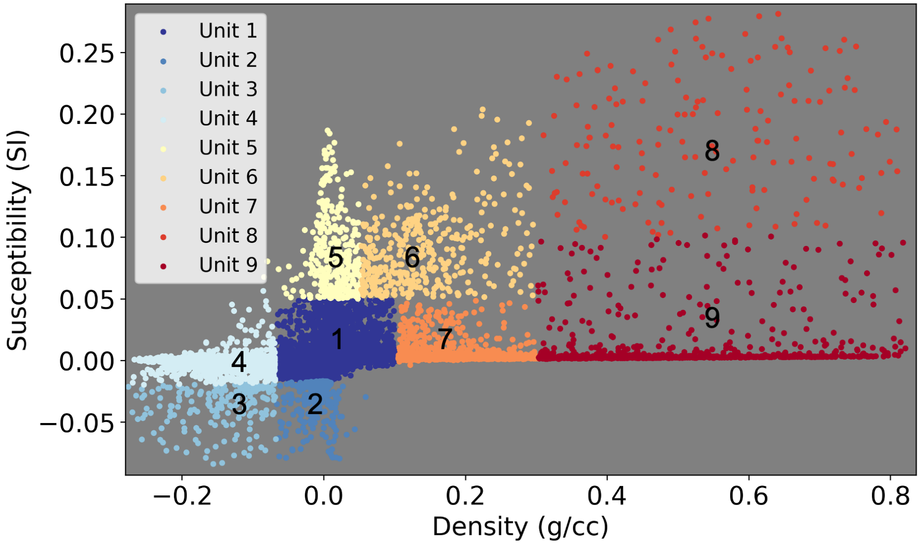


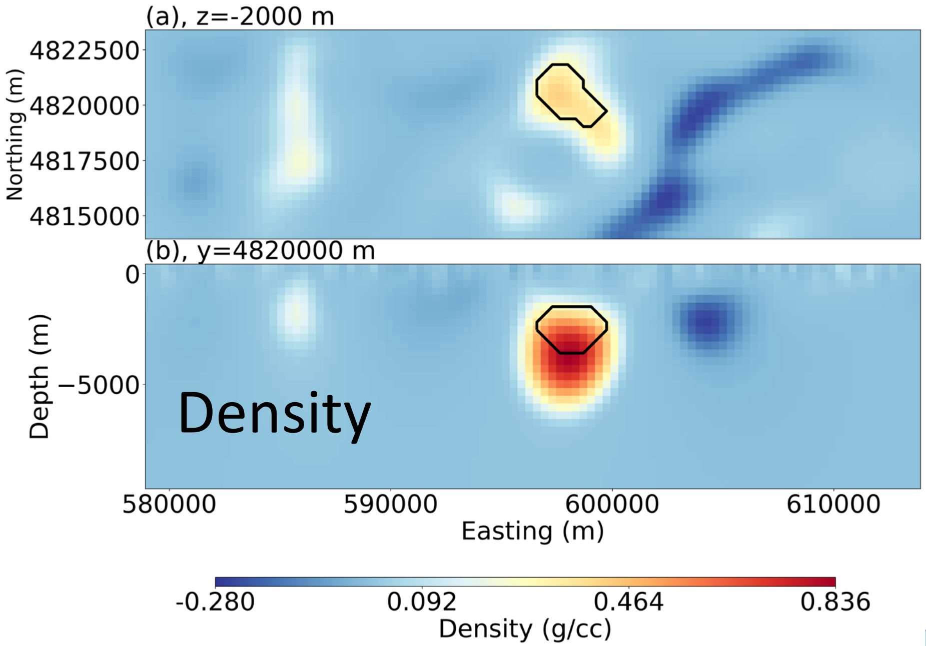


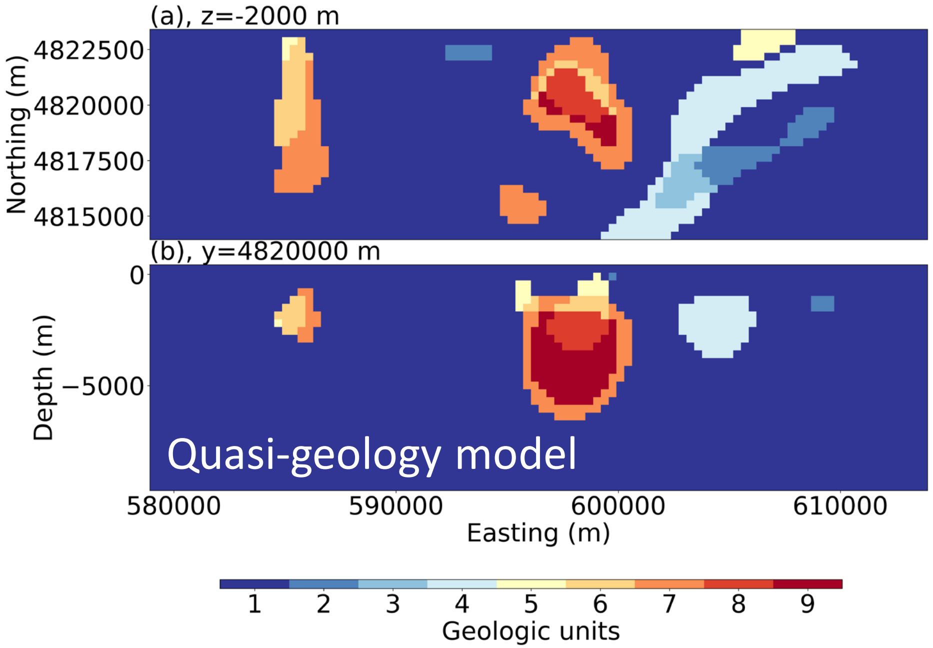


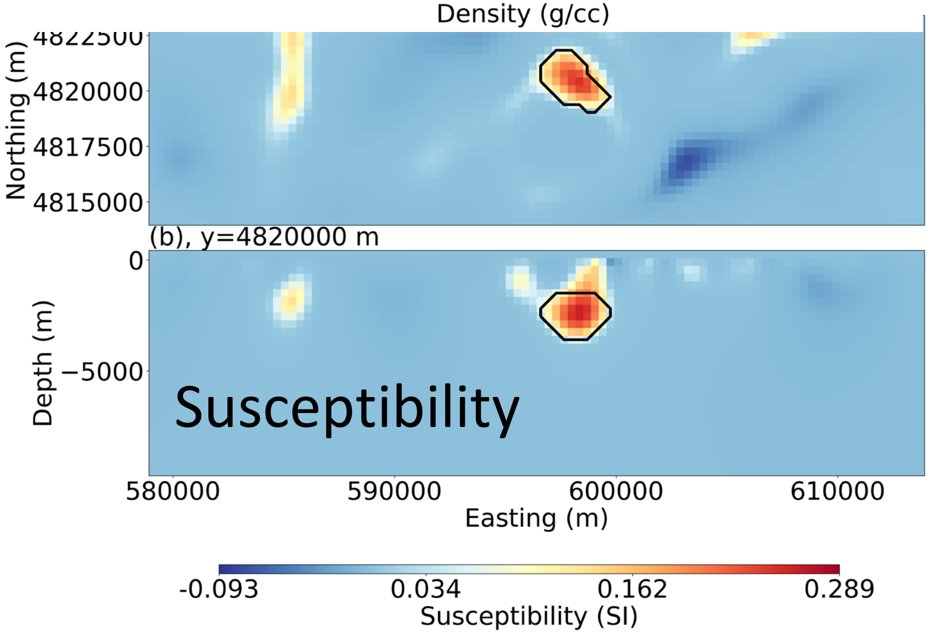


Geology differentiation: Unit 8

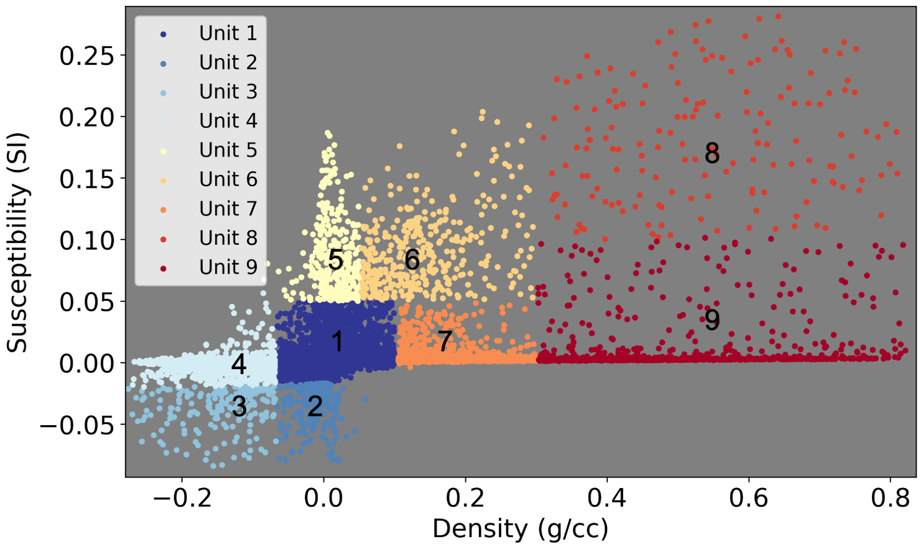


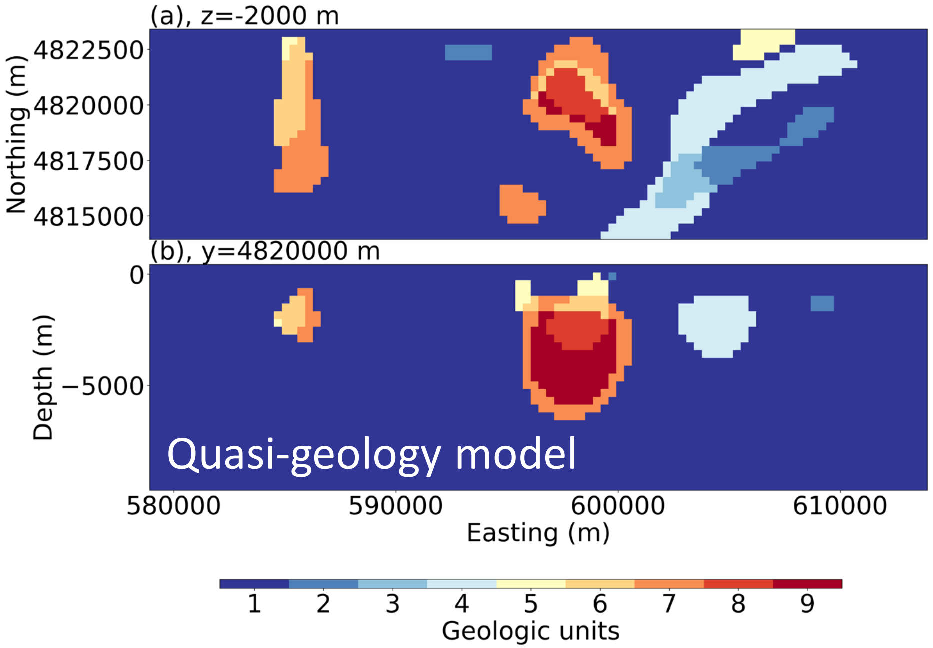


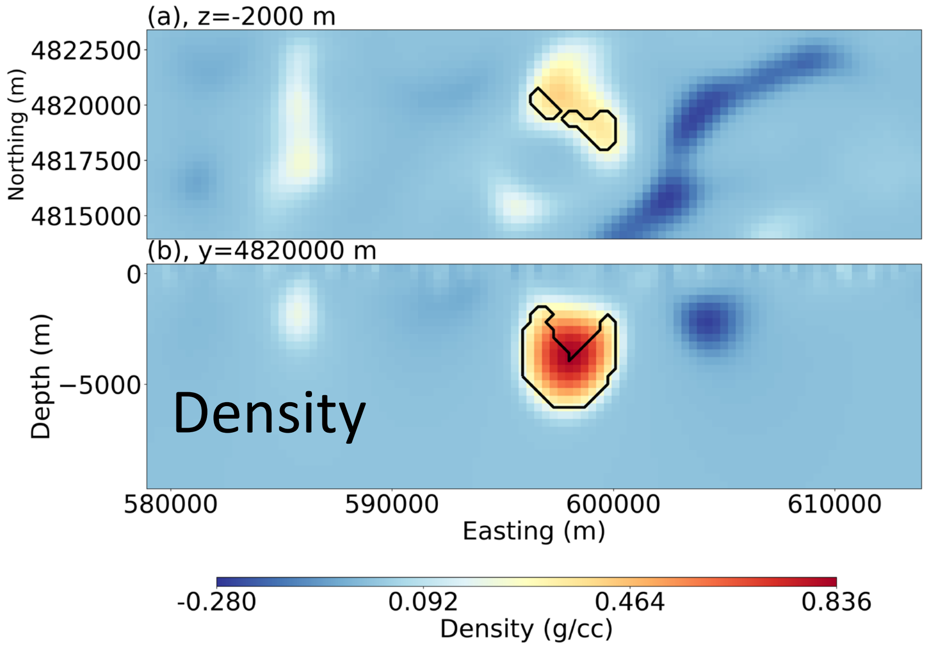


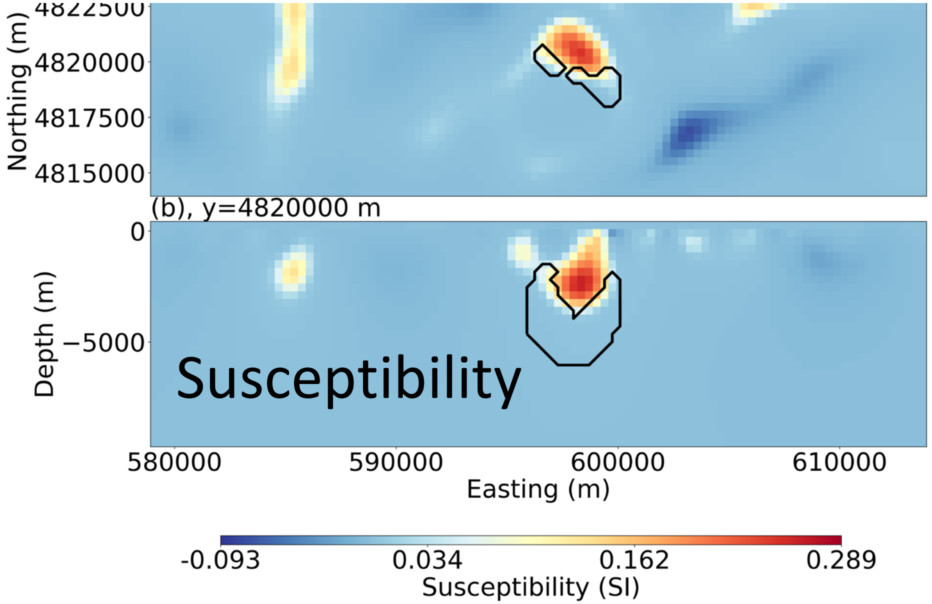


Geology differentiation: Unit 9

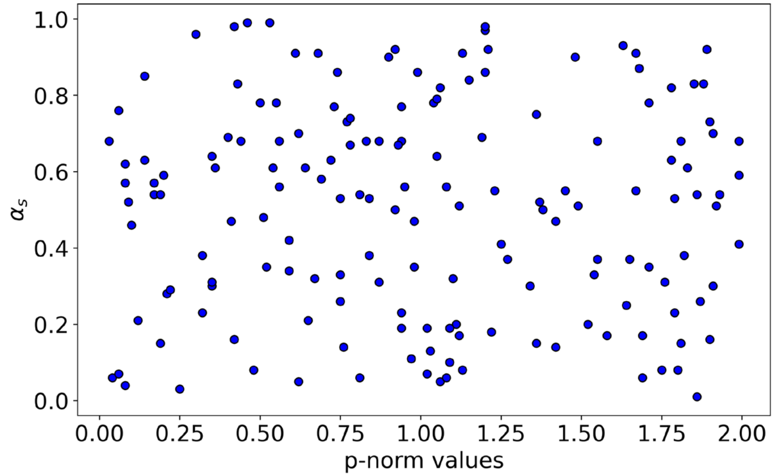








Probabilistic geology differentiation



1. Randomly sample tuning parameters (p and α_s)

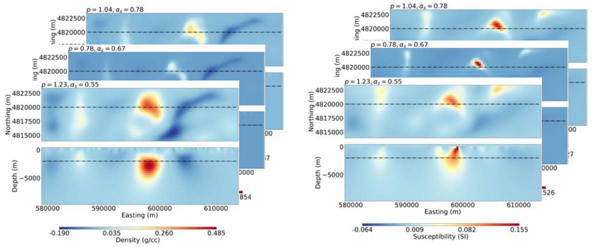
2. Perform 162 mixed Lp norm joint inversions

3. Obtain 162 pairs of jointly recovered density and susceptibility models

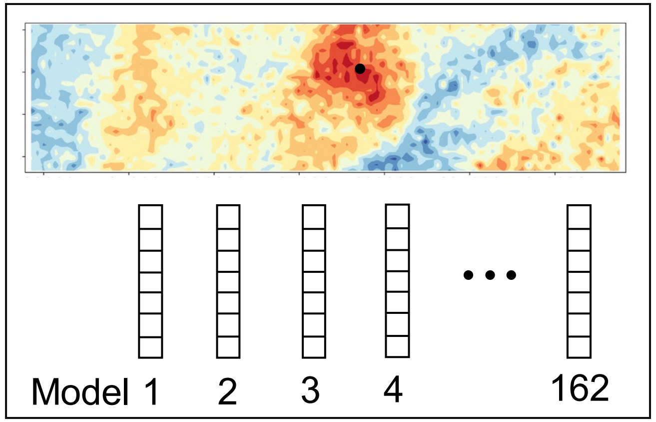
Are all models consistent with rock sample measurements?

Probabilistic geology differentiation

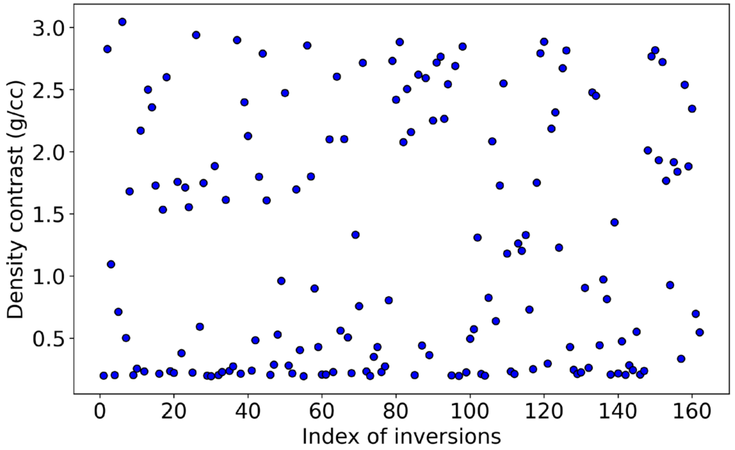
A set of jointly inverted 3D density and susc models



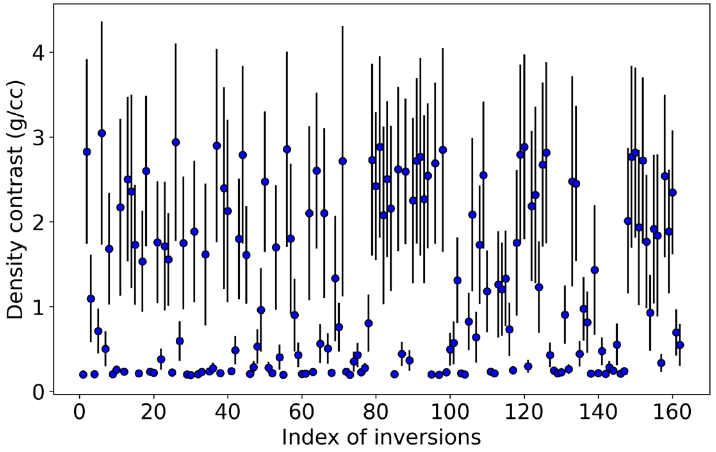
Extract inverted density values at drillhole location



Compute mean density value for each model

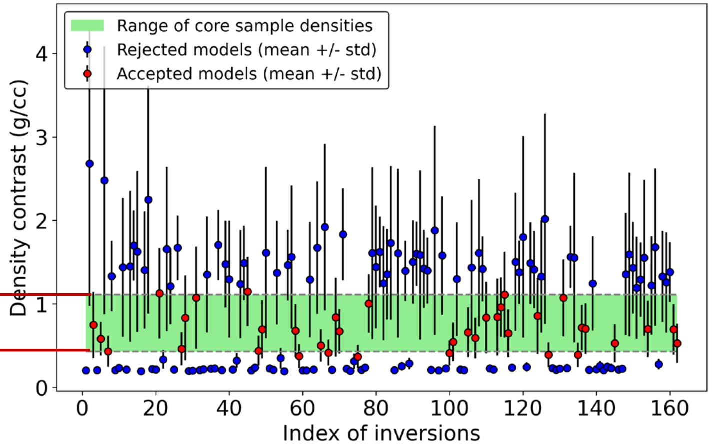


Compute standard deviation for each model

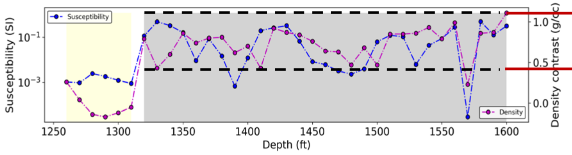


Physical property measurements on rock samples

Density contrast range: [0.43, 1.1]

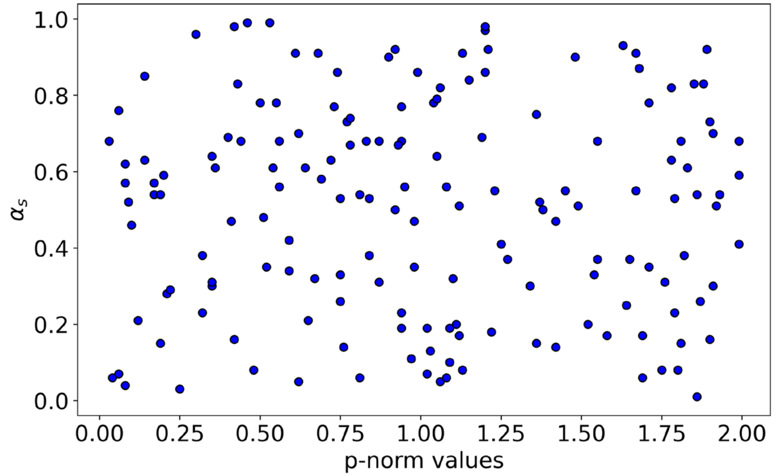


Density contrast
Max: 1.1 g/cc
Min: 0.43 g/cc



Wei and Sun (2022, GEOPHYSICS)

Probabilistic geology differentiation



1. Randomly sample tuning parameters (p and α_s)

2. Perform 162 mixed Lp norm joint inversions

3. Obtain 162 pairs of jointly recovered density and susceptibility models

4. 37 pairs of density and susceptibility models consistent with the rock measurements (dens [0.43 g/cc, 1.1 g/cc], susc [0.115 SI, 0.495 SI])

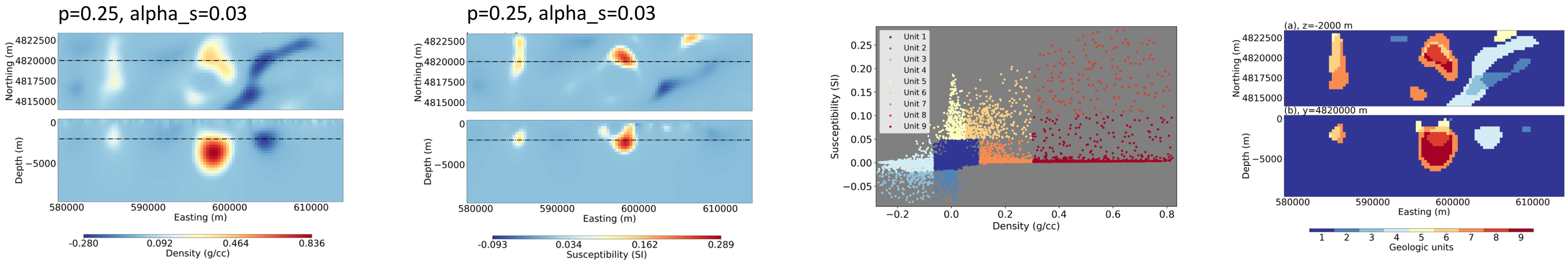
5. 37 quasi-geology models

Wei and Sun (2022, GEOPHYSICS)

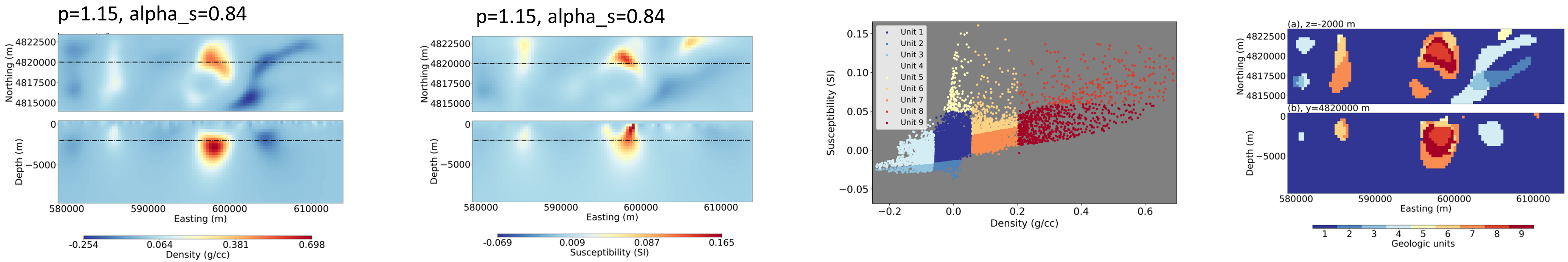
Geology differentiation: accepted models

Density models | Susceptibility models | Scatter plots | Quasi-geology models

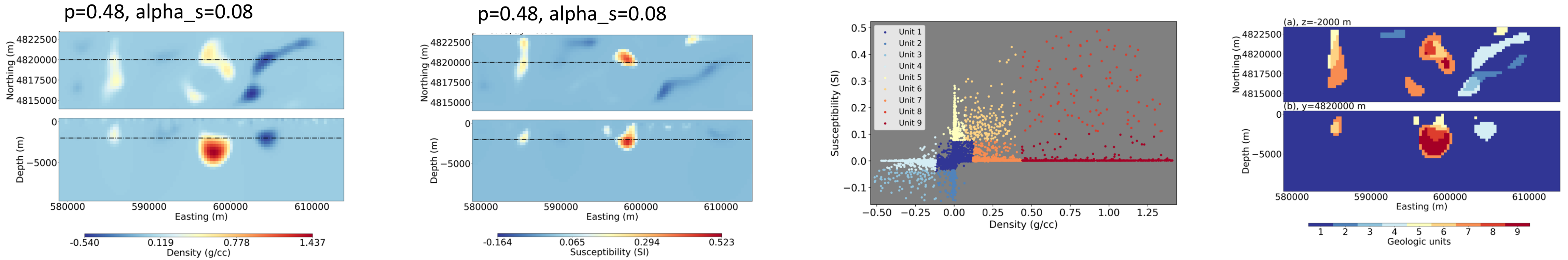
A



B



C



Geology differentiation: rejected models

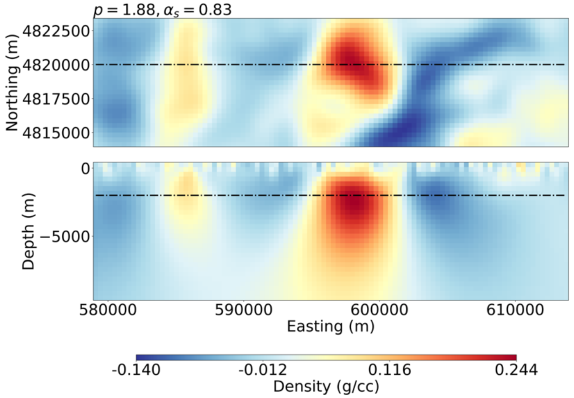
Density model

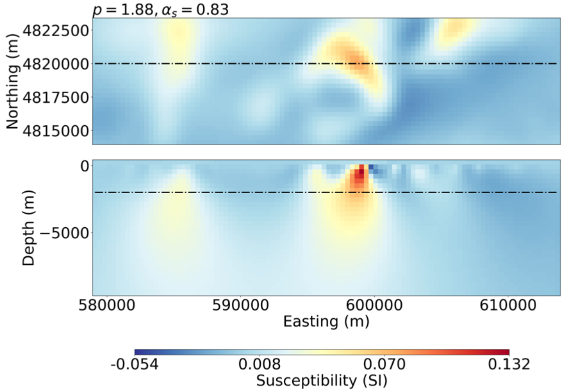
Susceptibility model

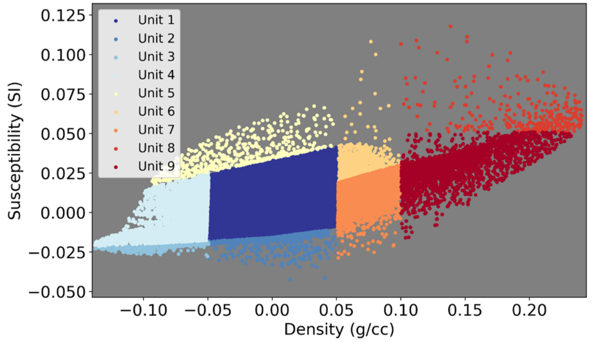
Scatter plots

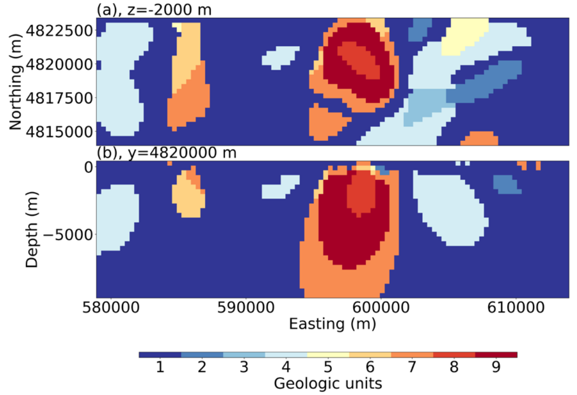
Quasi-geology model

A









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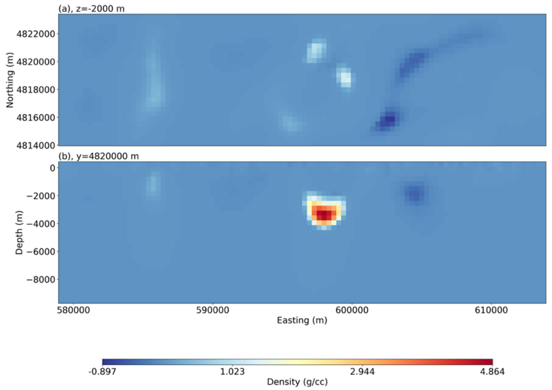
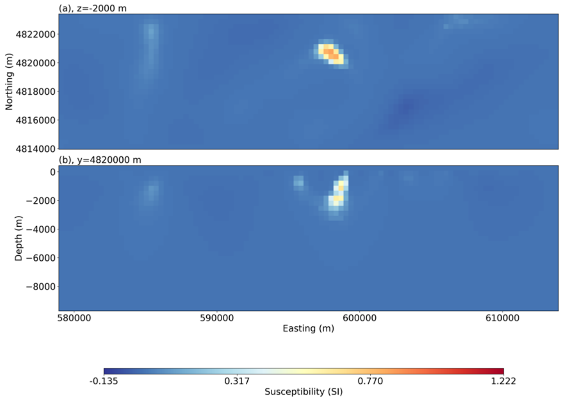
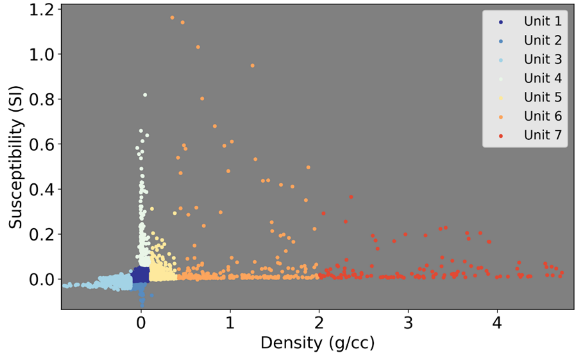
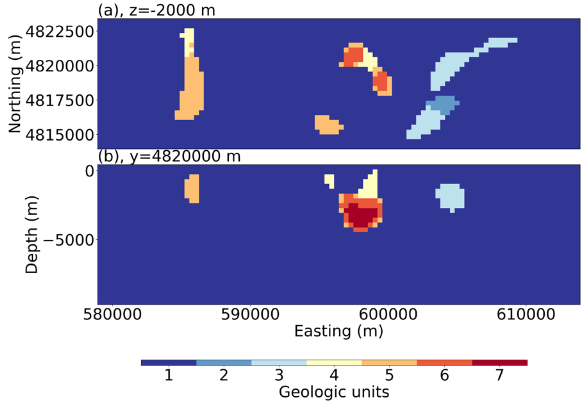








Wei and Sun (2022, GEOPHYSICS)

Workflow for probabilistic quasi-geology model

Multiple geophysical data

1. Randomly sample tuning parameters (p and alpha_s)

2. Mixed Lp norm joint inversion

3. Jointly recovered density and susceptibility models

4. Accept or reject

5. Geology differentiation

6. Repeat step 1 - 5

7. Obtain a sequence of quasi-geology models

8. Uncertainty analysis

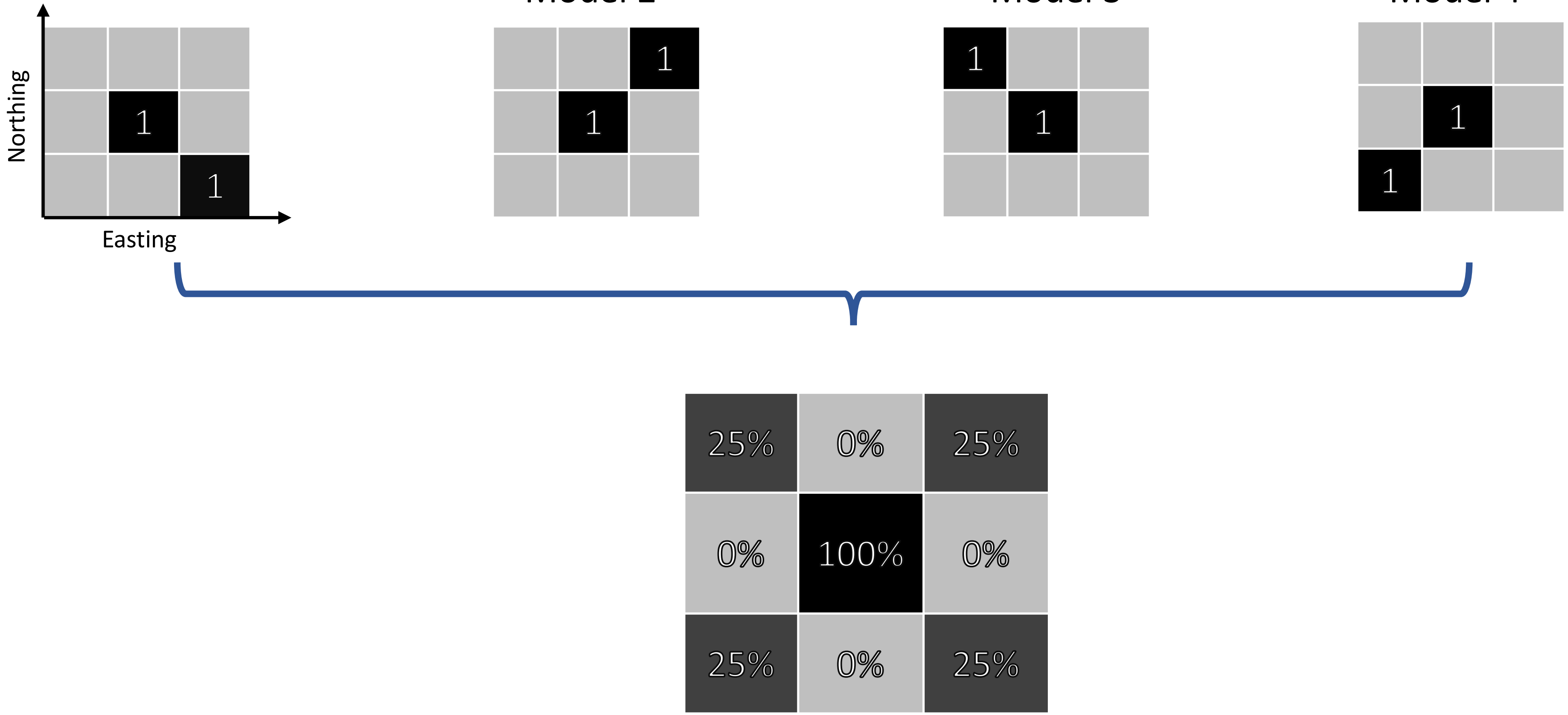
Uncertainty analysis: uncertainty of spatial distribution

A simplified quasi-geology model 1

Model 2

Model 3

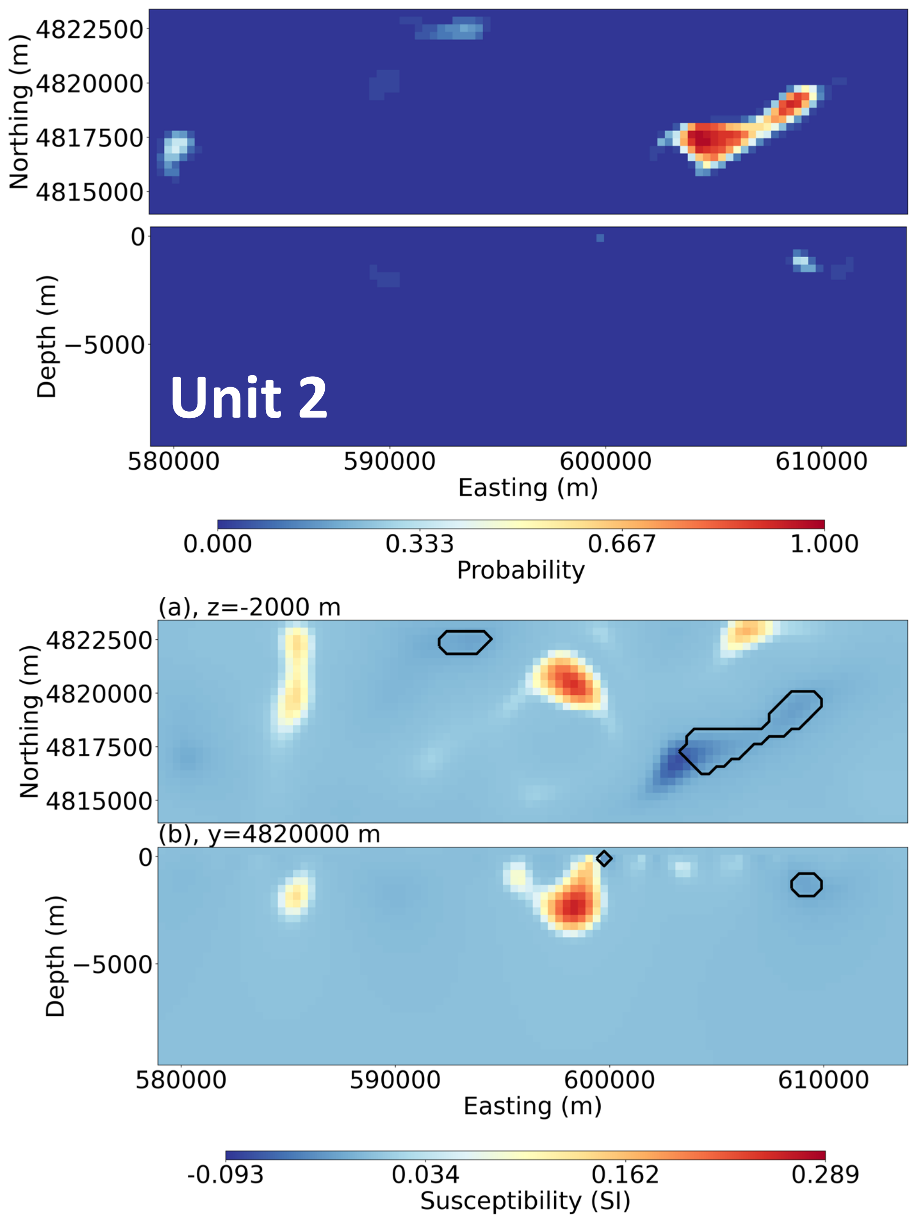
Model 4

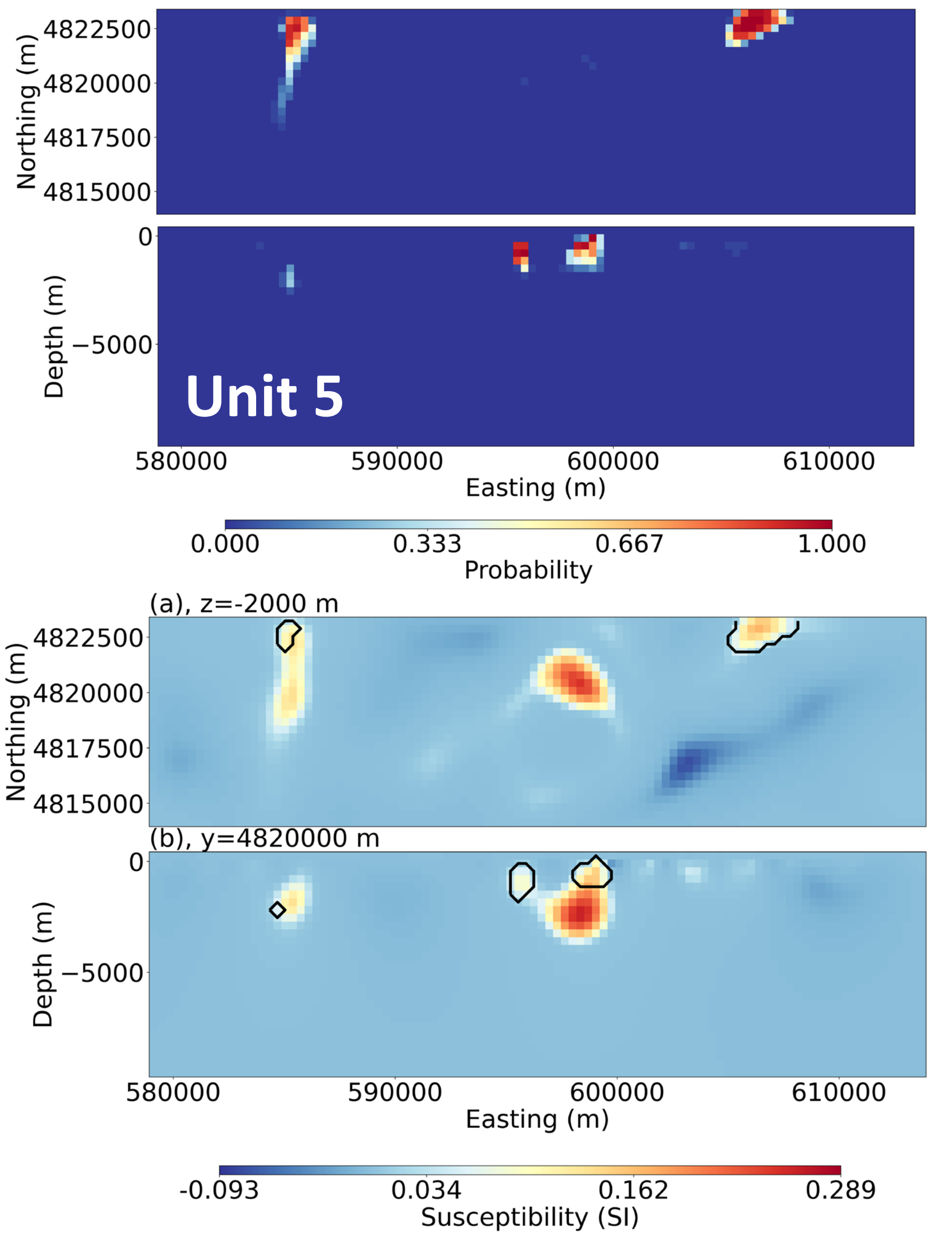


Probabilistic quasi-geology model

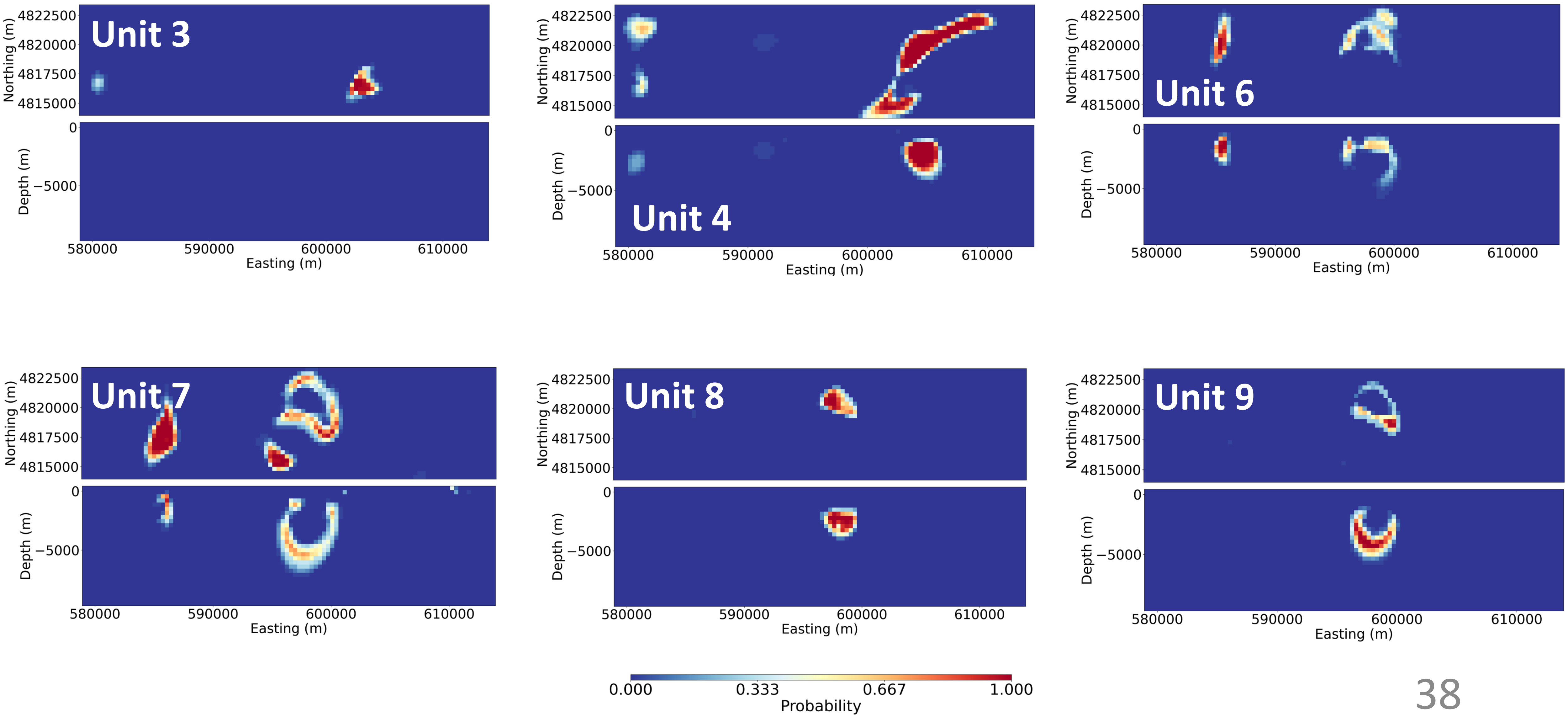
Wei and Sun (2022, GEOPHYSICS)

Uncertainty analysis: uncertainty of spatial distribution

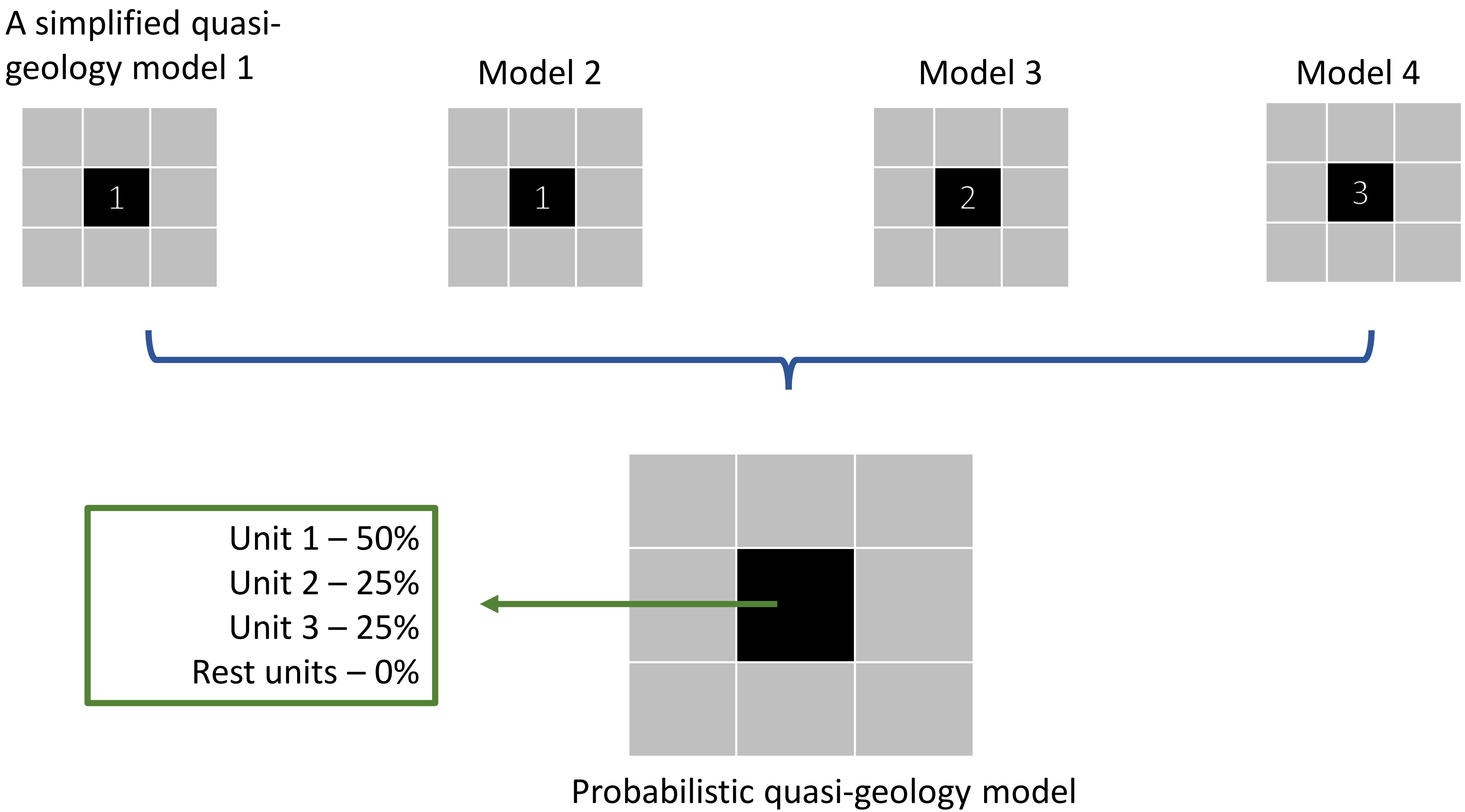




Uncertainty analysis: uncertainty of spatial distribution

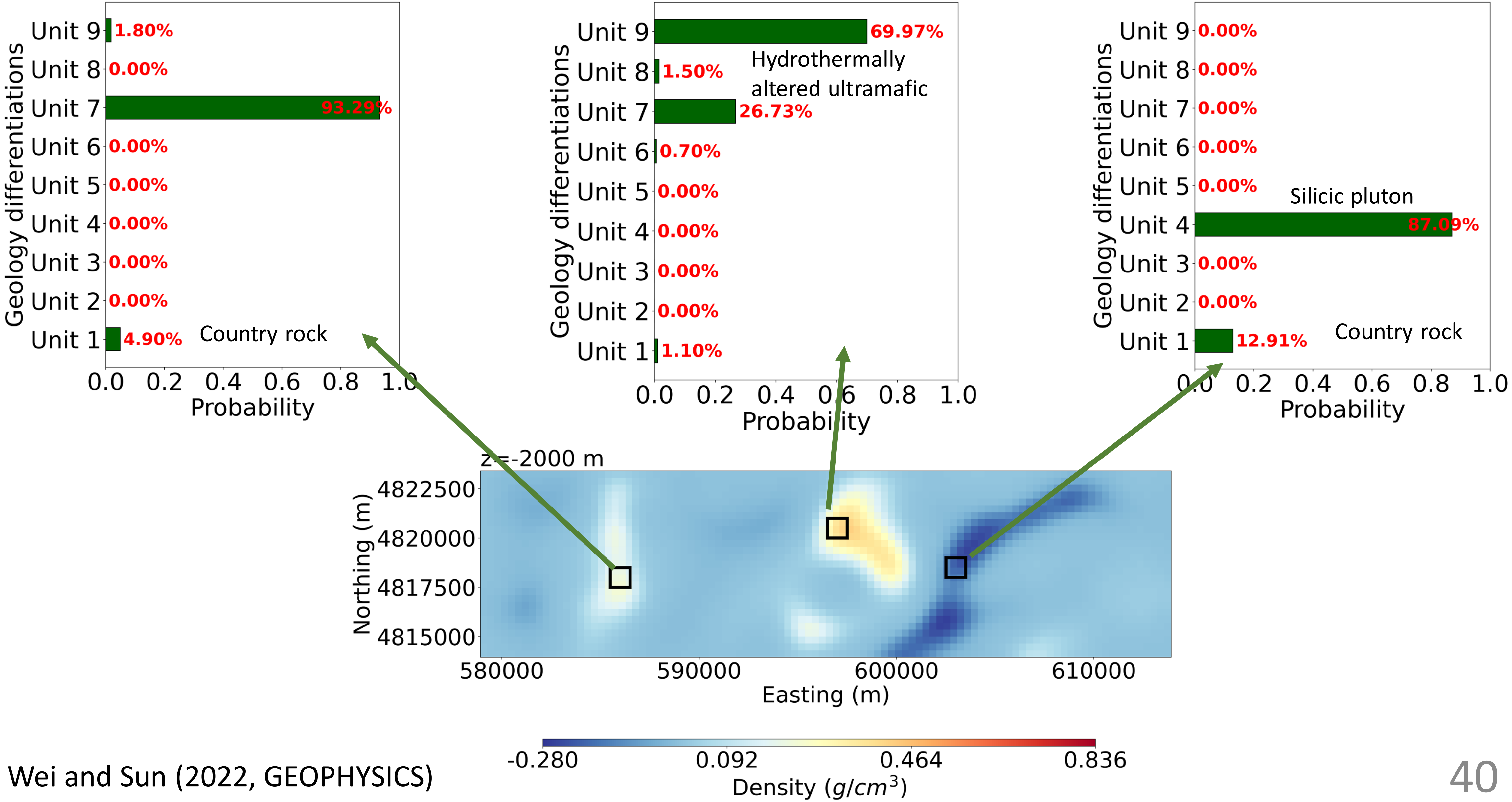


Uncertainty analysis: probability of lithologic types



Wei and Sun (2022, GEOPHYSICS)

Uncertainty analysis: probability of lithologic types



Wei and Sun (2022, GEOPHYSICS)

3D probabilistic quasi-geology model

Wei and Sun (2022, GEOPHYSICS)

OUTLINE

- Introduction
- Part I: Building probabilistic quasi-geology model
  - Methodology
  - Geological setting and geophysical data
  - Probabilistic geology differentiation
- Part II: Predicting mineral resources
- Conclusions

OUTLINE

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- Part I: Building probabilistic quasi-geology model
  - Methodology
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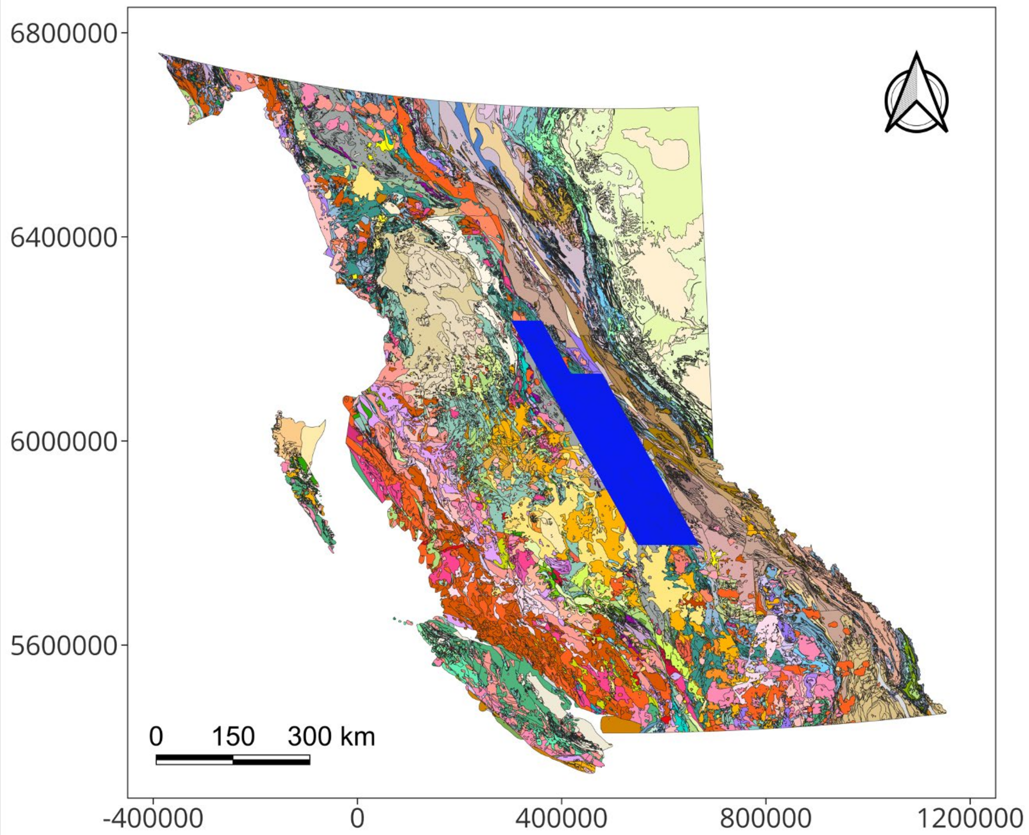
- **Part II: Predicting mineral resources**
- Conclusions

Research background

- QUEST area, British Columbia, Canada
- Plenty of mineral resources



Cui et al. (2017, BC Digital Geology)

Research background

- QUEST area, British Columbia, Canada
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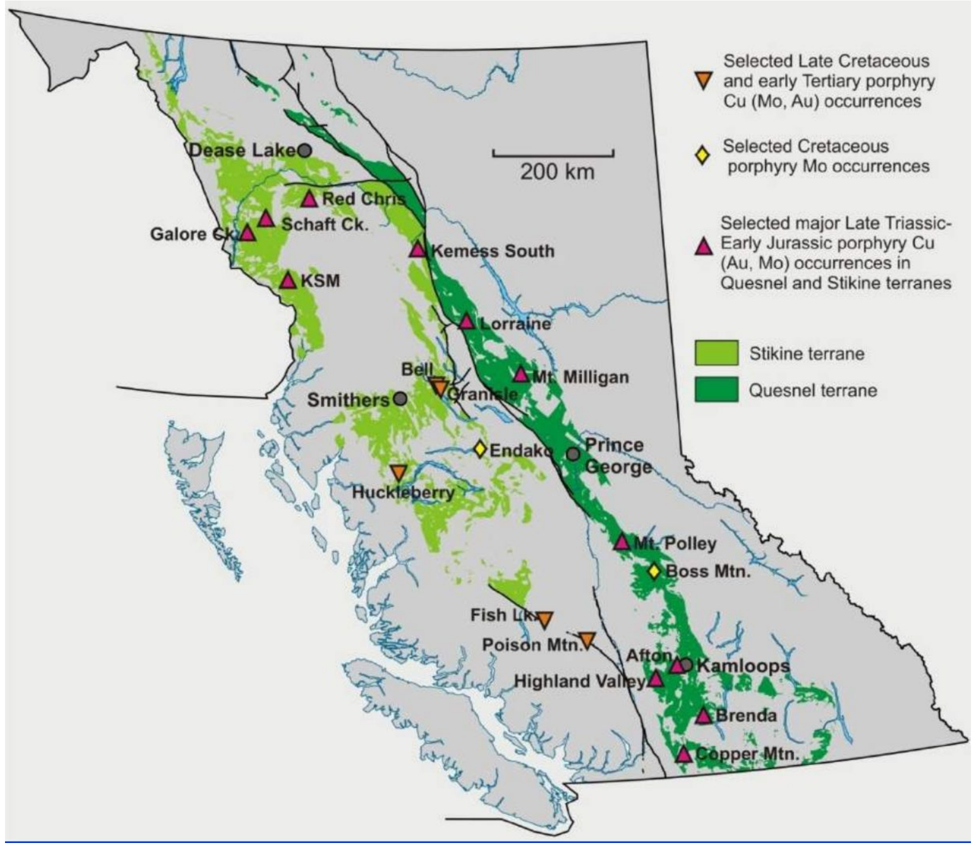

Logan & Schiarizza (2011, BCGS talk)

Research background

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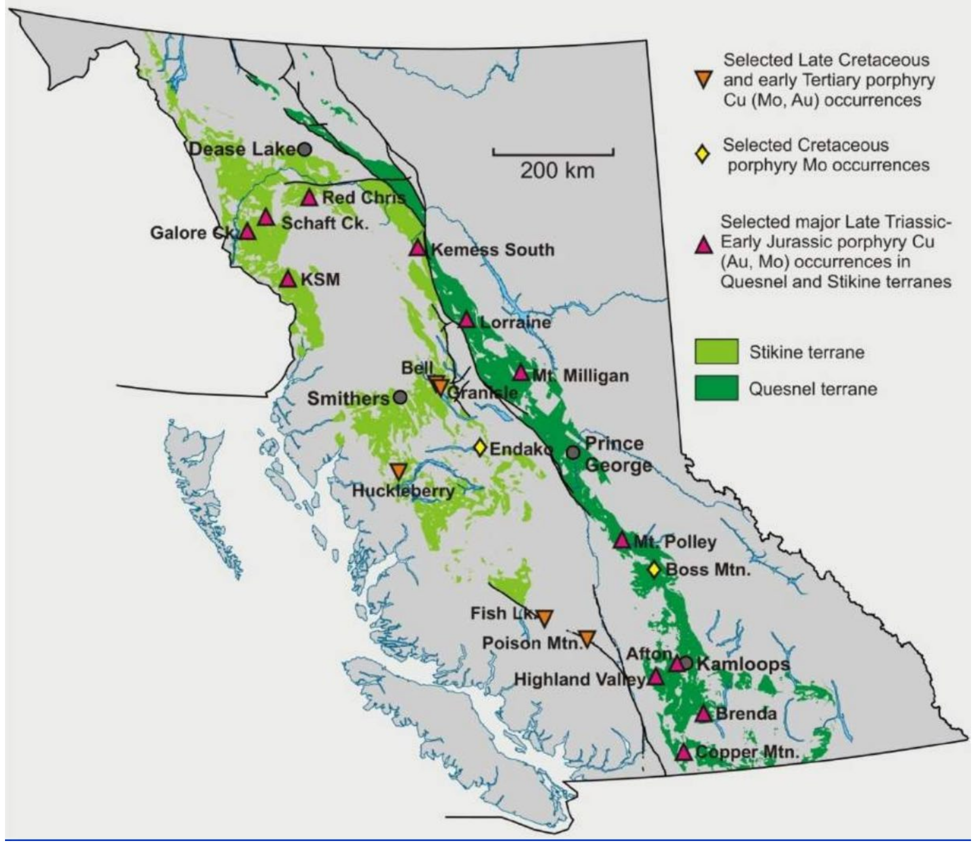
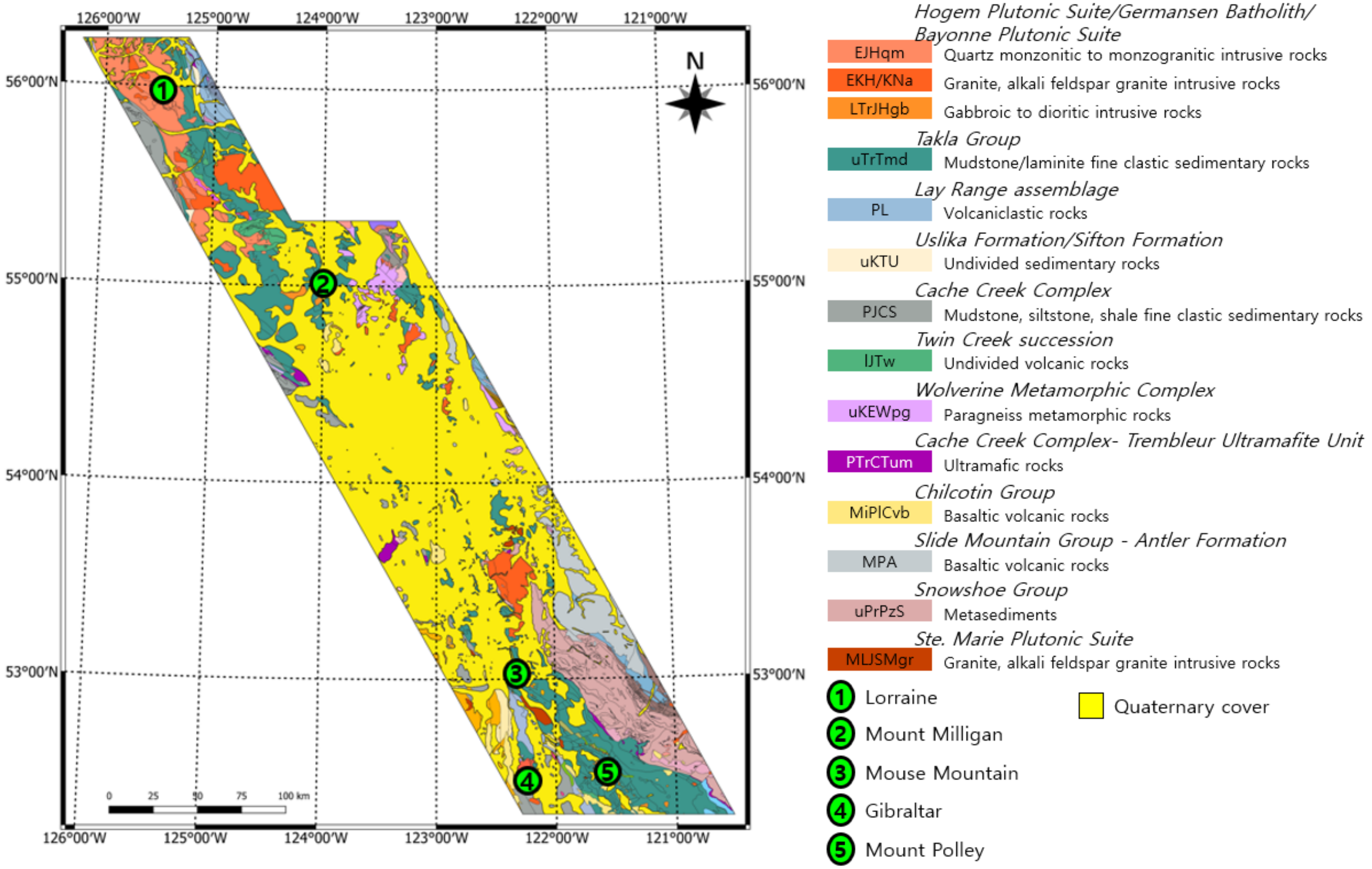
- Plenty of mineral resources



Logan & Schiarizza (2011, BCGS talk)

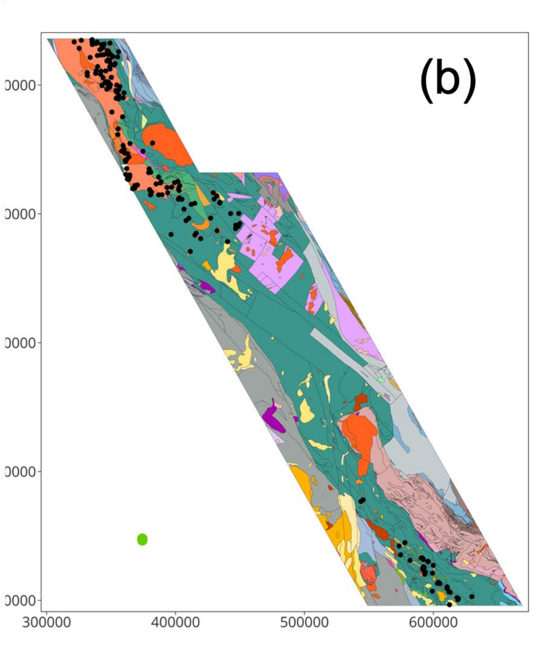
Challenge: a thick layer of Quaternary glacial sediments (yellow area)



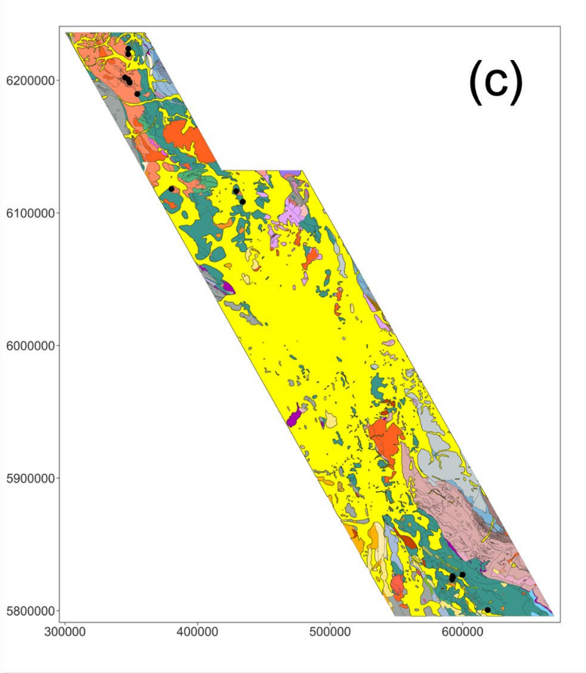
Cui et al. (2017, BC Digital Geology)

An overview of data

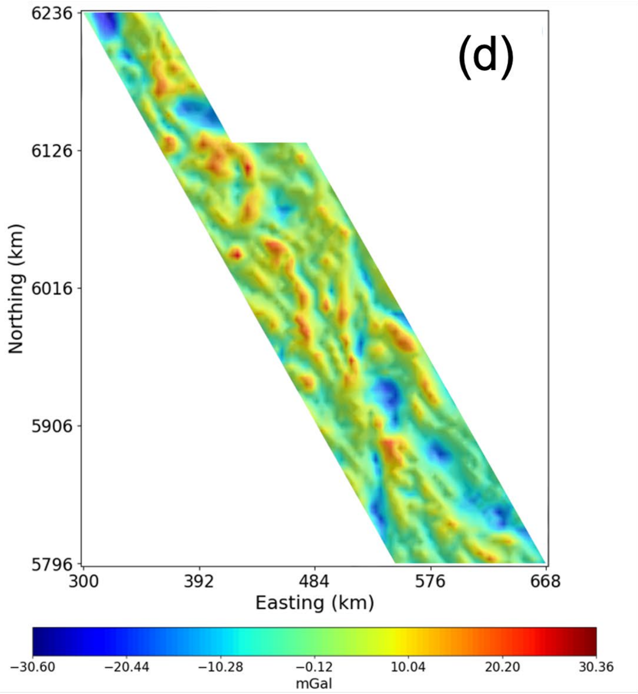
Bedrock map & rock sample measurements (black dots are copper-gold porphyry)



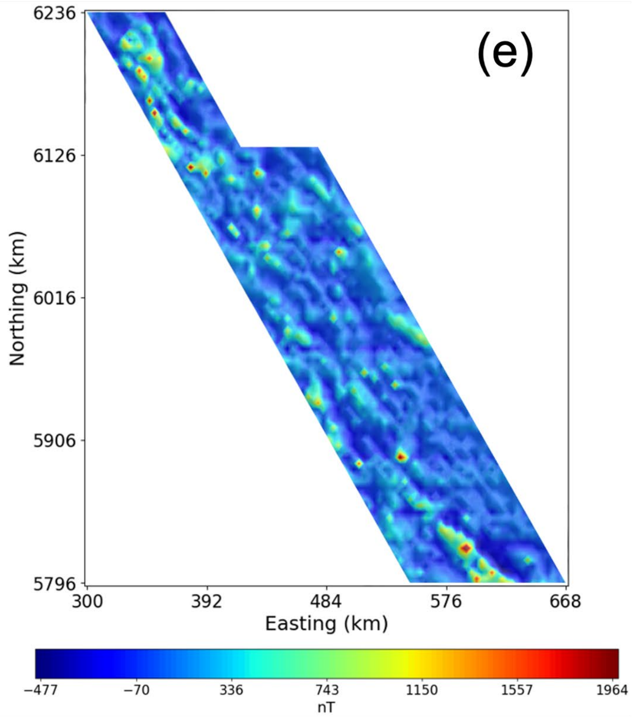
Sediments



Airborne gravity



Airborne magnetic



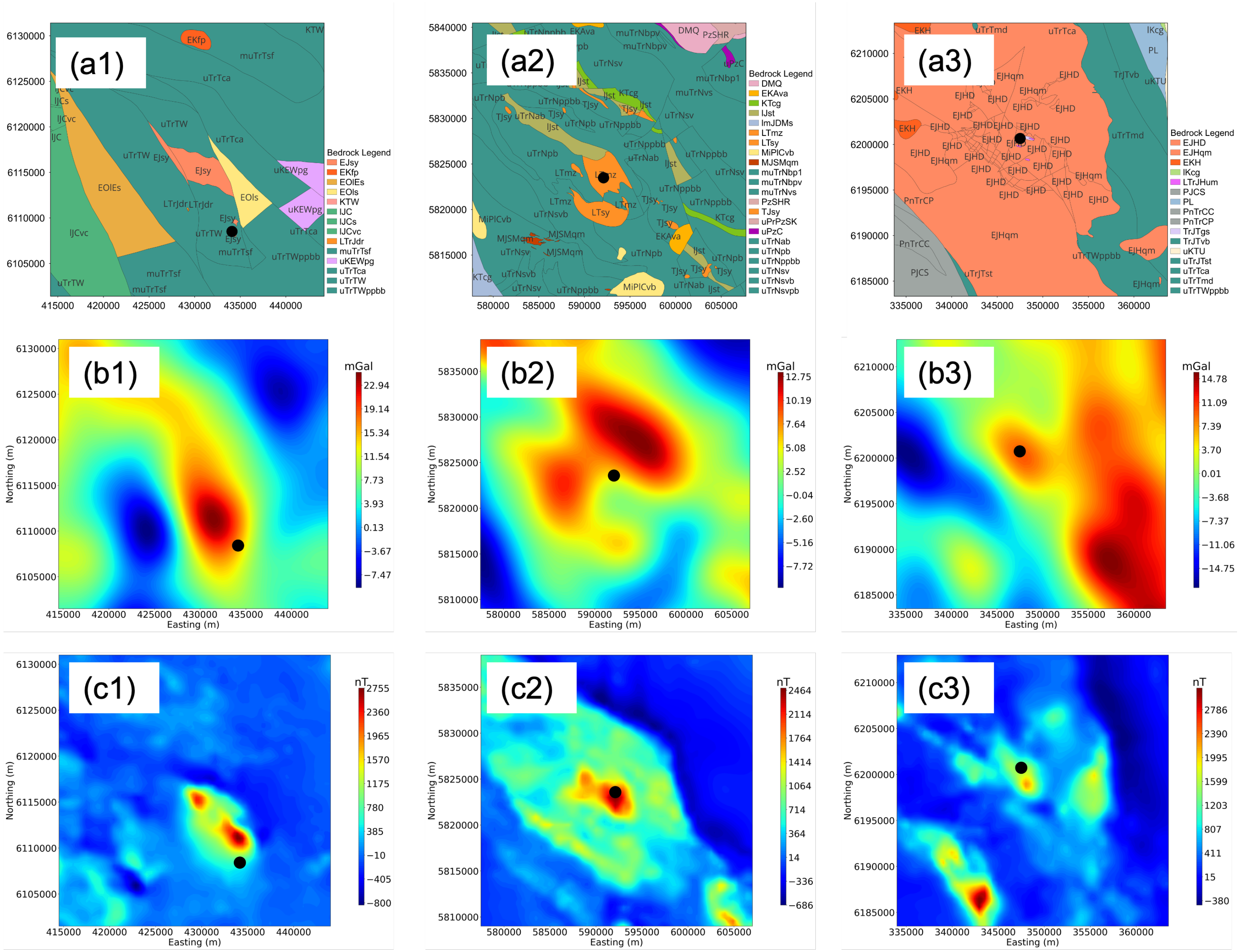
Wei et al. (2023, to be submitted)

Geology & geophysical response of porphyry copper-gold deposits

Bedrock maps

Gravity

Magnetic



Wei et al. (2023, to be submitted)

Mt. Milligan

Mt. Polley

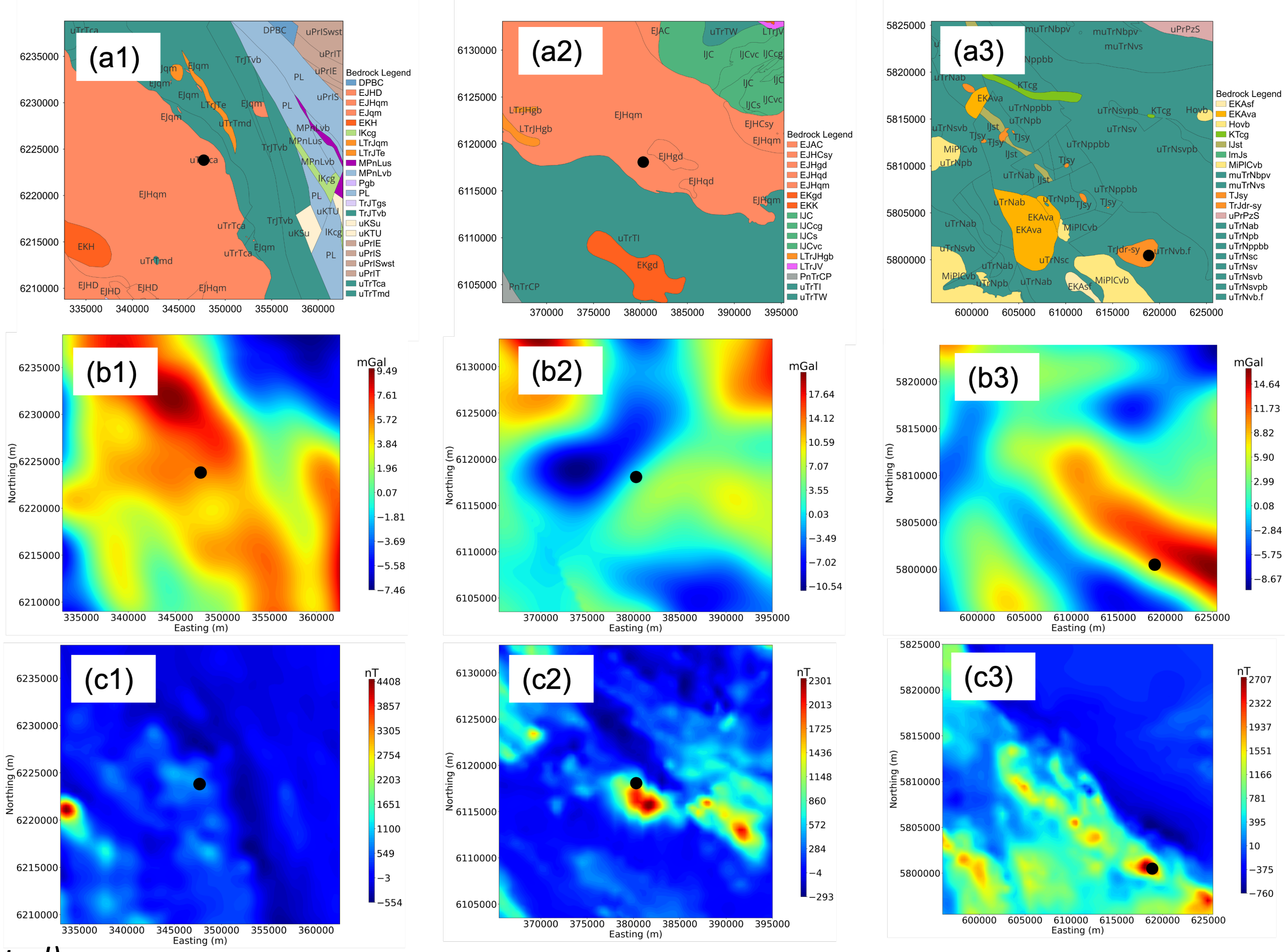
Lorraine

Geology & geophysical response of porphyry copper-gold deposits

Bedrock maps

Gravity

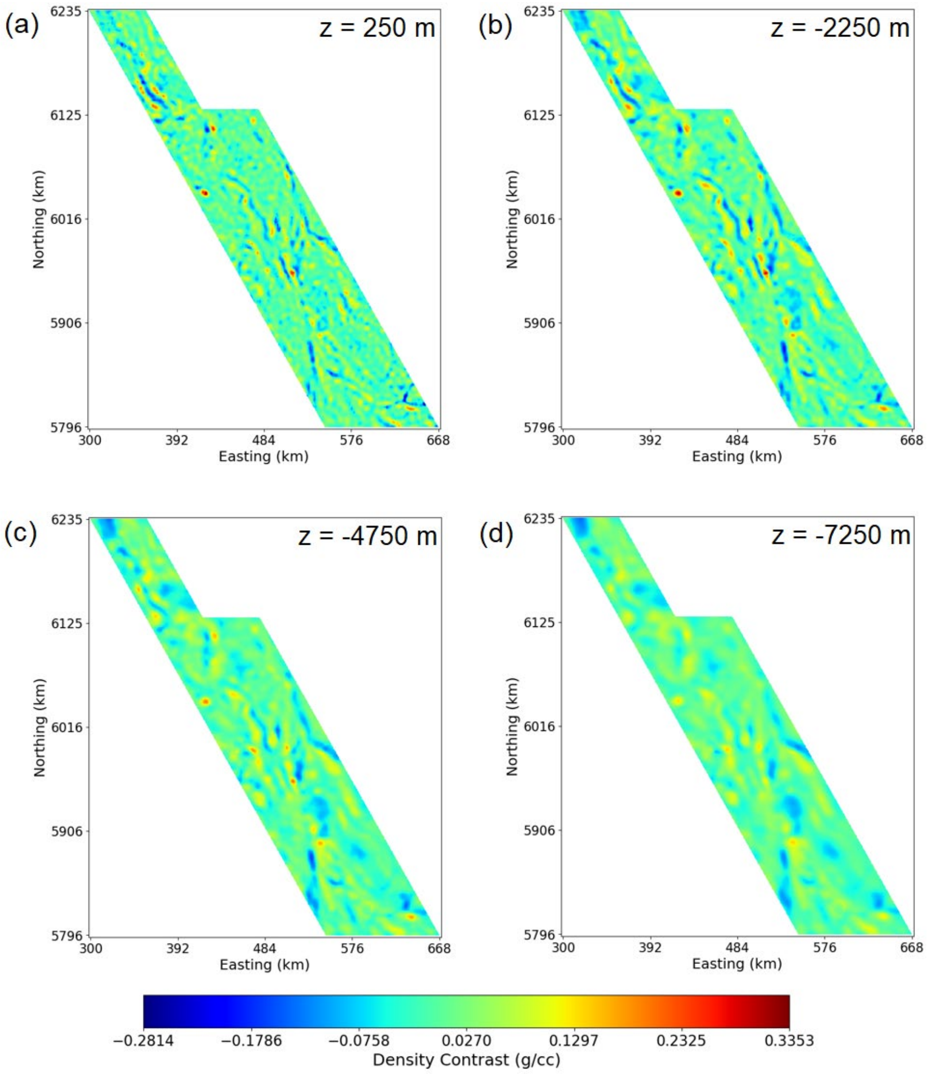
Magnetic



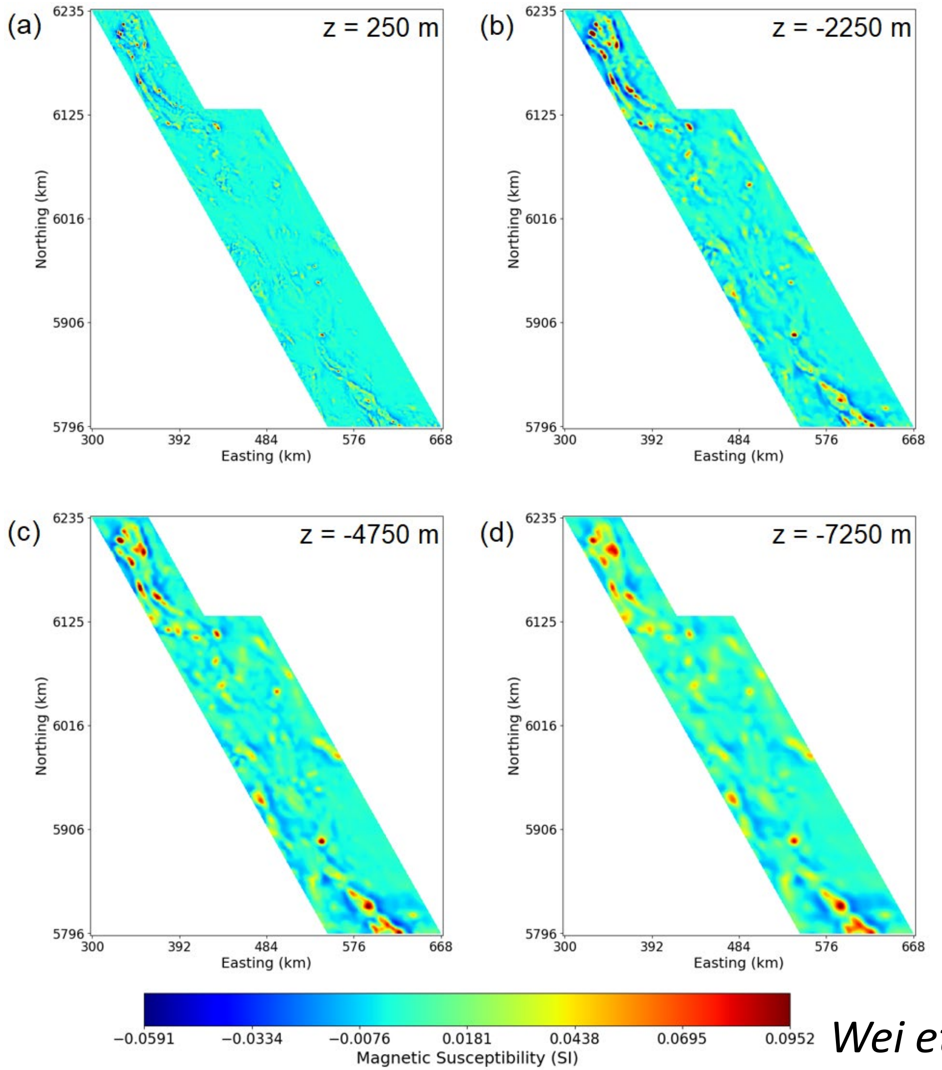
Wei et al. (2023, to be submitted)

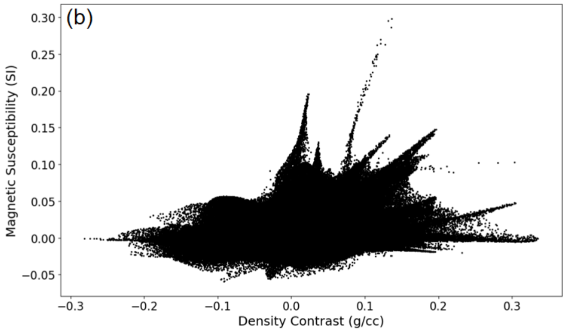
3D joint inversion for whole area (over 12 million model parameters)

3D density model at different depth



3D susceptibility model at different depth

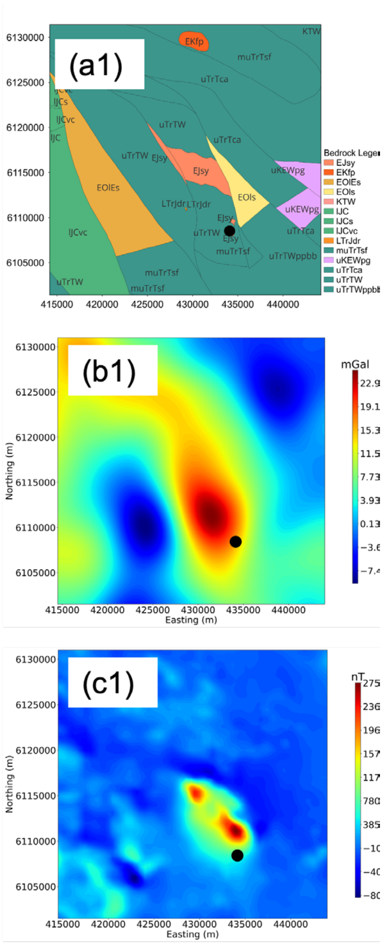




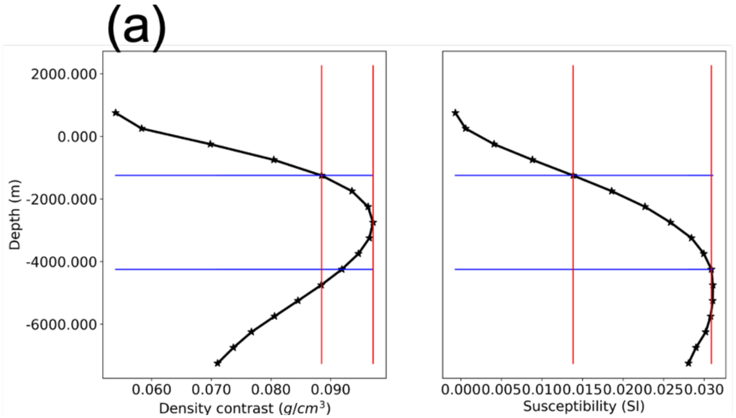
Wei et al. (2023, to be submitted)

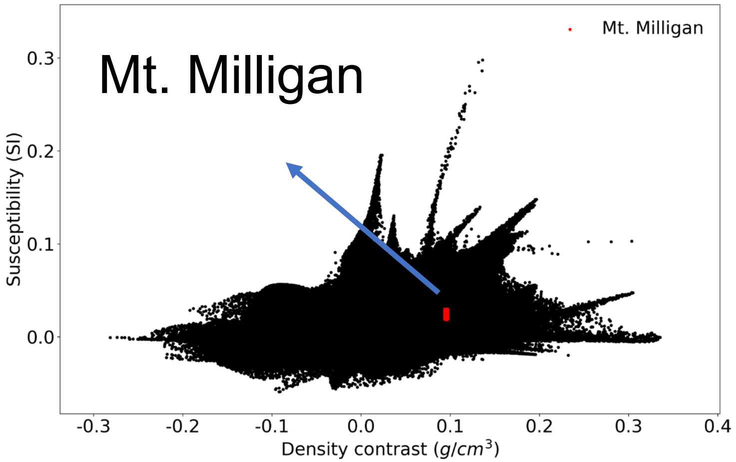
Mapping mineral resources

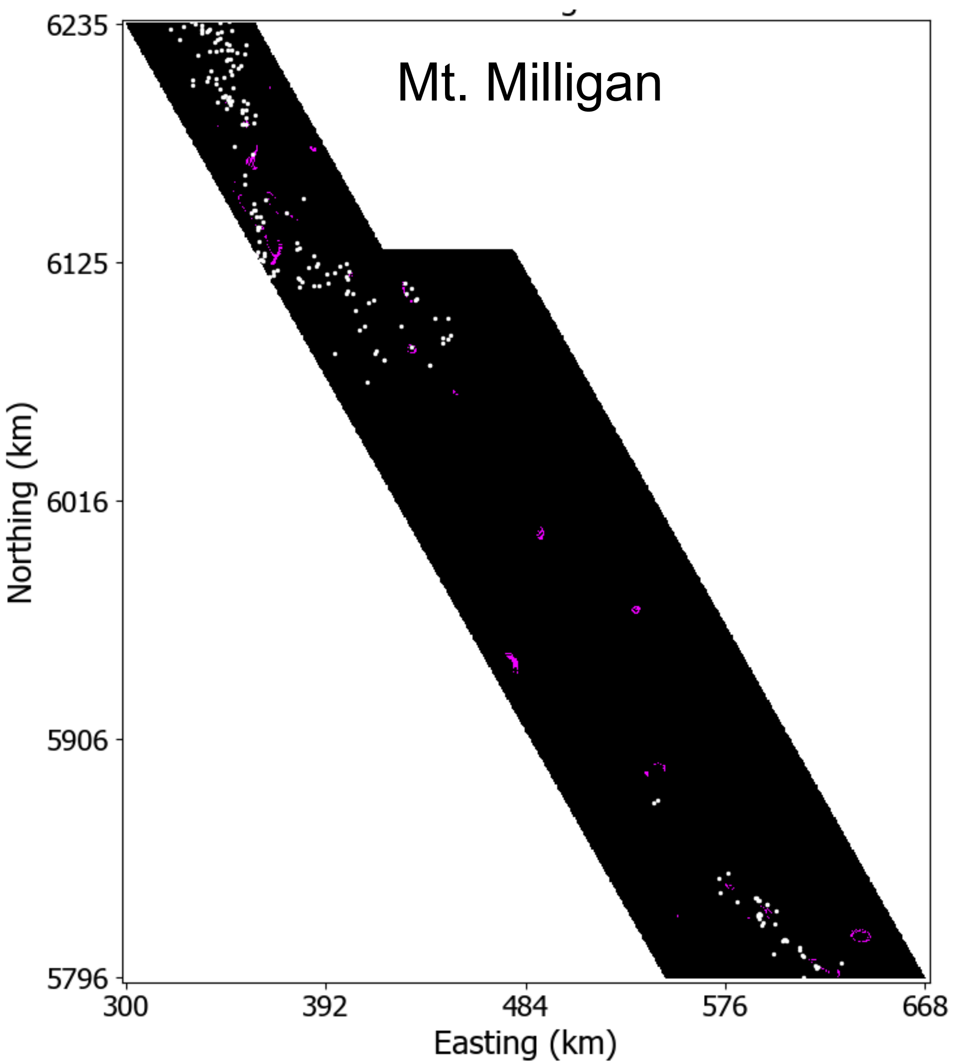
Mt. Milligan
(Intermedia gravity and lower magnetic signals)



Extract density and susceptibility in depth



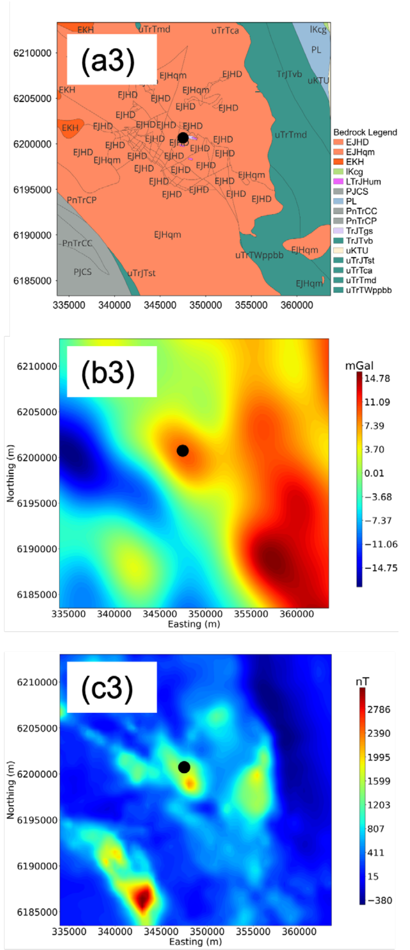




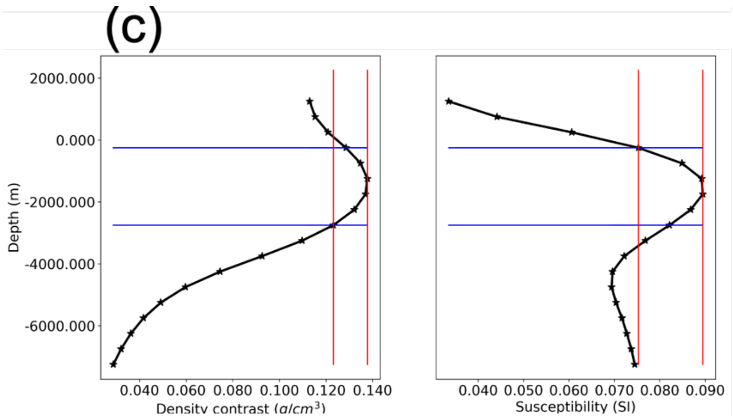
Wei et al. (2023, to be submitted)

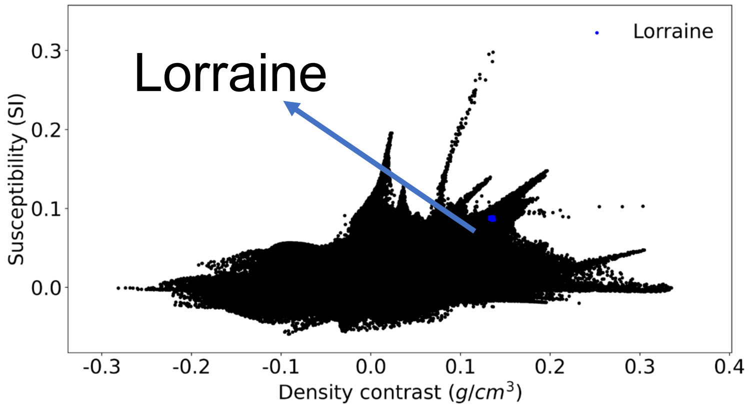
Mapping mineral resources

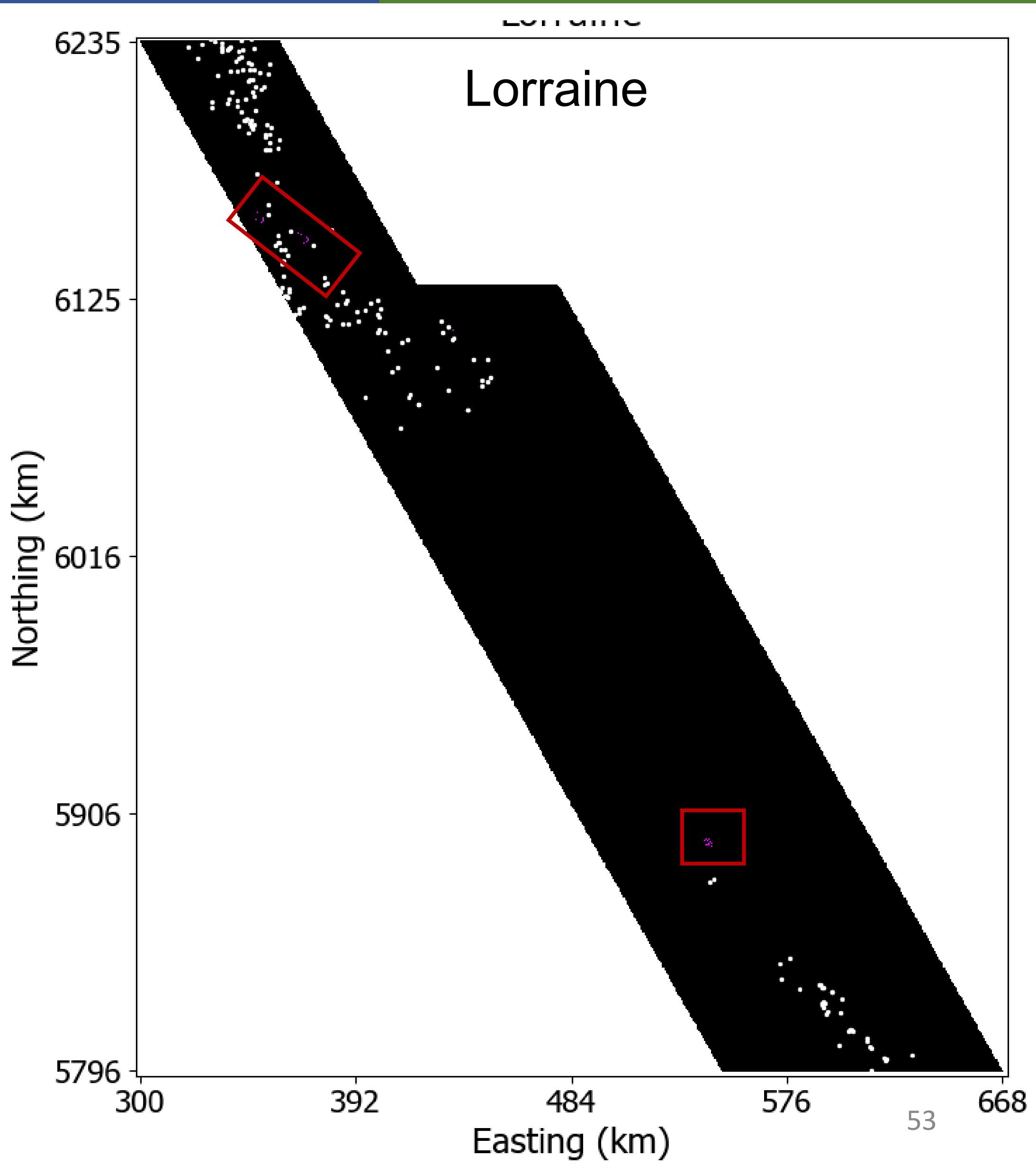
Lorraine
(Strong gravity and magnetic signals)



Extract density and susceptibility in depth

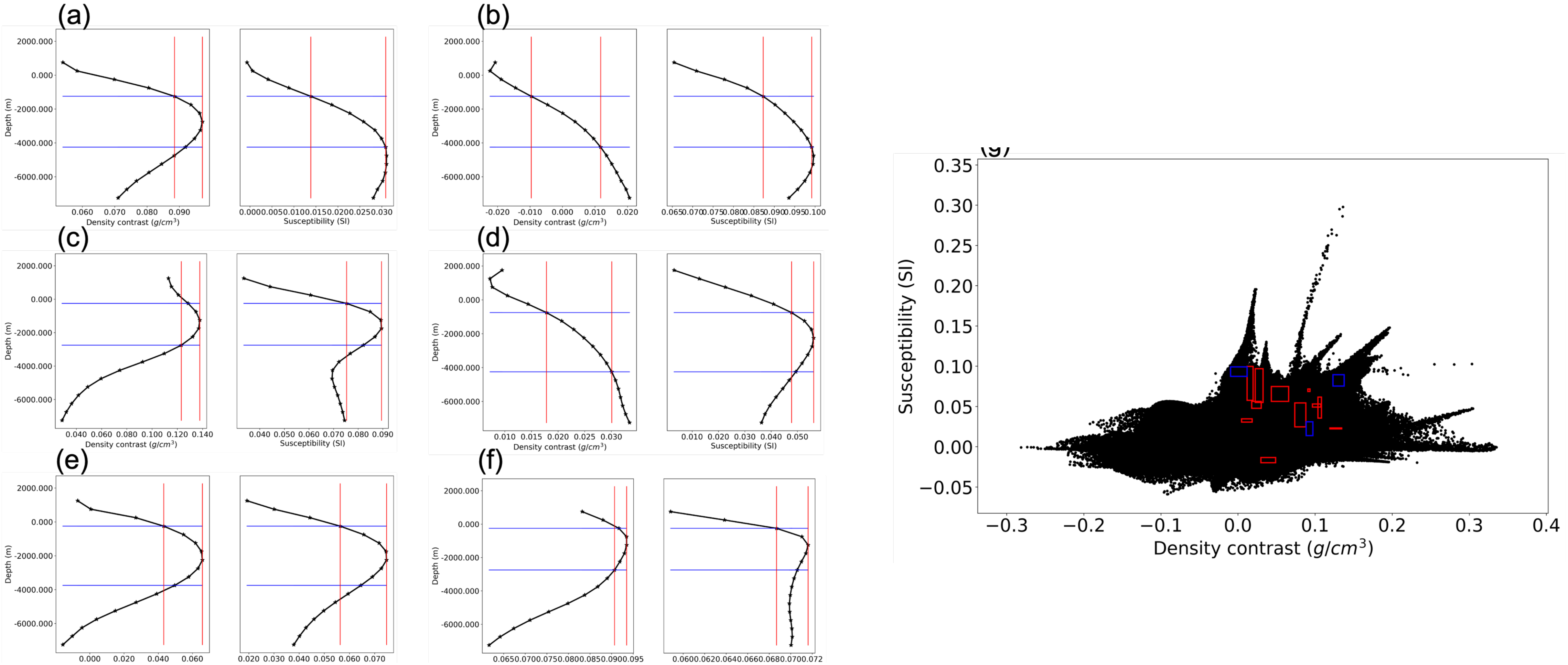




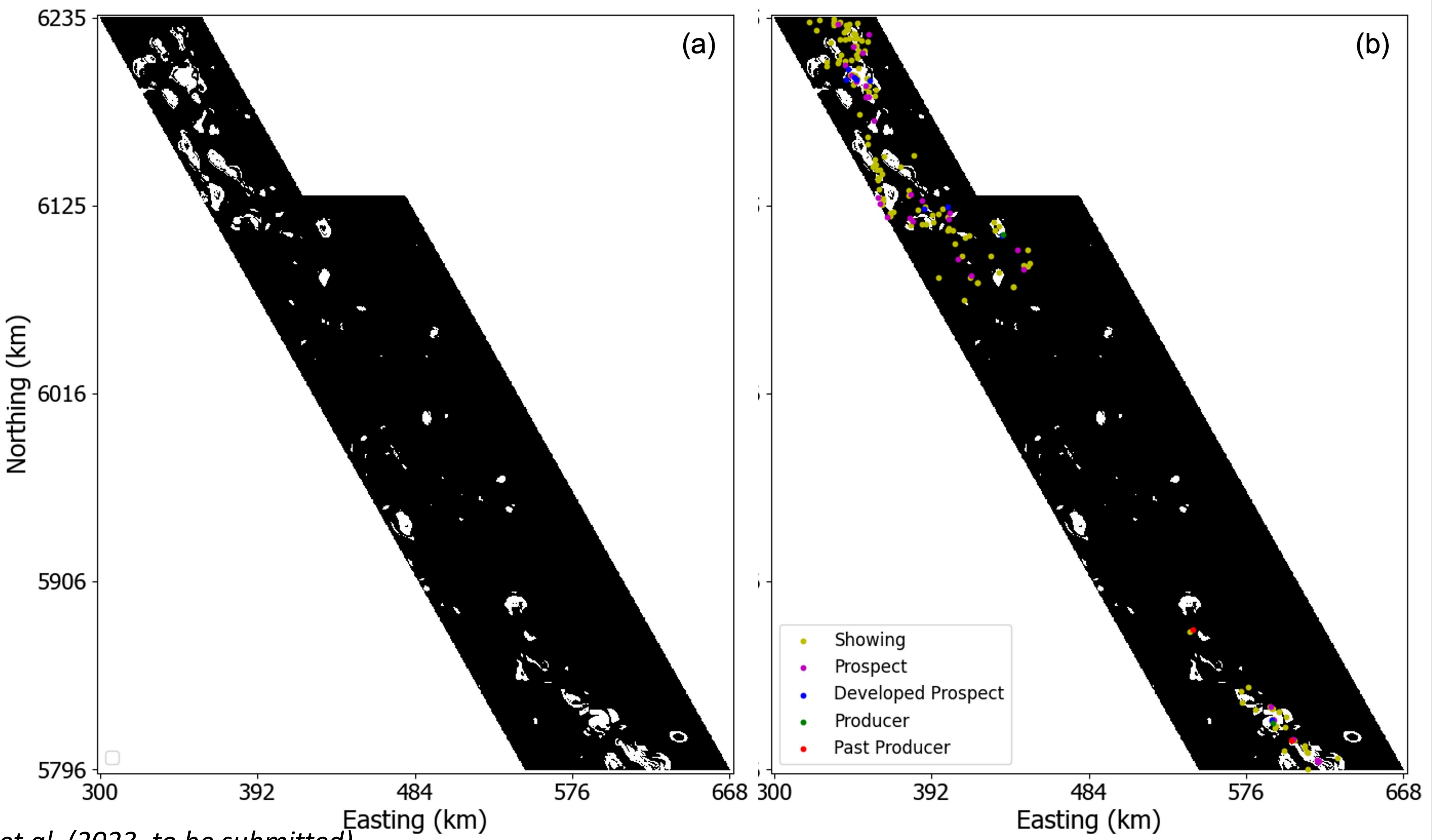


Wei et al. (2023, to be submitted)

Mapping mineral resources



Wei et al. (2023, to be submitted)



Wei et al. (2023, to be submitted)

Discussions

- Our differentiation and prediction work is based on regularized inversions of geophysical data.

- Therefore, it is fundamentally limited by the spatial resolution of geophysical data and regularization.

- Some of the features might be due to smoothing.

- Machine learning methods can be useful for automating and improving the results.

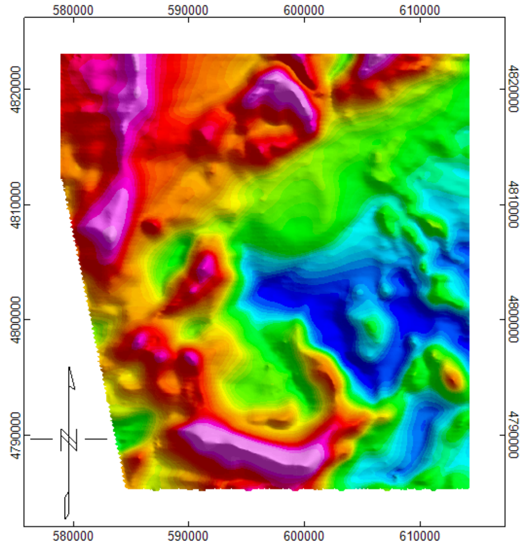
Conclusions

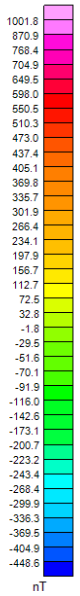
- Develop an empirical method to construct 3D probabilistic quasi-geology models.
- Physical property measurements used to accept and reject inverted models.
- Analyze uncertainties of spatial distribution for geologic units.
- Quantify uncertainties of lithologic types at any location in research area.
- Uncertainty provides new constraints for interpretations and should always be considered

Conclusions

- Extract geophysical signatures from randomly selected sites (training set).
- Make predictions of potential mineral resources (test set).
- Represent testable hypotheses and provide guidance for future drilling activities and geophysical data acquisition.
- Building quasi-geology models and predicting mineral resources help extract more information from geophysical data and maximize its value.

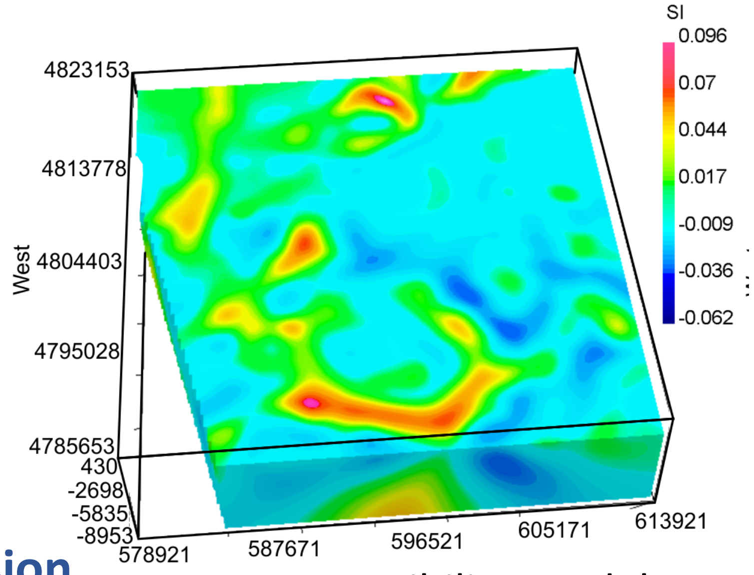
Conclusions



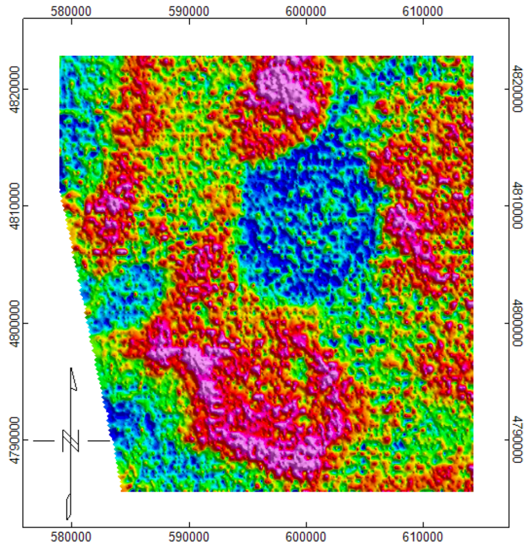


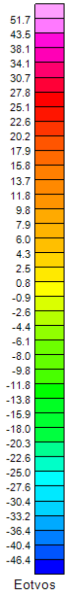
Magnetic data

Inversion

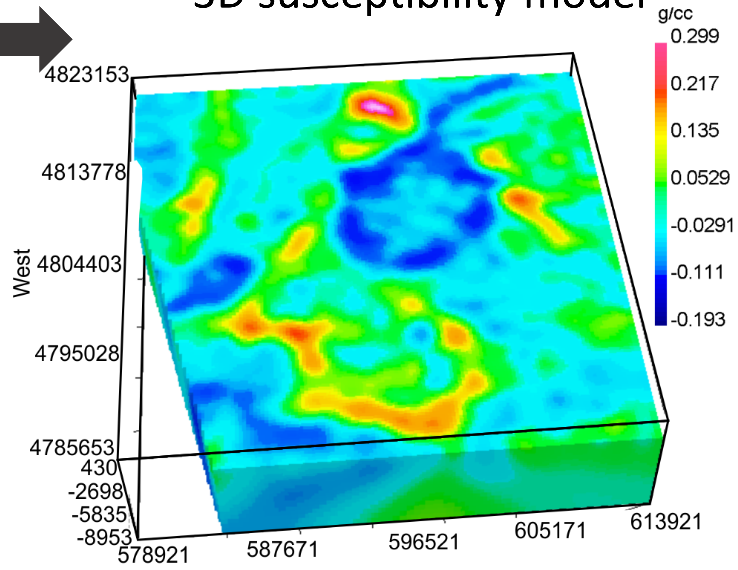


3D susceptibility model



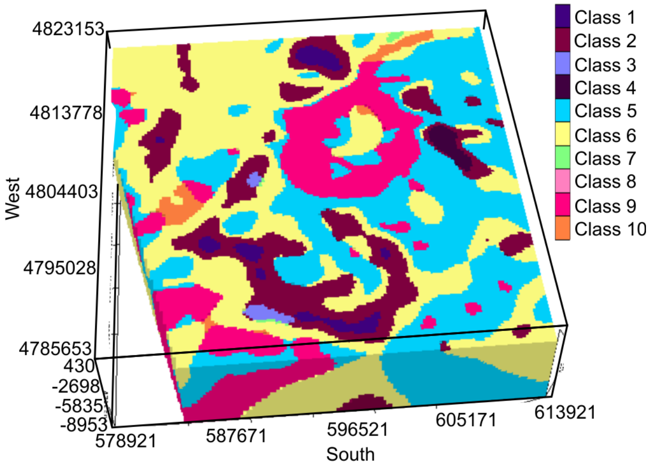


Gravity gradient data

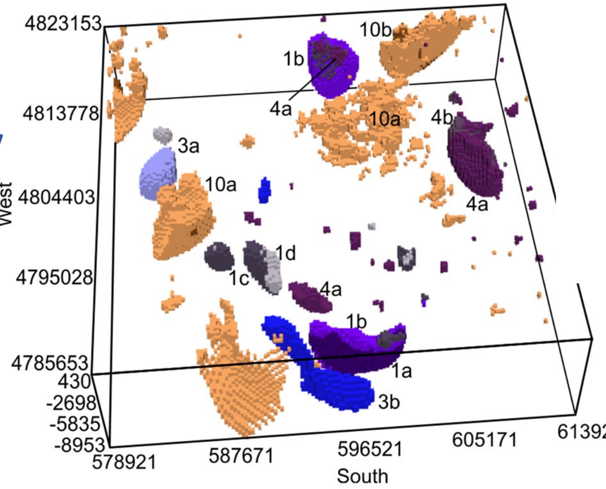


3D density contrast model

Differentiation



Mineral prospectivity



Sun et al. (2020, Interpretation)

ACKNOWLEDGMENTS

- Benjamin Drenth for making core sample measurements available for our work in the Decorah area.
- The SimPEG team for developing the open source package upon which we built our work.
- HPE Data Science Institute at University of Houston for the computing resources.

THANKS FOR YOUR ATTENTION!

QUESTIONS?

Existing methods for uncertainty analysis

MC sampling

Mosegaard and Tarantola, 1995; Sambridge, 1995; Malinverno, 2002; Bodin, 2009; Agostinetti and Malinverno, 2010; Piana Agostinetti et al., 2015; Zhang et al., 2018, 2020.

Model covariance matrix

Alumbaugh and Newman, 2000; Duet and Sinoquet, 2006; Osypov et al., 2013; Zhu et al., 2016; Eliasson and Romdhane, 2017

Null space shuttles

Deal and Nolet, 1996; Munoz and Rath, 2006; De Wit et al., 2012; Fichtner and Zunino, 2019

Varying initial models or reference models

Kelbert et al., 2012; Maag-Capriotti and Li, 2019

Physical property models

Computational time

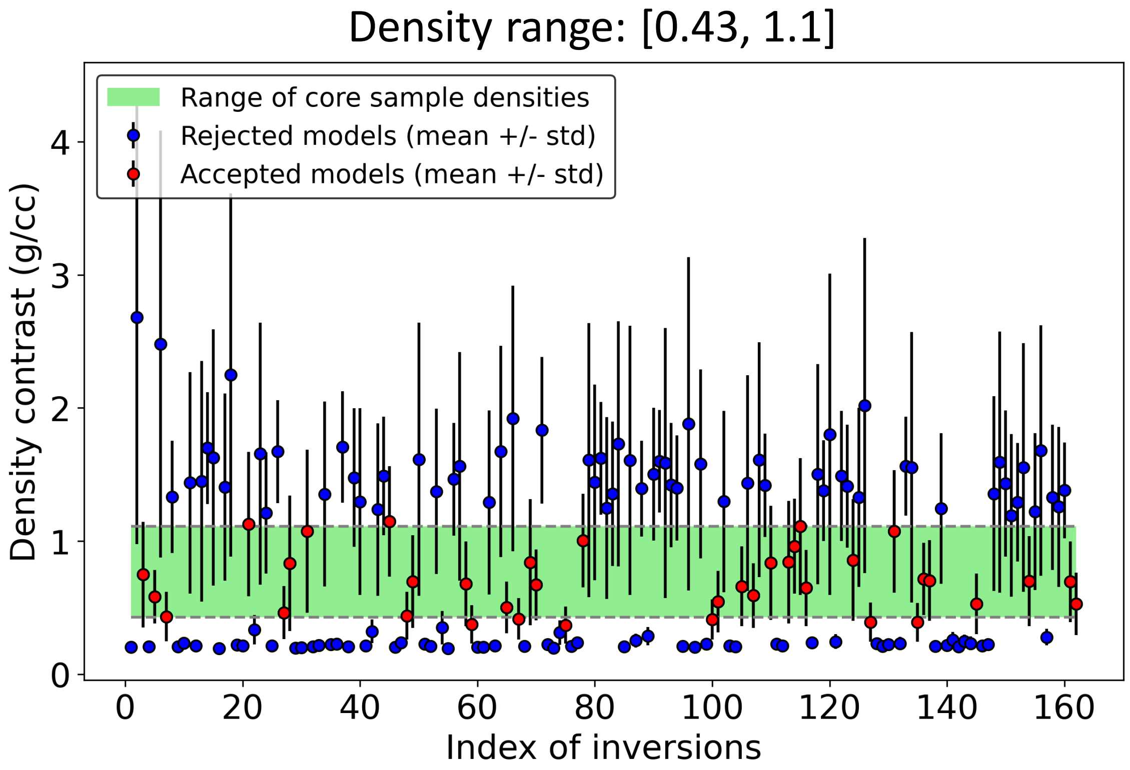
	Our method	MC sampling
Unknown parameters	287100	Up to few thousand
Computational time	Less than 1 month (12 cores and 256 Gb memory)	Few weeks to months

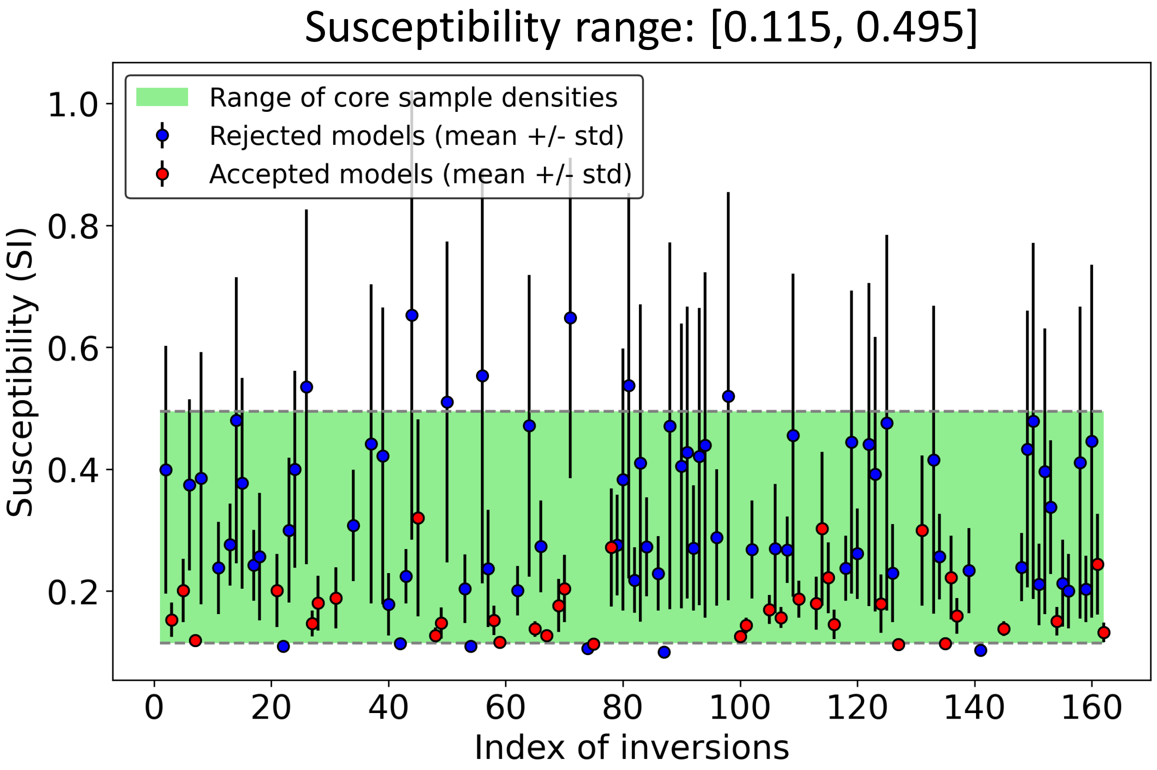
Mixed Lp norm joint inversion is time consuming, but it is manageable!

Why 162 inversions

Wei and Sun (2020) noted that the 30 accepted models are enough to analyze uncertainties. We kept performing inversions until we obtained over 30 accepted models.

How to determine 37 accepted models





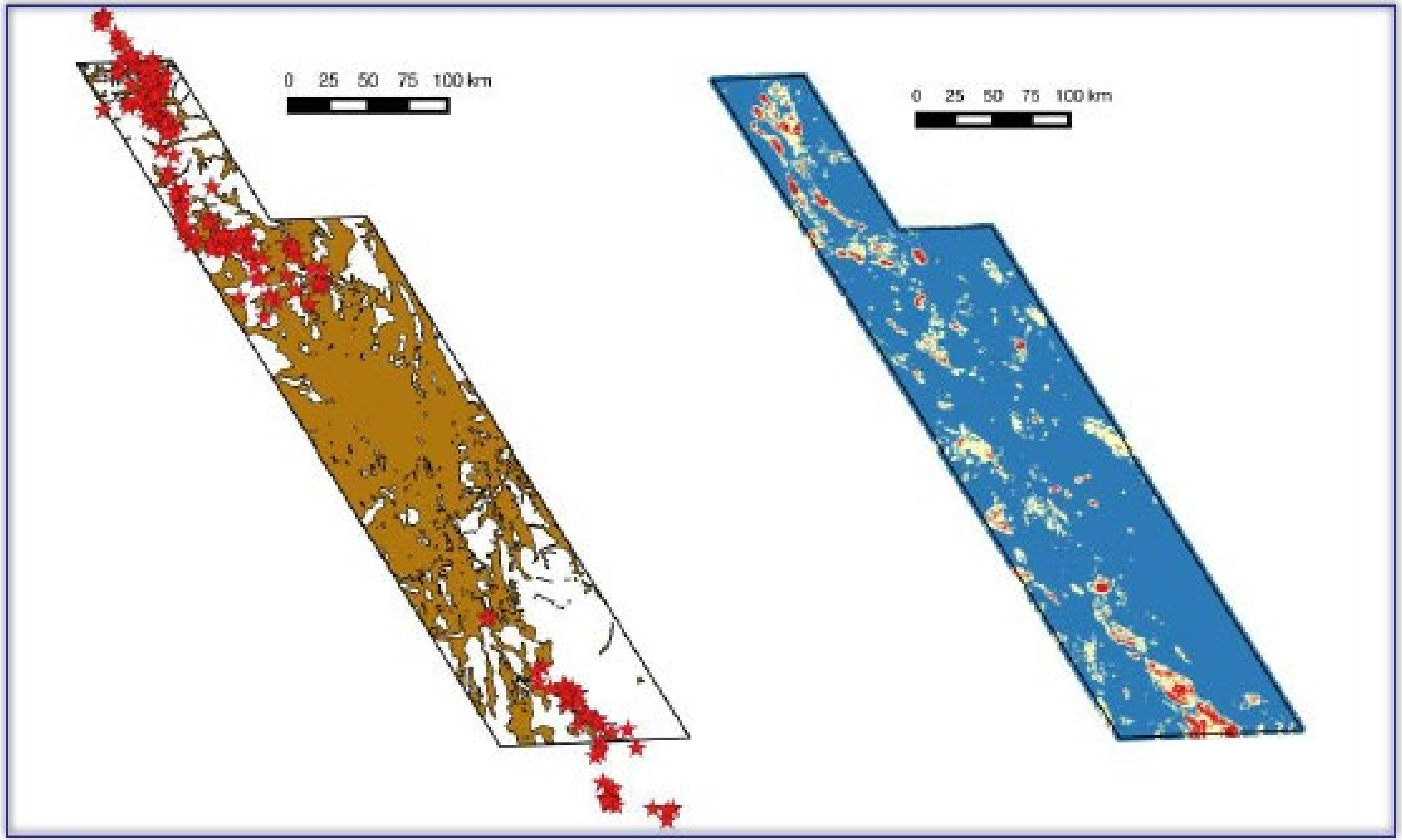
Can machine learning classify geologic units?

No,

- ❖ We don't have enough labels for supervised machine learning in our research area
- ❖ If we have labels (drillhole sample measurements), the inverted values are still different with rock sample measurements. We need to shift the inverted values (more research need here).

Yes,

- ❖ Geology differentiation by applying unsupervised machine learning to multiple independent geophysical inversions (Melo and Li, 2021)



Left: Known mineralization & overburden **Right:** Predicted mineral potential (red is high)