

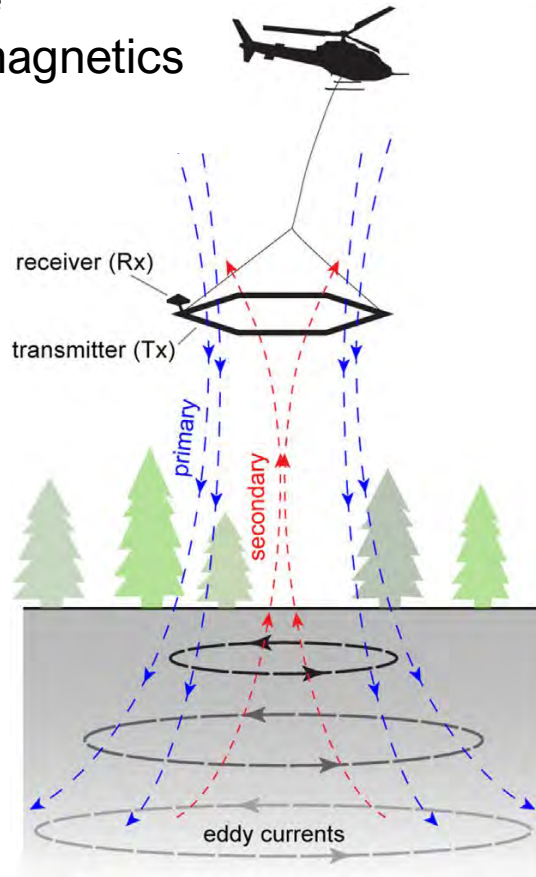


Current research on aquifer heterogeneity at the Conservation and Survey Division

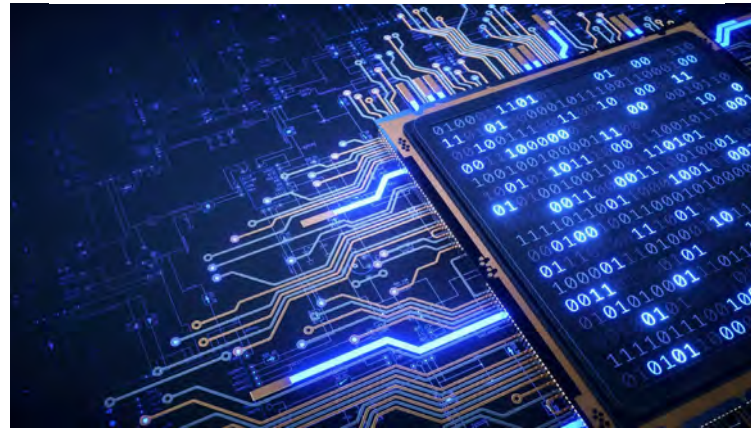
Jesse Korus – Associate Professor – University of Nebraska-Lincoln
Tewodros Tilahun – PhD Candidate – University of Nebraska-Lincoln
Nafyad Kawo – PhD Candidate – University of Nebraska-Lincoln

Combining modern methods to advance our understanding of aquifer heterogeneity

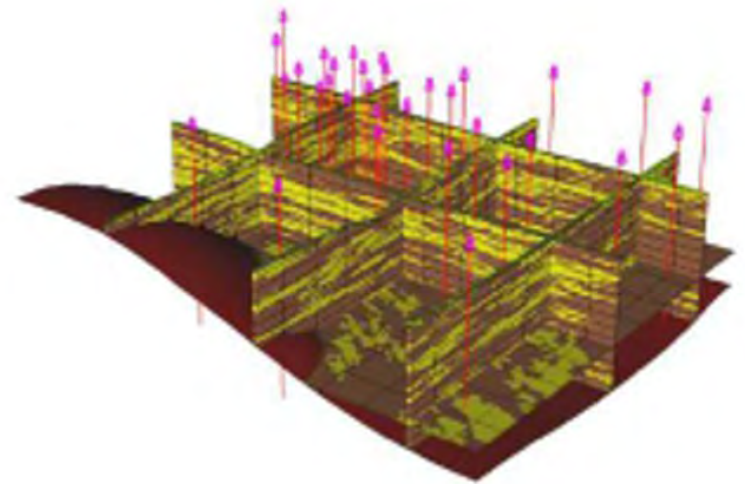
Airborne
Electromagnetics
(AEM)



Data Science, Statistics, &
Machine Learning



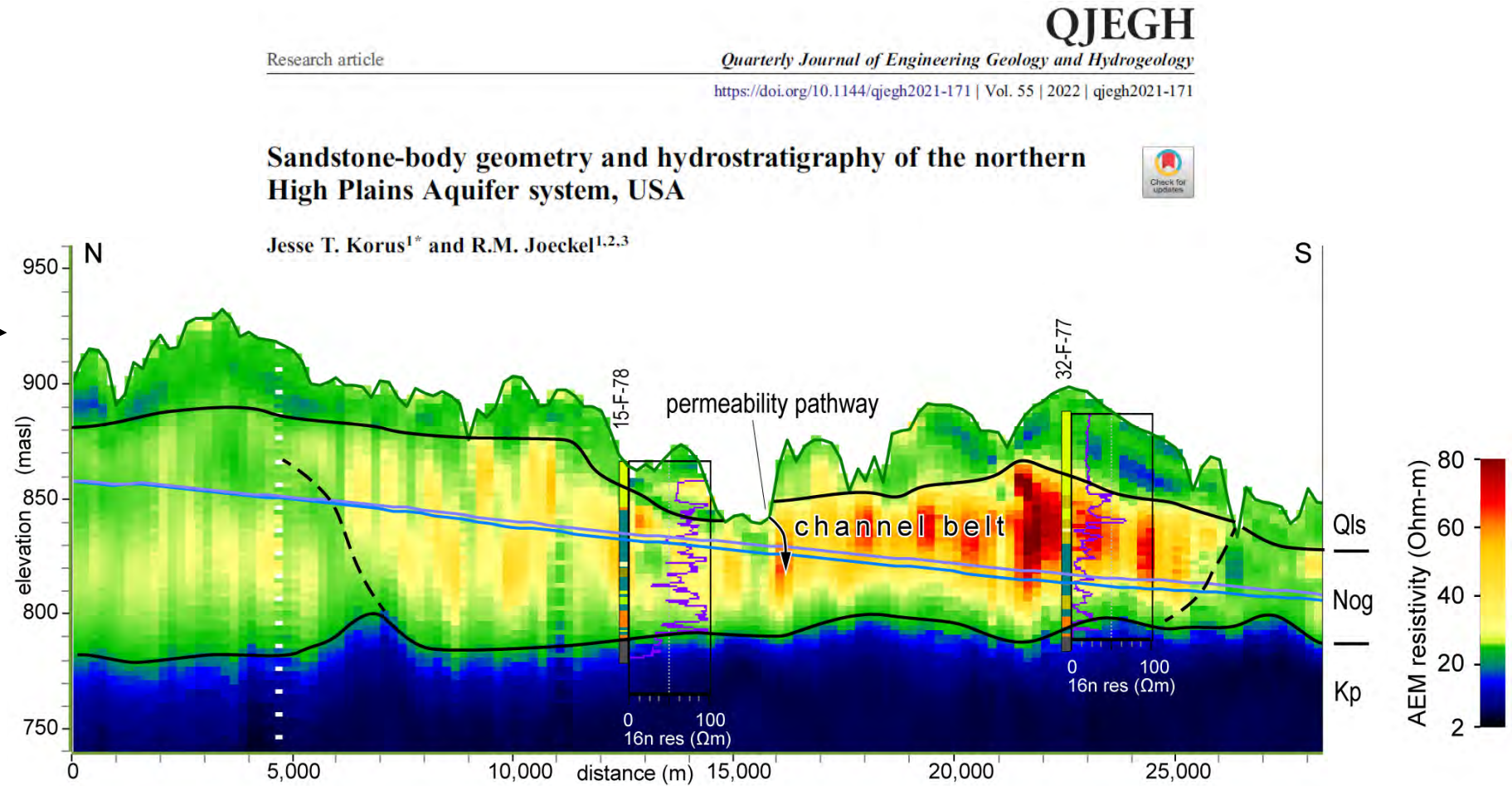
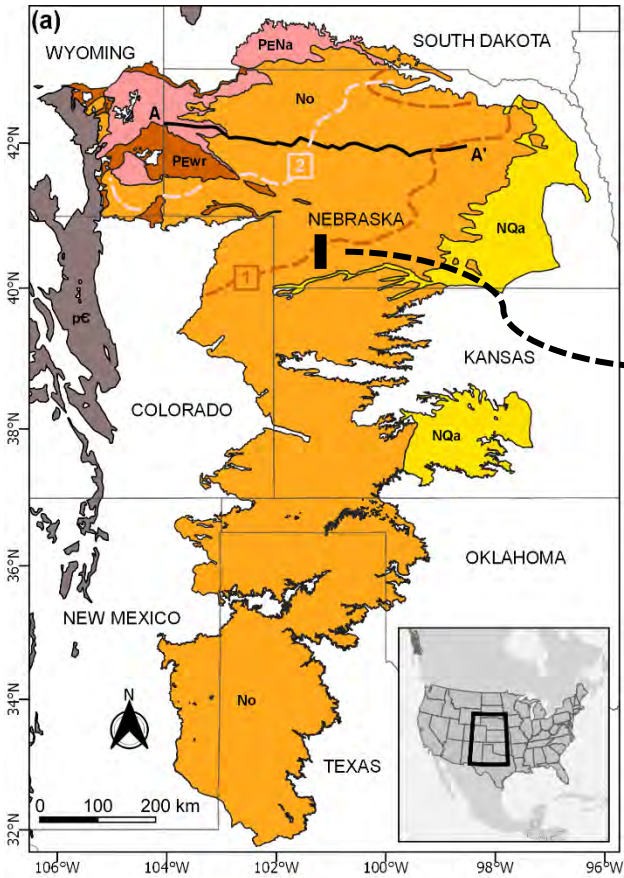
3D Geological Modeling



Acknowledgements

- Jackie (Polashek) Morrissey, MS, 2019
- Tewodros “Teddy” Tilahun, PhD Candidate
- Nafyad Kawo, PhD Candidate
- Middle Republican NRD
- Lower Platte North NRD
- Nebraska Department of Natural Resources
- Nebraska Water Sustainability Fund
- Nebraska Environmental Trust
- Daugherty Water for Food Global Institute
- USGS 104b Water Resources Research

AEM reveals new insights on fluvial channel bodies in the Ogallala Group

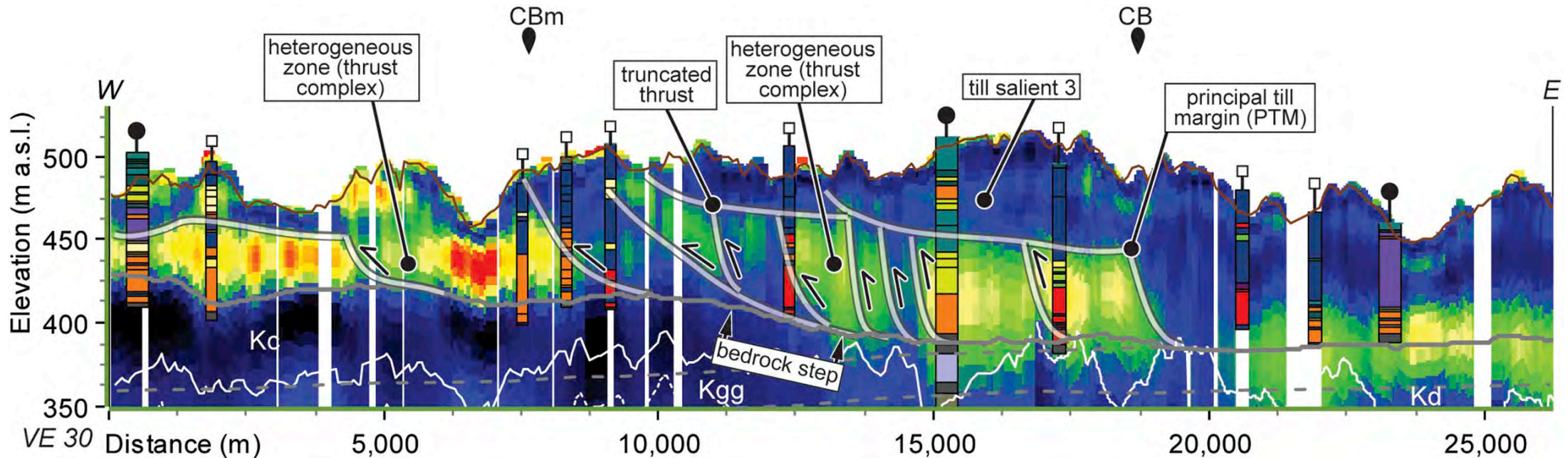
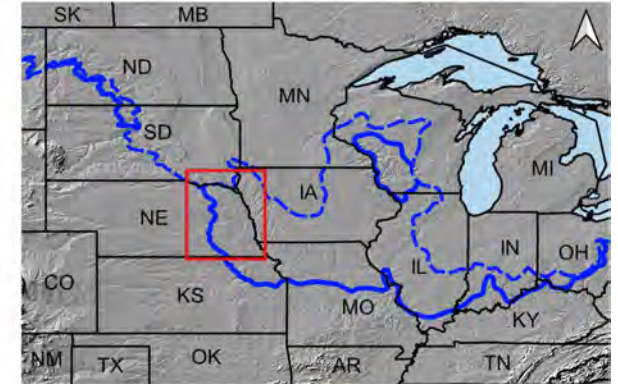
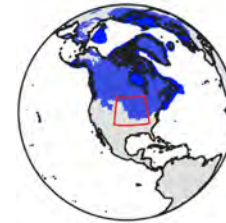


AEM reveals new insights on glacial geology in eastern Nebraska



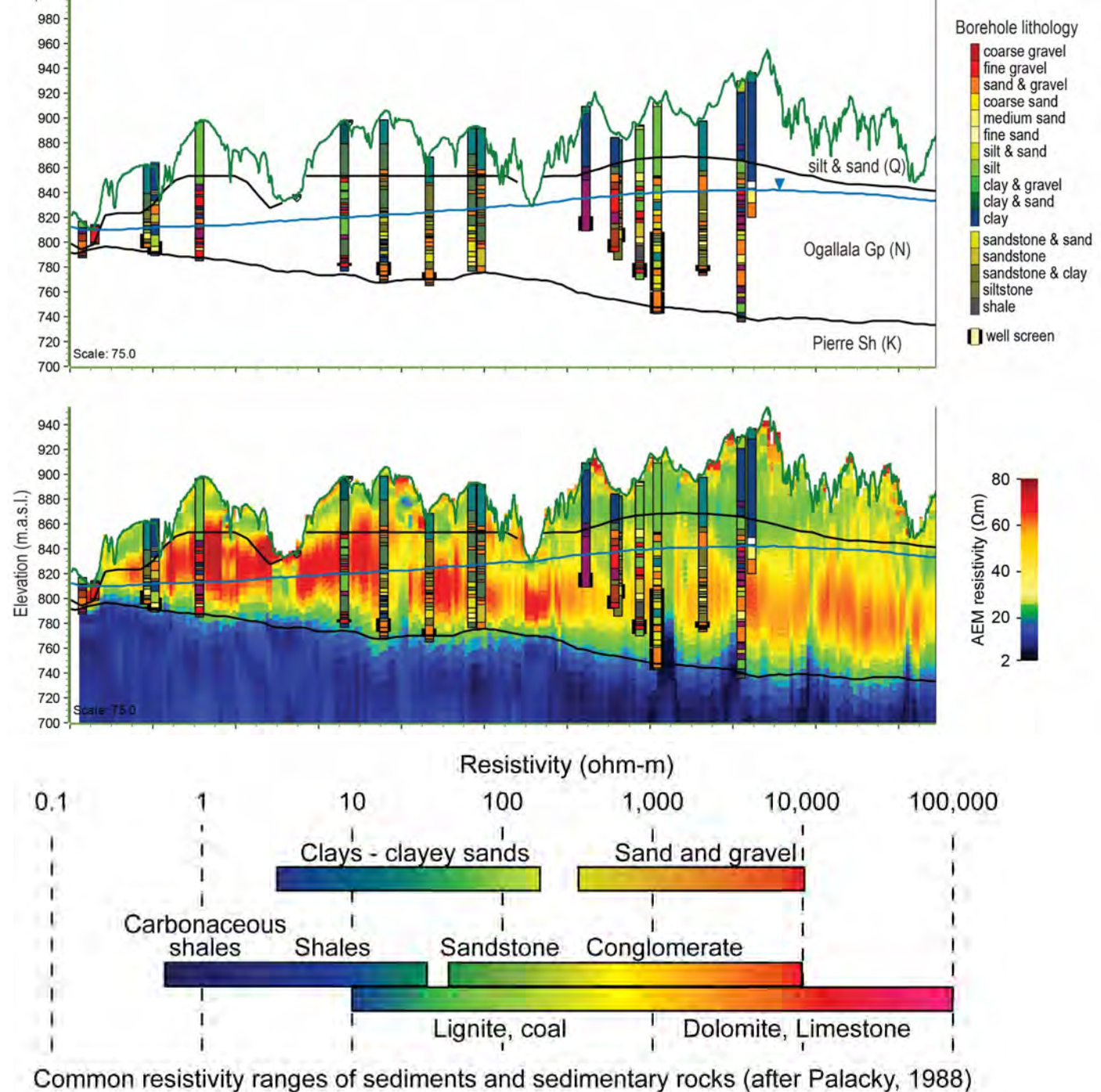
Reconstruction of pre-Illinoian ice margins and glaciotectonic structures from airborne ElectroMagnetic (AEM) surveys at the western limit of Laurentide glaciation, Midcontinent U.S.A.

Jesse T. Korus^{a,*}, R.M. Joeckel^{a,b}, Jared D. Abraham^c, Anne-Sophie Høyer^d, Flemming Jørgensen^e



Problem statement

- Groundwater resource managers demand models with improved resolution
 - Borehole lithology (of good quality) is sparse horizontally, but it has high vertical resolution.
- AEM resistivity has high horizontal resolution, but vertical resolution decreases with depth.
 - The relationship between resistivity and lithology is nonunique, nonlinear, & nonuniversal.

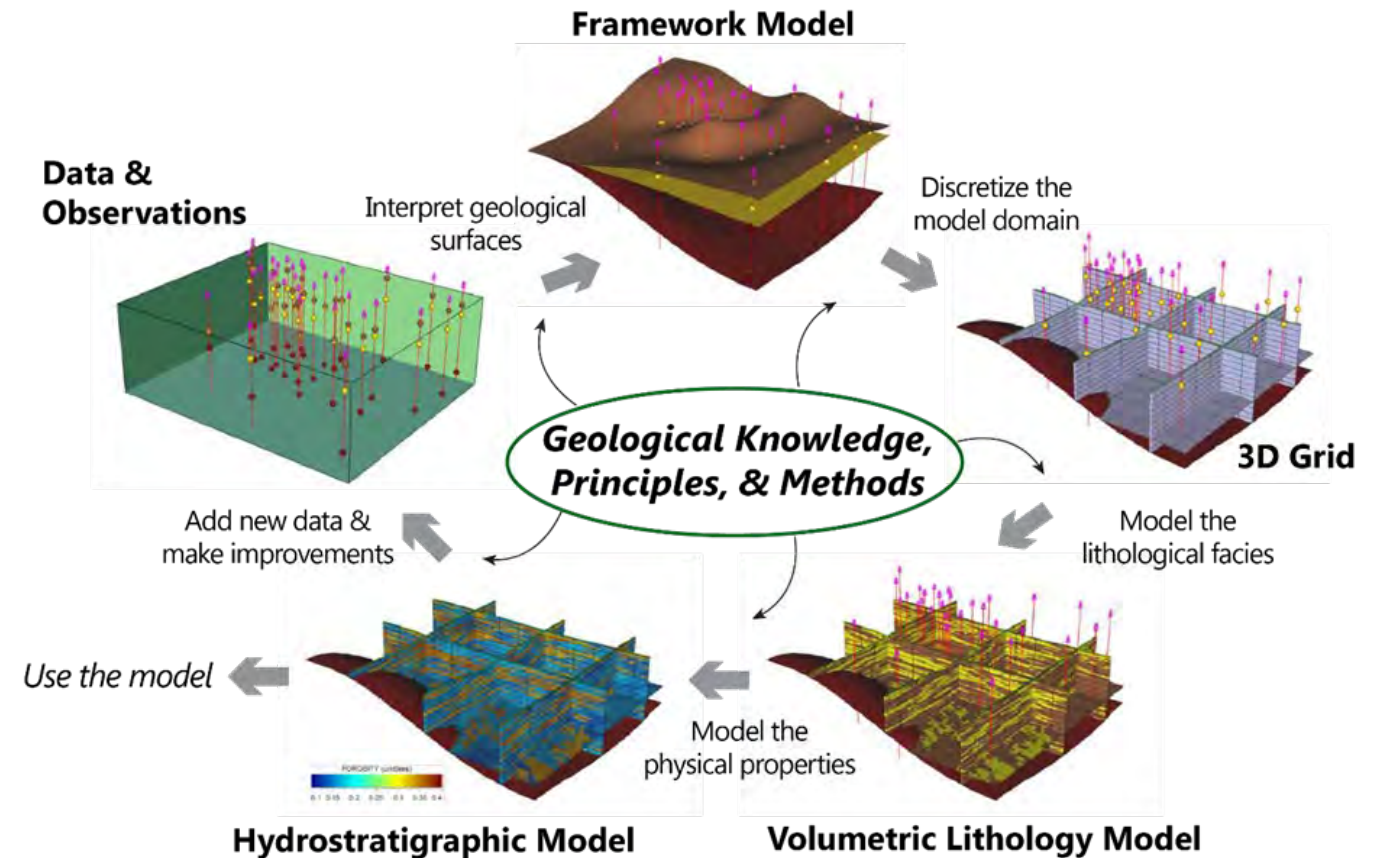


Research Question

- How can we combine dense AEM data and sparse borehole data to build robust 3D HSU models?

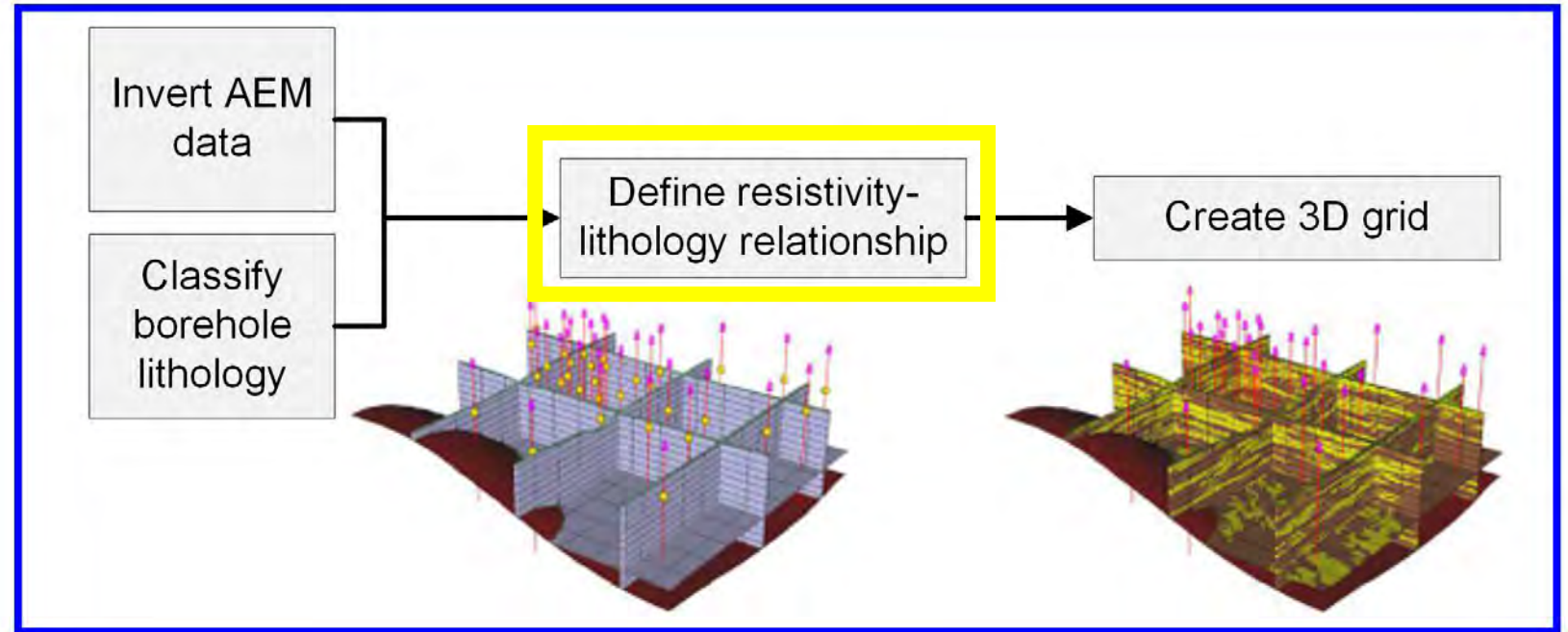
Objective

- Develop a fast, efficient workflow for automated prediction of HSUs from AEM and borehole lithology



Modified from Jerome, T., 2020, Intro/Geomodeling, Volume 2020, GMDK Geomodeling Knowledge. <https://gmdk.ca/science/intro-geomodeling>

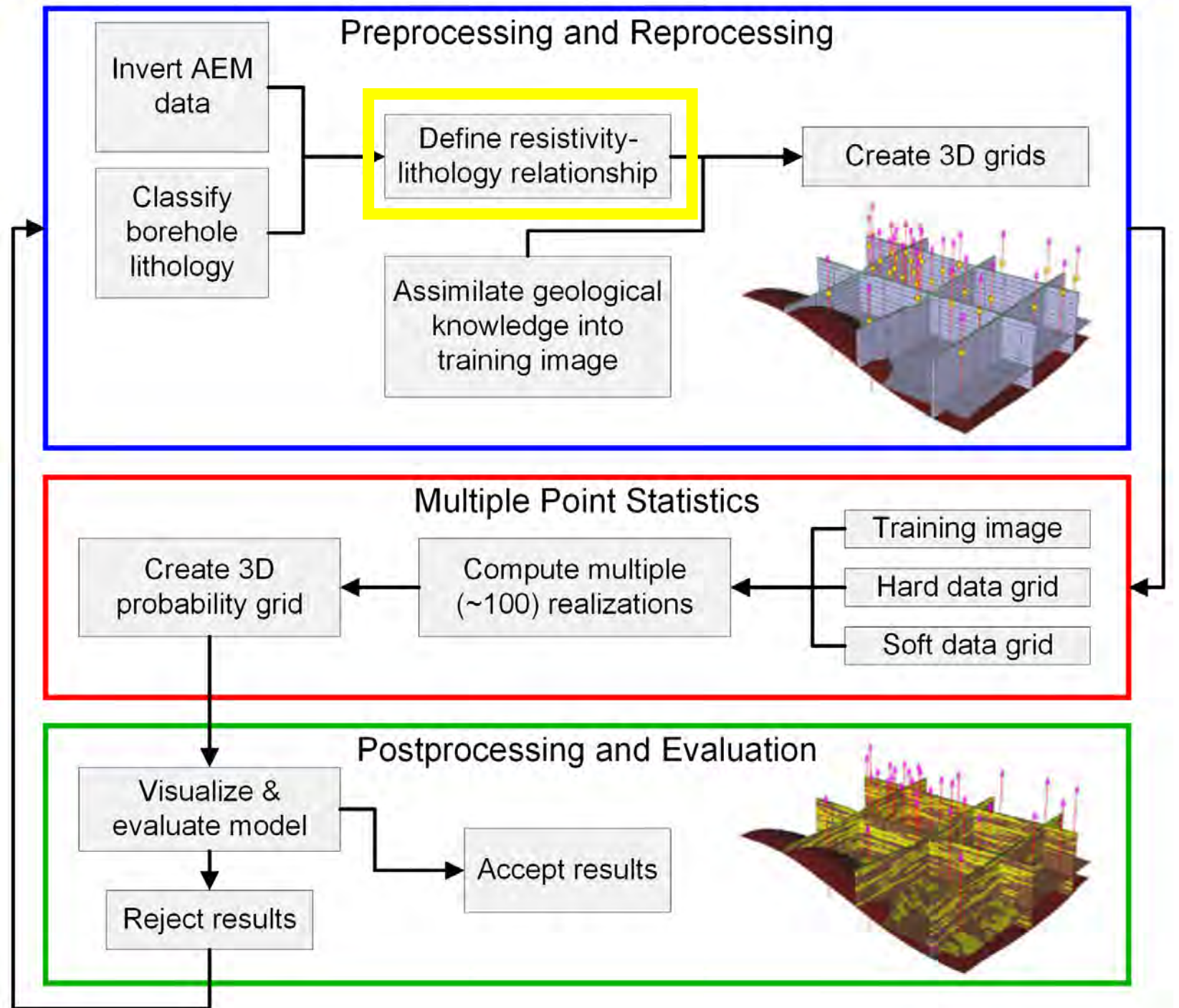
Generalized workflow for resistivity-classification HSU modeling



Deterministic model

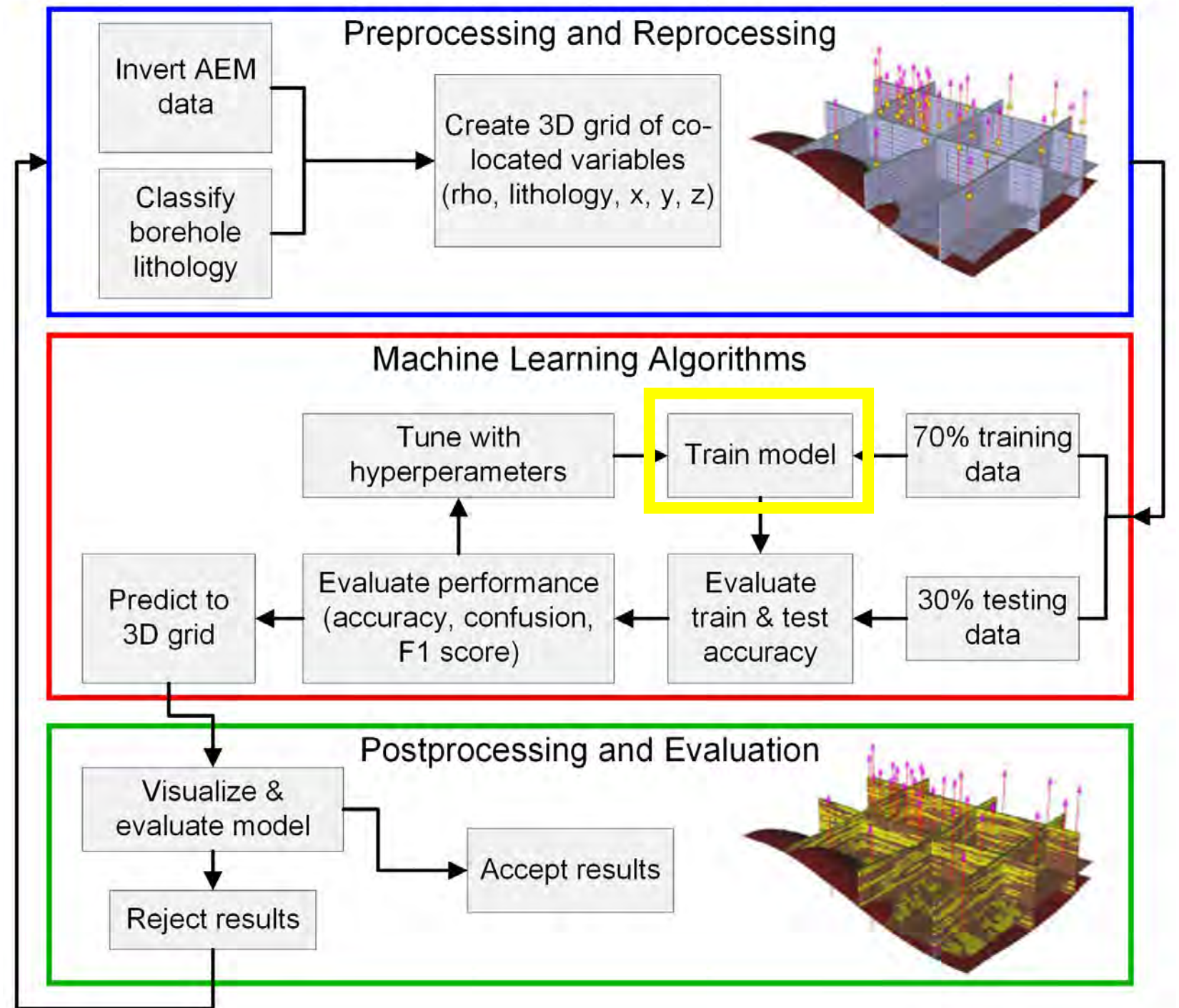
Generalized multiple point statistics (MPS) workflow for HSU modeling

Probabilistic model



Generalized machine learning (ML) workflow for HSU modeling

Probabilistic model



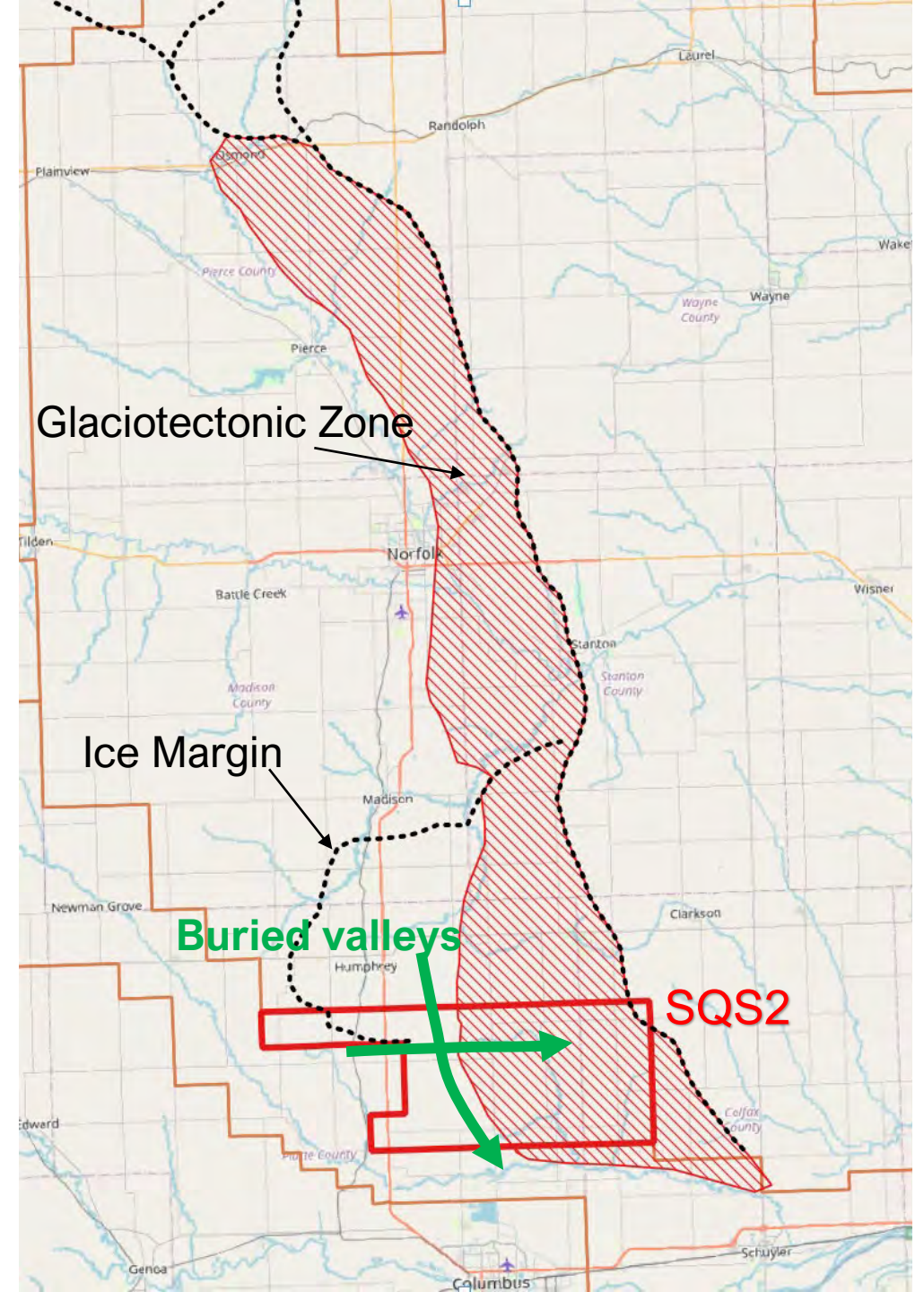
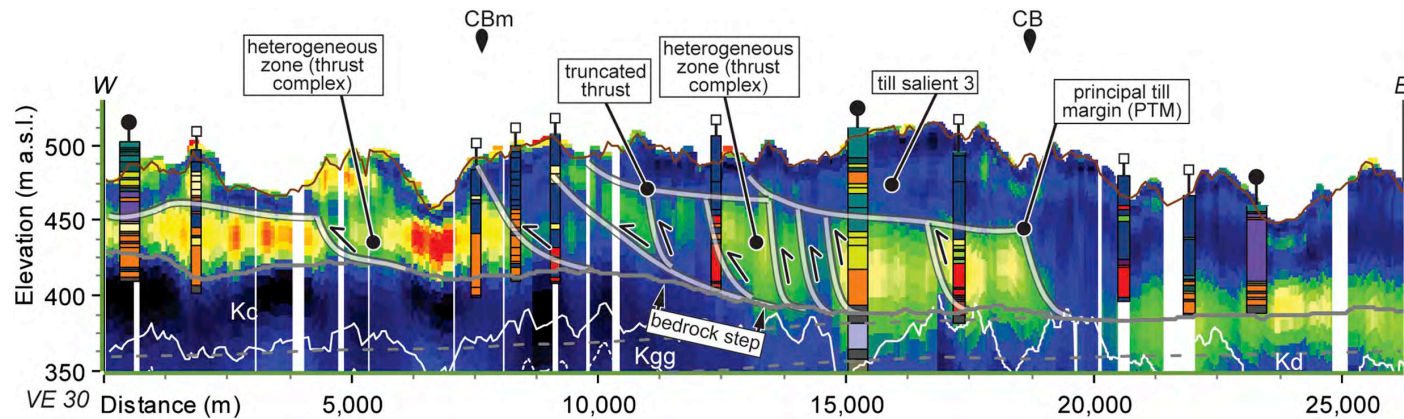
Geological complexity of the SQS2 area

Multiple till sheets & salients

Glaciotectonic deformation (folding, faulting)

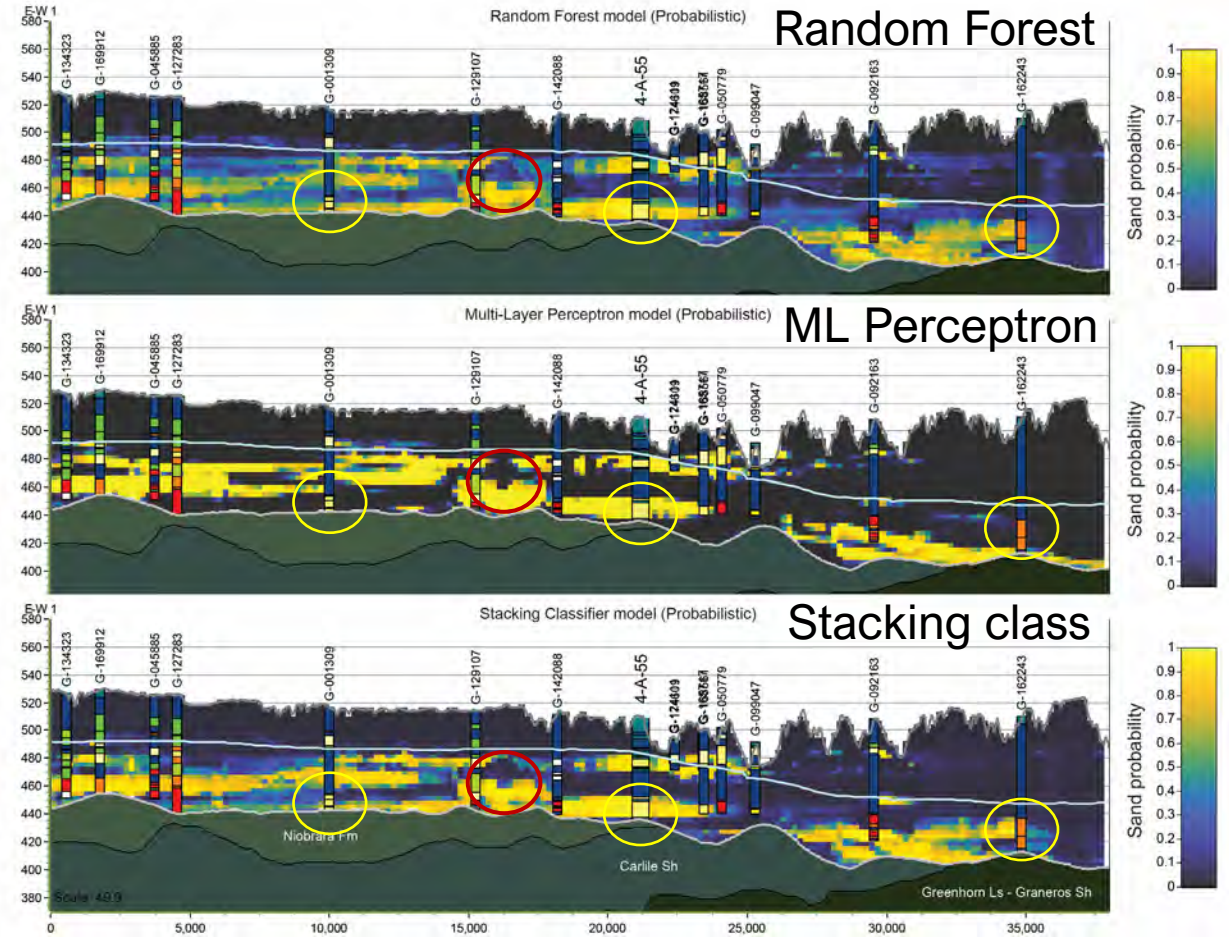
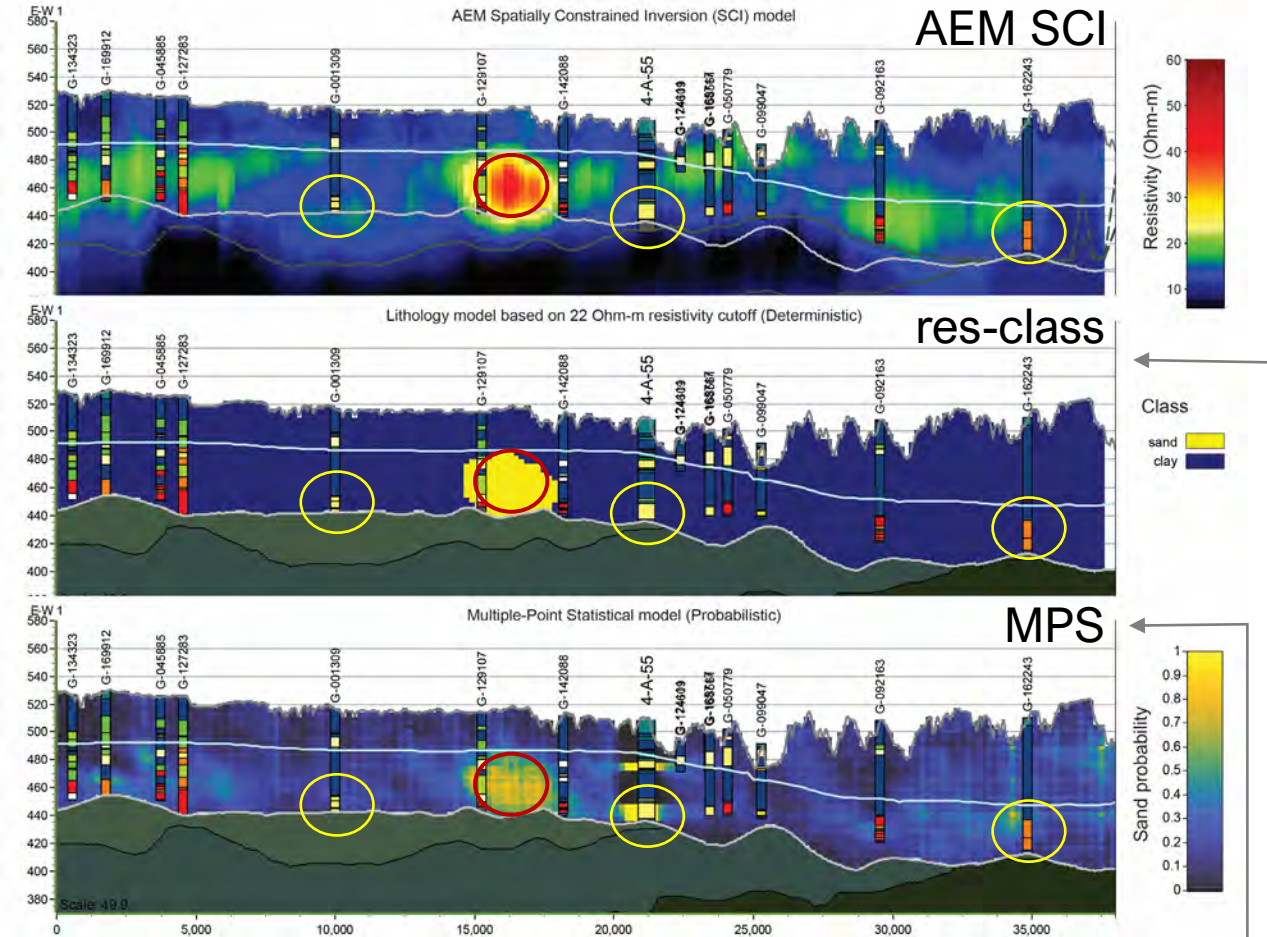
Intersecting buried valleys

Juxtaposed aquifers (High Plains & glacial aquifers)



Deterministic model

Probabilistic models

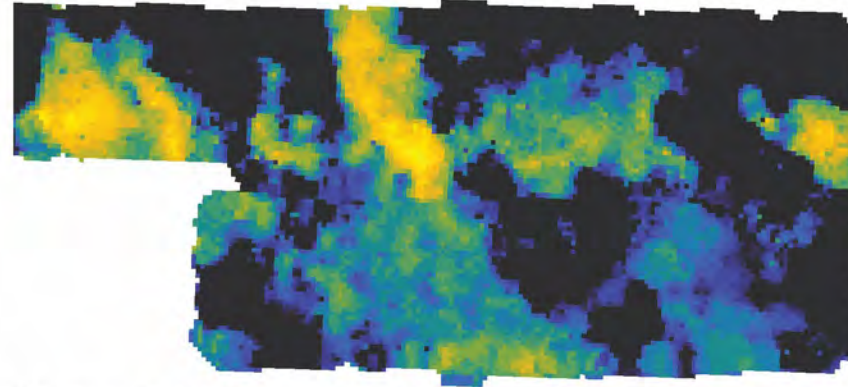


Probabilistic model

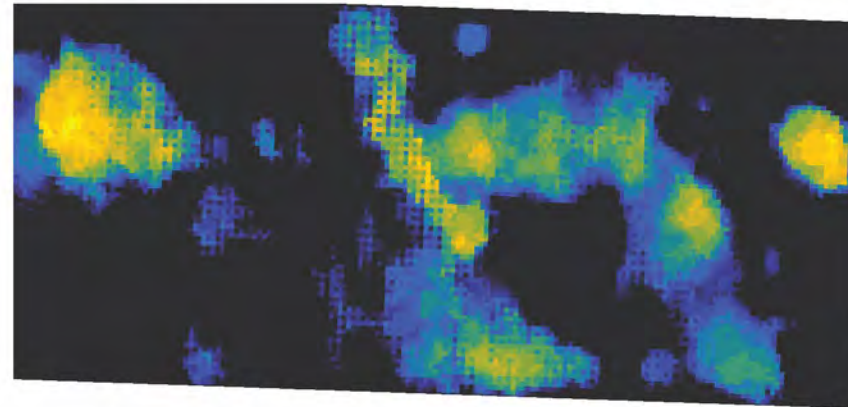
Maps of total sand thickness for Quaternary aquifer

For probabilistic models, sand is defined as $p_{\text{sand}} > 65\%$

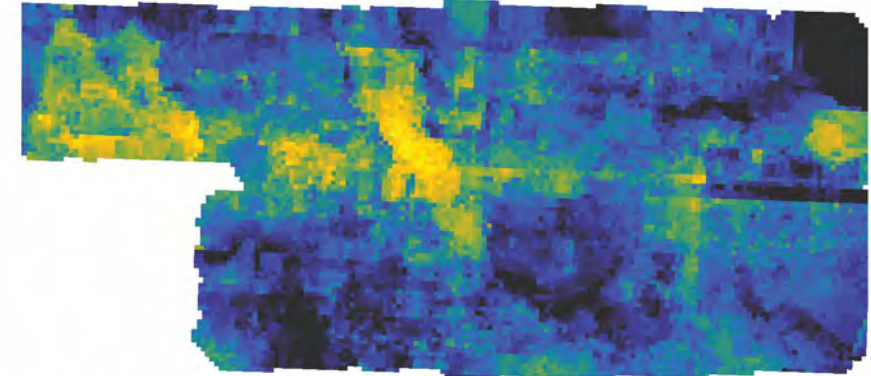
Lithology model - 22 Ohm-m resistivity cutoff (Deterministic)



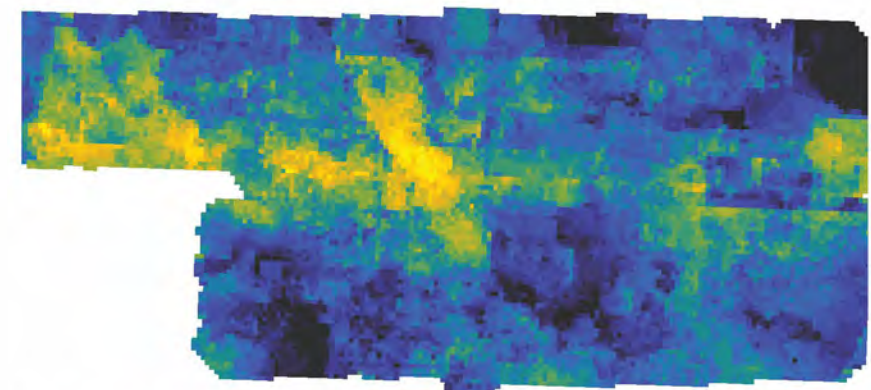
Multiple-Point Statistical model (Probabilistic)



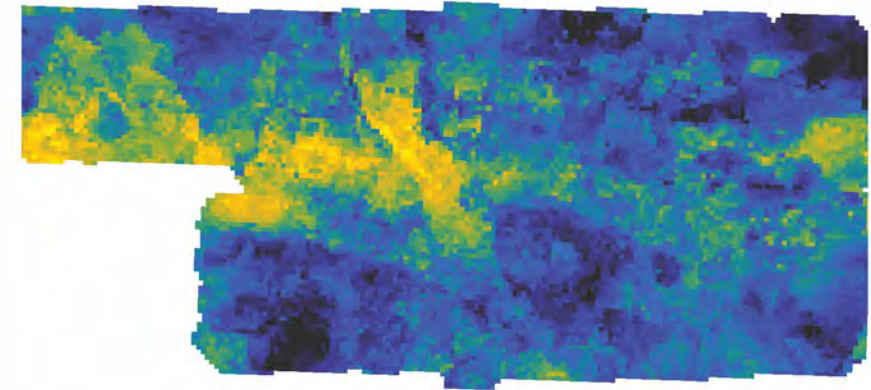
Random Forest model (Probabilistic)



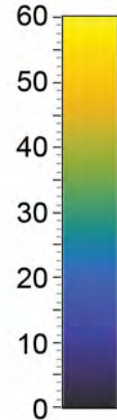
Multi-Layer Perceptron model (Probabilistic)



Stacking Classifier model (Probabilistic)

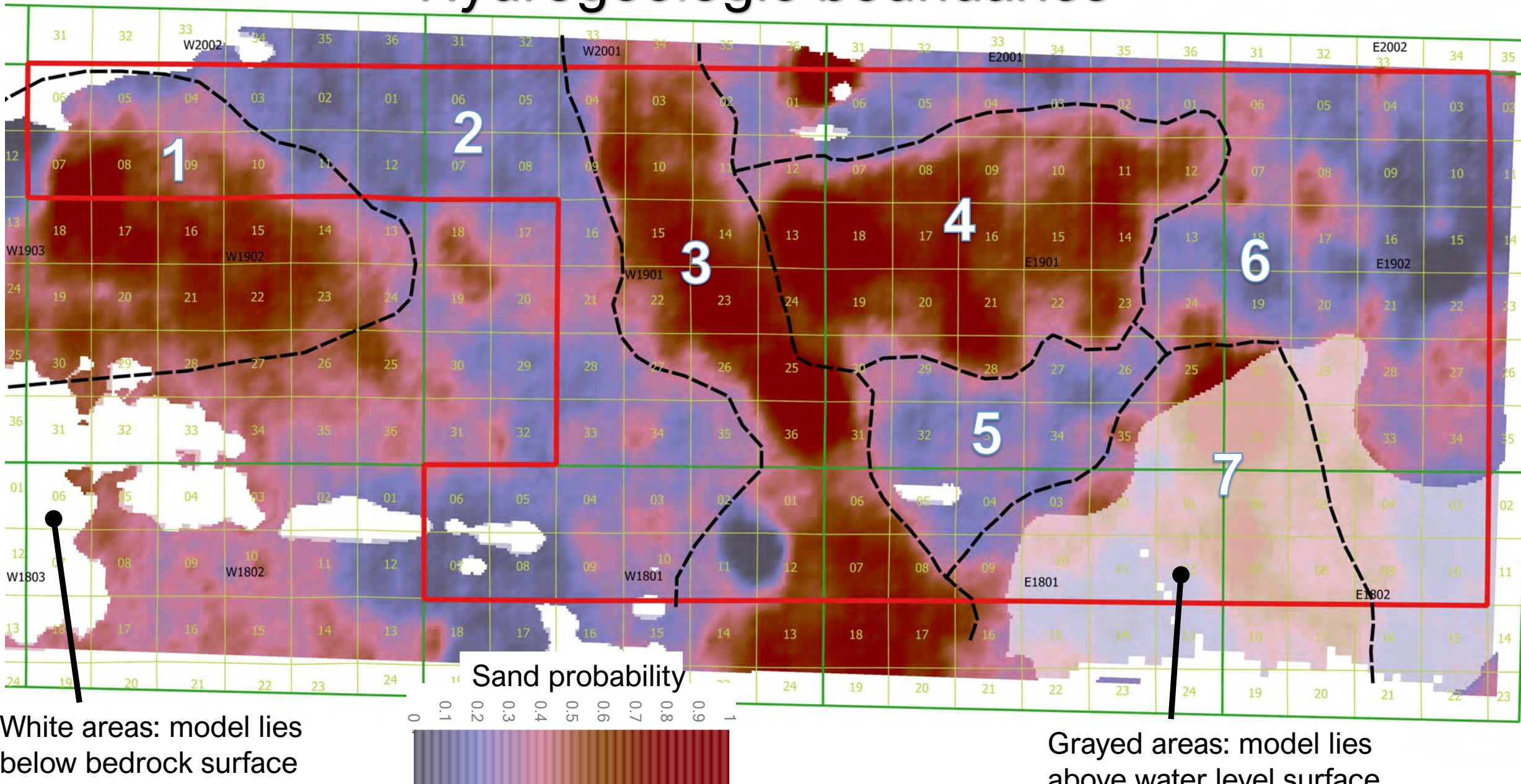


Sand thickness (m)

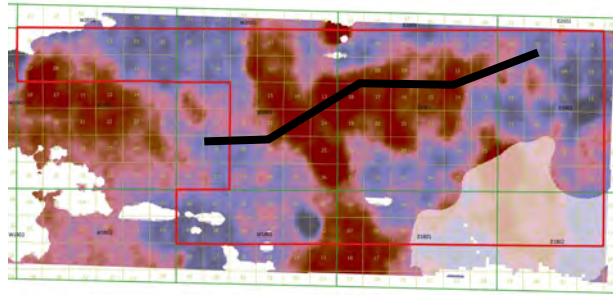


0 5 10 km

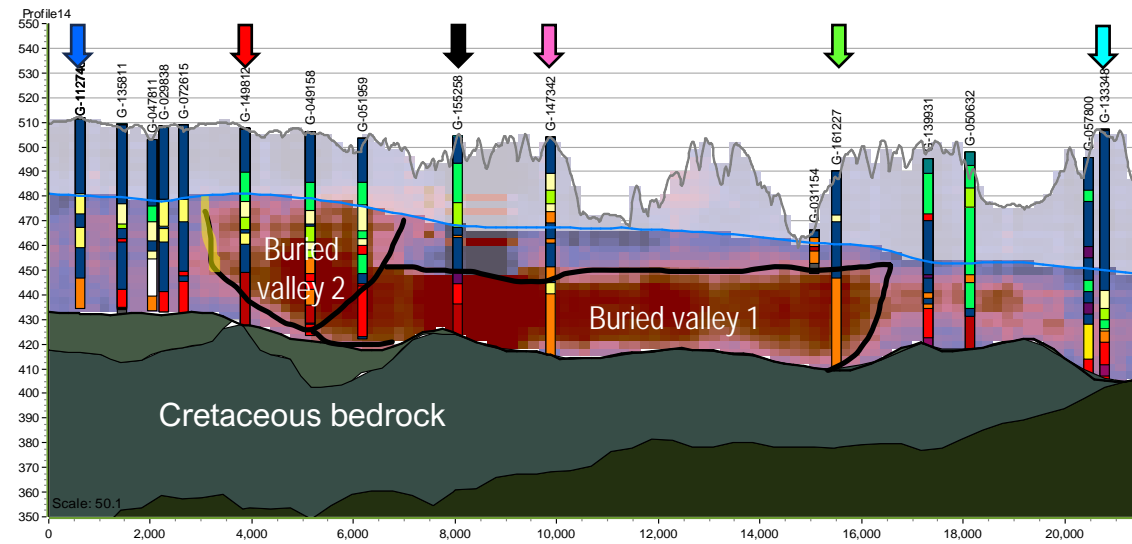
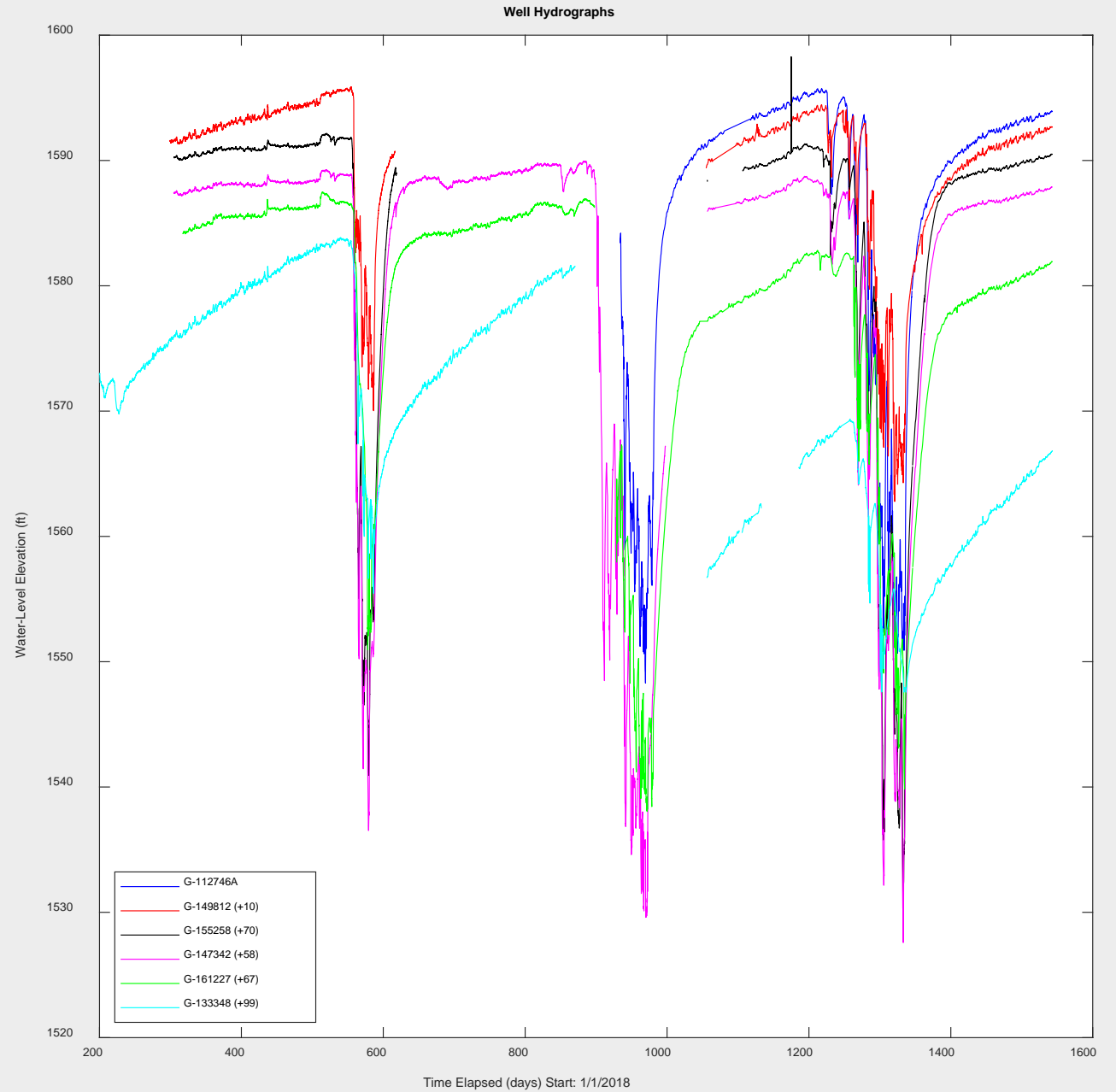
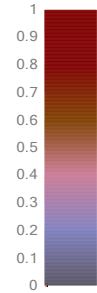
Hydrogeologic boundaries



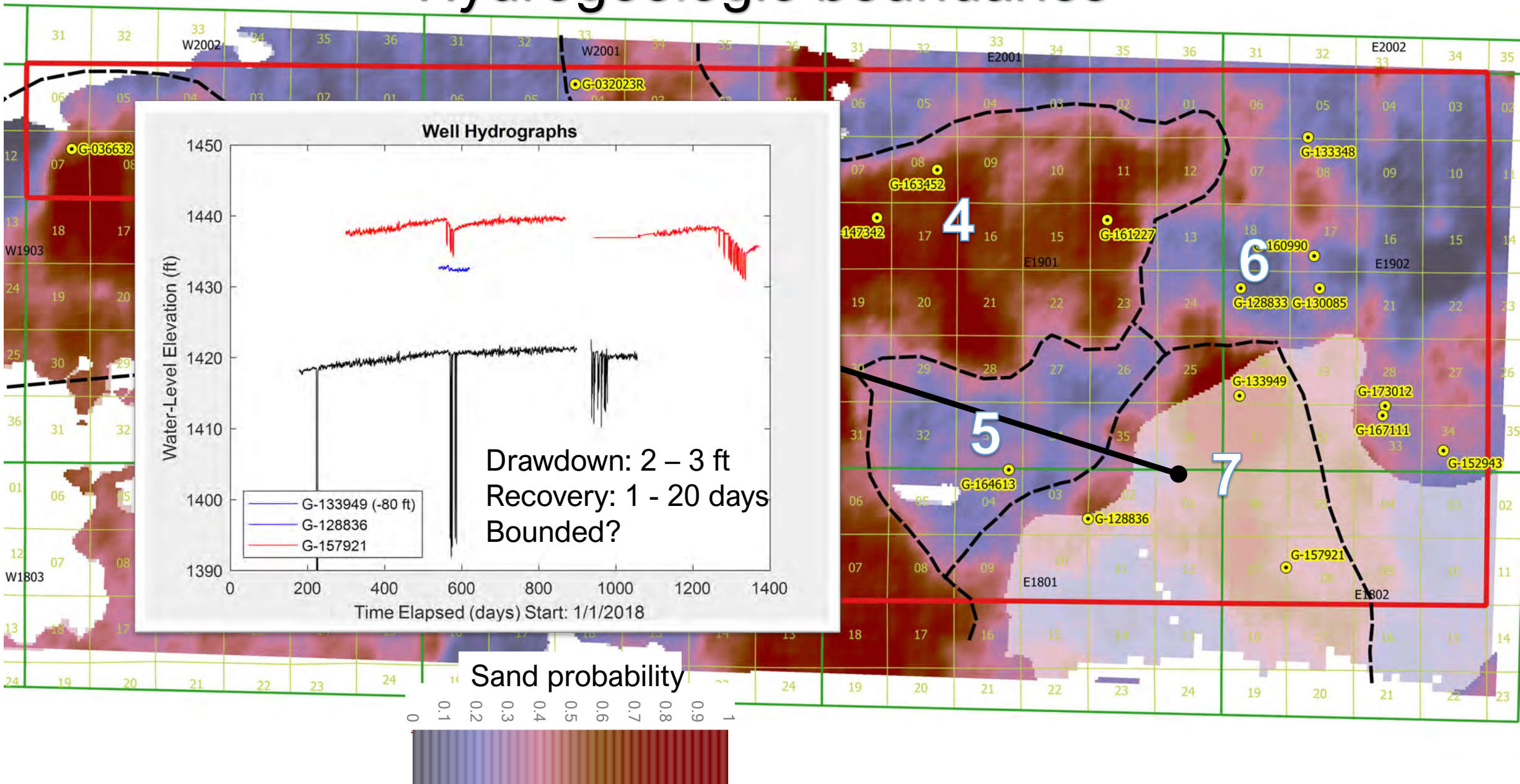
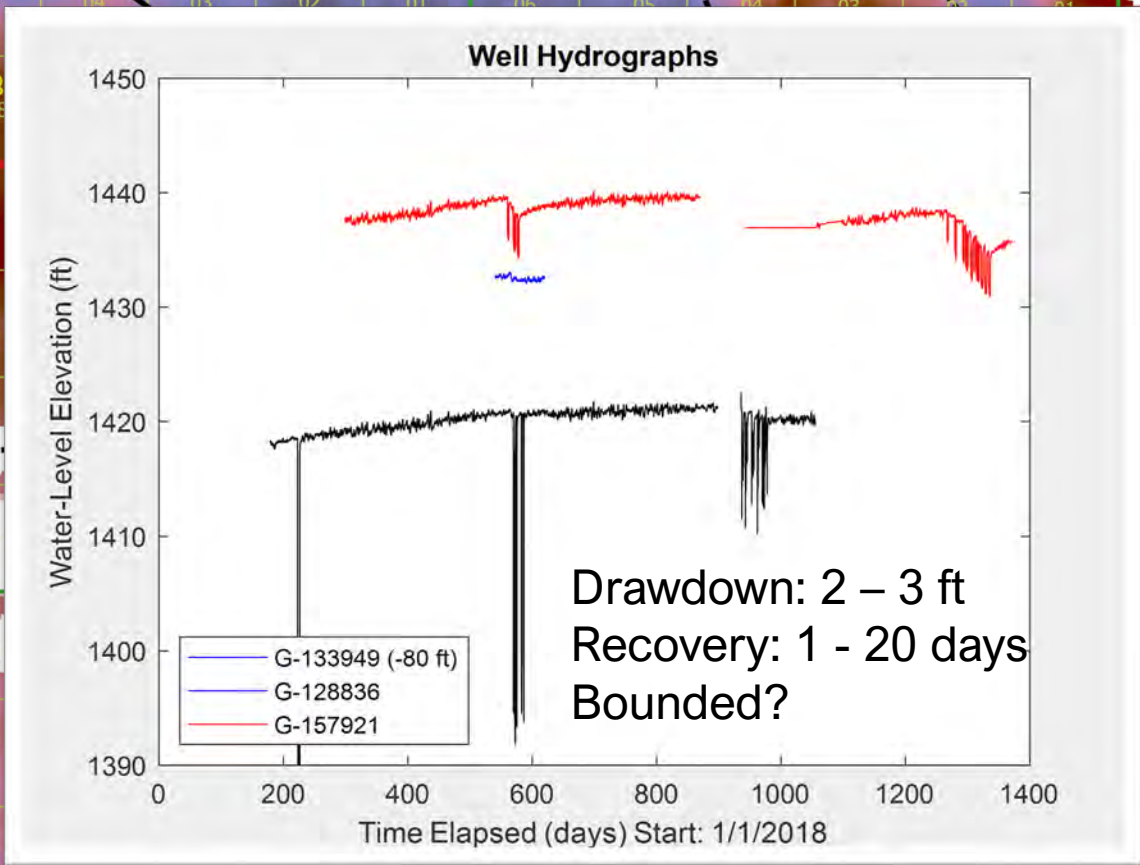
Groundwater-level hydrographs along west-east profile



Sand probability



Hydrogeologic boundaries



Hydrogeology Journal

<https://doi.org/10.1007/s10040-023-02658-x>



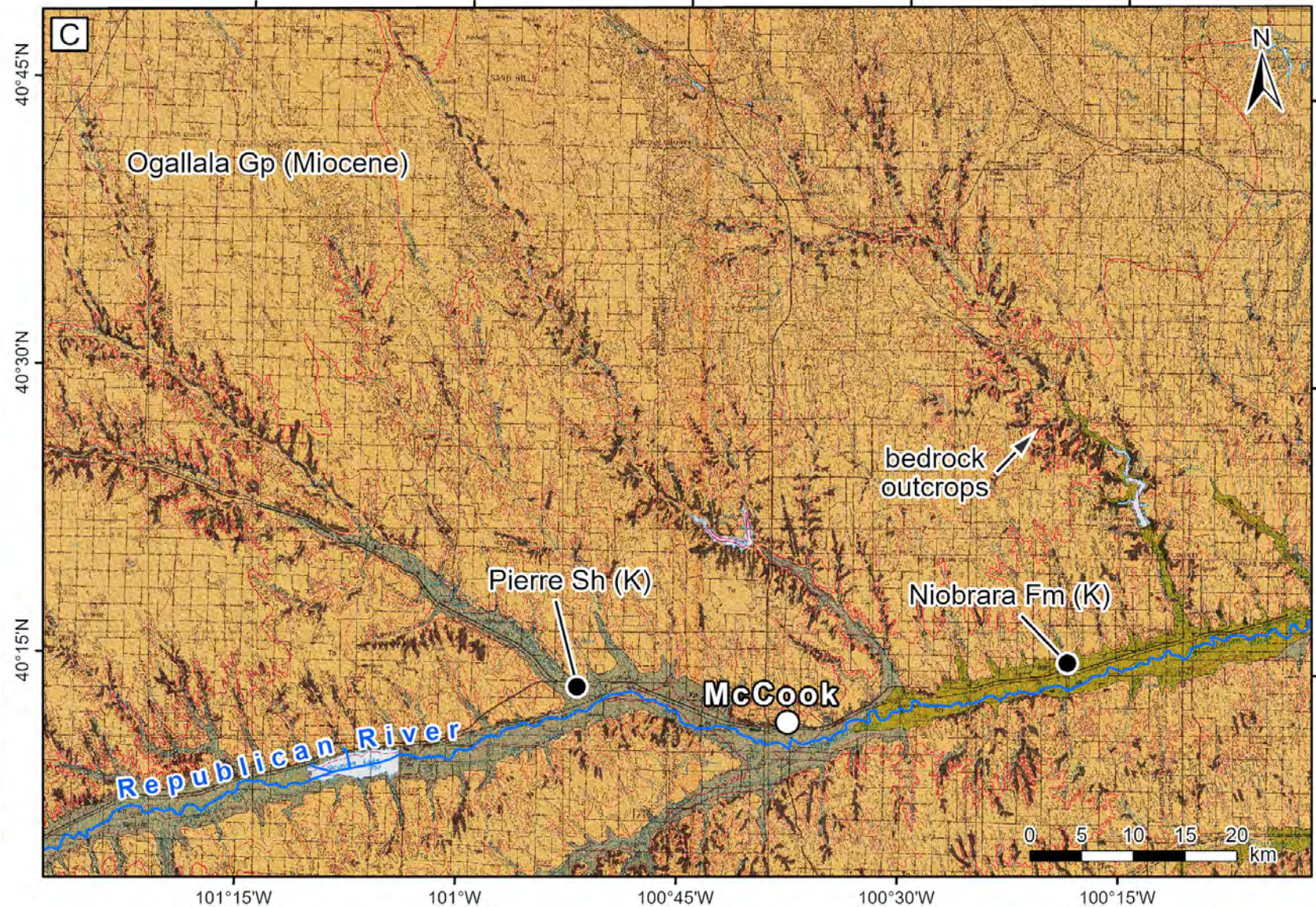
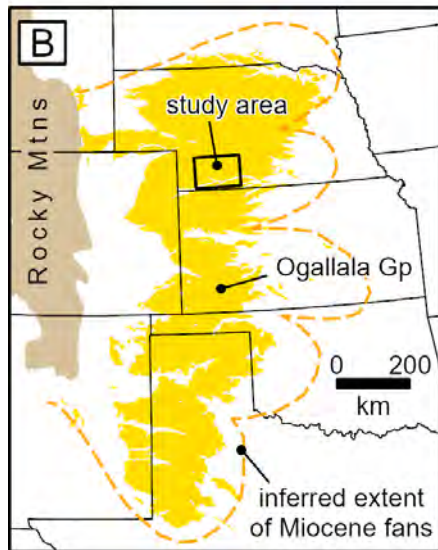
PAPER



Multiple-point statistical modeling of three-dimensional glacial aquifer heterogeneity for improved groundwater management

Nafyad Serre Kawo¹ · Jesse Korus² · Mats Lundh Gulbrandsen³

Bedrock geology of Middle Republican NRD



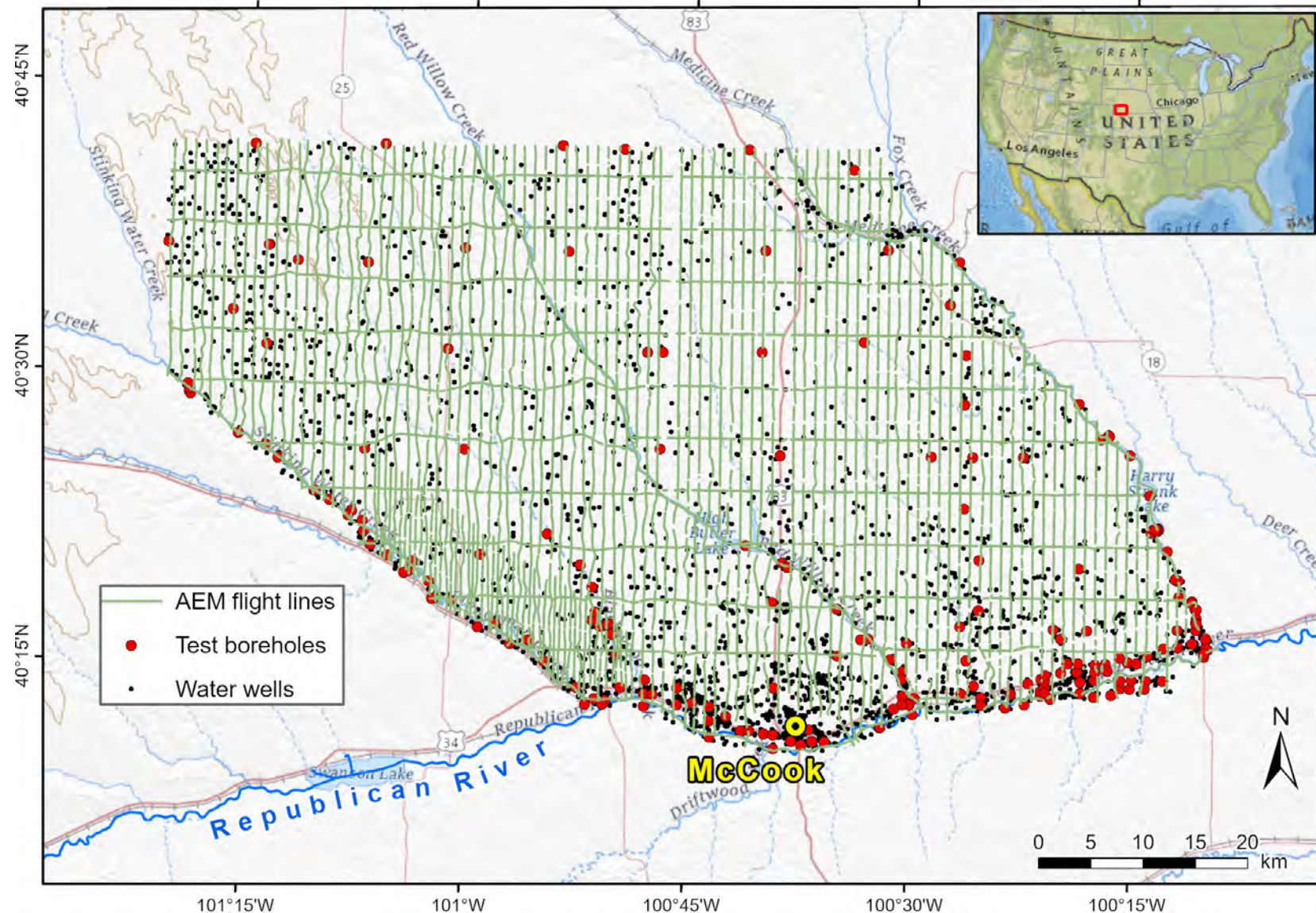
Geological setting

- Relatively homogenous Quaternary deposits
- Heterogeneous Neogene Ogallala Group: includes unconsolidated and consolidated materials (sands & gravels; calcium-carbonate-cemented sandstones & conglomerates; silts & clays; siltstones & claystones)
- Paleogene & Cretaceous units dominated by claystone & shale

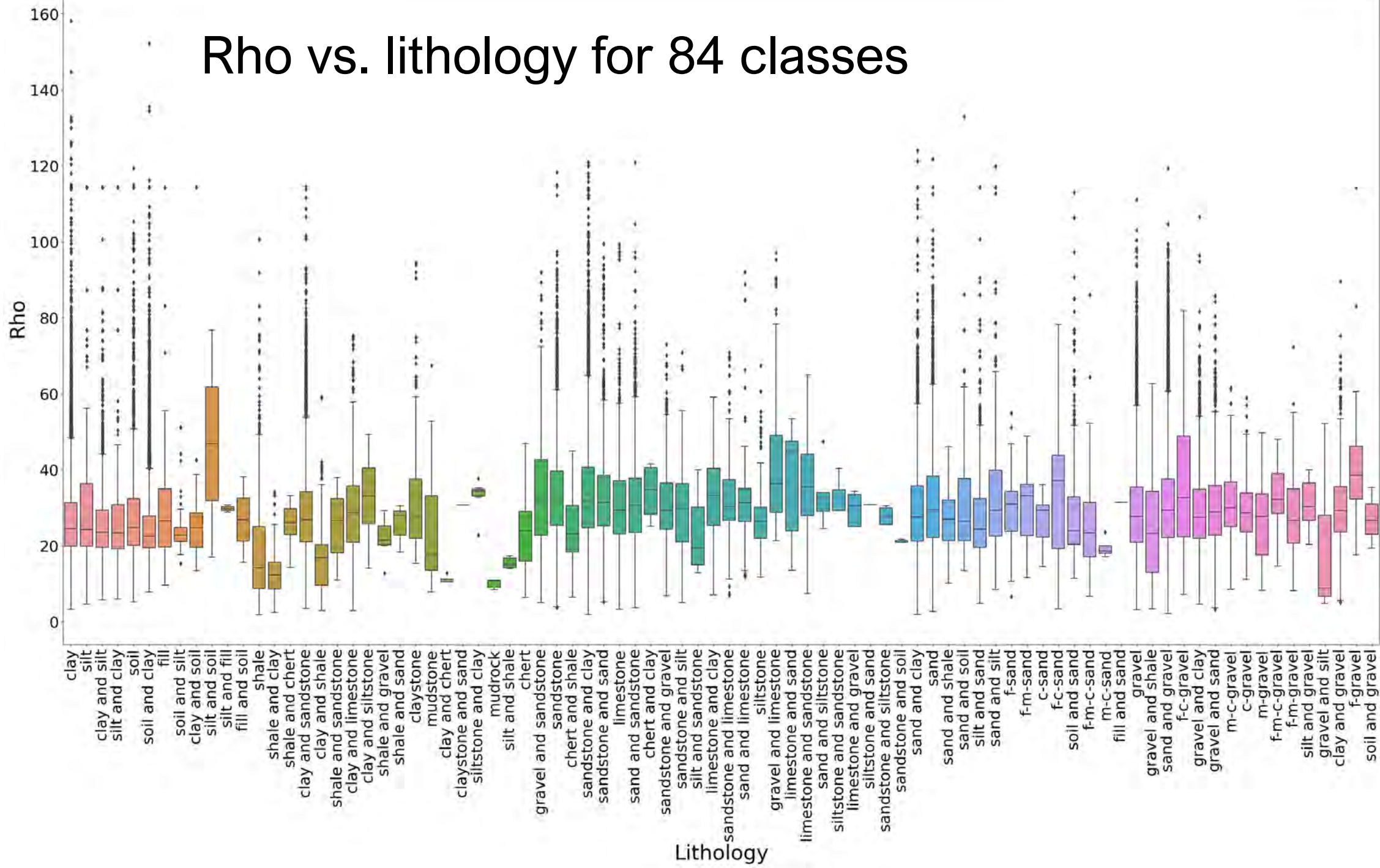
Period	Stratigraphy	Lithology	Composite Section
Quaternary	sand dunes	sand	
	loess	silt, very fine sand, slightly clayey	
Neogene	Ogallala Gp.	sand, sandstone, siltstone, gravel, partially consolidated	
Paleogene	Chadron Fm.	claystone	
Cretaceous	Pierre Shale	shale	
	Niobrara Fm.	chalk, shaly	

AEM and borehole data

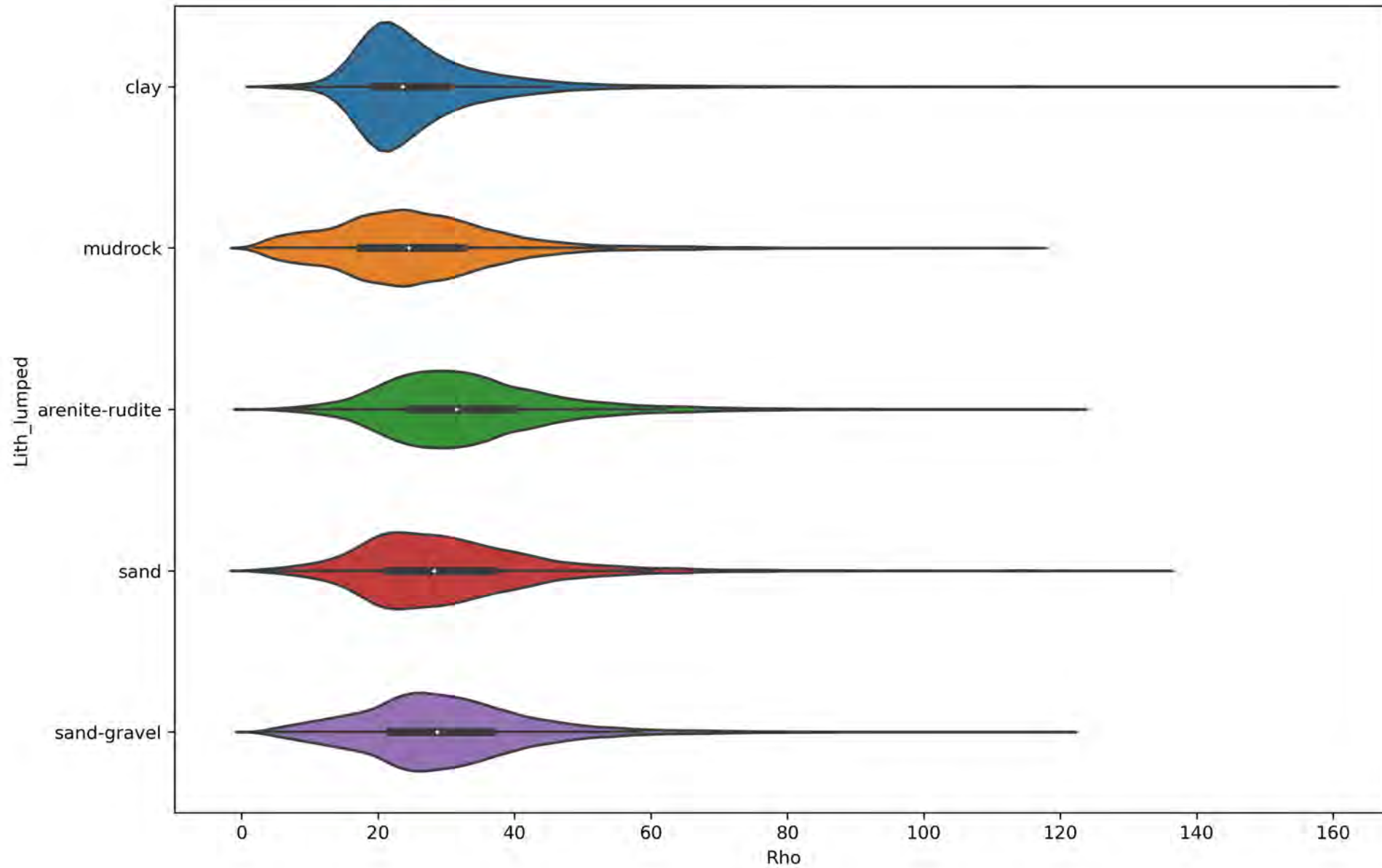
- 3,418 water-well logs (no res logs)
- 223 geologic test borehole logs (res logs, but not calibrated)
- 4,658 line-km of AEM
- Smooth inversion, 40 layers



Rho vs. lithology for 84 classes



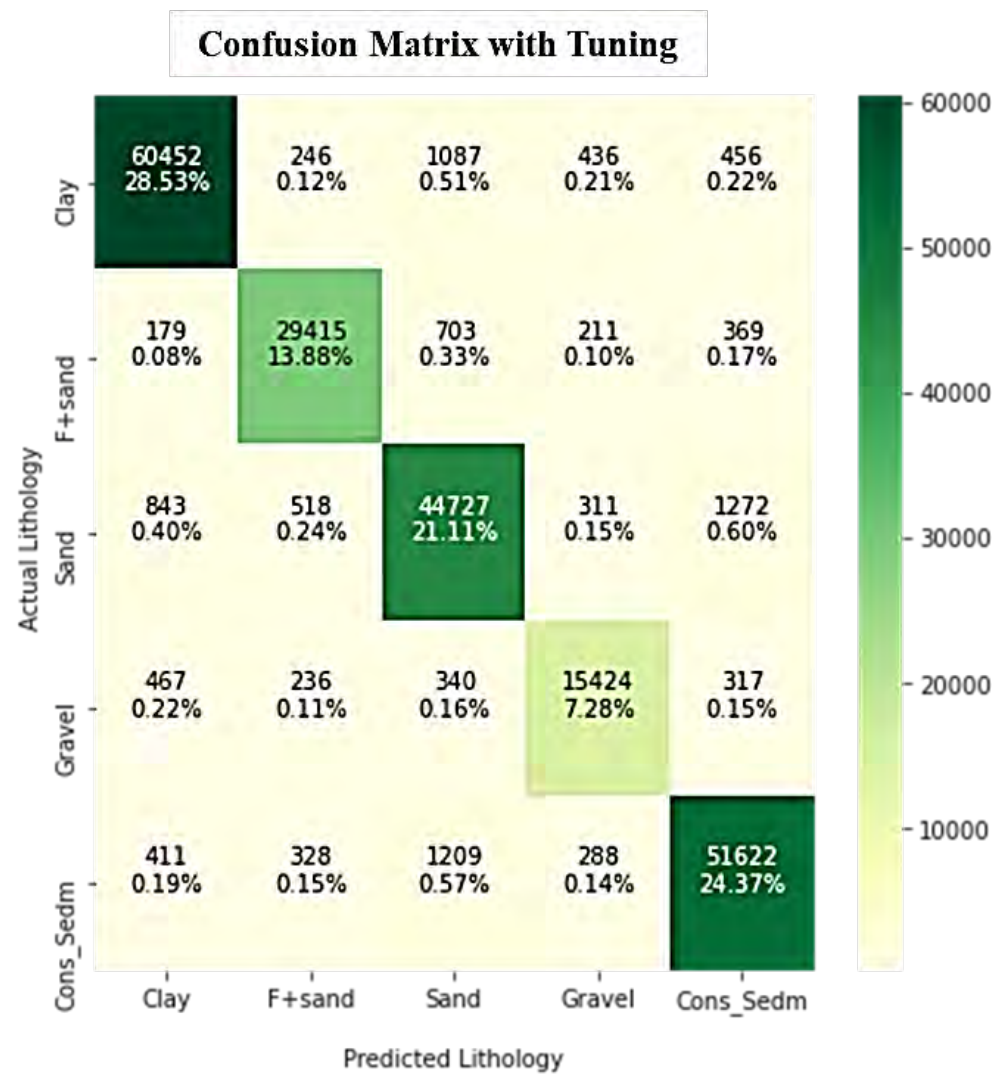
Rho vs. lithology for 5 classes



Initial tests of machine learning methods

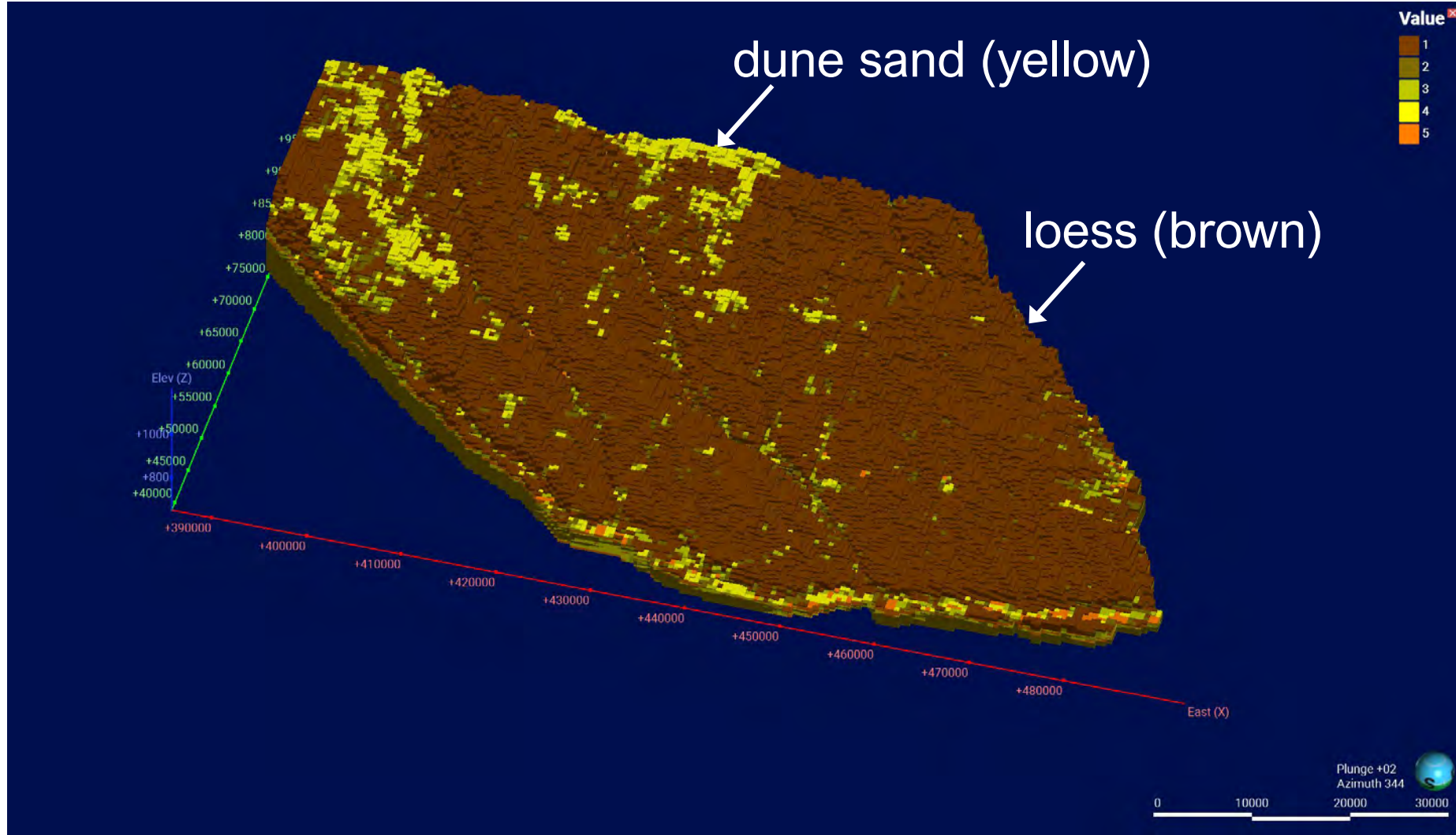
Model	Train Accuracy	Test Accuracy
KNN	0.7932	0.728032
Logistic Regression	0.301459	0.299476
Naive Bayes	0.341216	0.340327
Support Vector Machine (Linear)	0.385938	0.385105
Decision Tree	0.877026	0.839041
Ensemble: Random Forest	0.966813	0.906814
Multi-Layer Perceptron	0.469935	0.466439

Confusion Matrix

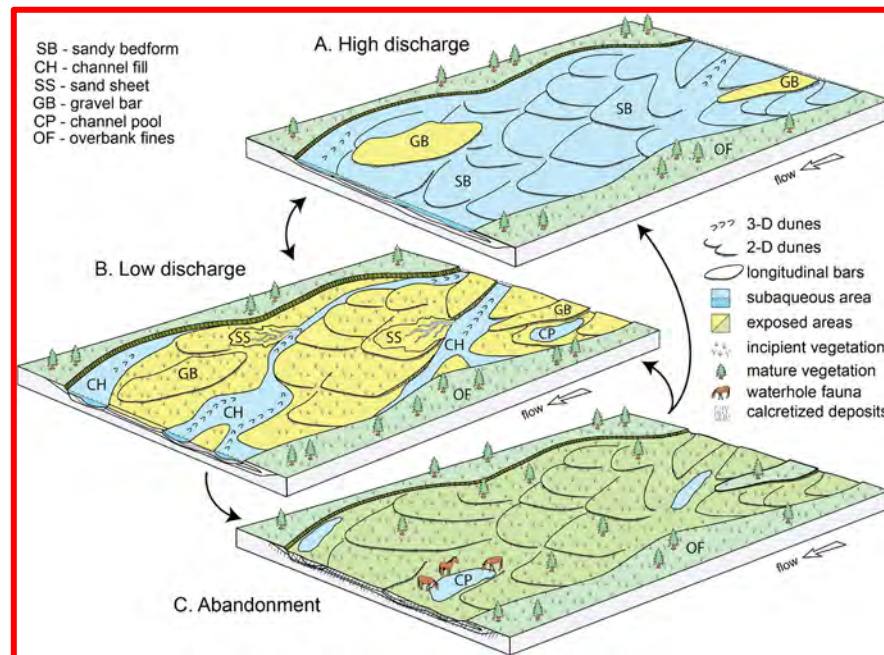


Is the model geologically realistic?

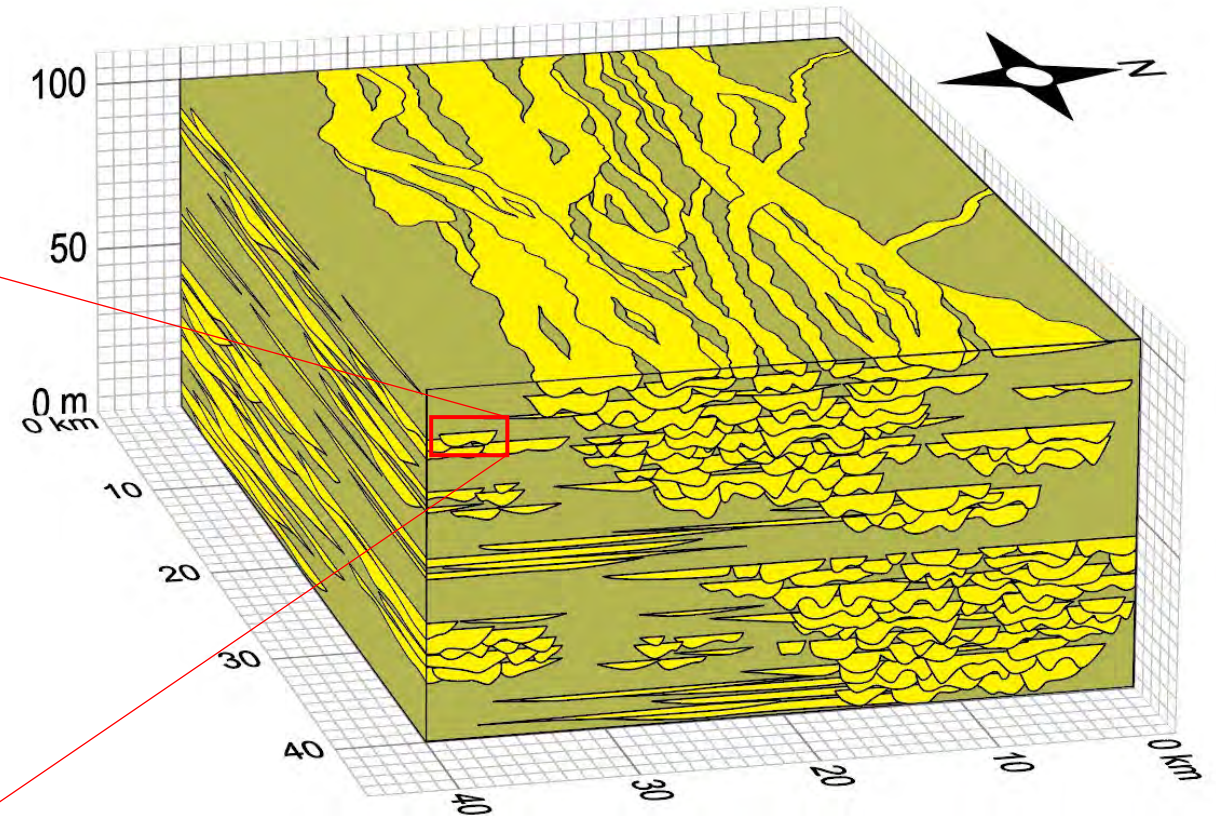
Modeled surficial
geology matches
known
distribution of
loess and dune
sand



Geological conceptual models of the Ogallala Group

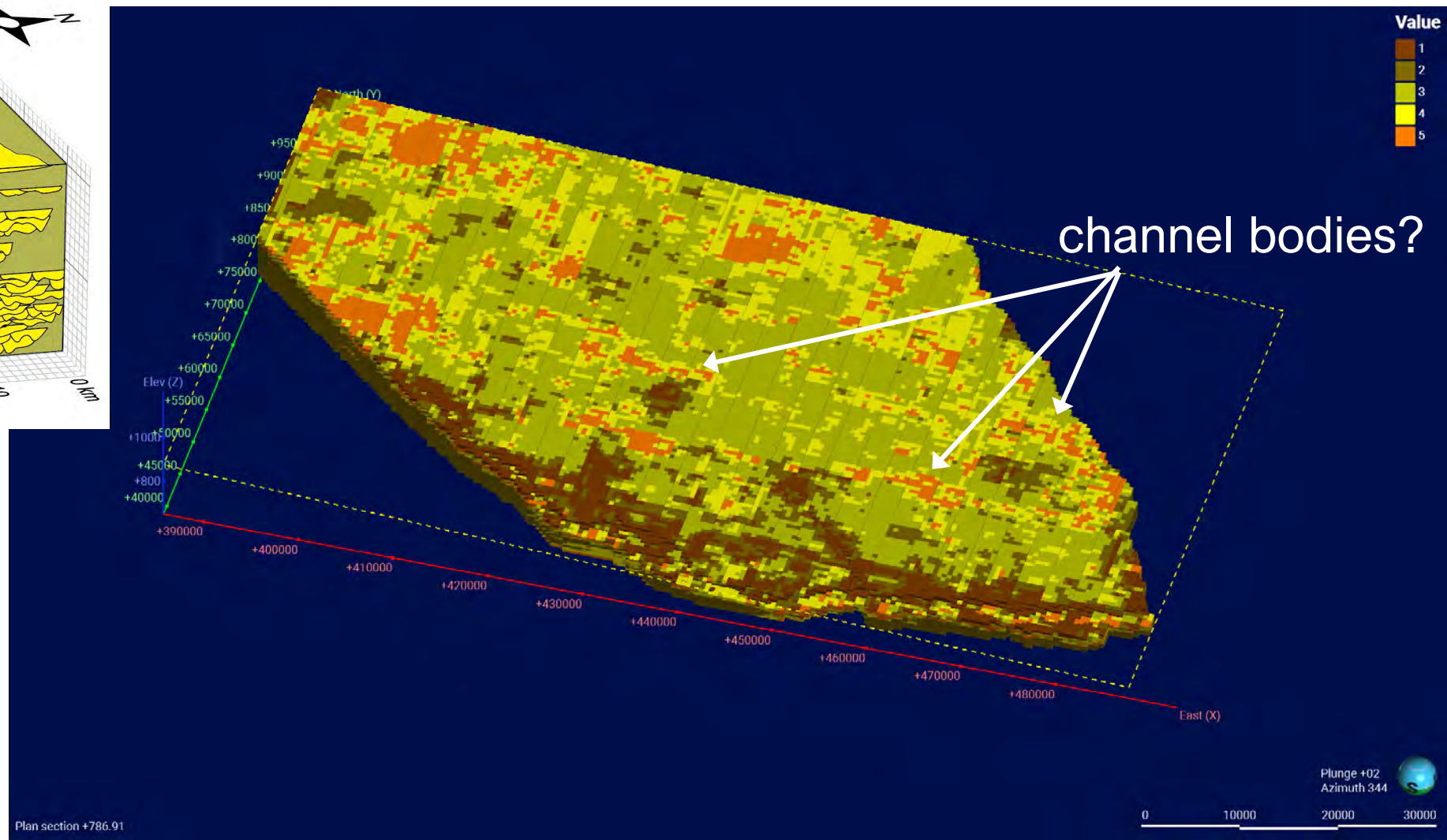
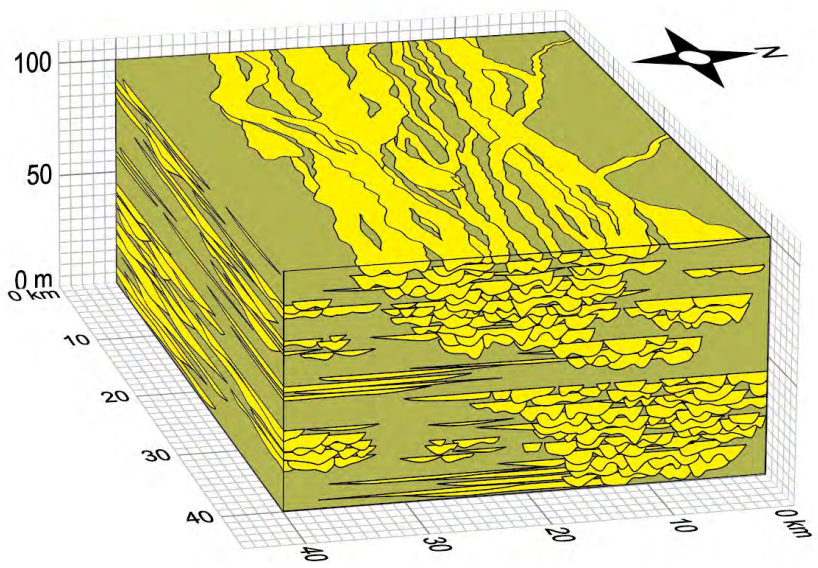


Smith, J. J., and Platt, B. F., 2023, Reconstructing late Miocene depositional environments in the central High Plains, USA: Lithofacies and architectural elements of the Ogallala Formation: *Sedimentary Geology*, v. 443, p. 106303.

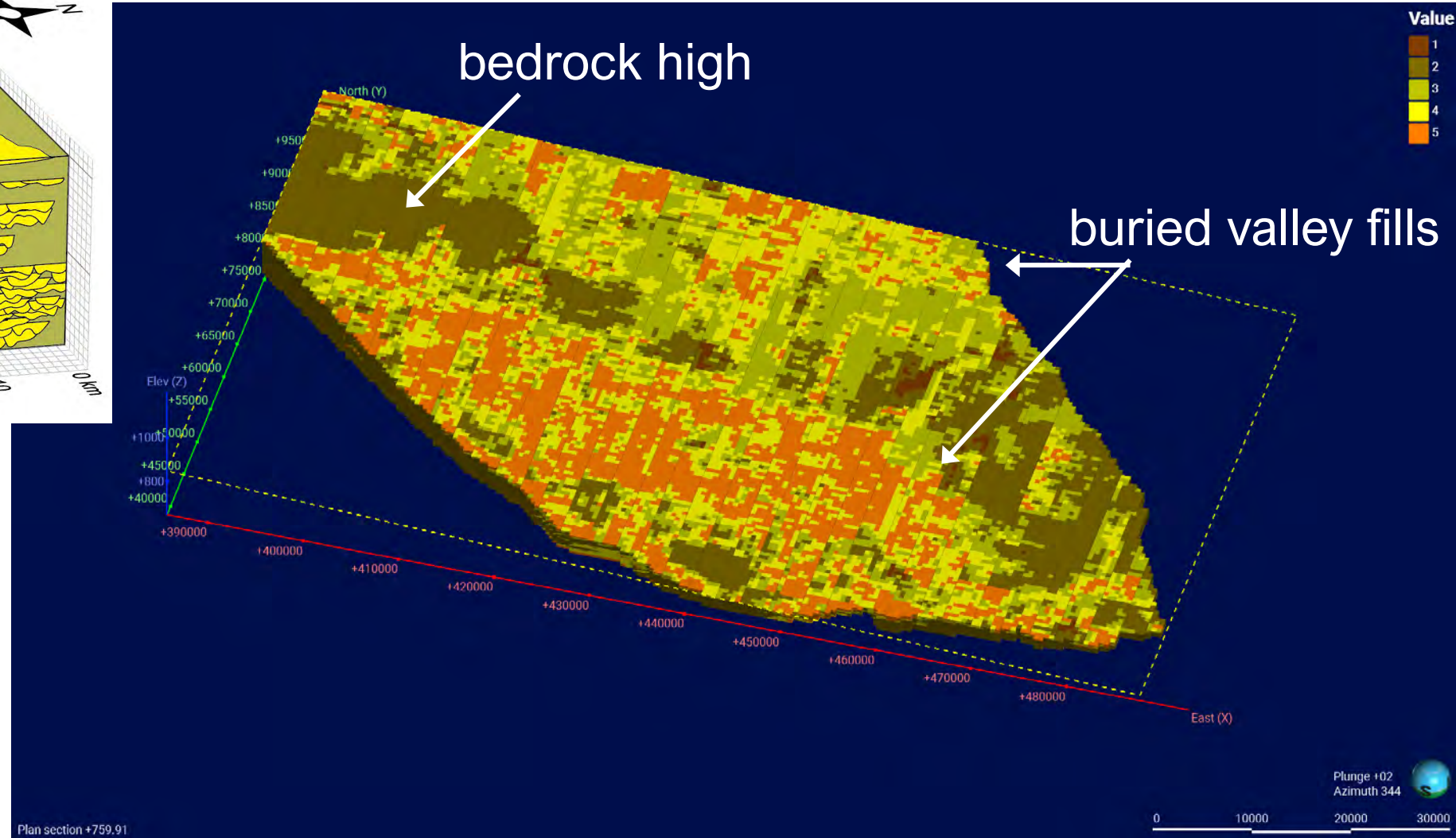
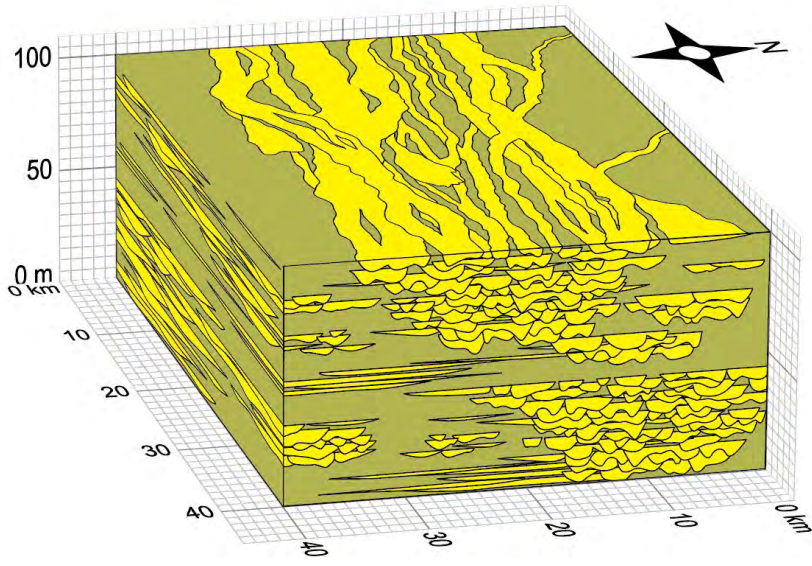


Korus, J. T., and Joeckel, R. M., 2022, Sandstone-body geometry and hydrostratigraphy of the northern High Plains Aquifer system, USA: *Quarterly Journal of Engineering Geology and Hydrogeology*, v. 55, no. 3, p. qjeh2021-2171.

Is the model geologically realistic?

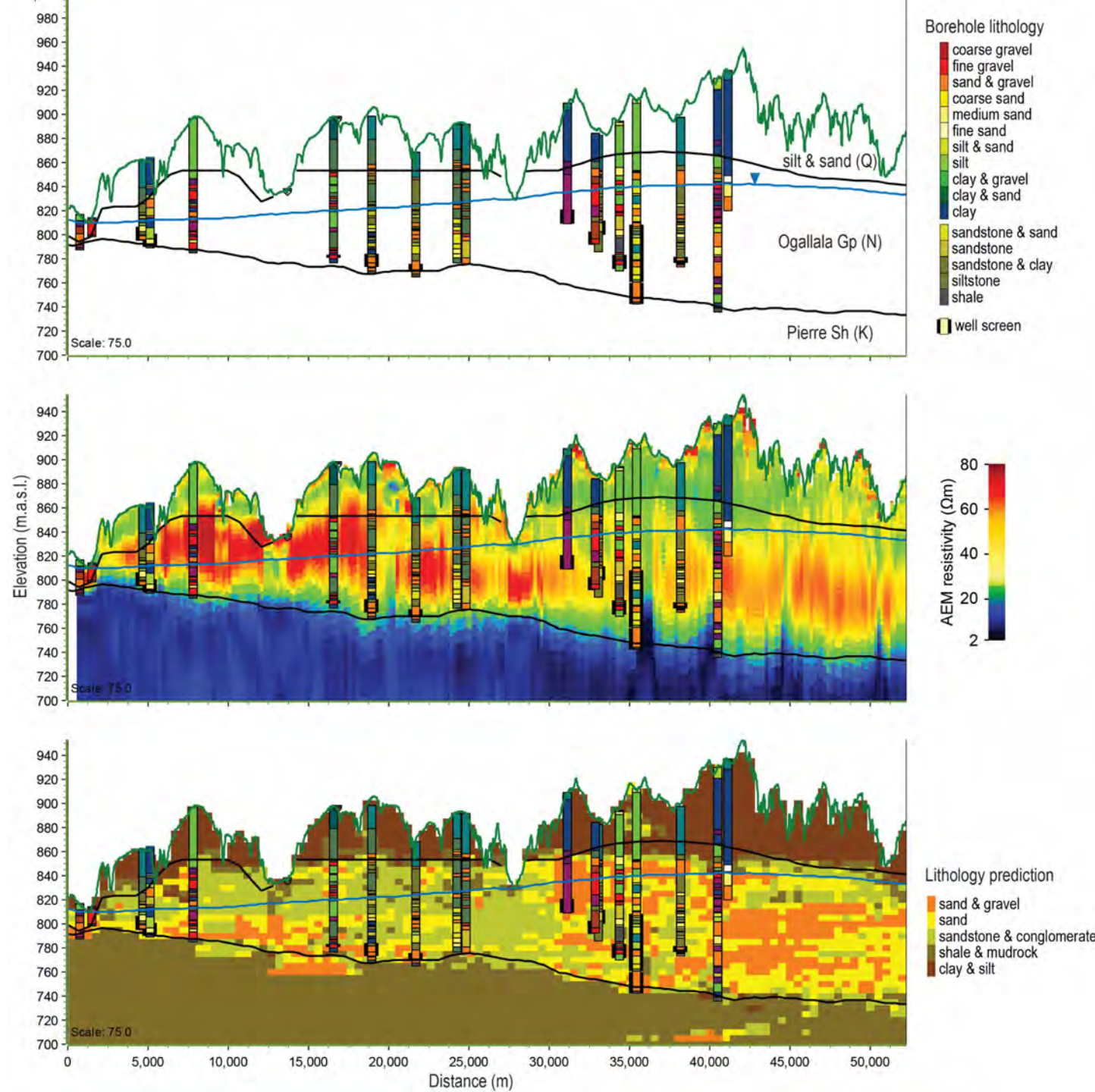


Is the model geologically realistic?



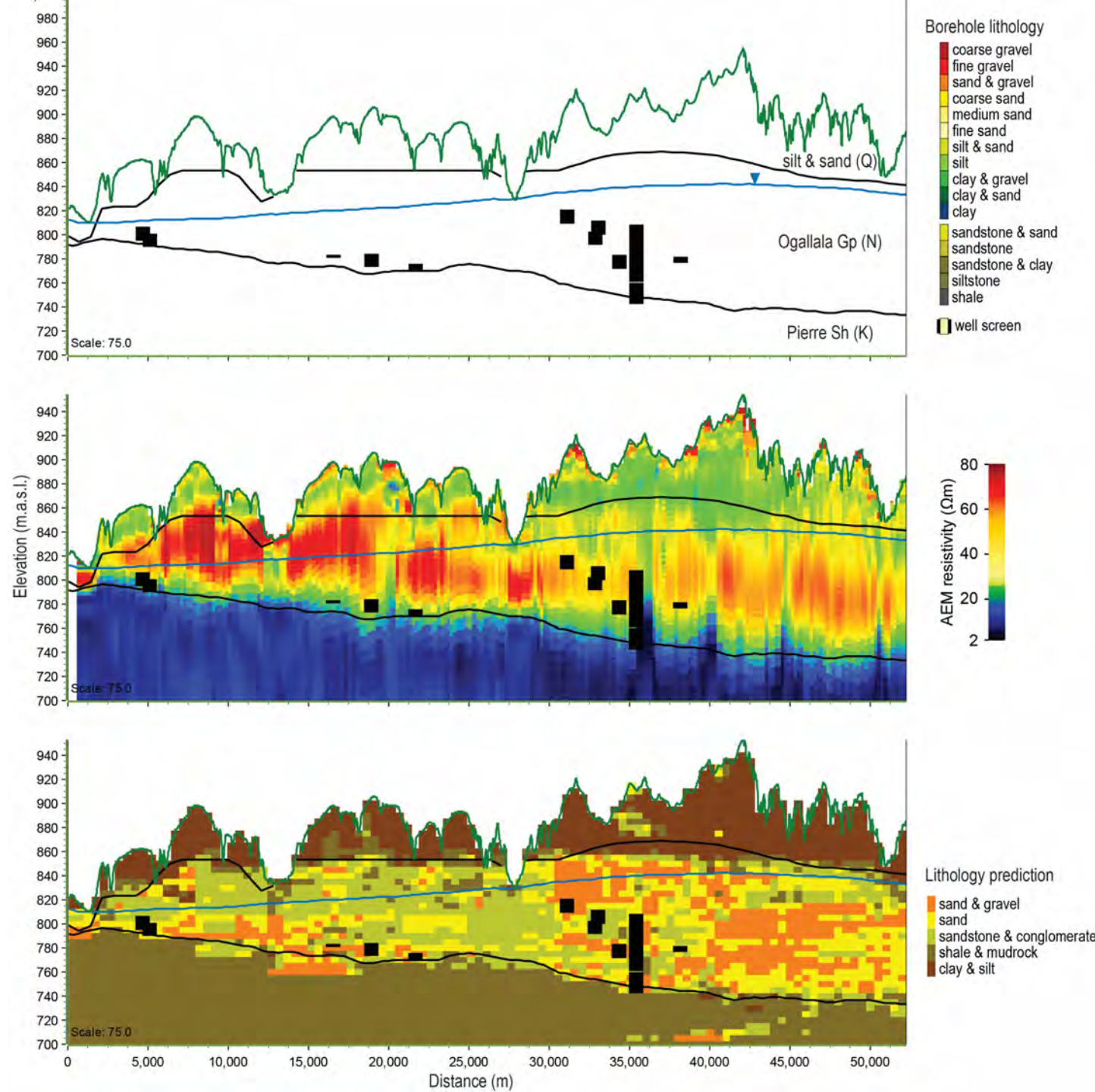
Is the model hydrogeologically realistic?

- Well screens correspond to the permeable units, even though some of these units are relatively conductive.



Is the model hydrogeologically realistic?

- Well screens correspond to the permeable units, even though some of these units are relatively conductive.





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3D hydrostratigraphic and hydraulic conductivity modelling using supervised machine learning

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^b Conservation and Survey Division, School of Natural Resources, University of Nebraska Lincoln, 3310 Holdrege Street, Lincoln, NE, 68583-0996, USA



Summary

Benefits of Machine Learning models

- Machine learning finds the co-linear relationship between rho and lithology
- Predictions are objective and account for uncertainty
- Computation is fast and efficient

Summary

Limitations of Machine Learning

- Poor quality borehole logs can impact results.
- Does not always “match” the geometries observed in AEM.
- Does not explicitly incorporate geological knowledge (i.e. no training image)

Summary

- Combining modern methods in geophysics, computing, and 3D modeling yields new insights on aquifer heterogeneity
- Traditional methods and basic data are necessary as model inputs and for model validation

Stacking Classifier model (Probabilistic)

