

# Science-informed machine learning for reservoir characterization

Velimir (“monty”) Vesselinov  
Tracy Kliphuis

[monty@envitrace.com](mailto:monty@envitrace.com)  
[trais@envitrace.com](mailto:trais@envitrace.com)

EnviTrace, Santa Fe, New Mexico

[info@envitrace.com](mailto:info@envitrace.com)  
<http://envitrace.com>

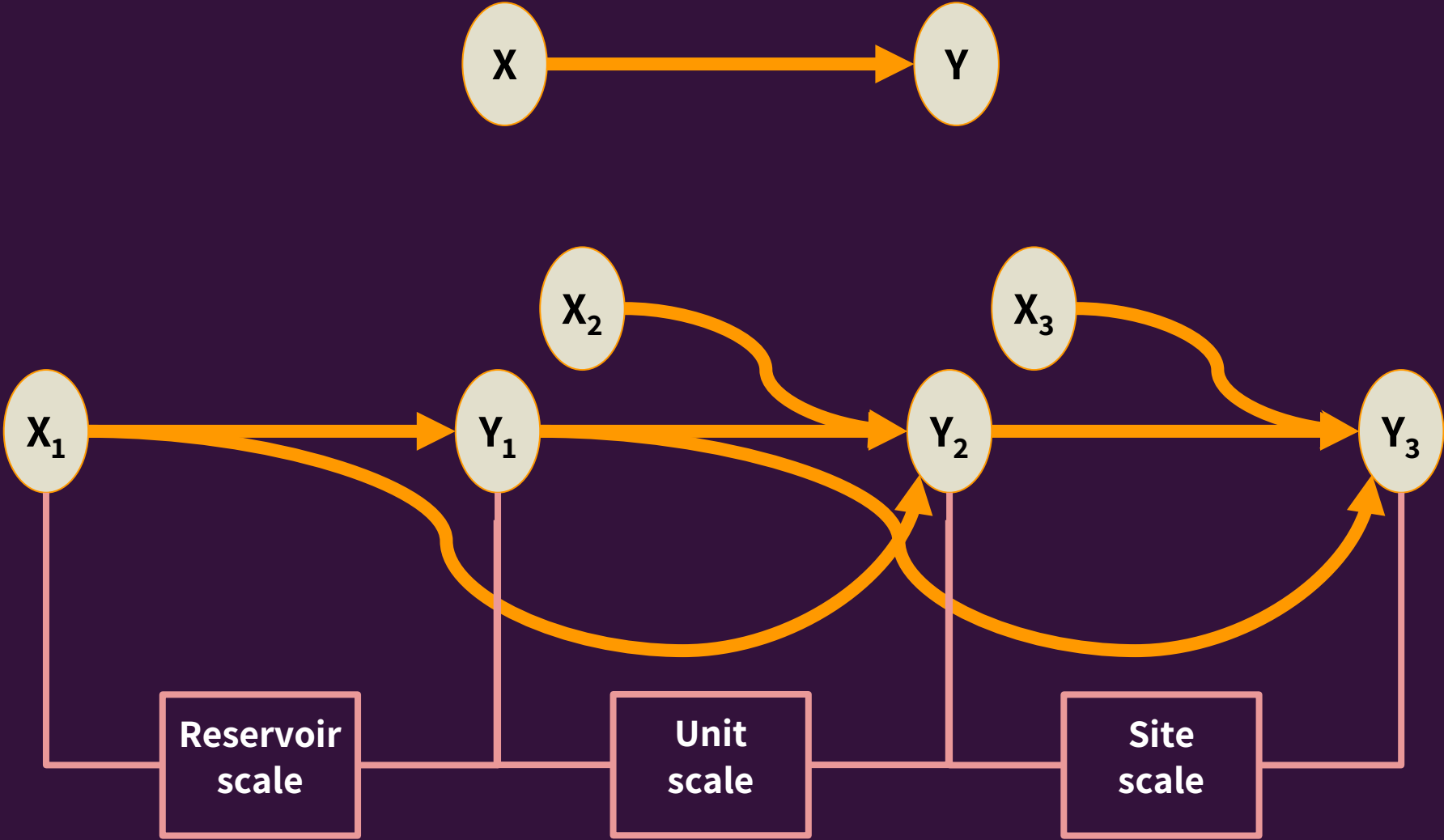
# Geologic Reservoir Data Issues

- Gaps, Uncertainties, Errors & Inaccuracies
- Representativeness & Information Content
- Differences in spatiotemporal support scales of data & features/processes
- Heterogeneity (faults, facies, layers, synclinals, vents, volcanos, ...)
- “Hidden” (latent) features/signatures

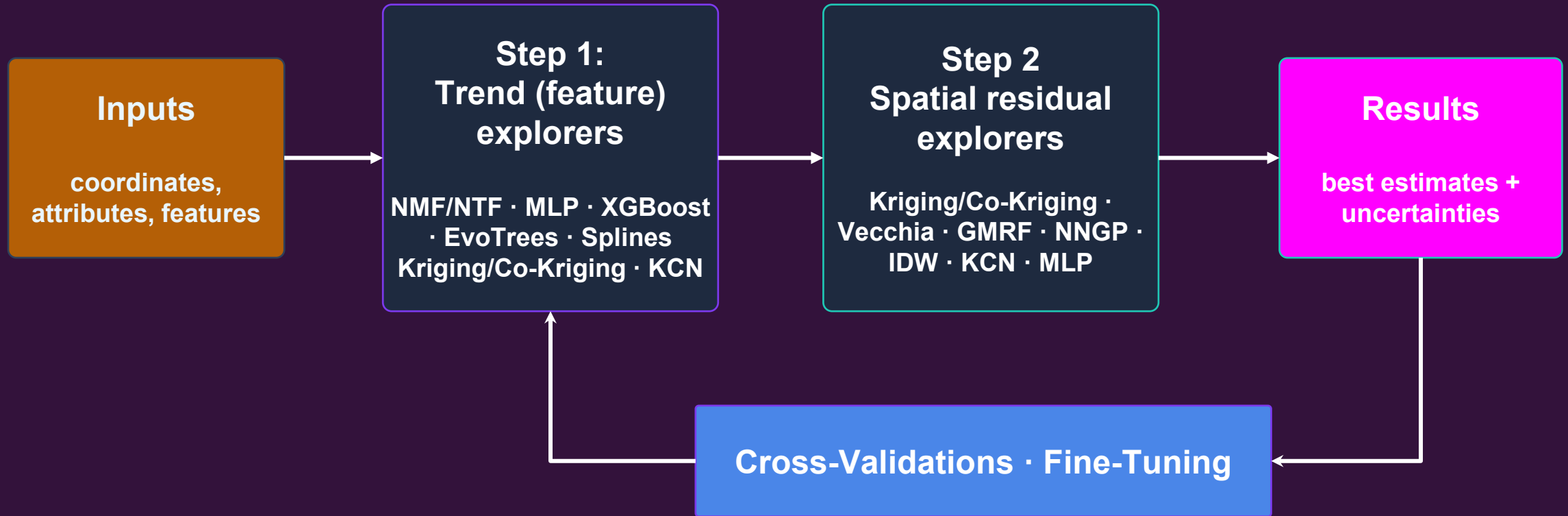
# GeoML: Cloud software suite for geospatial ML analyses

- Physics- and geology-aware ML algorithms
- Automated cross-validations and fine tuning
- Identifying the best **multi-scale(step)** approach for a given dataset/problem
- Geospatial test problems & benchmarks
- ML **multi-scale(step)** techniques (with standardized APIs):
  - Nonnegative matrix/tensor factorization (NMFk/NTFk)
  - Support Vectors (SVM/SVR)
  - XGBoost/EvoTrees
  - Inverse Distance Weighted (IDW)
  - Spatial splines/Minimum curvature (Biggs FD and classical)
  - Kriging/Vecchia/Gaussian Process/Nearest Neighbour Gaussian Process
  - Kriging Convolutional Neural Networks (KCN)
  - Gaussian Markov Random Field (GMRF)
  - GNNs, MLPs, CNNs, LSTMs, Diffusion Models (DMs)
  - Stochastic PDEs (SPDE)
  - Transformers
  - Differentiable physics models (analytical/numerical)

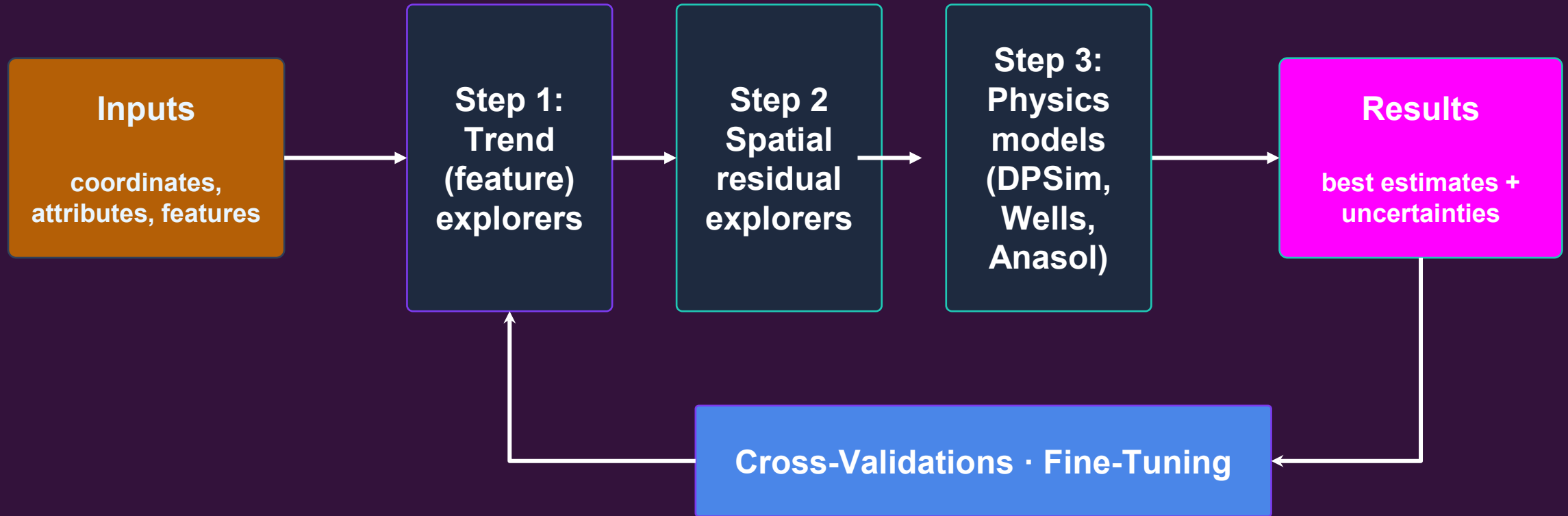
# Multi-scale(step) ML approach for geospatial analyses



# GeoML: Multi-scale(step) approach for geospatial analyses



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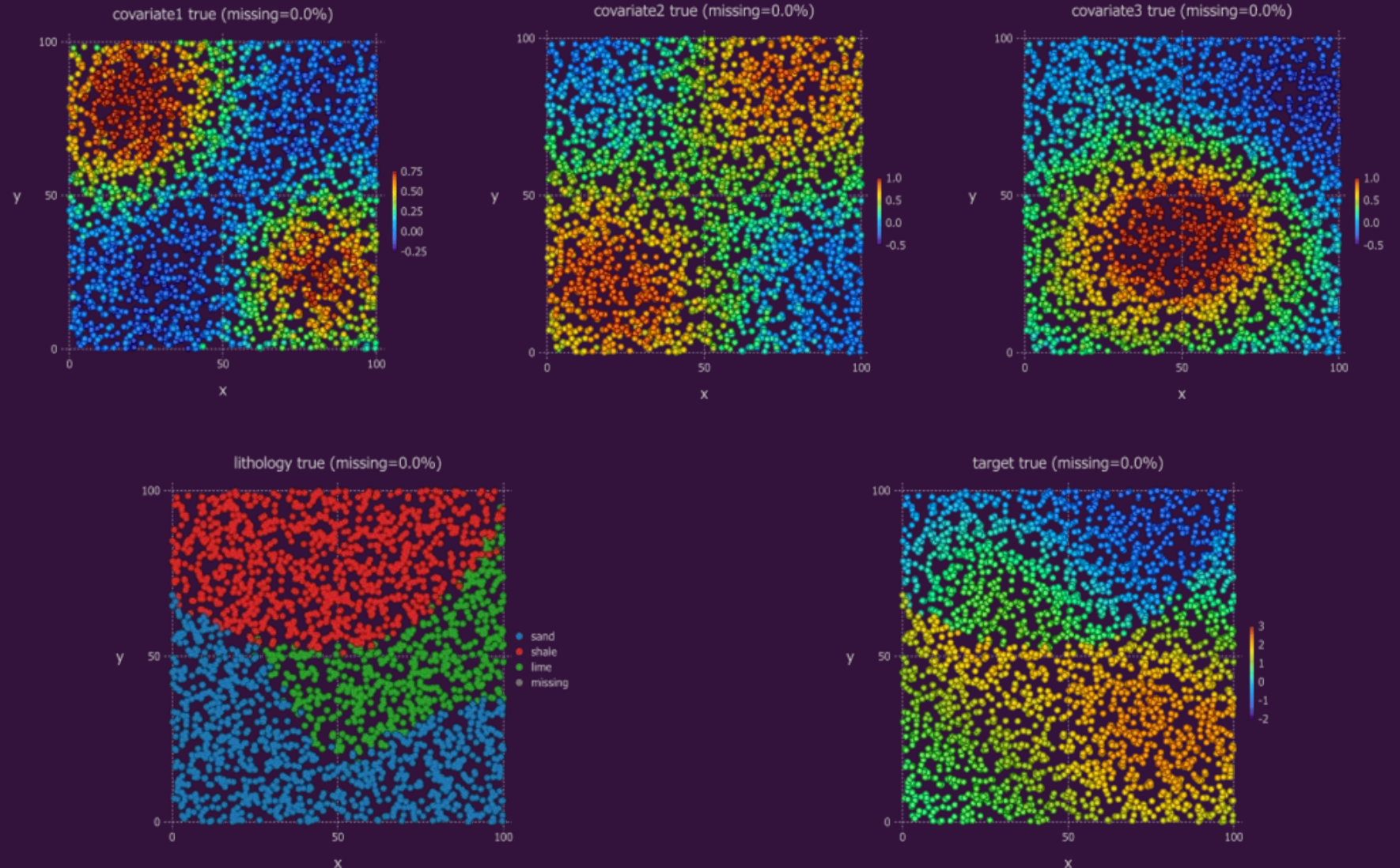
## Physics integration

- Analytical flow expressions (well equations: Theis, Hantush, etc.)
- Analytical transport expressions (Fickian and non-Fickian dispersion models)
- Numerical simulators (DPSIm)
  
- Differentiable programming (Julia)

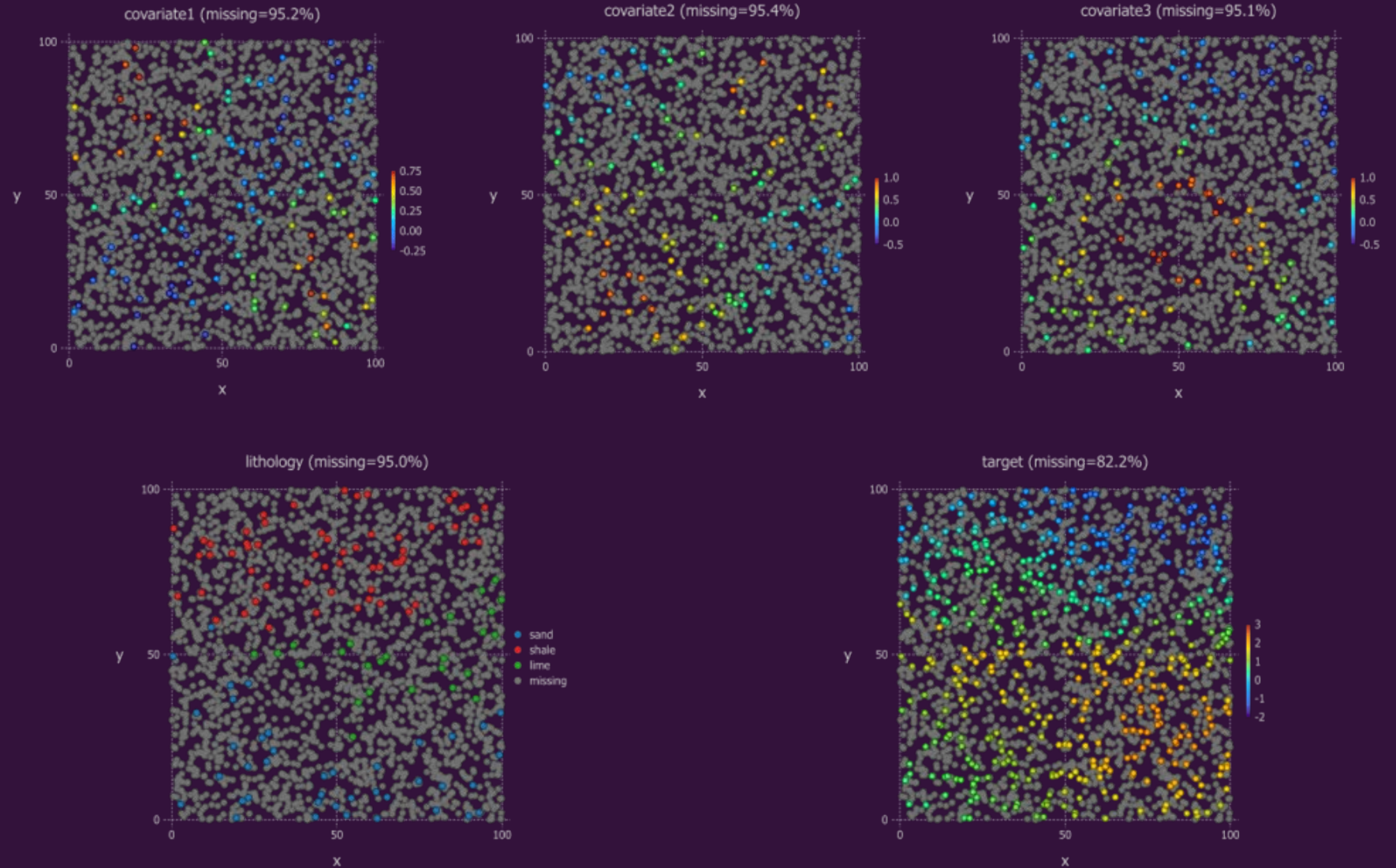
# Data, Models, Machine Learning ...

- Data assimilation
  - Data imputation
  - Model inversion (calibration)
- 
- All infer missing or hidden information from uncertain observations
  - In Bayesian view, they can be viewed as conditional inference

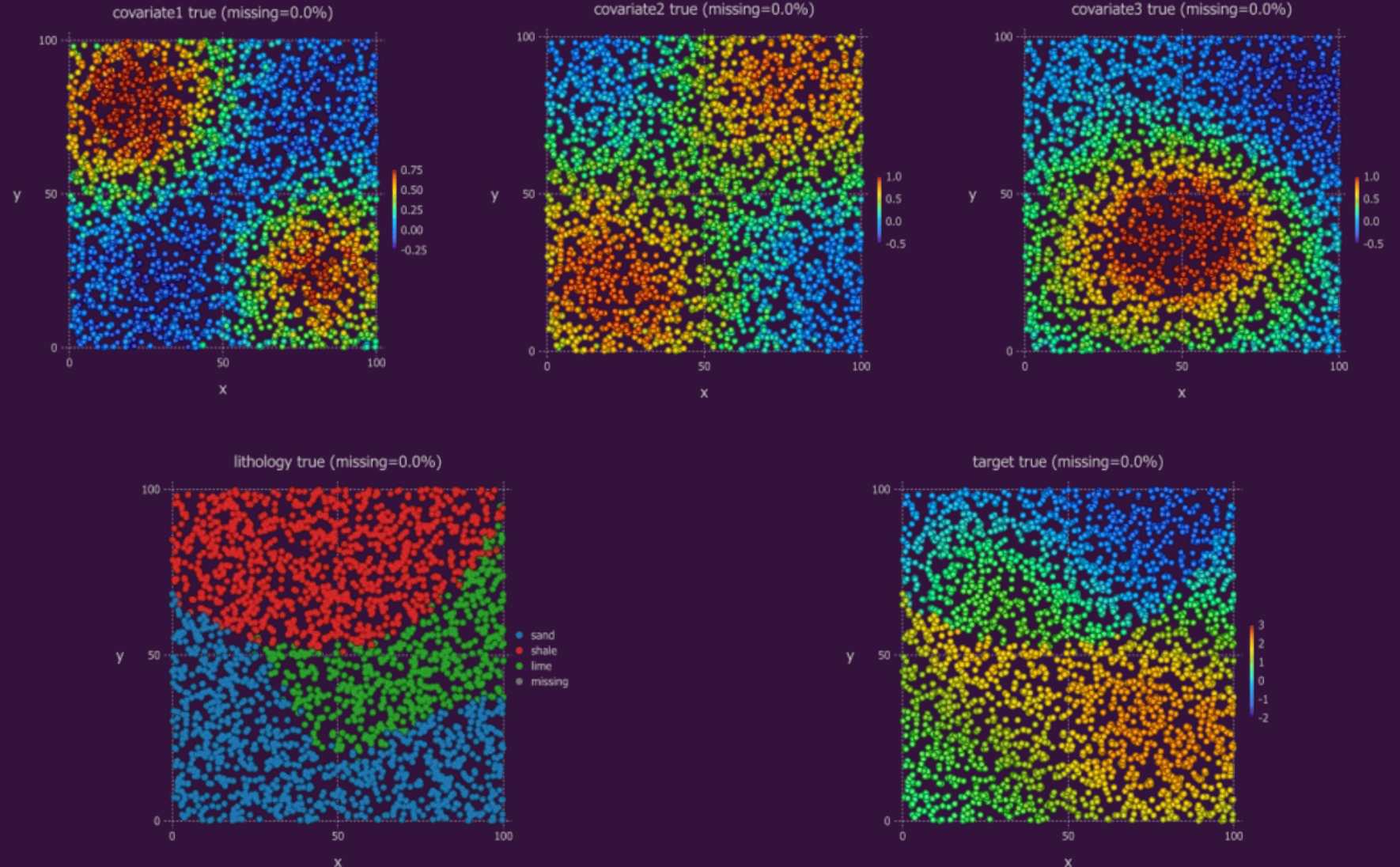
# Geospatial problem



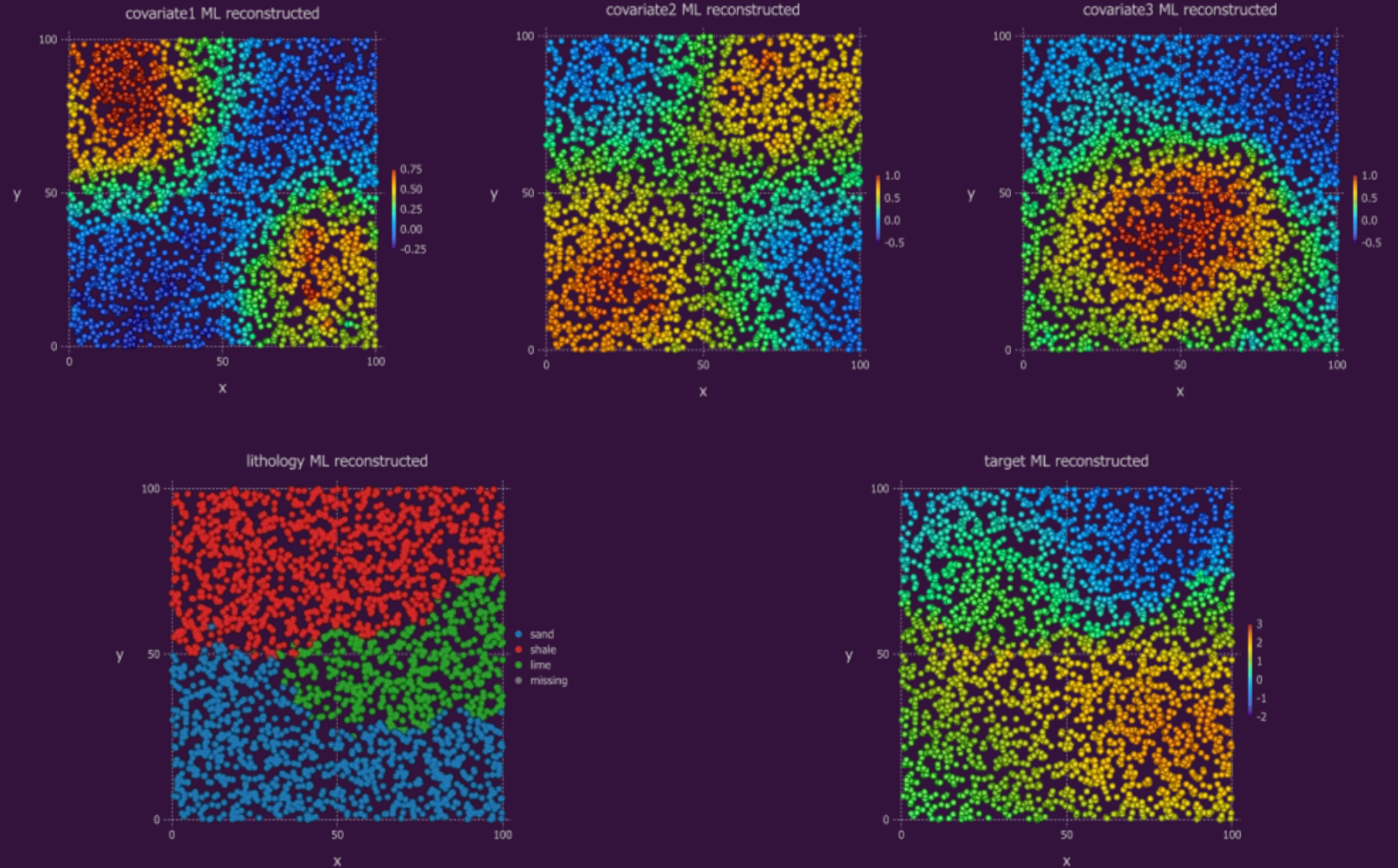
# Geospatial problem (~95%)



# Geospatial problem (truth)



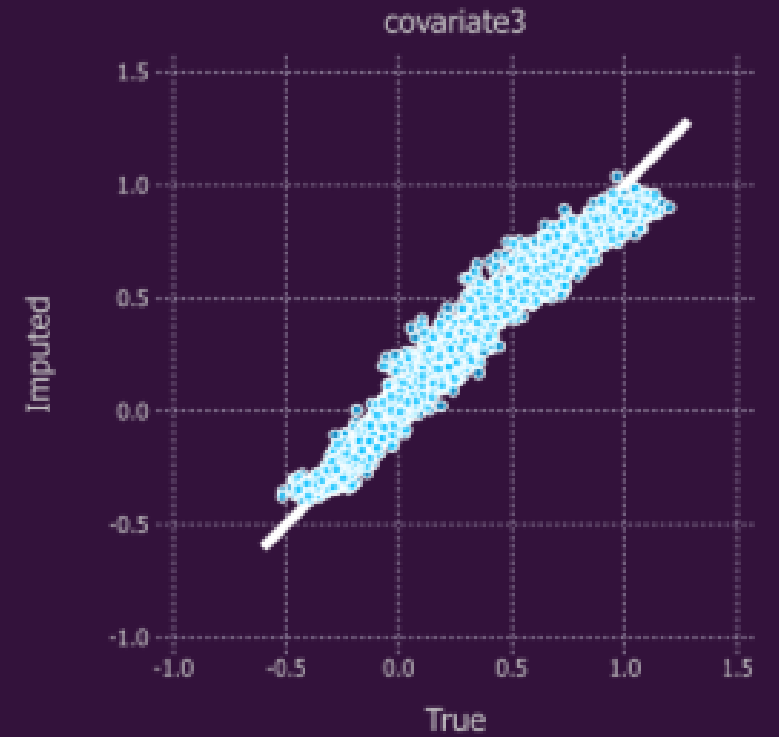
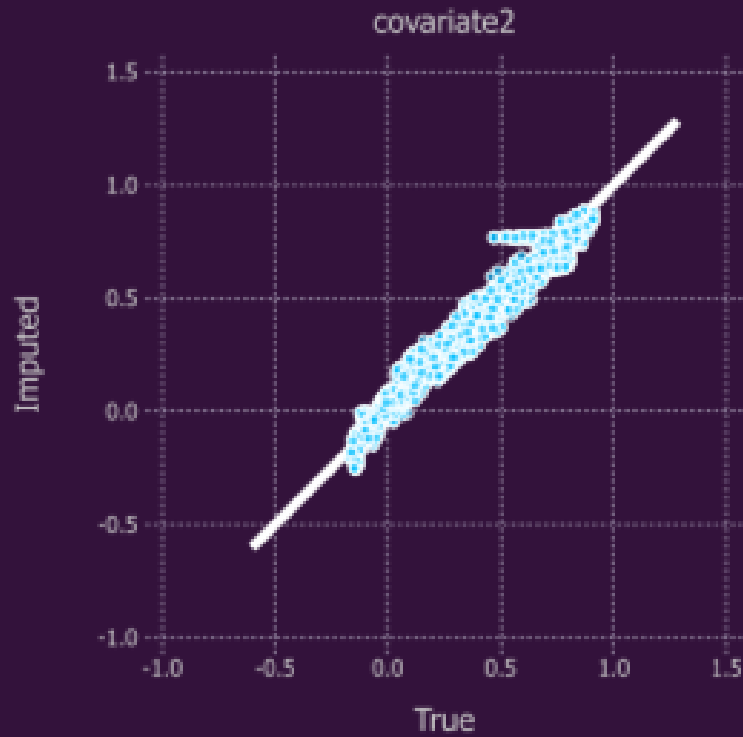
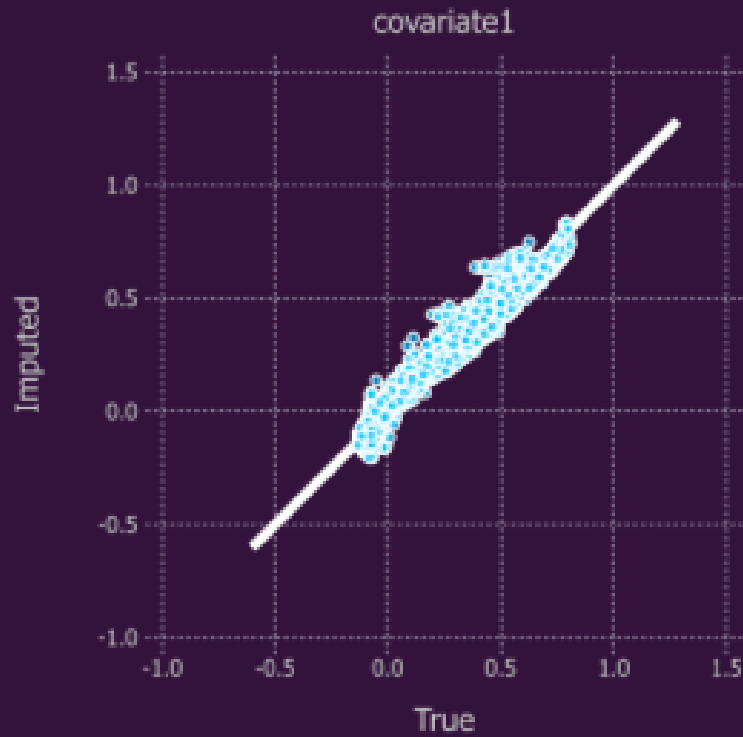
# Geospatial problem



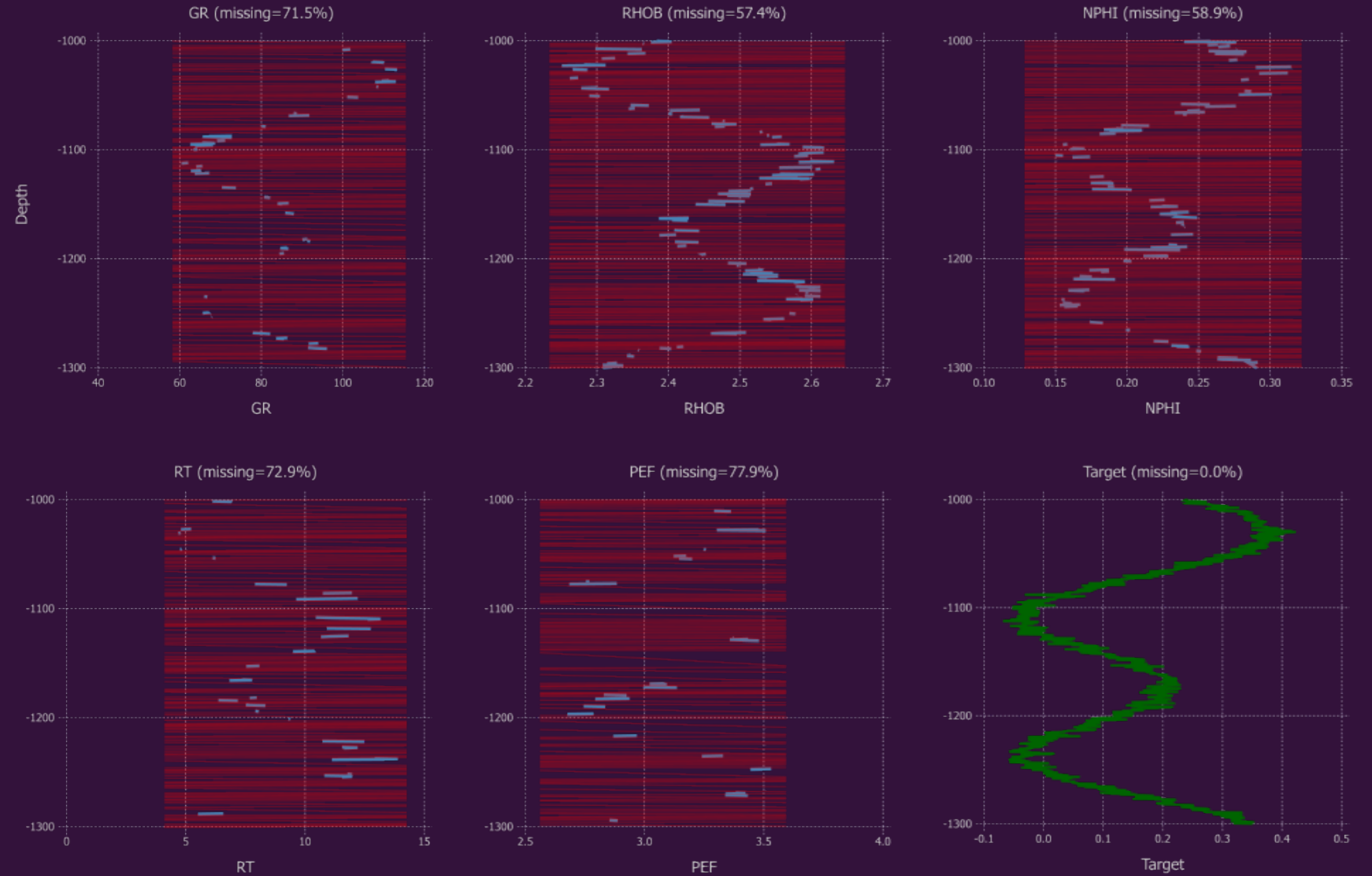
# Geospatial problem



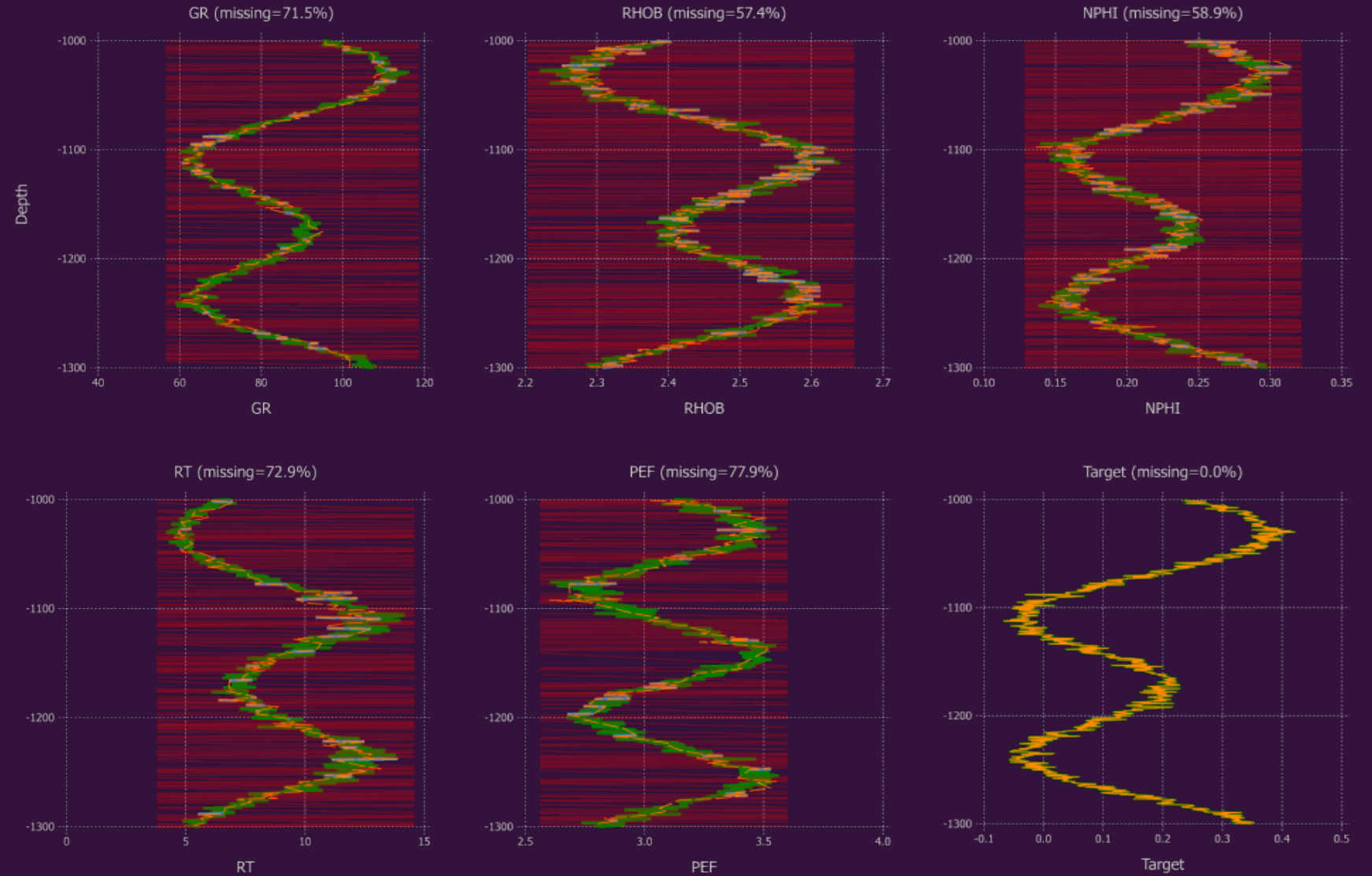
# Geospatial problem



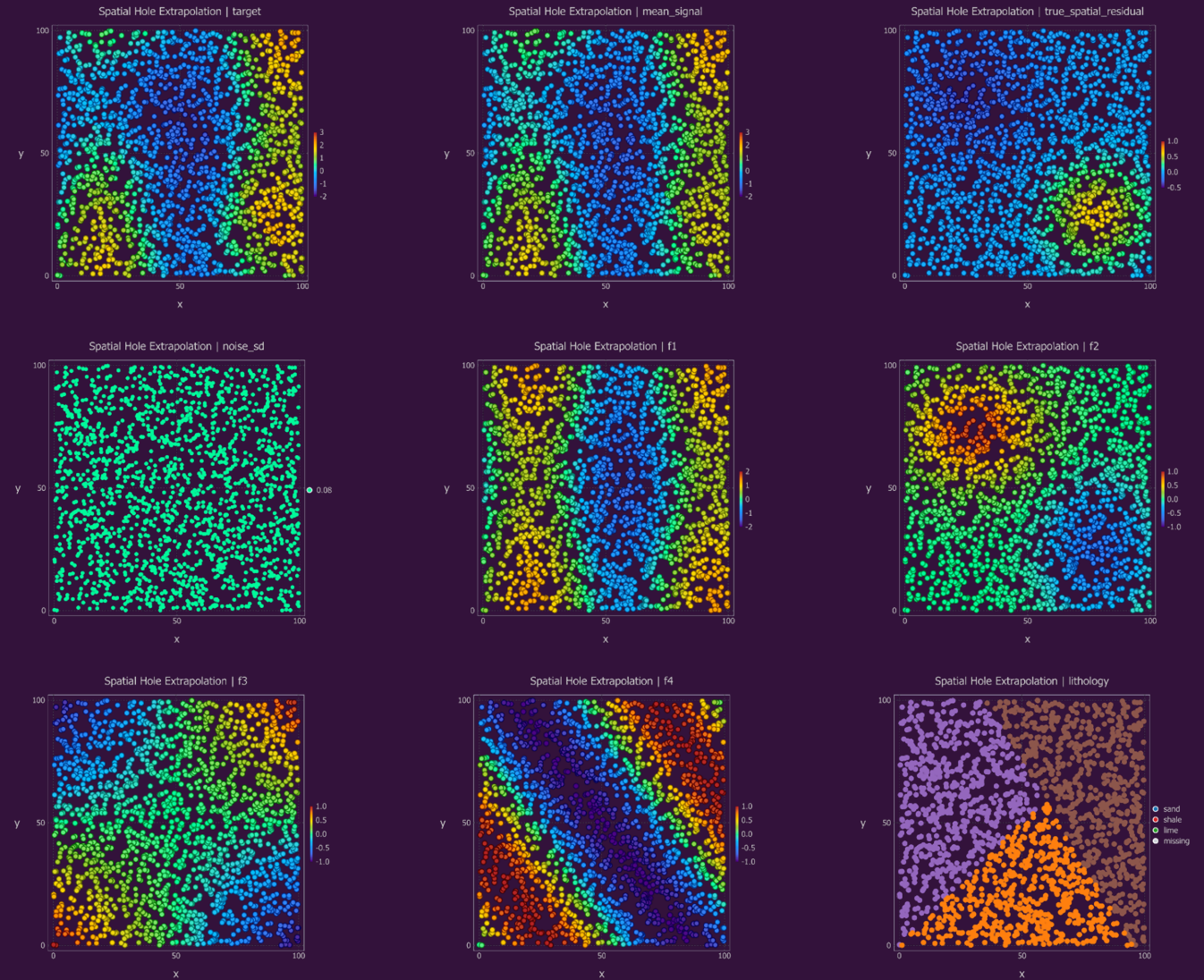
# Well-log demo problem



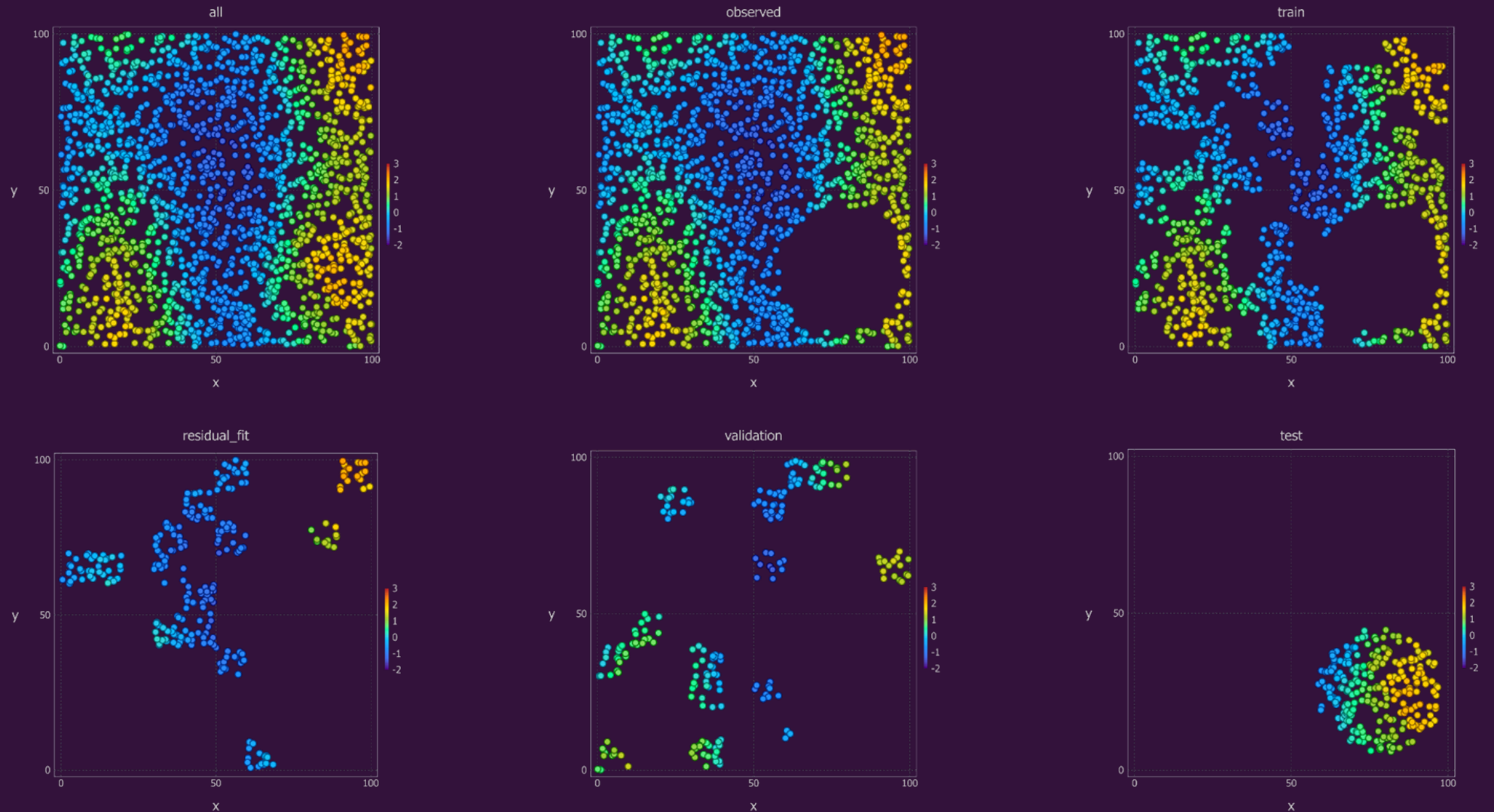
# Well-log demo problem



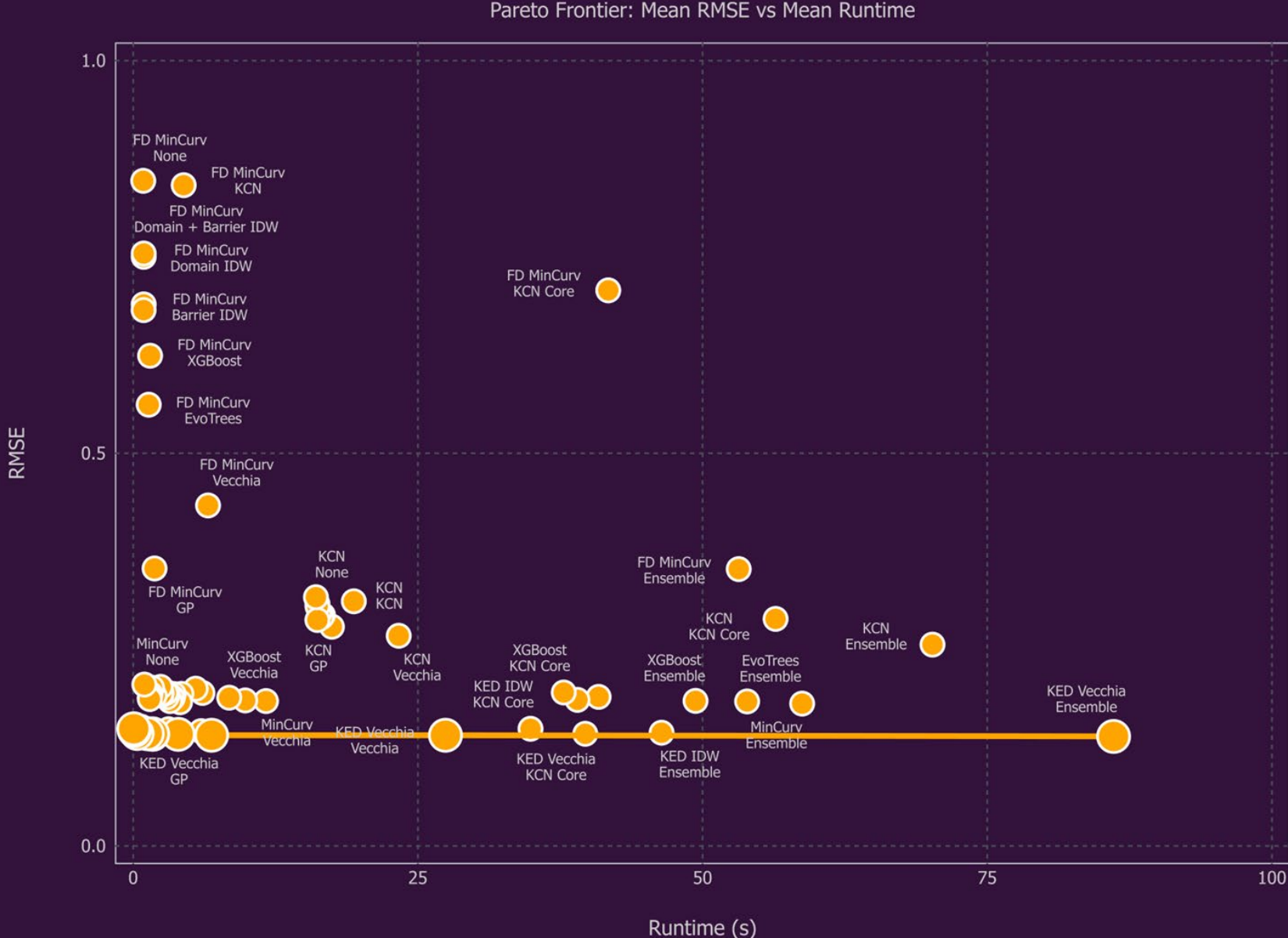
# Big data gap imputation



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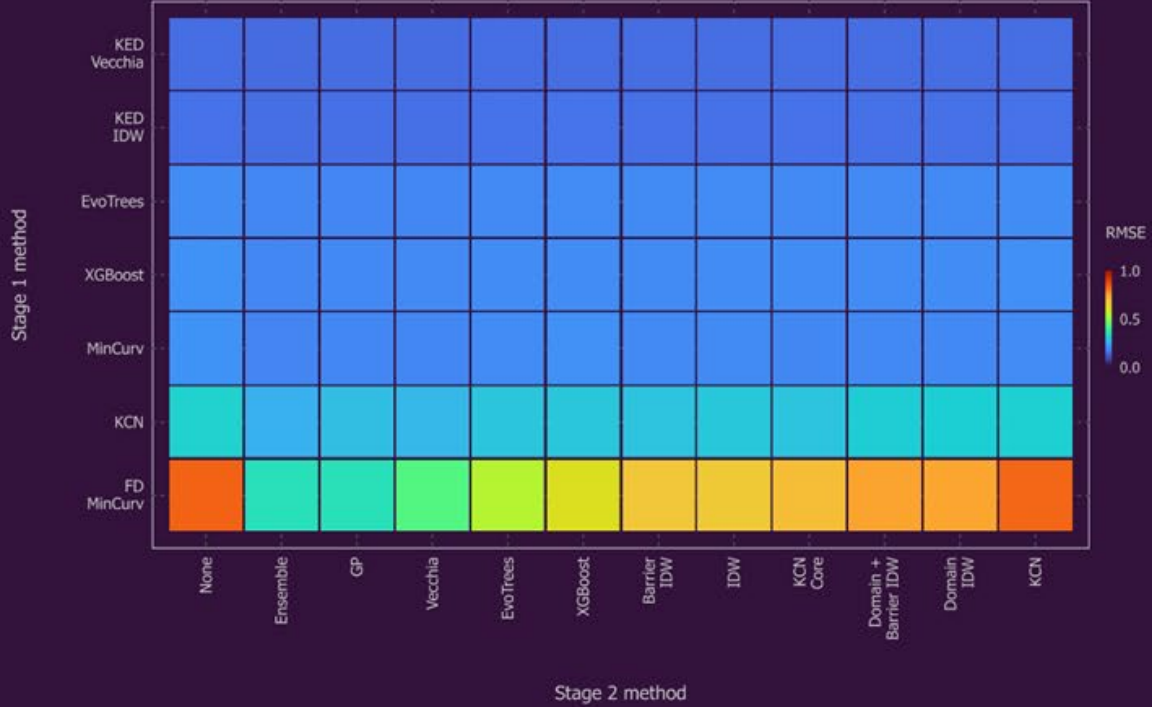


# Performance

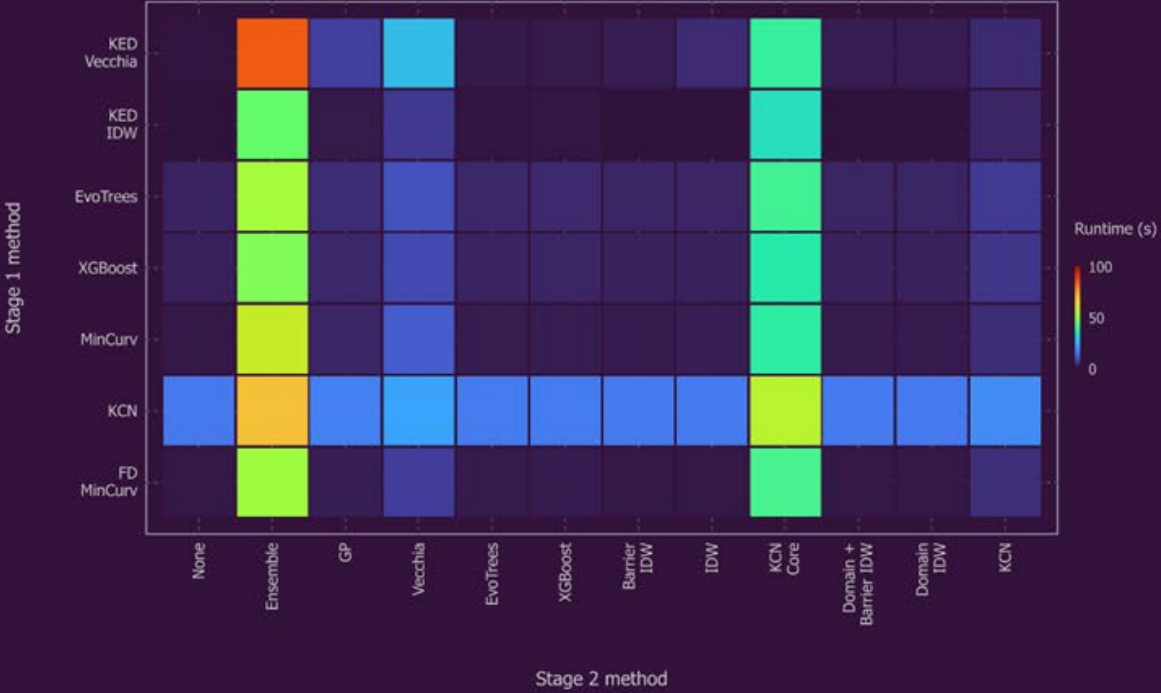


# Performance

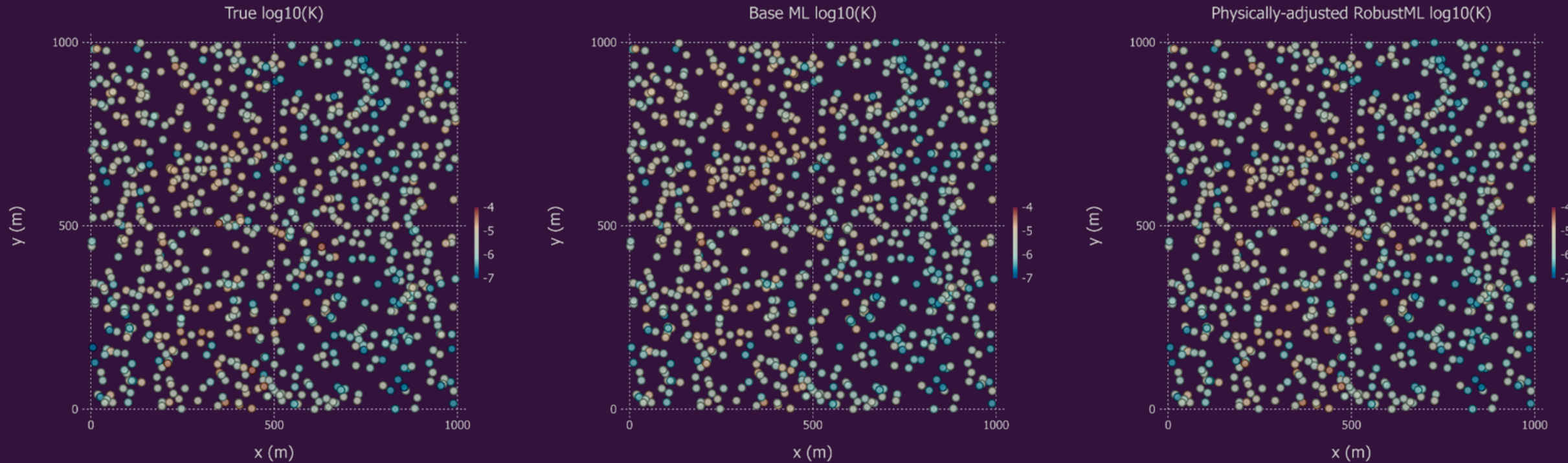
RMSE Heatmap



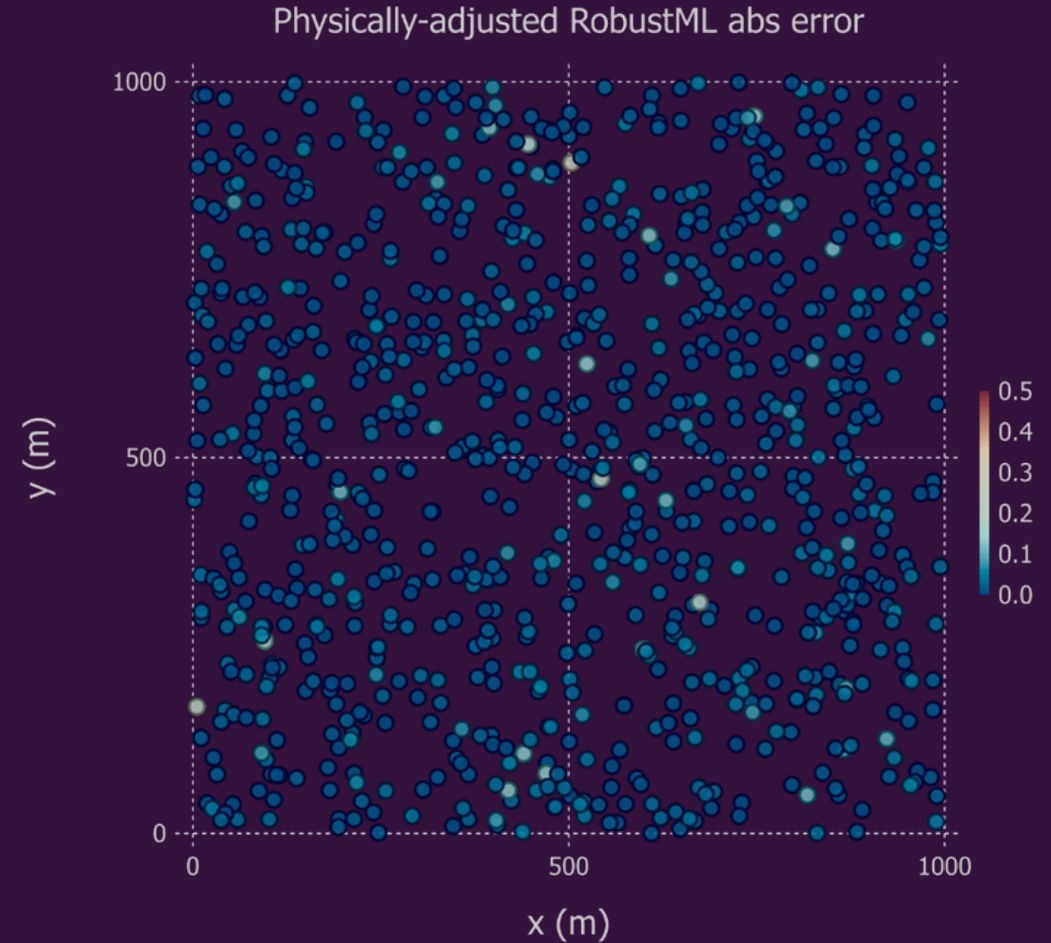
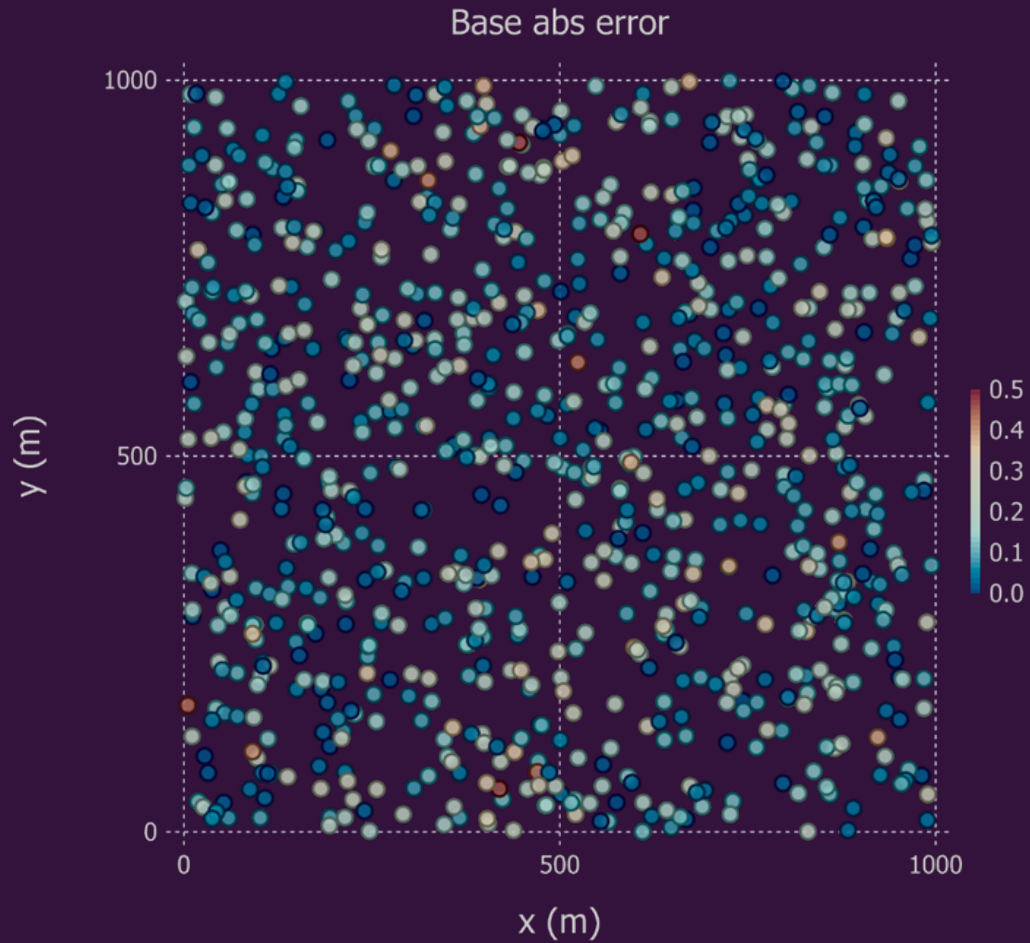
Runtime Heatmap



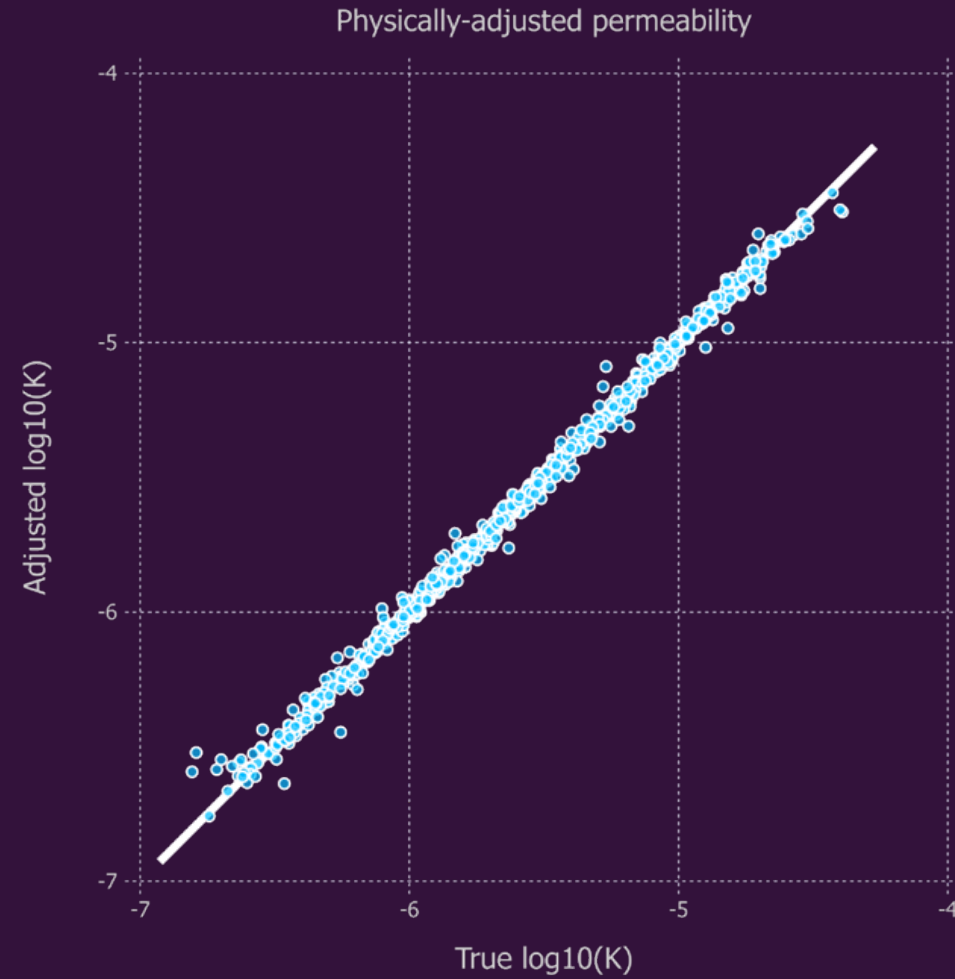
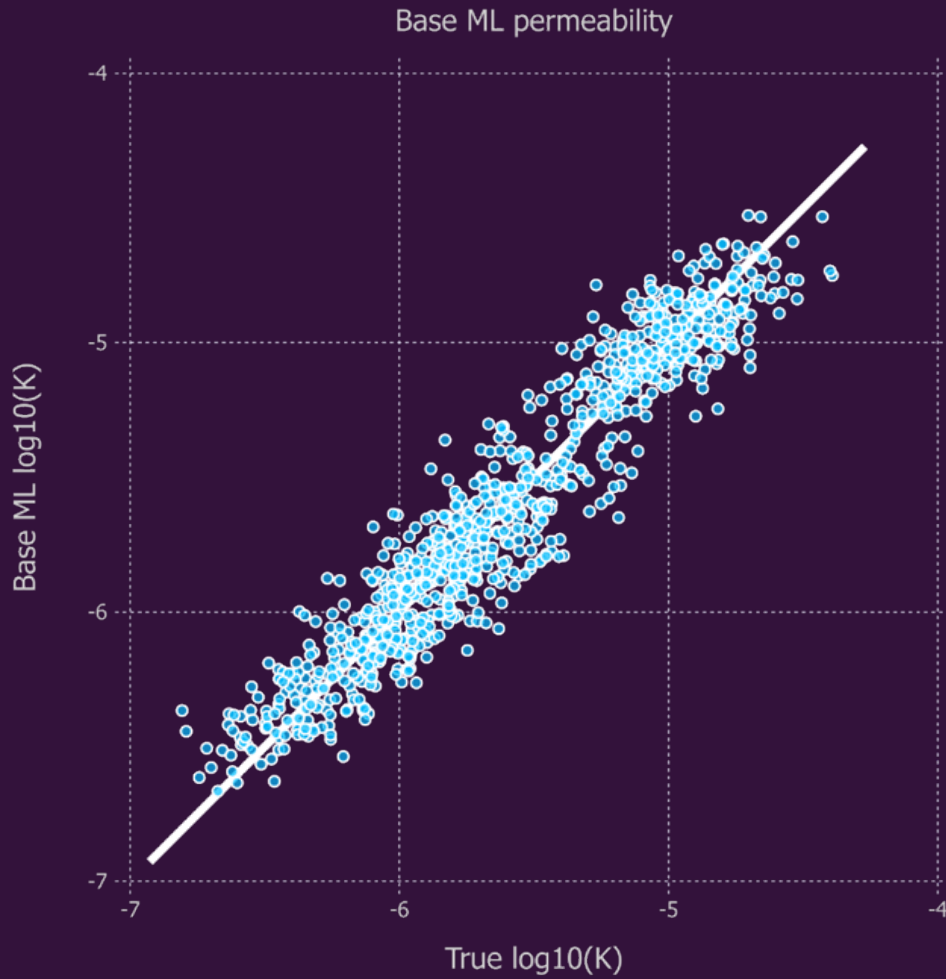
# Physics layer (pumping tests)



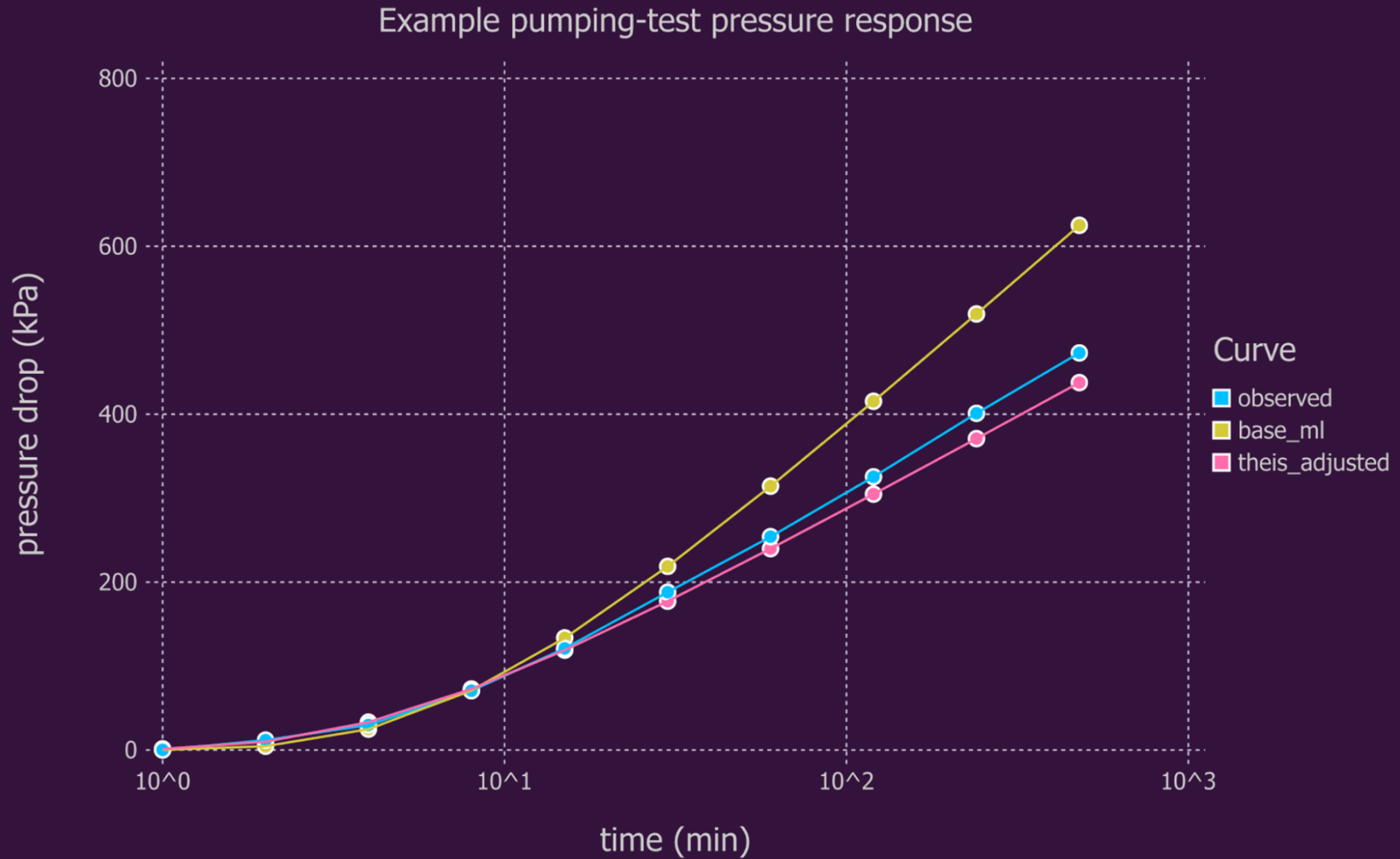
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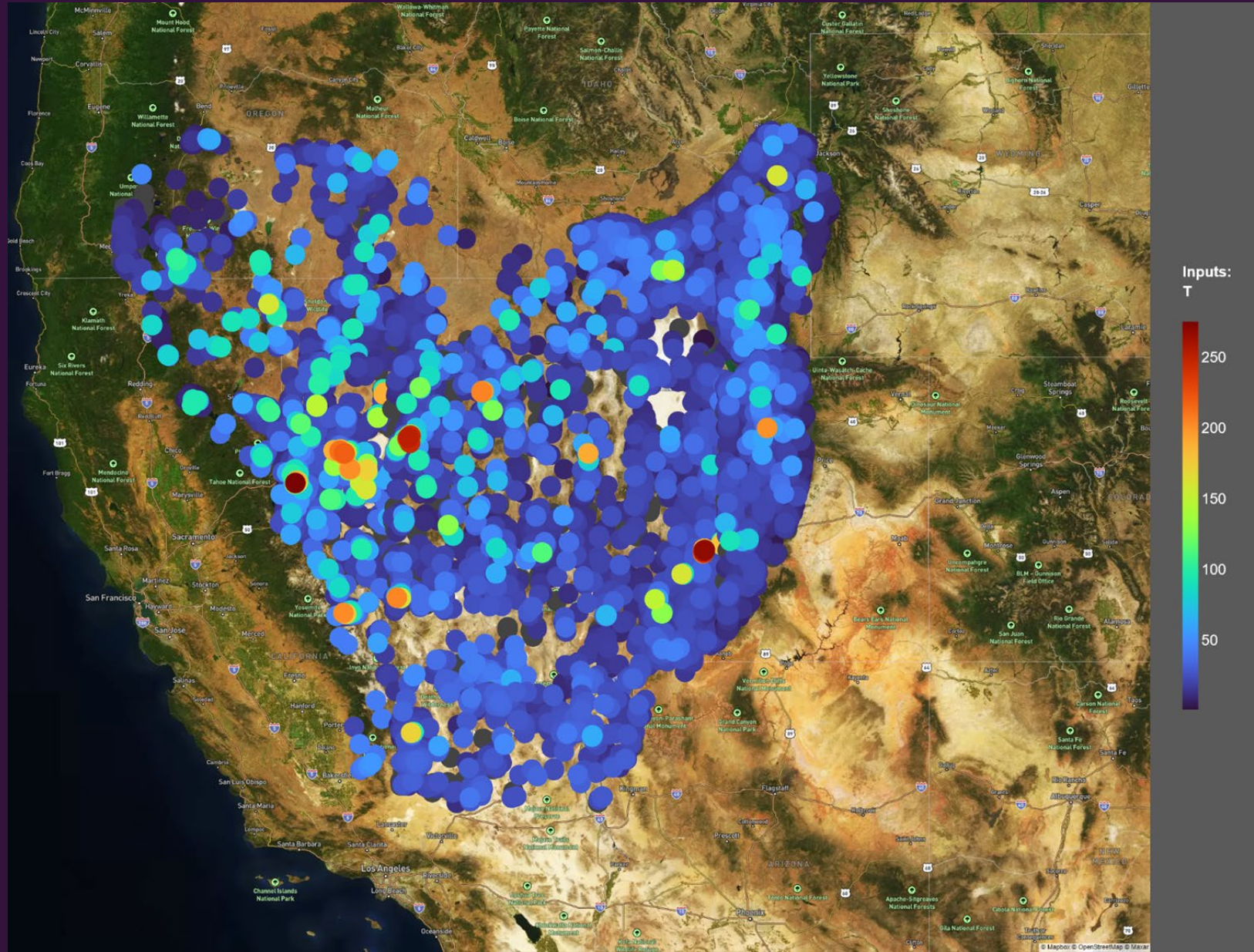


# Physics layer (pumping tests)



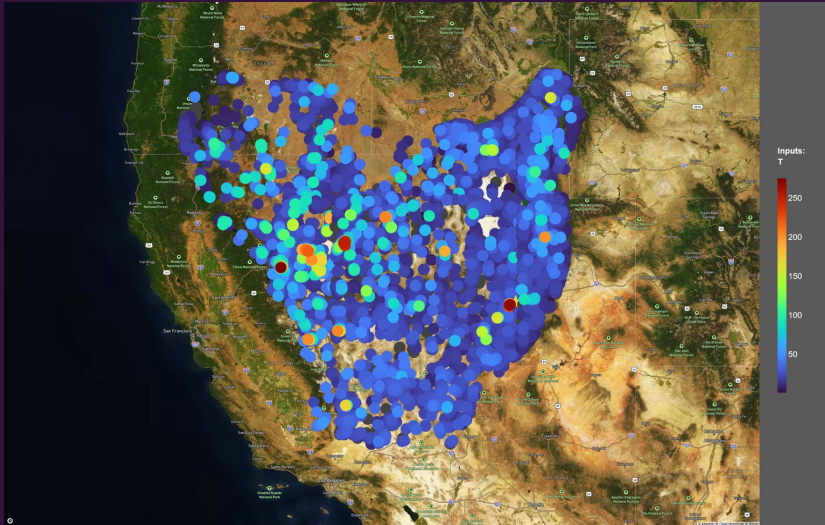
# Great Basin Datasets (126 attributes in total)

- Magnetics
- Radiometry
- Gravity
- Li, Mg, Na, Fe, HCO<sub>3</sub>, SiO<sub>2</sub>, Ba, F, SO<sub>4</sub>, K, B, Ca, Cl, As, ...
- Heat flow
- Favorable Geothermal Structural Settings (INGENIOUS project)
- Quaternary Faults
- Well & Spring Chemistry
- Principal Aquifers

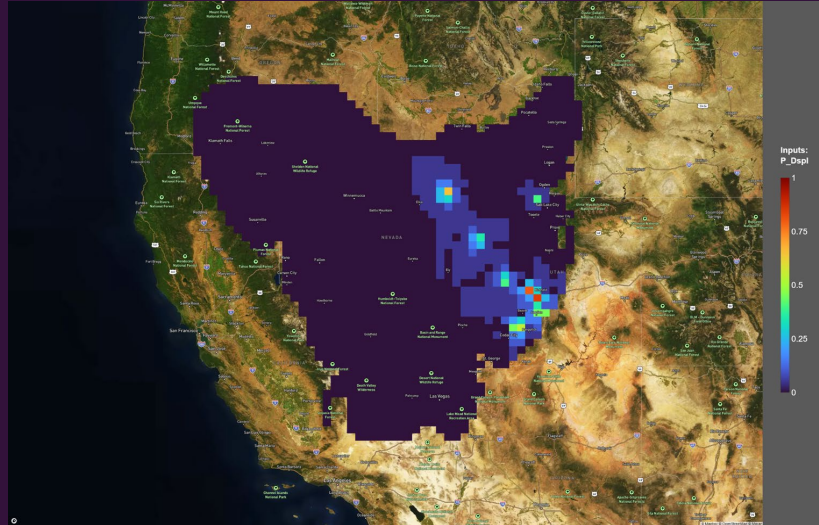


# Finding a Needle in a Haystack

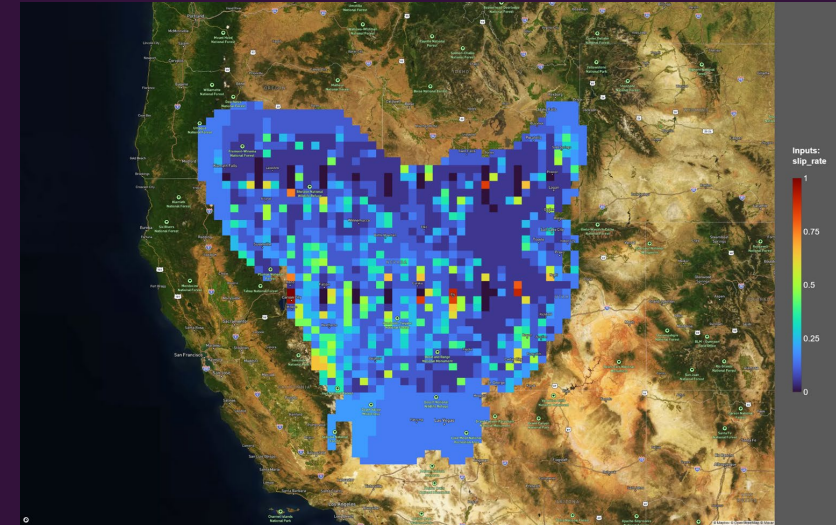
Temperature [°C]



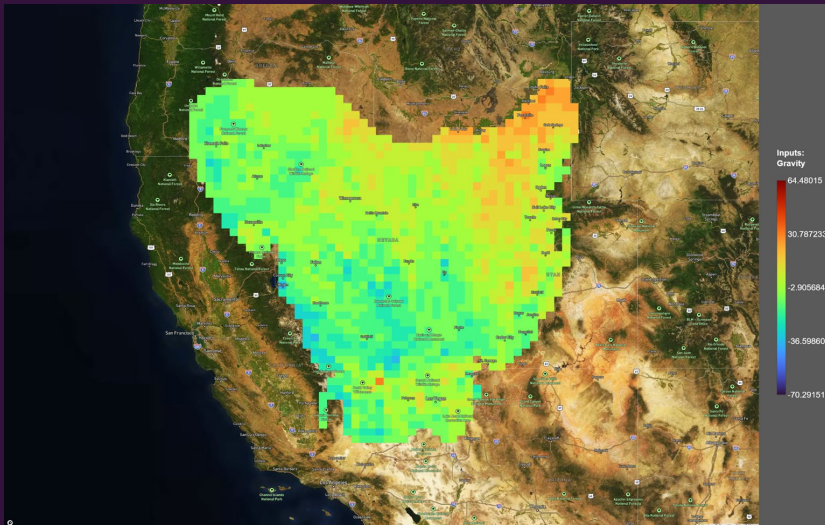
Displacement [normalized]



Slep Rate [normalized]



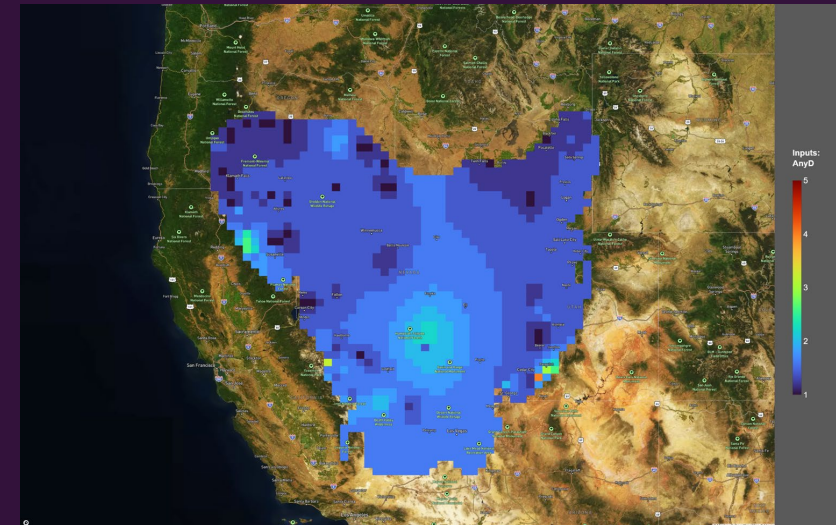
Gravity [m/s<sup>2</sup>]



Magnetics [nT]

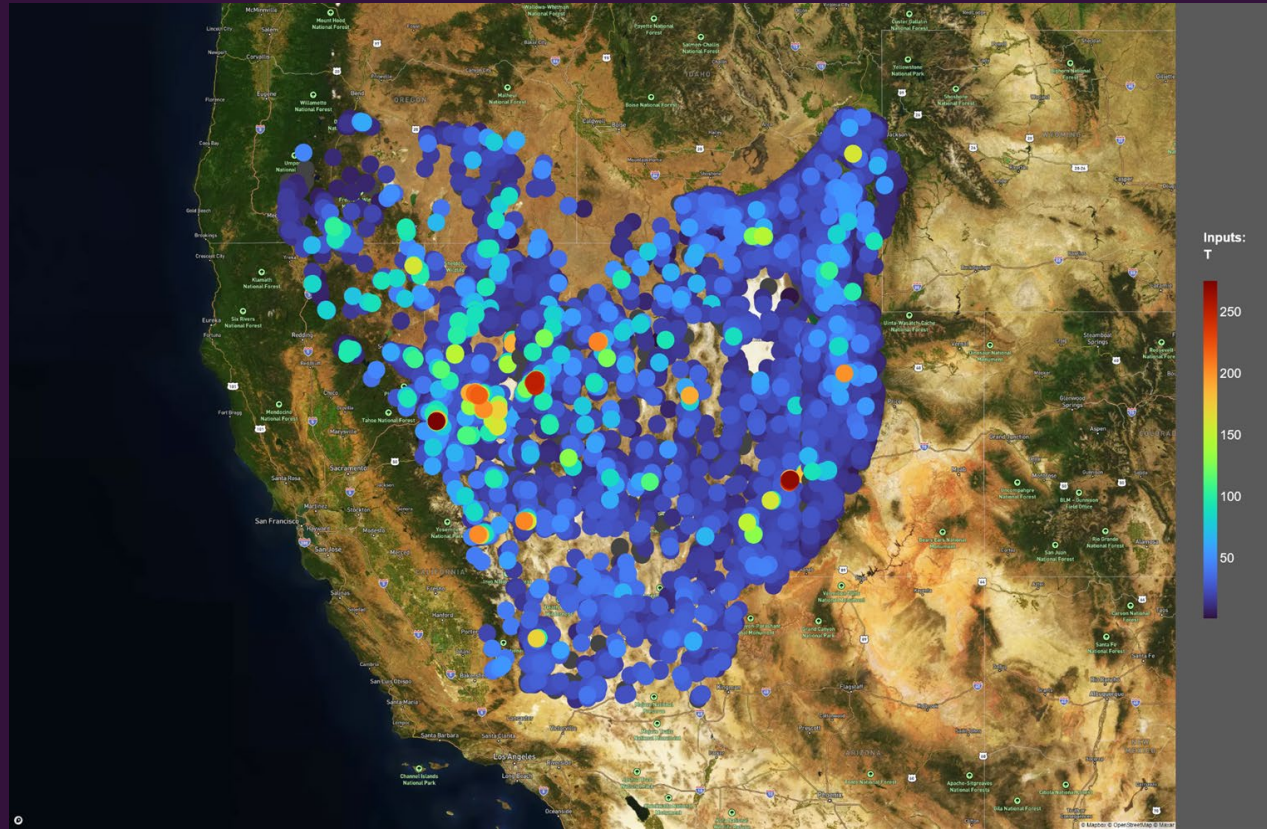


Vent Density [-]

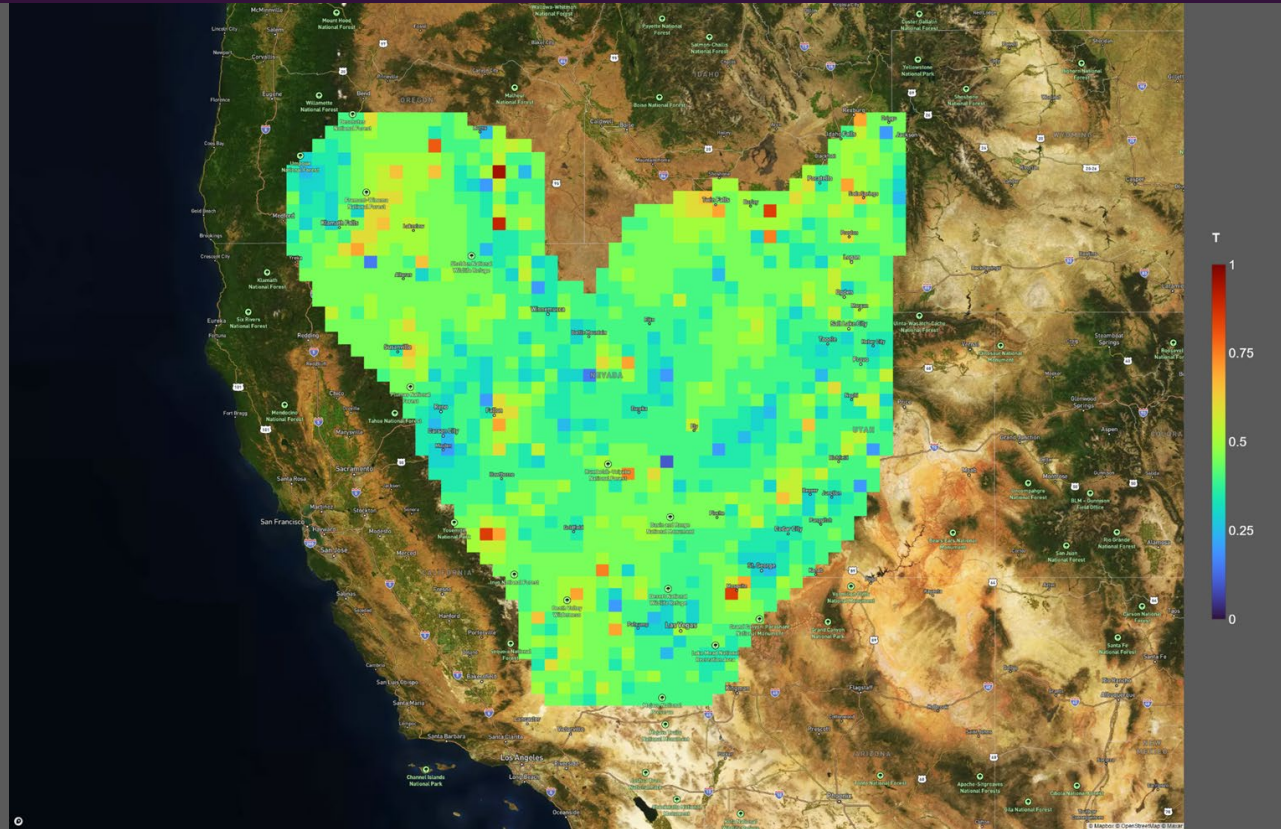


# Geothermal Temperature: Data vs Prospectivity

Temperature [°C]

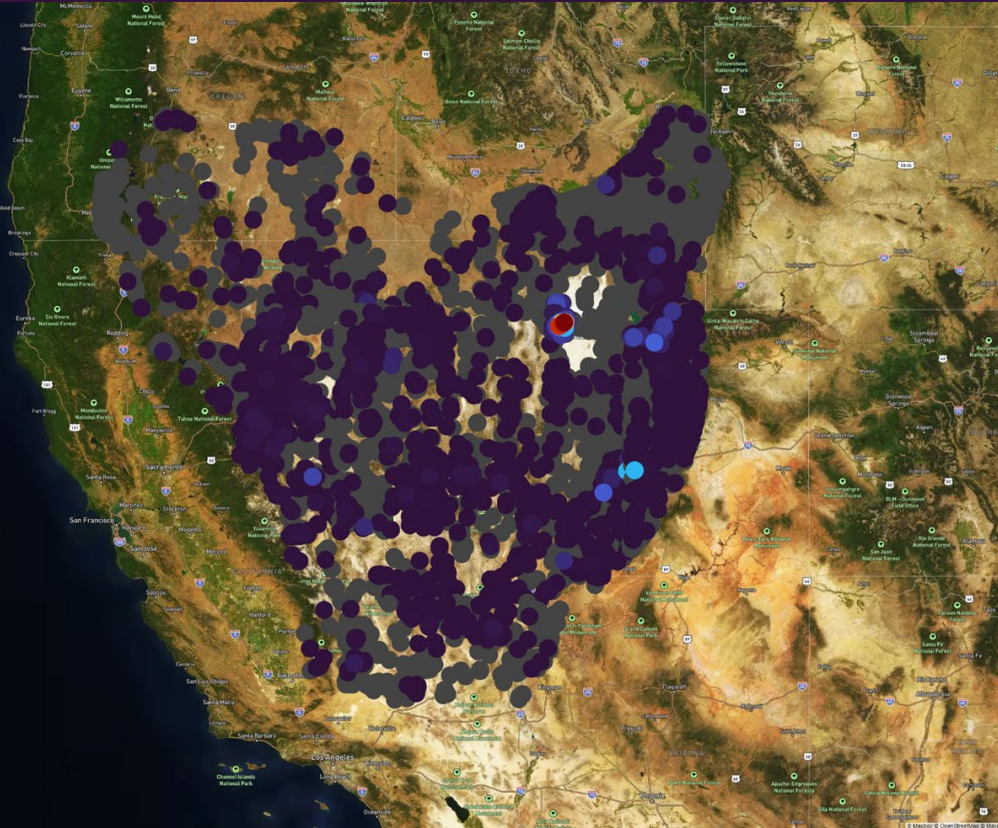


Geothermal Prospectivity [normalized]

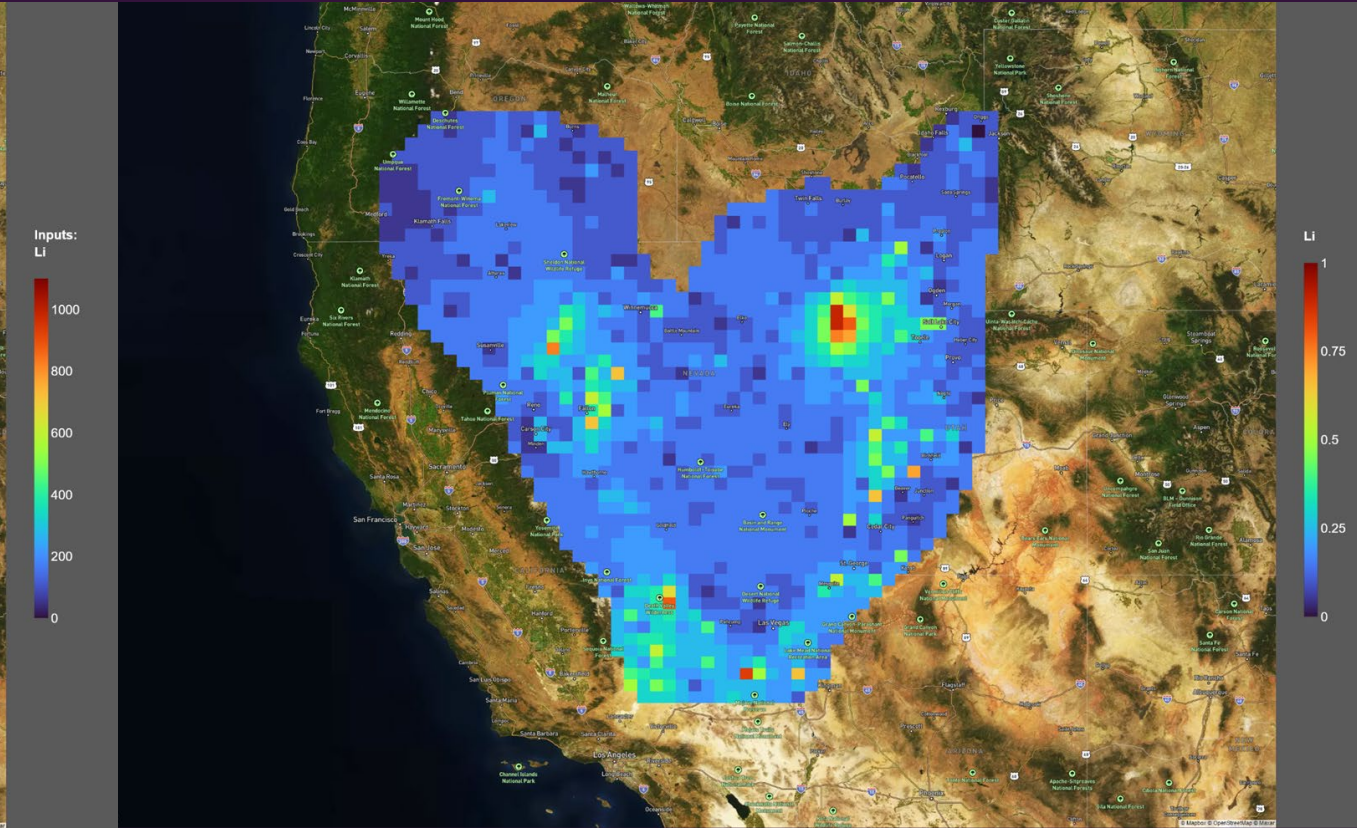


# Lithium: Data vs Prospectivity

Lithium Groundwater Concentrations [ppb]

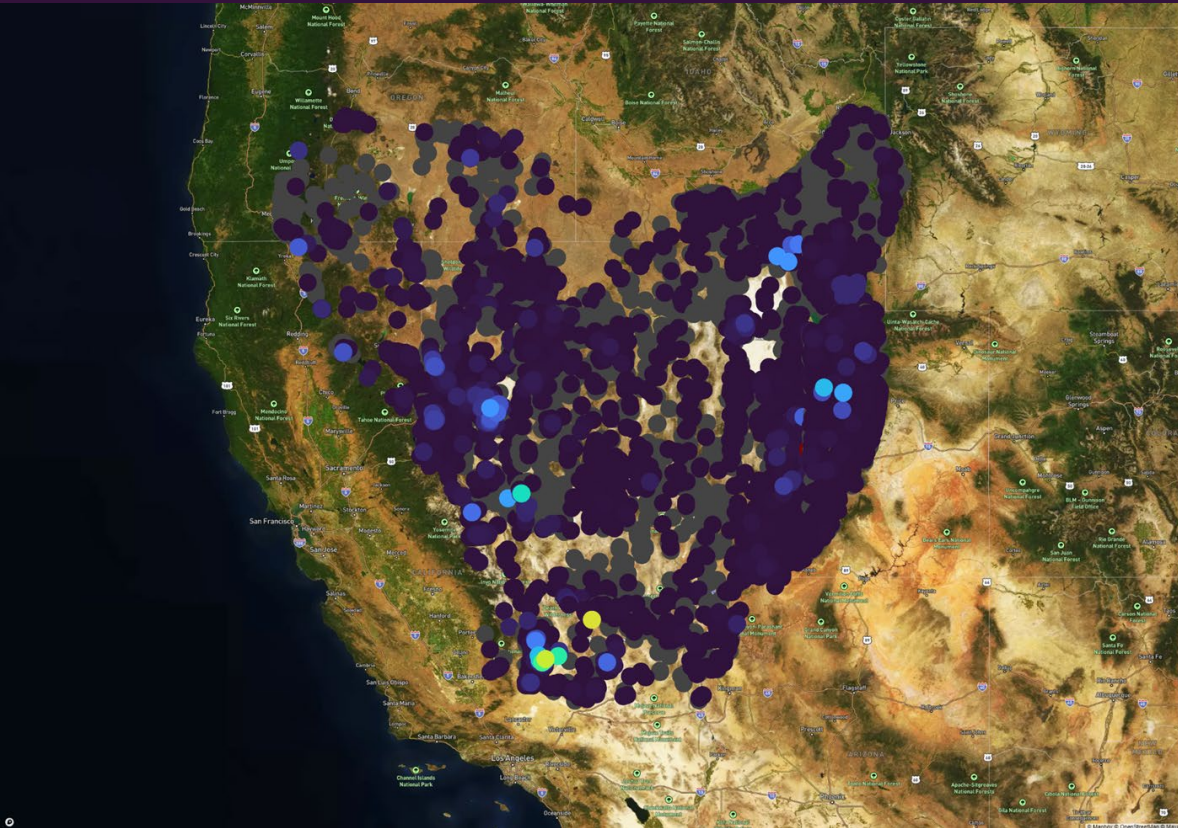


Lithium Prospectivity [normalized]

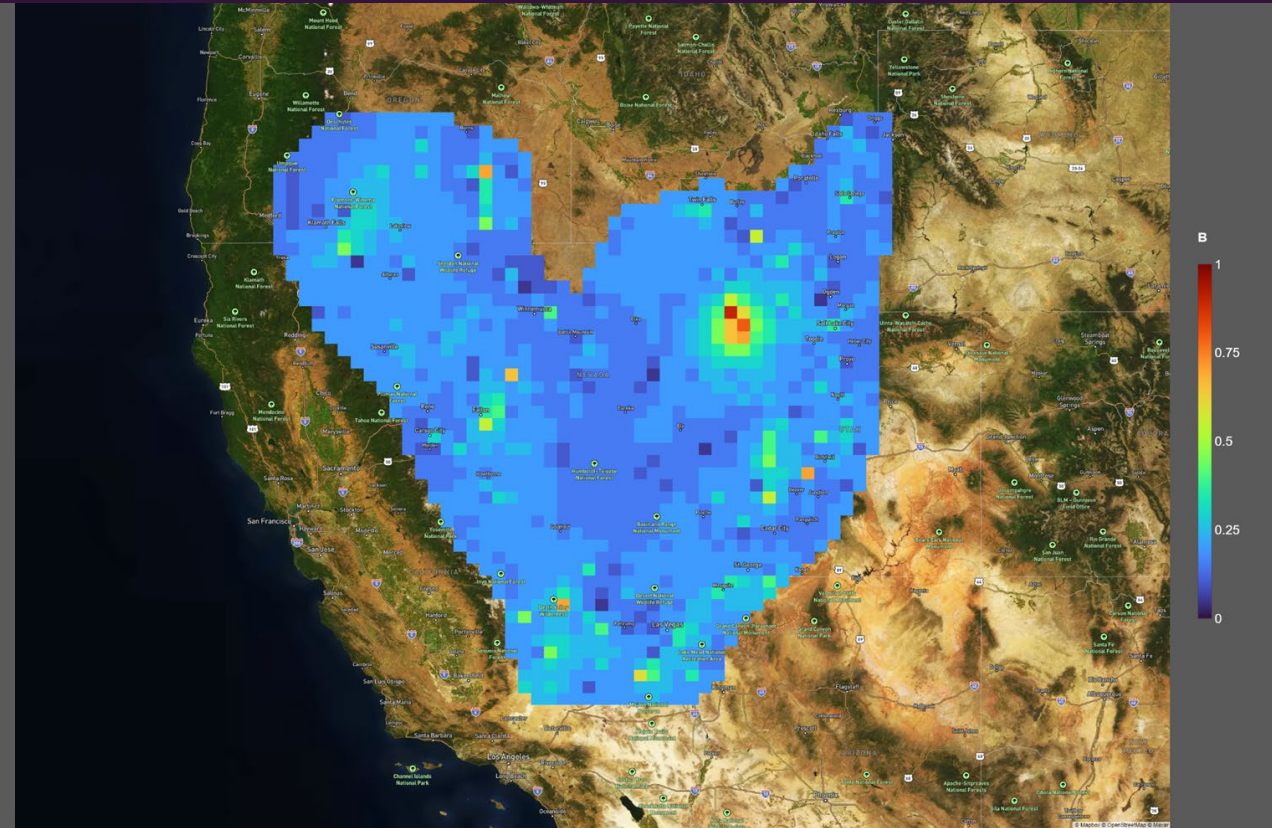


# Boron: Data vs Prospectivity

Boron Groundwater Concentrations [ppb]



Boron Prospectivity [normalized]

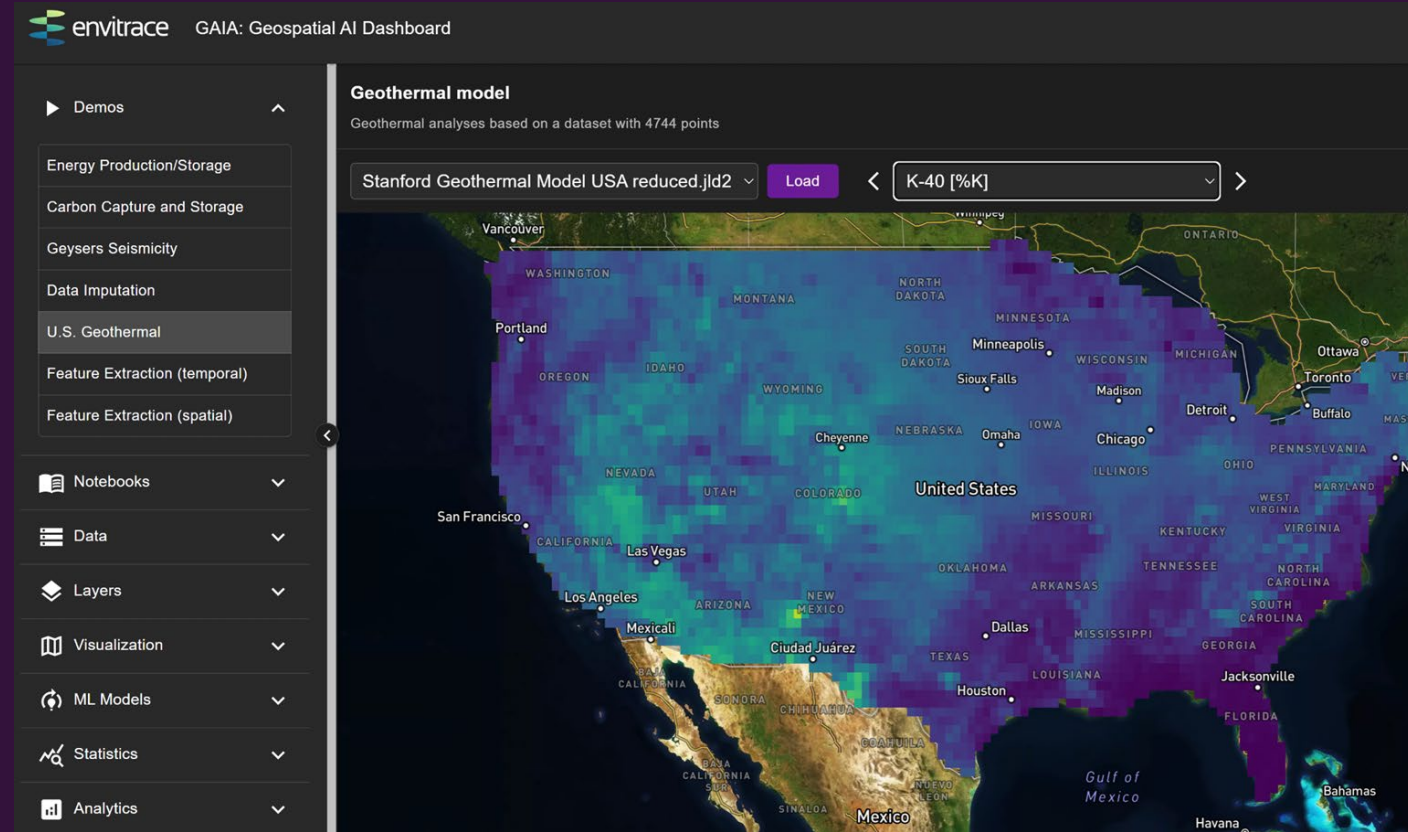


# Our SaaS

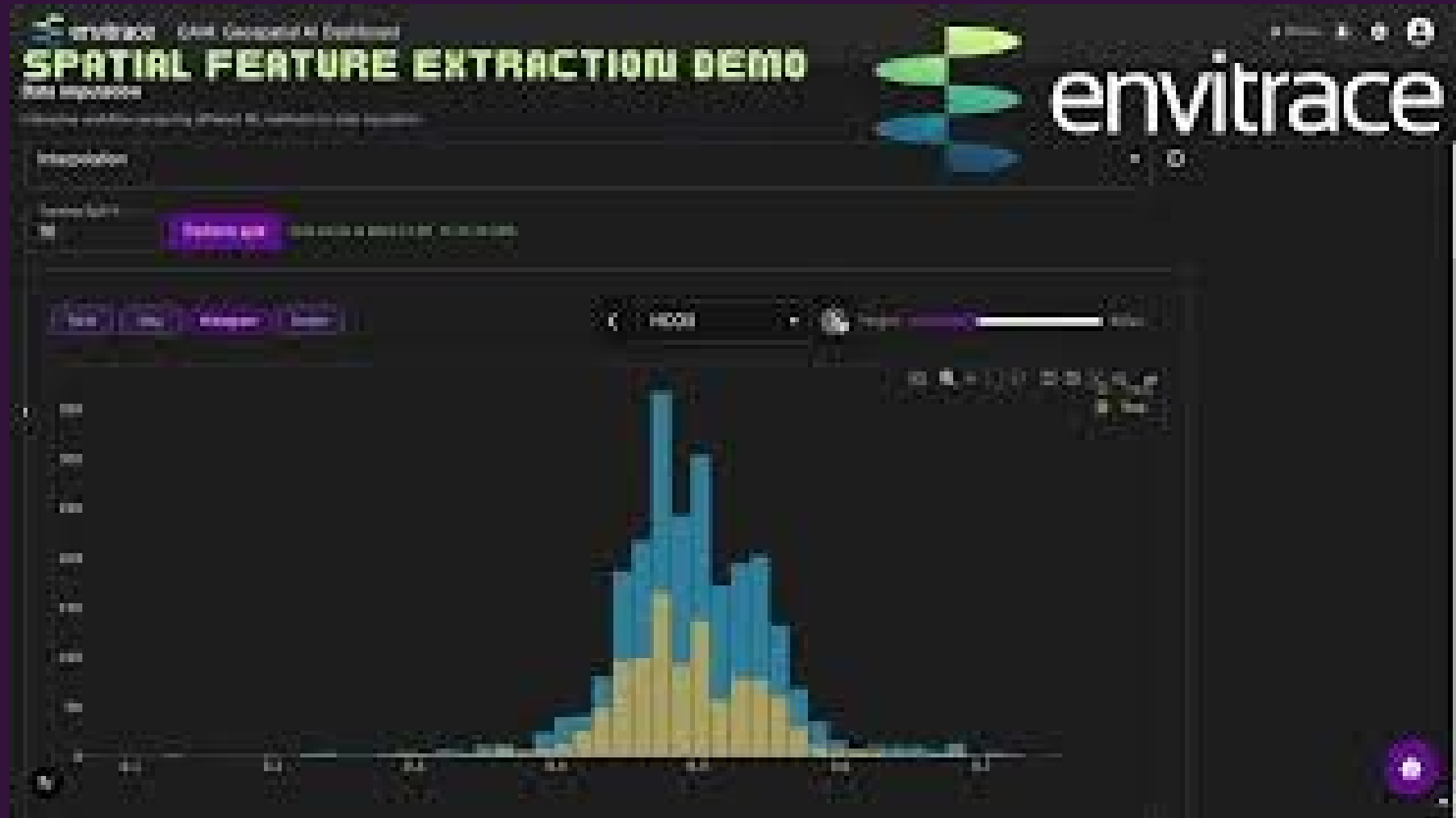
## AI/ML cloud product for geospatial analyses

- Public and proprietary data
- Various supervised, unsupervised, and physics-informed ML methods
- Accounting for physics and geology
- Accounting for data gaps and measurement errors
- Extraction of hidden geologic features
- Estimation of prospectivity and productivity

<http://envitrace.com/saas>



# Spatial Feature Extraction



# Conclusions

[info@envitrace.com](mailto:info@envitrace.com), <http://envitrace.com>

- o Our AI workflows allow for efficient, fast and robust data assimilation
- o Exploration of ML alternatives
- o Testing & Benchmarking
- o Extracts features
- o Imputes data
- o Evaluates prospectivities
- o SaaS dashboard: <http://envitrace.com/saas>



# Acknowledgement

[info@envitrace.com](mailto:info@envitrace.com), <http://envitrace.com>

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