Machine Learning for Identifying Subsurface Targets Using Small Datasets: Applications to Geothermal Energy and Carbon Sequestration

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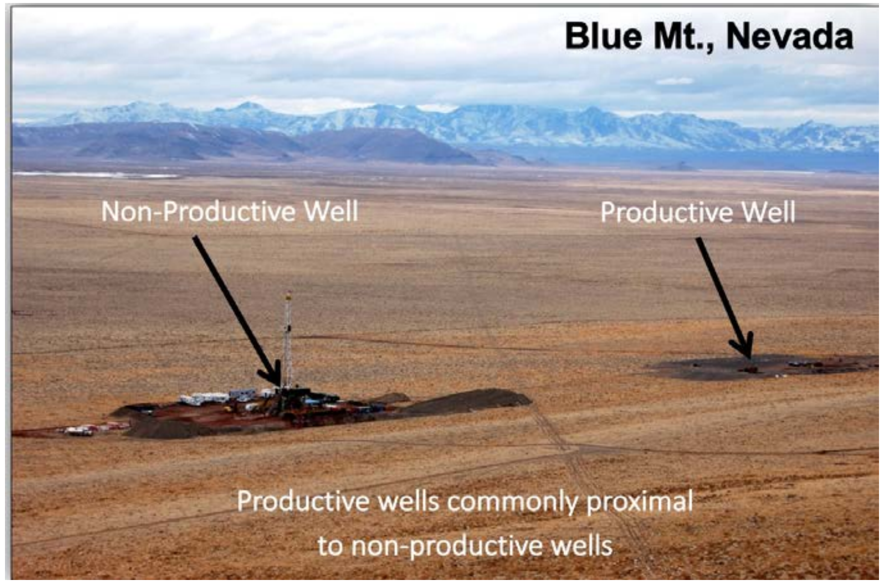
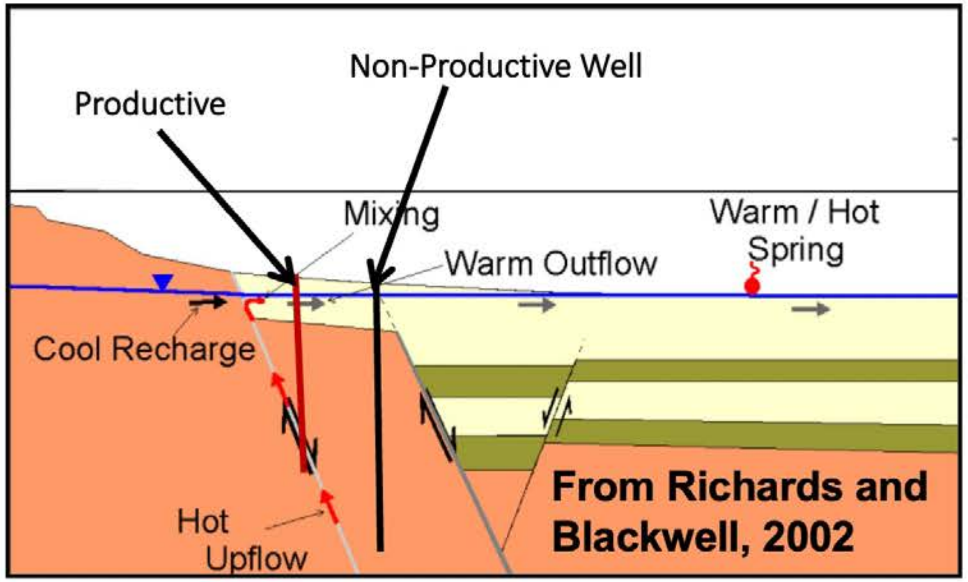
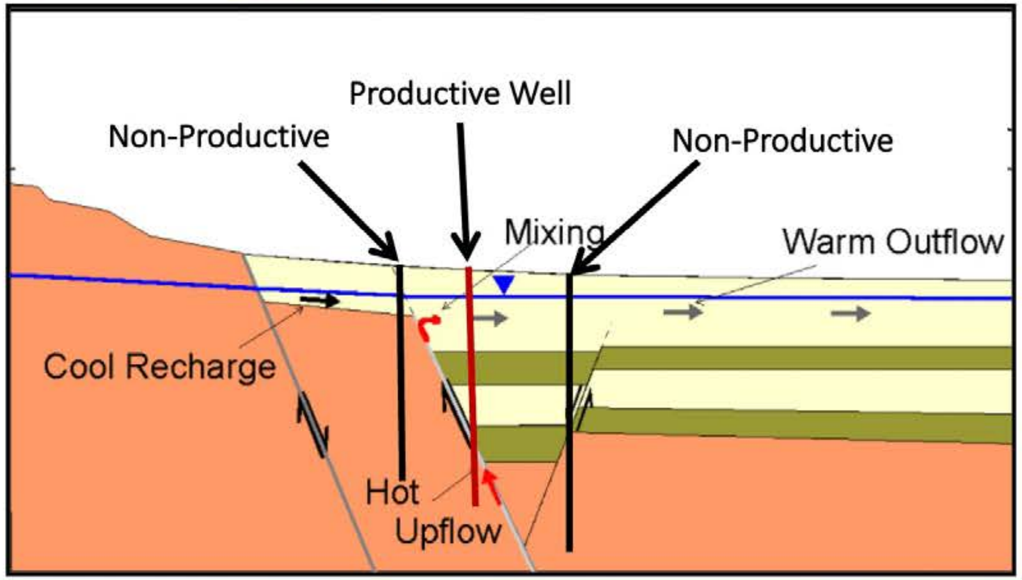
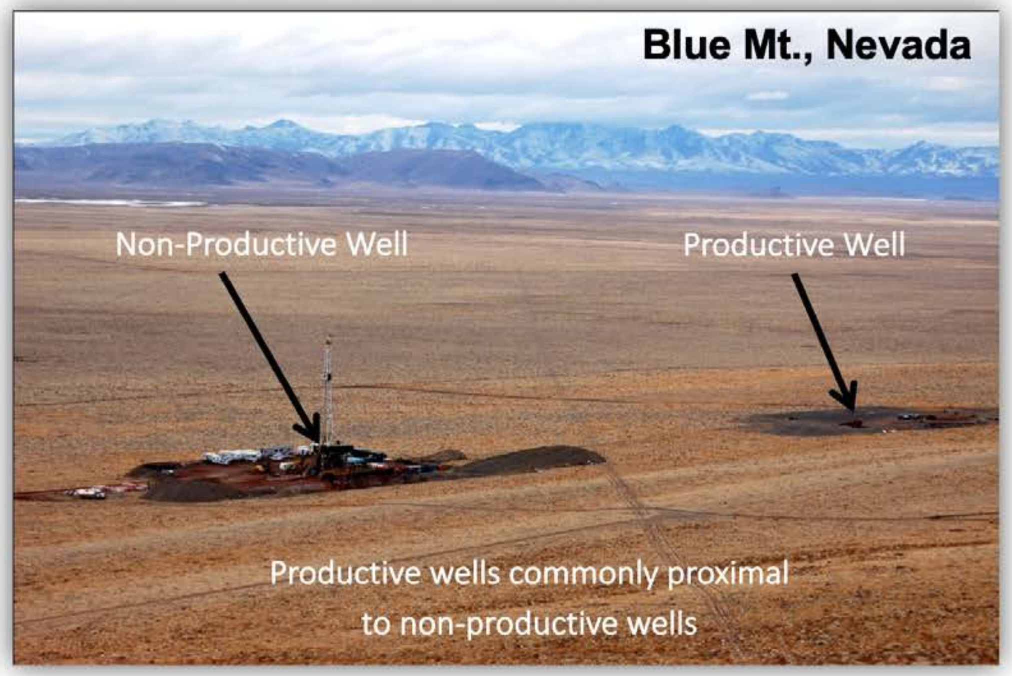


Assistance in conducting geothermal exploration work from Jim Faulds, Sven Treitel, John Queen and Connor Smith

Major Challenge – Hidden Geothermal Systems



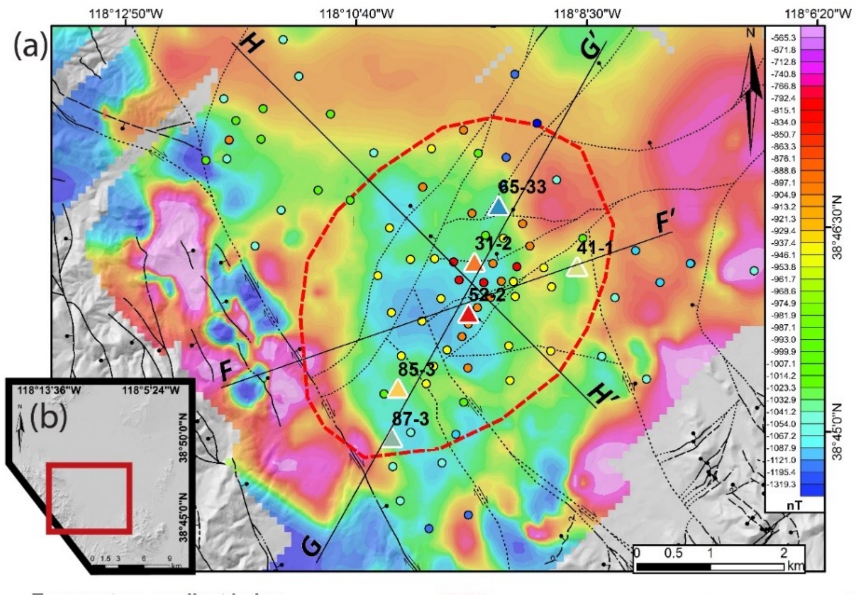




- **40% of known systems blind**
- **Estimated 75% of all systems hidden**
- **Significant drilling risk**
- **Need high-quality geologic and geophysical data to elucidate surface and subsurface to permit development of better conceptual models**

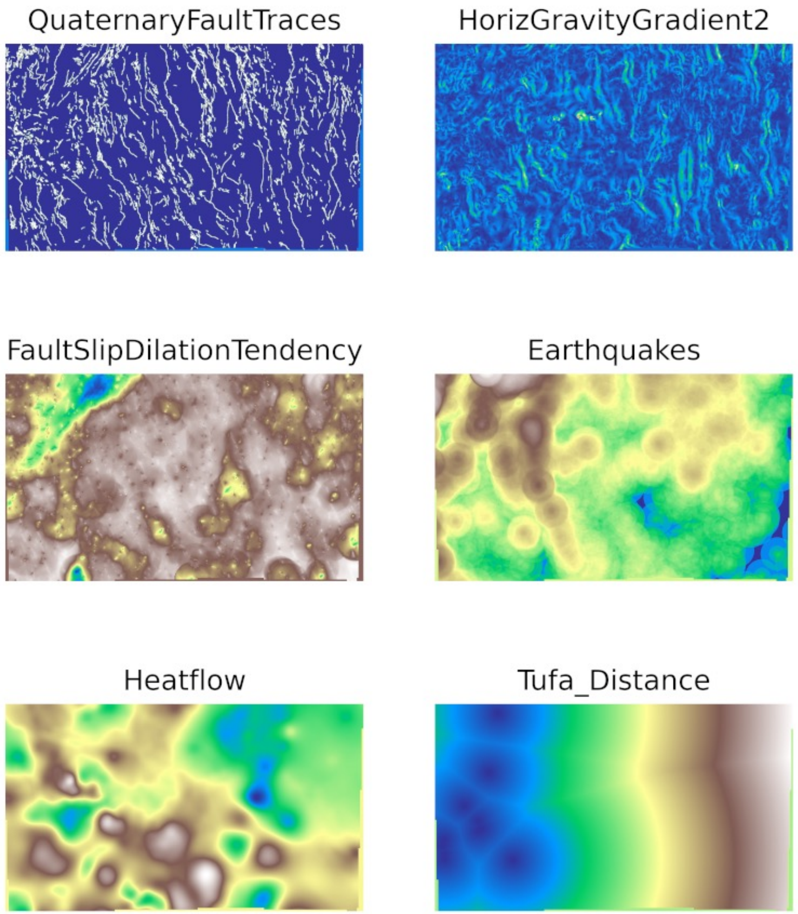
Challenges in Applying Machine Learning to Geothermal Exploration

- **Some geophysical techniques do not work or are too expensive**
  - **e.g. Active seismic**
- **Few training sites**
  - **Can lead to overfitting**
  - **Need both positive and negative sites**
- **Mix of data types:**
  - **Numerical variables (temp, distance to fault, gravity values)**
  - **Categorical variables (mineral assemblage, rock type)**
  - **Ordinal variables (size of feature)**
  - **Variation in resolution or uncertainty**
- **Some features not continuous**
  - **Requires special treatment to avoid bias**

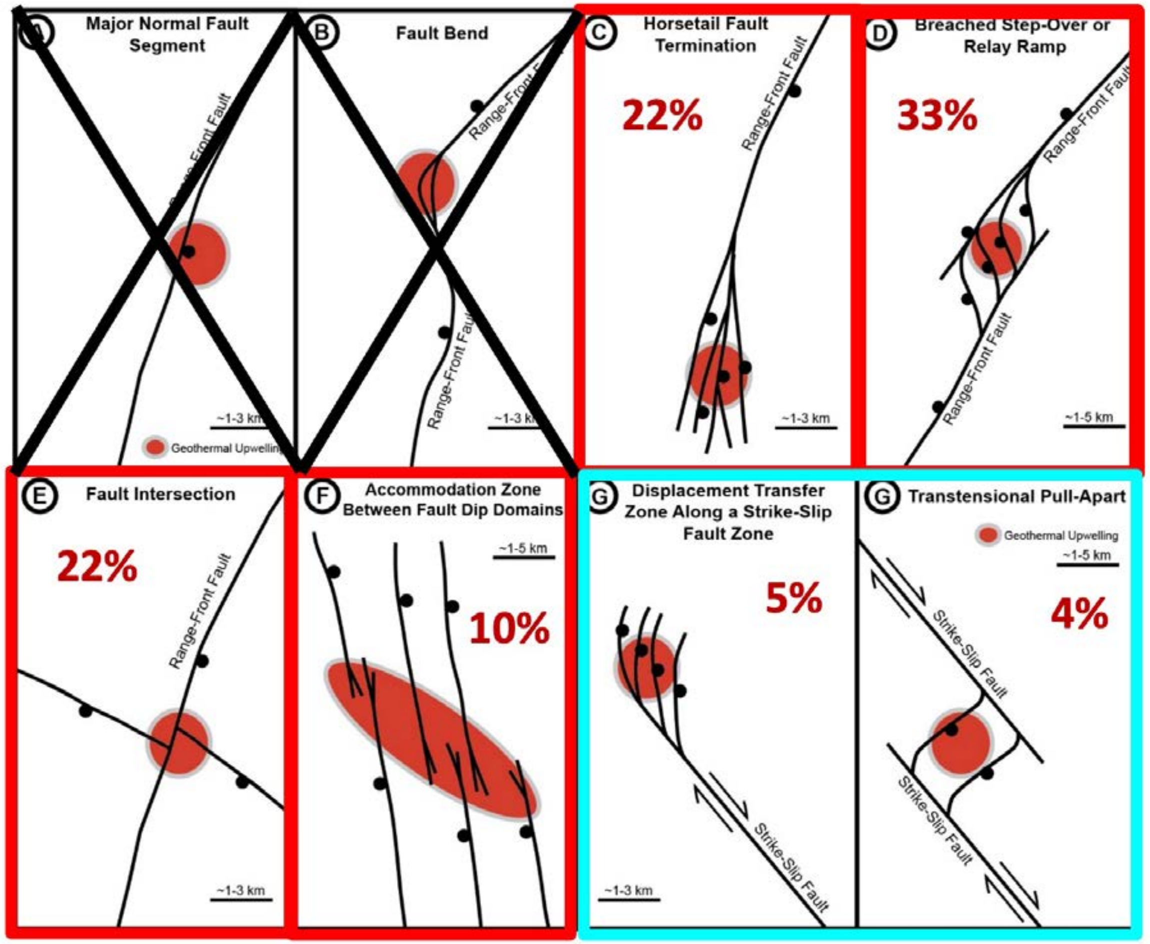


Example Numerical and Categorical Features for Nevada Study Area

Numerical



Categorical: Structural Setting



Site Classification Problem

- A potential geothermal site is associated with
  - A class y:

$$y = \begin{cases} 1, \text{if the site is a positive prospect} \\ 0, \text{if the site is a negative prospect} \end{cases}$$

  - A feature vector $\boldsymbol{x} = (x_1, x_2 \dots \dots)$ containing geological, geophysical and geochemical measurements/information
- The **Prediction** Problem
  - Given $\boldsymbol{x}$, what is the probability that the site is $y = 1$ *vs.* $y = 0$
  - e.g. infer $\mathrm{Prob}\{y|\boldsymbol{x}\}$ (and its uncertainty)
- The **Decision** problem
  - Given $\mathrm{Prob}\{y|\boldsymbol{x}\}$ and its uncertainty, decide if $y = 1$ or $y = 0$

    (considering mis-calculation risks, etc.)
- We focus on the **Prediction** problem

Fully-Connected Network

Parameterize the probability of a positive site with a multilayer neural network, P:

$$p \stackrel{\text{def}}{=} \text{Prob}(y = 1|\boldsymbol{x}) = P(\boldsymbol{x}, \boldsymbol{\gamma})$$

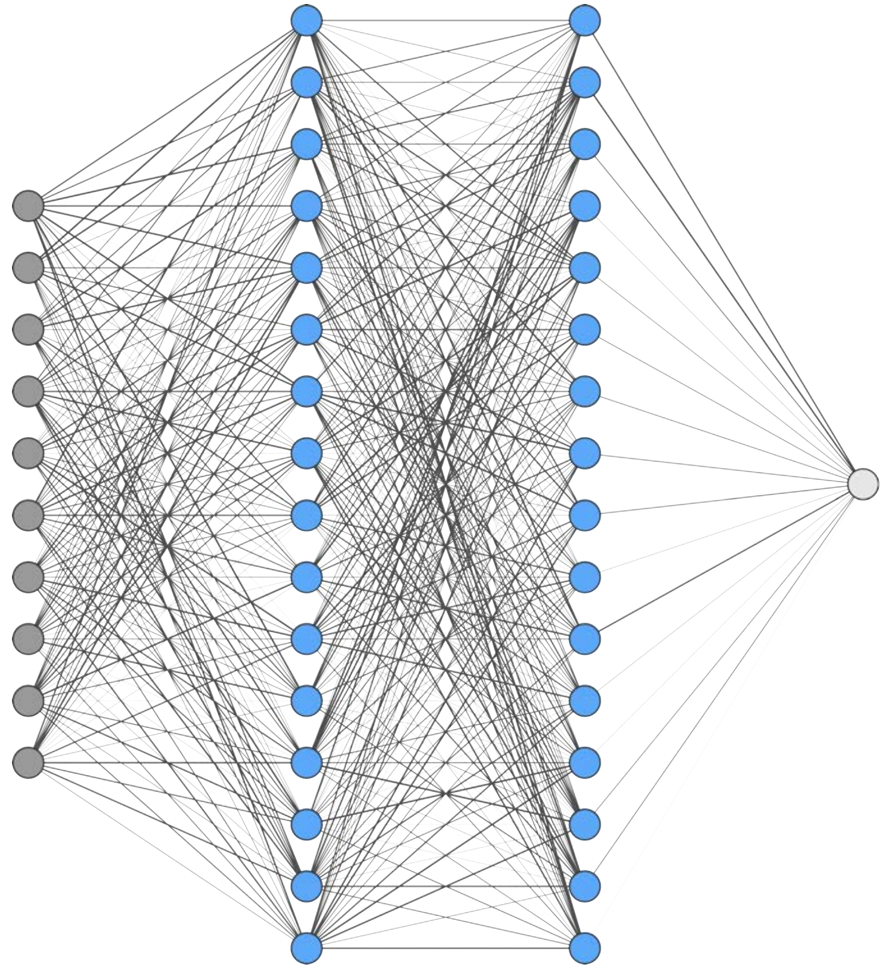
where

$\boldsymbol{x}$ = Neural Network input

p = Neural Network output

$\boldsymbol{\gamma} \stackrel{\text{def}}{=} (\boldsymbol{w}, \boldsymbol{b})$ = Neural Network weights and biases

Regularize by limiting size of weights and/or biases to limit overfitting and prevent small number of nodes from dominating



- Dark gray on left are 10 input features
- Light gray circle on right is output
- Blue are 16 neurons in each of 2 hidden layers (biases)
- Gray lines are connections (weights)

Traditional Machine Learning Approach

- The prediction problem reduces to inferring $\boldsymbol{\gamma}$ using training data from sites with known class

$$D = \{(x_i \, , y_i), i = 1,2 \ldots \ldots N\}$$

- A traditional (deterministic) Neural Network finds a single, optimal value of $\boldsymbol{\gamma}$, e.g. the *maximum likelihood* estimate:

$$\boldsymbol{\gamma}_{ML} \; = \arg max_{\gamma} \mathcal{L}(D; \boldsymbol{\gamma})$$

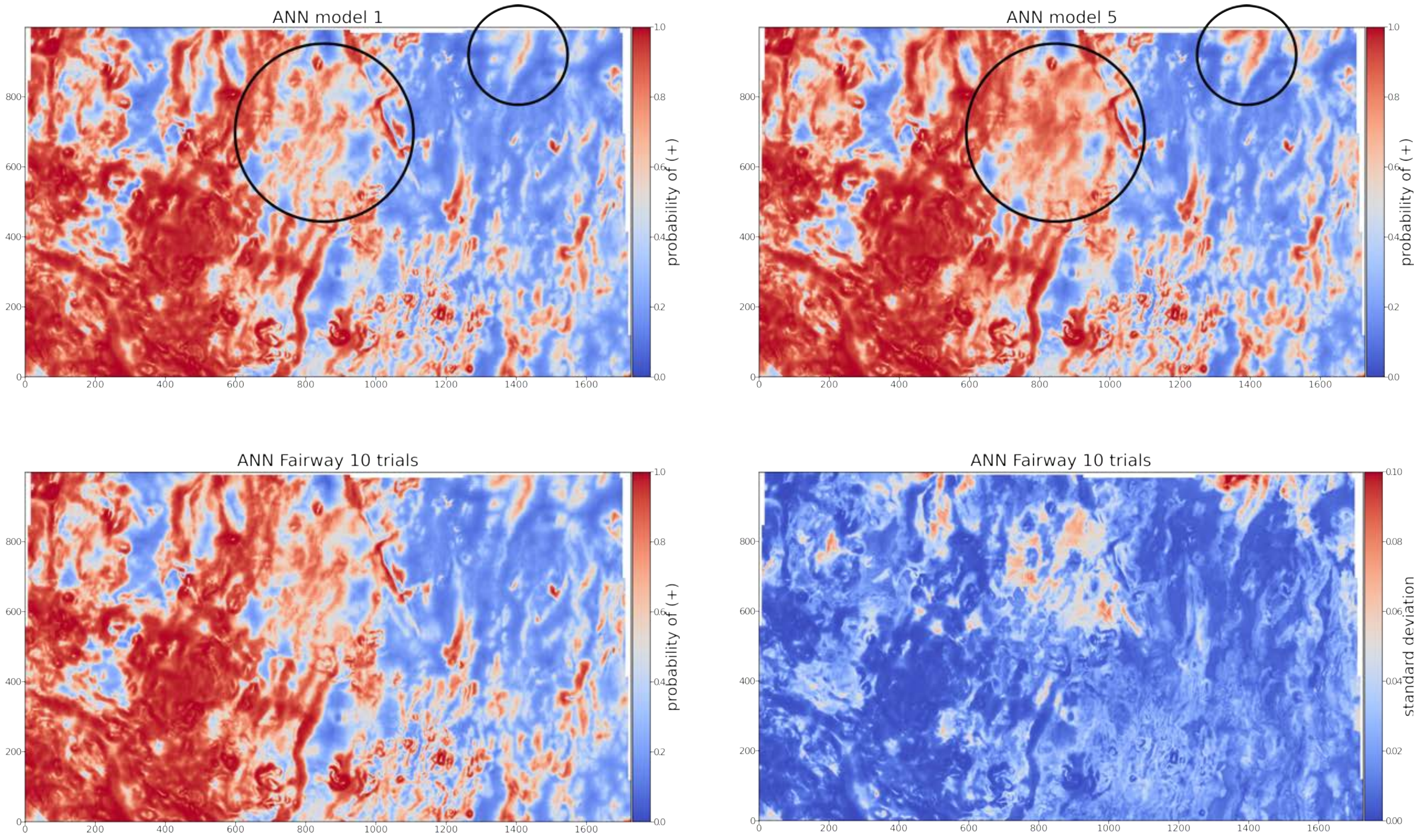
- The Trained Neural Network calculates, for any $\boldsymbol{x}$,

$$p = P(\boldsymbol{x}, \boldsymbol{\gamma}_{ML})$$

- Our algorithm for likelihood maximation initializes $\boldsymbol{\gamma}$ to a random seed

Problem: Variability with Multiple Runs

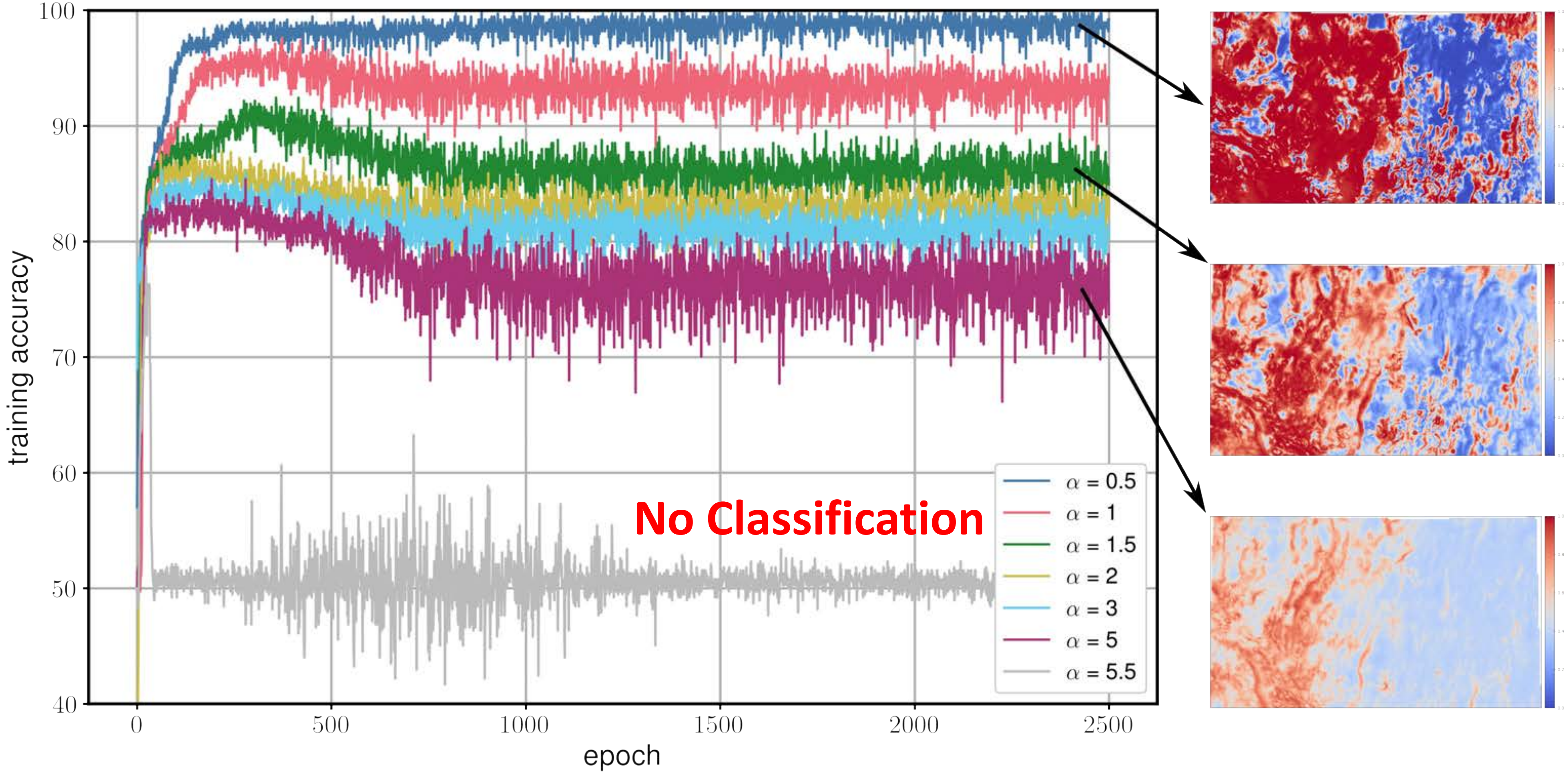
- Ran 10 test models with differing seeds
- Top two images: models 1 and 5 represent extreme variability
- Lower left: mean of 10 runs
- Lower right: standard deviation of 10 runs



Bayesian Approach

- A Bayesian Neural Network applies Bayesian inference with the training data to determine a posterior probability distribution on $\boldsymbol{\gamma}$
- Our training algorithm uses the Variational Bayes method to find an approximation to the posterior distribution on $\boldsymbol{\gamma}$
- Tradeoff model complexity with fitting of training data
  - controlled by regularization parameter α chosen based on estimate of number of *degrees of freedom*
- We sample the distribution of $\boldsymbol{\gamma}$ in the network to get a posterior probability distribution on p

Bayes Approach: Training Curves

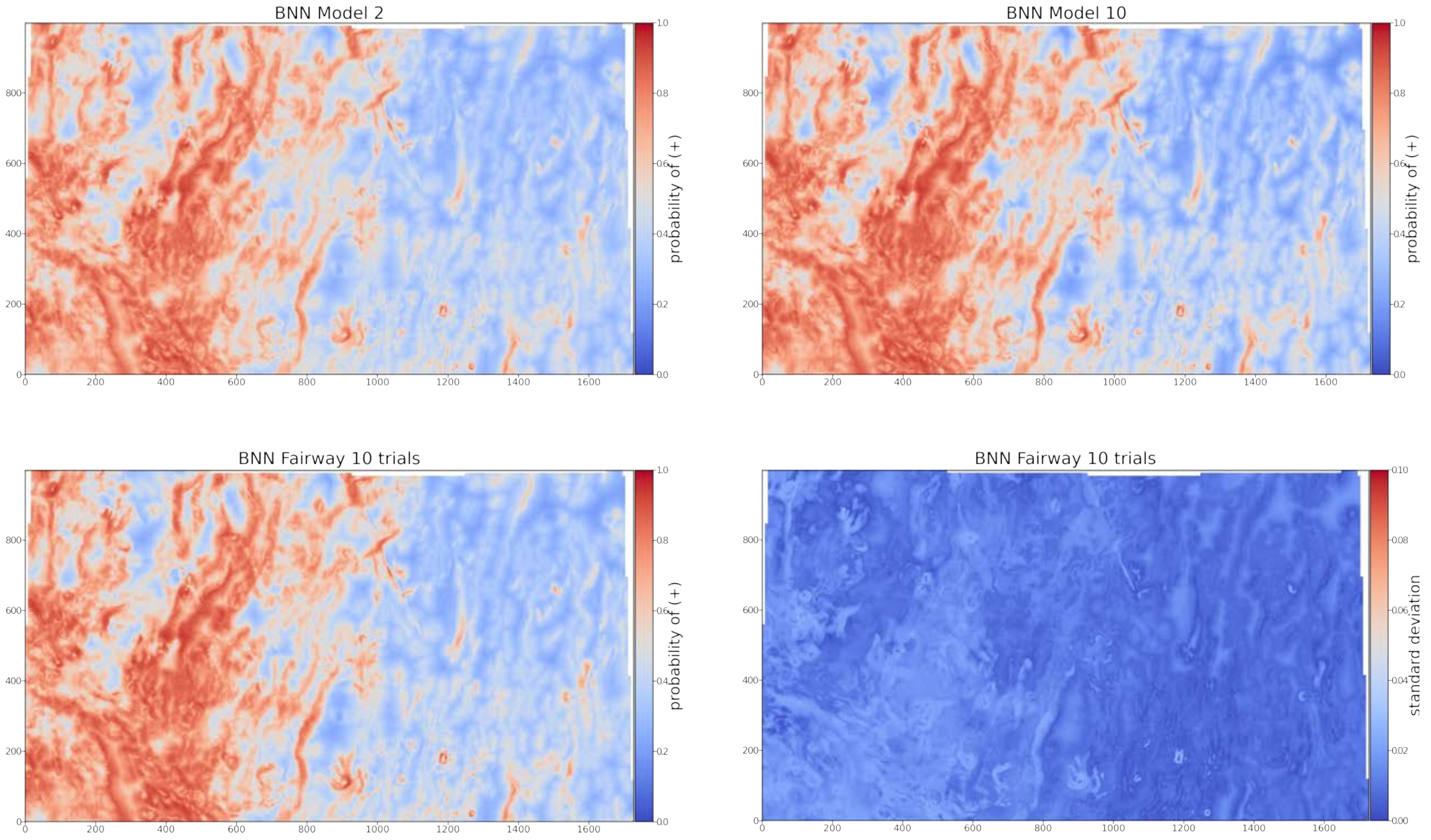


Overfit Data

Increasing NN model complexity

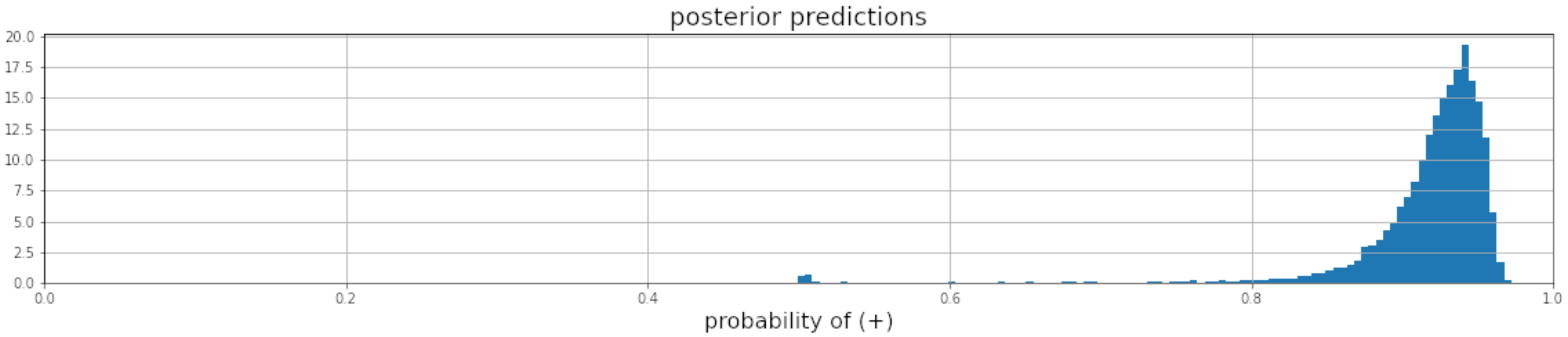
Results Using Bayesian Network

- Ran 10 test models with differing seeds
- Top two images: Maximum variability among multiple runs
- Lower left: mean of 10 runs
- Lower right: standard deviation of 10 runs

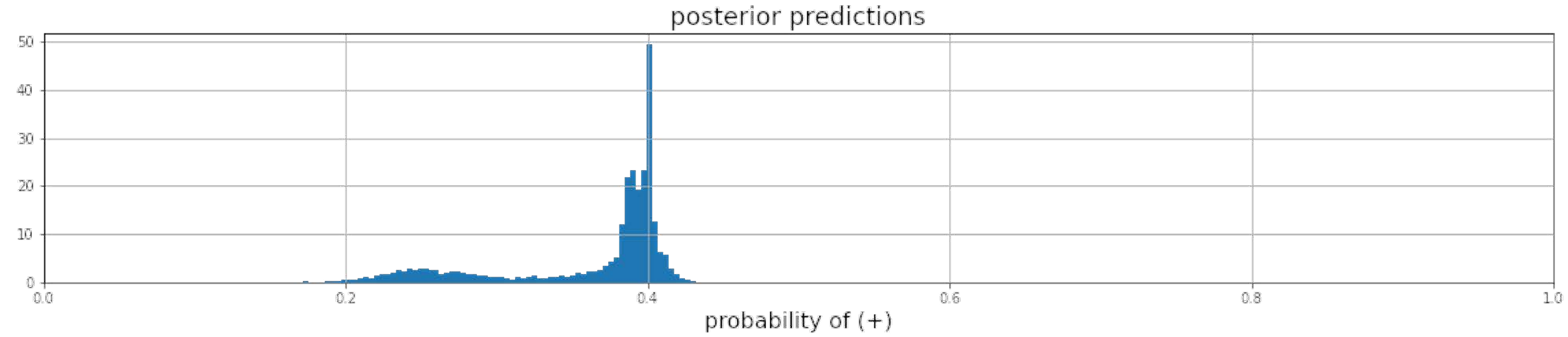


Posterior Probabilities from Bayesian Approach

R588C489 Dixie Meadows (in CNSB blue)

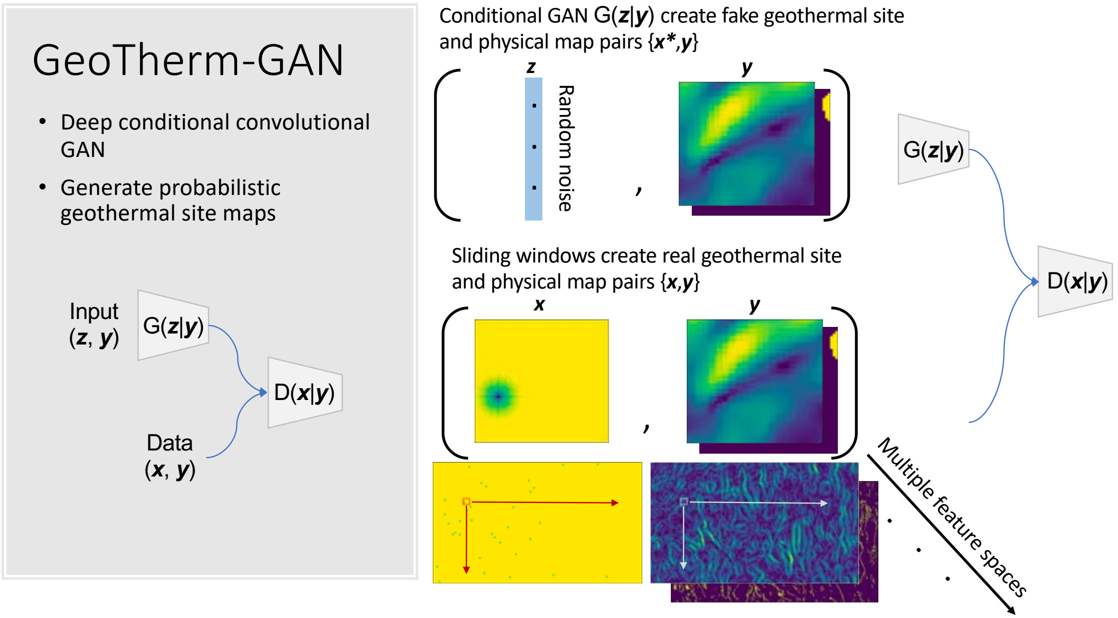


R428C1424 Negative (in CA purple)



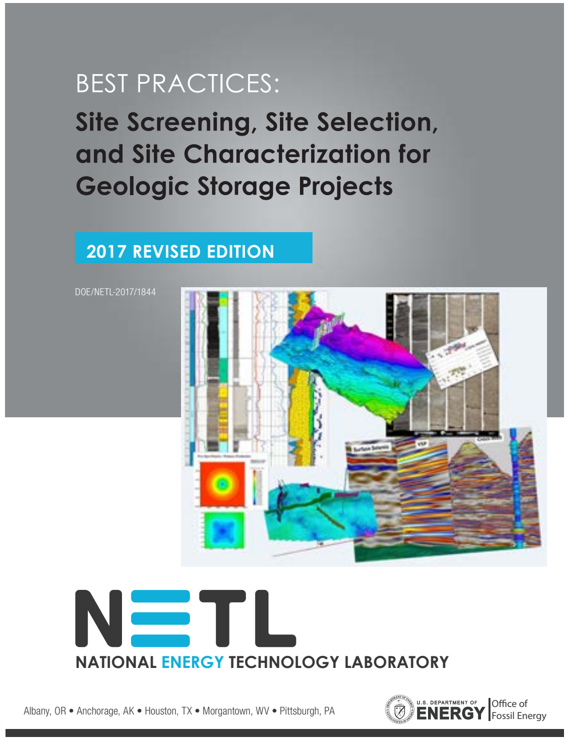
Follow-On Work

- Differing approaches for geothermal
  - Currently use positive and negative geothermal sites
    - Modify positive to be more general – e.g. temperature at depth; production rate, reservoir lifetime
  - Convolutional Neural Network
    - Take advantage of data spatial information
  - Find sites that are most like known geothermal sites (work underway)
  - Develop approach for using categorical data
  - Account for uncertainty in input data
  - Use GAN



Follow-On Work

- Application to site selection for CO_2 sequestration
  - Required characteristics
    - Trapping mechanism
    - Caprock integrity
    - Seismic risk
    - Reservoir capacity
    - Maximum safe injection rate
    - Risk to water table
    - Source of CO_2



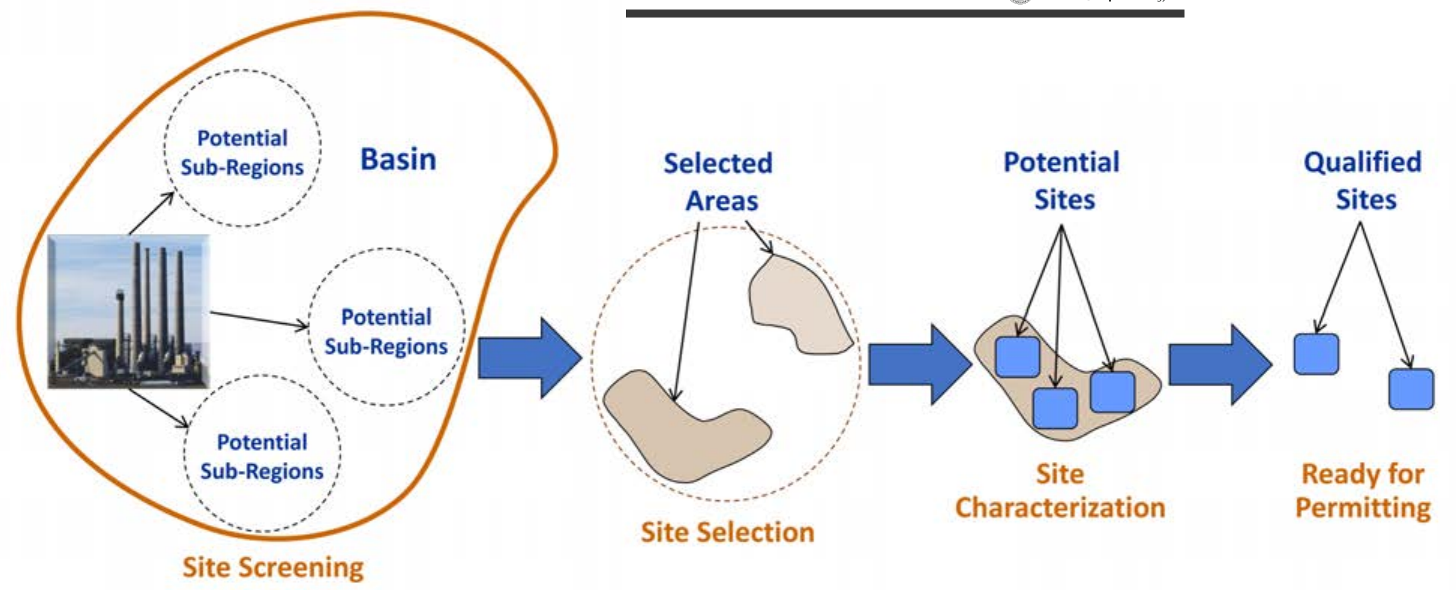
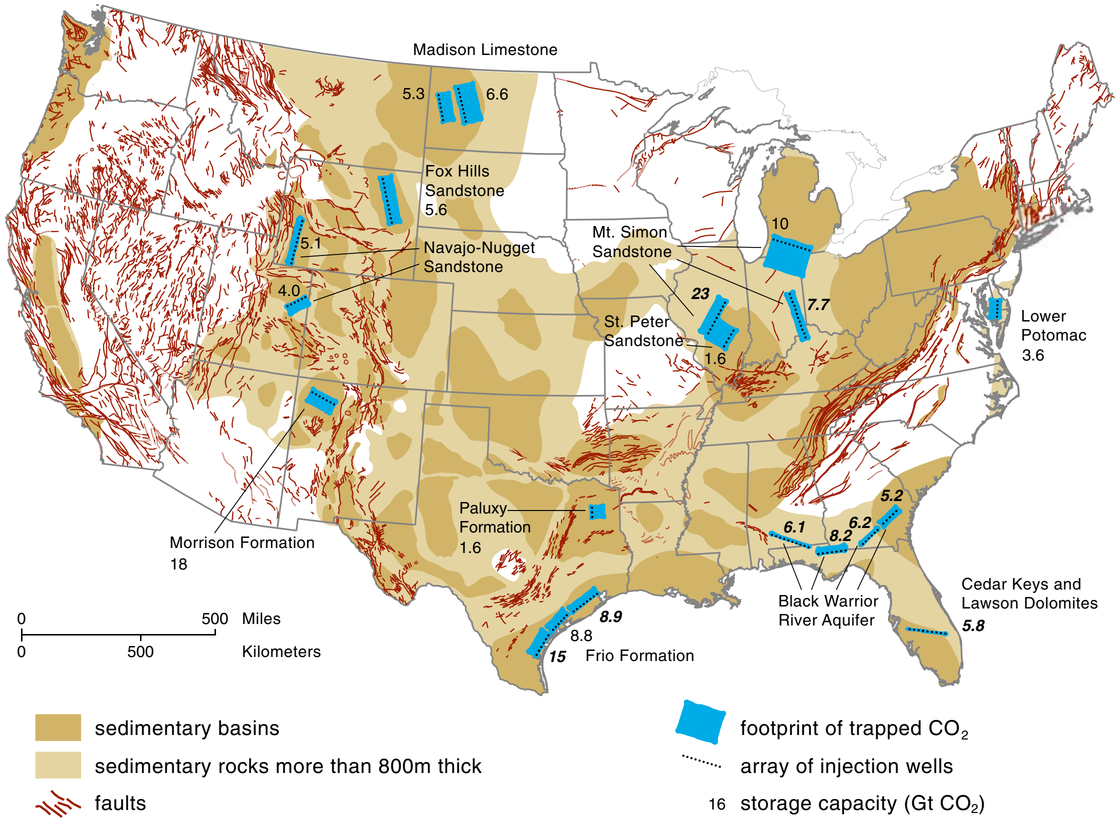


Figure 1.2: Illustration of the Relationship Between Scale of Investigation and Major Steps in Process of Finding and Developing Qualified Sites

Investigate sites for CO_2 Storage

- Start with existing data
  - USGS datasets of regional geophysics
  - Geothermal databases
  - Databases compiled for CO_2 sites
    - Regional partnerships
    - DOE-sponsored studies
  - US Array tomography studies
- Sites identified and tested
  - Regional partnerships
  - Those identified by industry
  - Include EOR sites?

CO_2 Storage Capacity of 20 Sites in US



Michael L. Szulczewski, Christopher W. MacMinn, Howard J. Herzog, and Ruben Juanes, Lifetime of carbon capture and storage as a climate-change mitigation technology, *PNAS,* www.pnas.org/cgi/doi/10.1073/pnas.1115347109, 2012

Framework for Additional Work

- Current geothermal work is near completion
  - Paper(s) being prepared
- Continue geothermal work with industrial partner(s)
  - Explore enhancements to current methodology
  - Apply to different regions where data are available
- Initiate CO_2 work with industrial partner(s) through ERL

Bayesian Approach

- A Bayesian Neural Network applies Bayesian inference to determine a posterior probability distribution on $\boldsymbol{\gamma}$:

$$f(\boldsymbol{\gamma}|D) = \text{"Bayes Rule"}$$

- For any $\boldsymbol{x}$, the Bayesian Neural Network transforms $f(\boldsymbol{\gamma}|D)$ to a probability distribution on p:

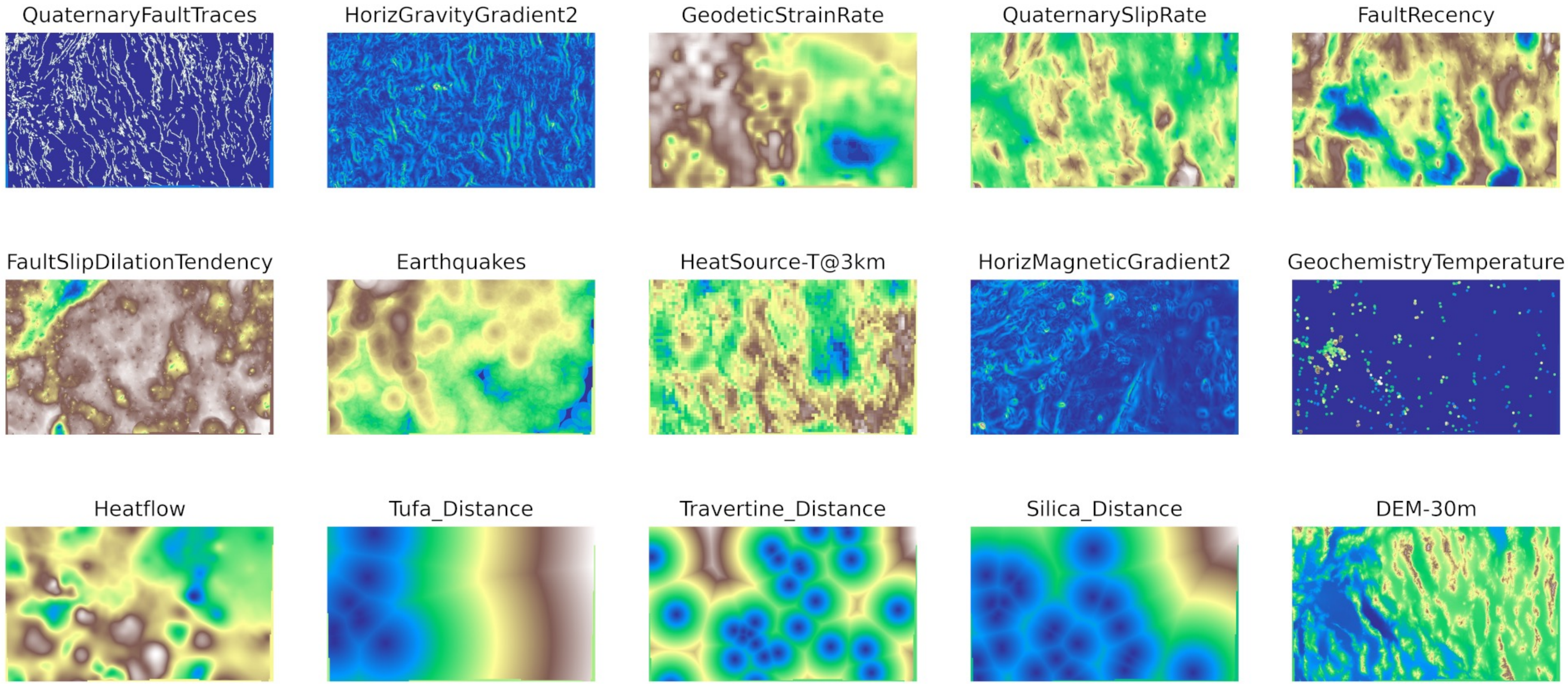
$$f(p|\boldsymbol{x}) = \text{"transformation of } f(\boldsymbol{\gamma}|D)\text{"}$$

Tradeoff model complexity with fitting of training data using regularization parameter chosen based on estimate of number of *degrees of freedom*

$$\mathcal{L}(D, \boldsymbol{\gamma}) = \alpha KL[\mathrm{q}(\boldsymbol{\gamma})||\mathcal{P}(\boldsymbol{\gamma})] + E$$

Where $KL[\mathrm{q}(\boldsymbol{\gamma})||\mathcal{P}(\boldsymbol{\gamma})]$ is the Kullback-Leibler Divergence representing model complexity, $q(\boldsymbol{\gamma})$ is the probability distribution on $\boldsymbol{\gamma}$, is the prior distribution on $\boldsymbol{\gamma}$, E represents the data misfit

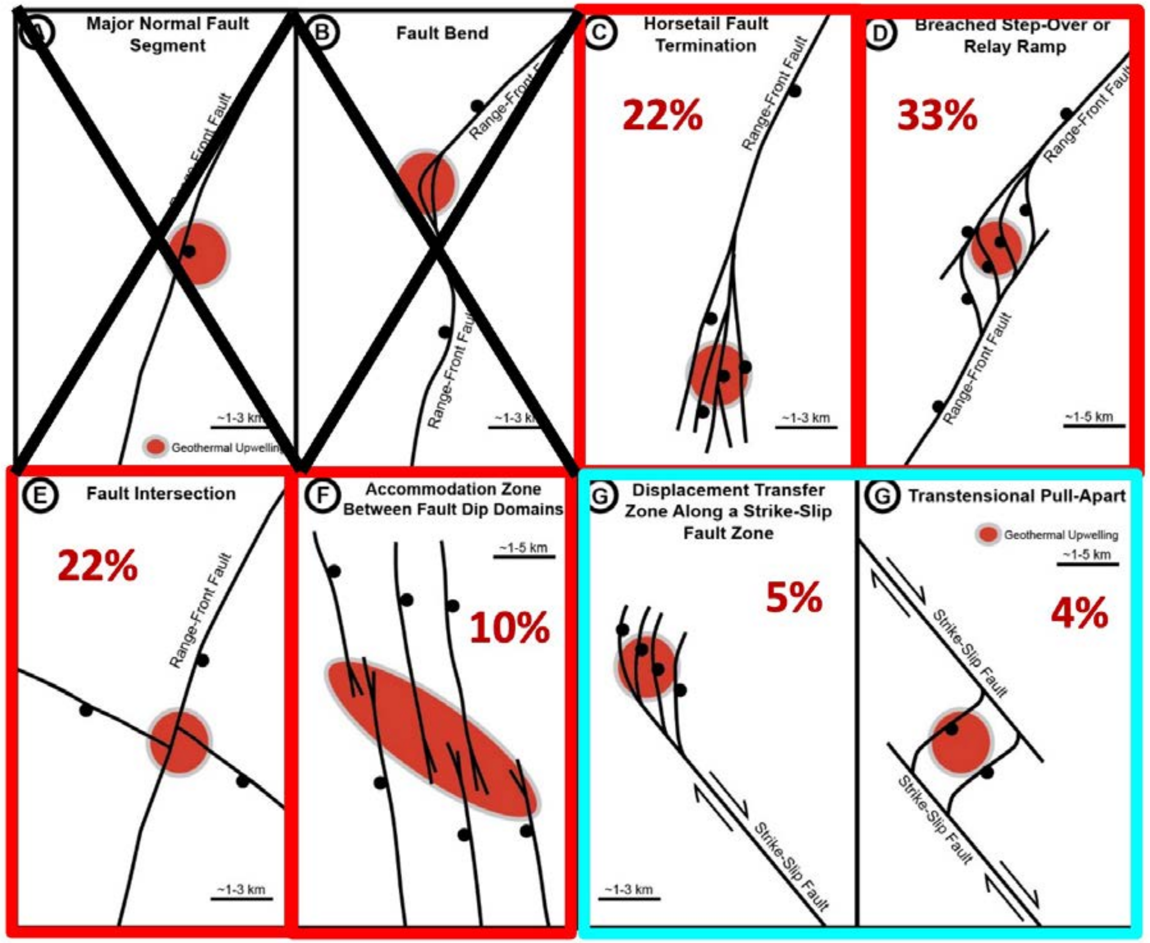
Numerical Features for Nevada Study Area*



* Some sampling bias

Categorical Features (Favorable Structural Setting)

- **450 systems analyzed; ~250 catalogued**
- **Most fields not on mid-segments of major faults**
- **Most on less conspicuous Quaternary normal faults**
- **Higher temp systems generally on faults <750 ka**
- **Hybrid settings most productive**



Faulds et al., DOE Project Review 2020