



IIT Bombay

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Poster & PICO Contest

Unsupervised machine learning driven Prospectivity analysis of REEs in NE India

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Standard prospectivity modelling workflow



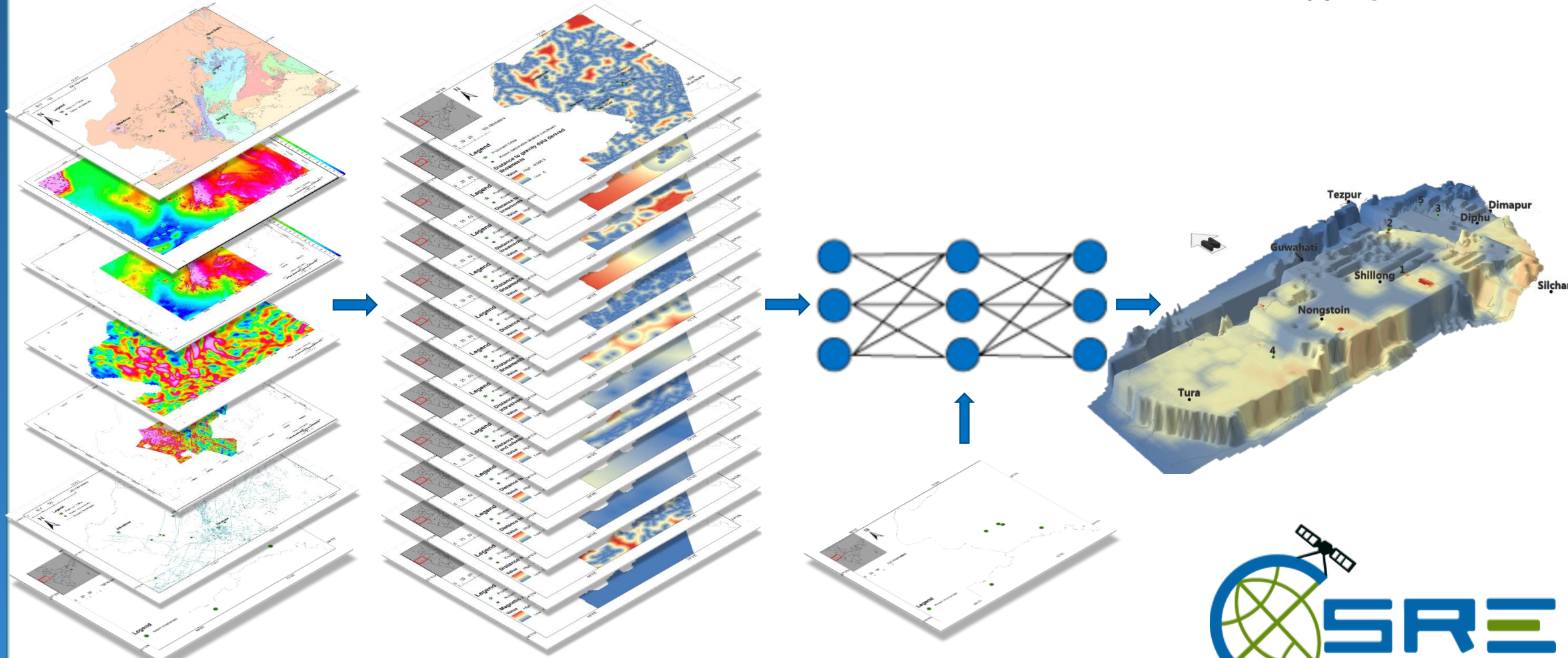
Most machine learning use **human-designed (hand-crafted) representations** of input data

PRIMARY DATASETS

MANUALLY EXTRACTED FEATURES

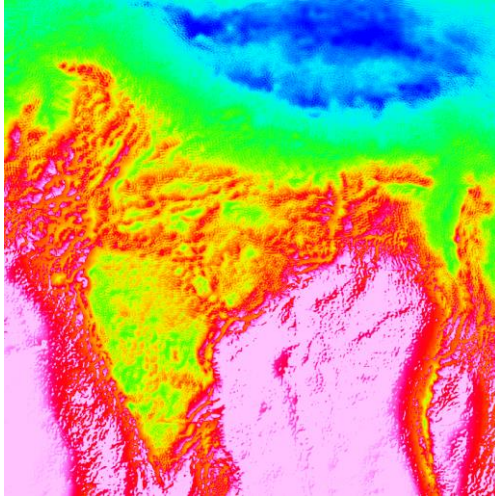
LEARNING ALGORITHM

OUTPUT



ML simply involves **optimisation of parameters** to make the best prediction

Primary data

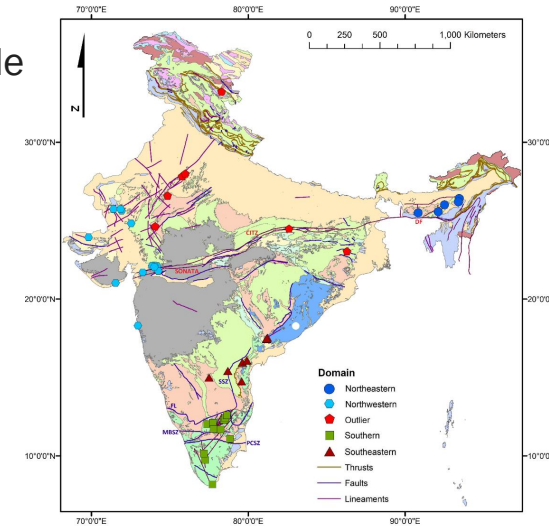


- Directly measured, uniformly sampled, gridded
- e.g., air-borne magnetics, gamma rays spectrometric, remote sensing, SRTM
- Low degree of abstraction
- Low uncertainty

Public-domain data

Typically 1:50,000 to 1:250,000 scale

Two types:



- Interpreted from sparse measurements/observations, non-uniform sampling, vector
- Geology, structures
- High degree of abstraction
- High uncertainty

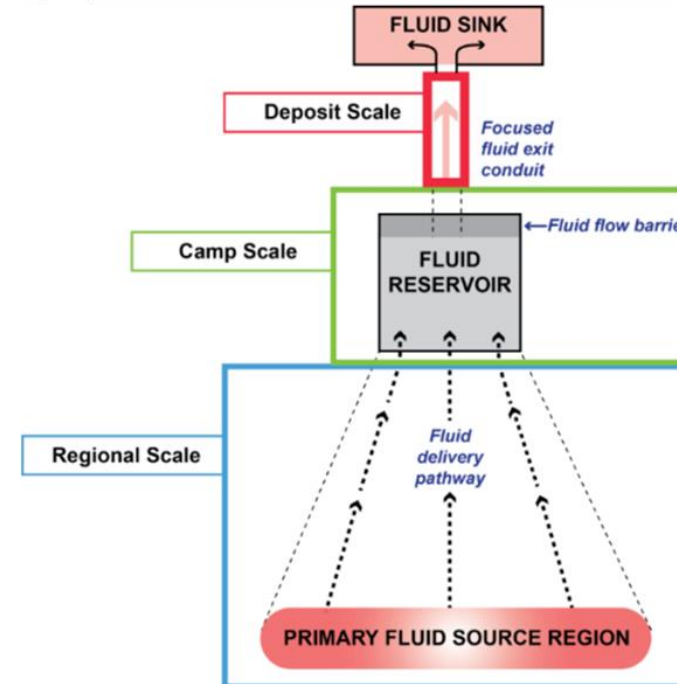
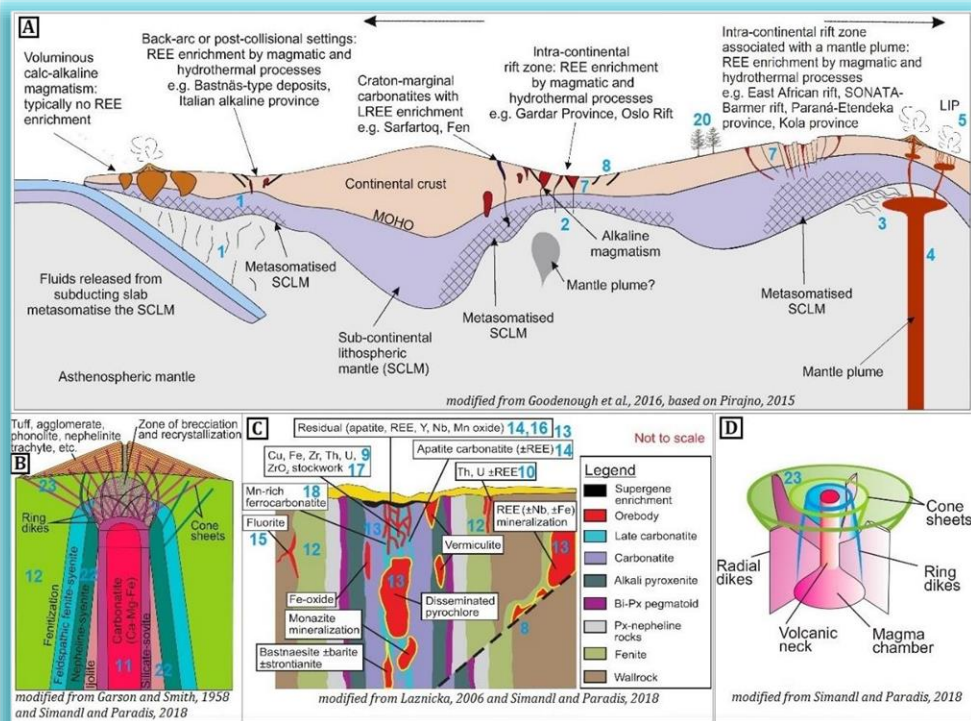
Subjective bias



Mineral-systems-guided feature engineering: Issues



Mineral systems model: compiles mineralization processes across scales (translithospheric to ore-body scale)



Deposit location is controlled by these processes

Most public-domain data (1:50,000 to 1,250,000 scale) map these processes

(McCuaig and Hronsky, 2014)

Handcrafted features are biased towards camp-scale features (e.g., transportation pathways, sources)

Metal deposition features are under-represented

Possible response of metal-deposition processes in gridded geophysical data, not easy to interpret visually?

Are we using right data for training?
Exploration targeting of deposits or fertile geology?

Inputs to ML: hand-crafted features



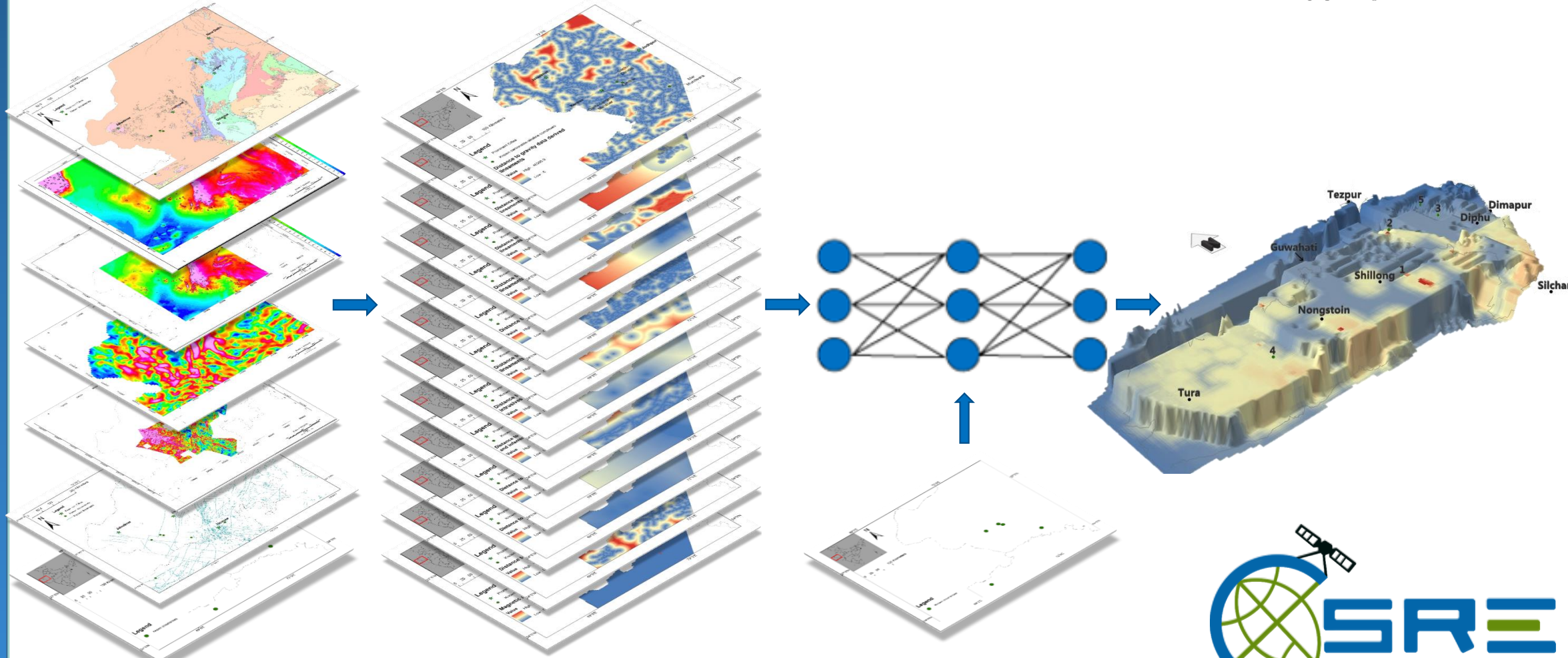
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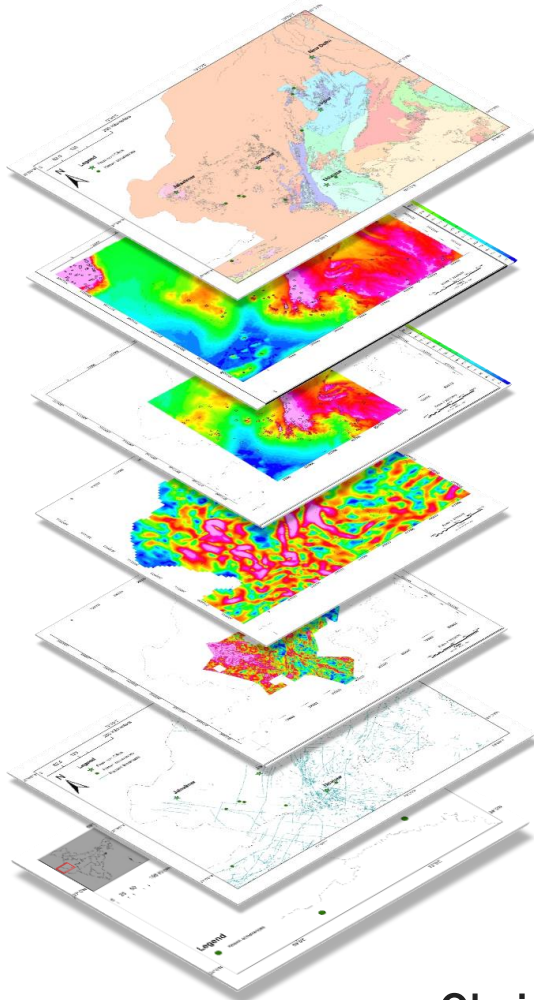


ML simply involves **optimisation of parameters** to make the best prediction

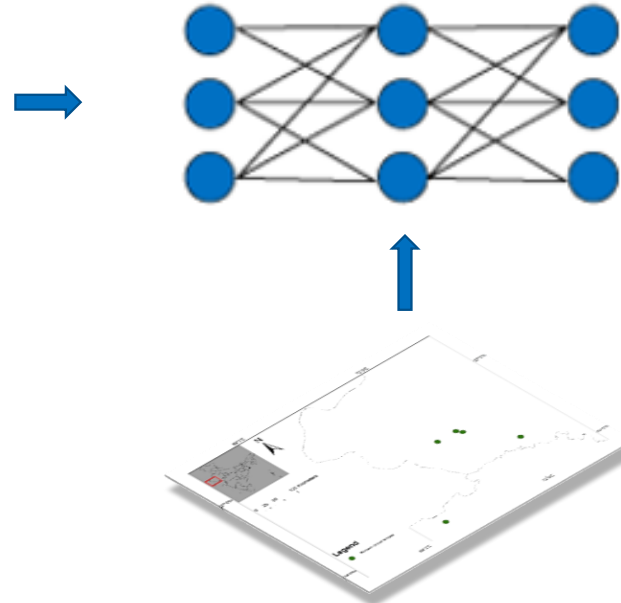
Input primary data directly to ML?



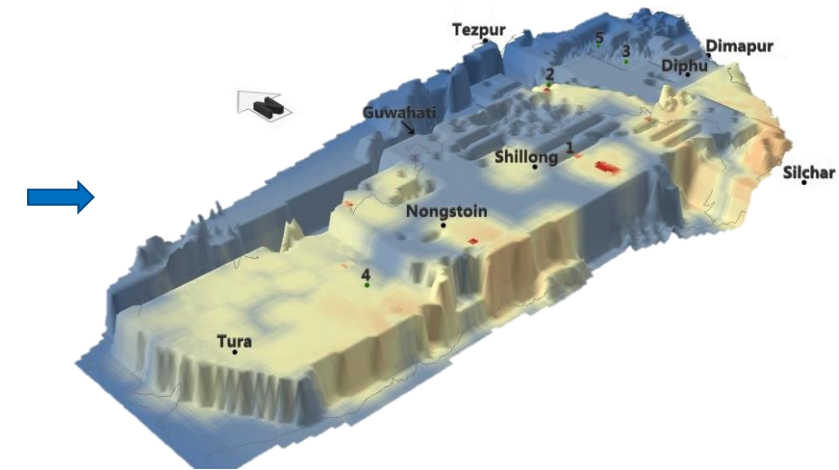
PRIMARY DATASETS



LEARNING ALGORITHM



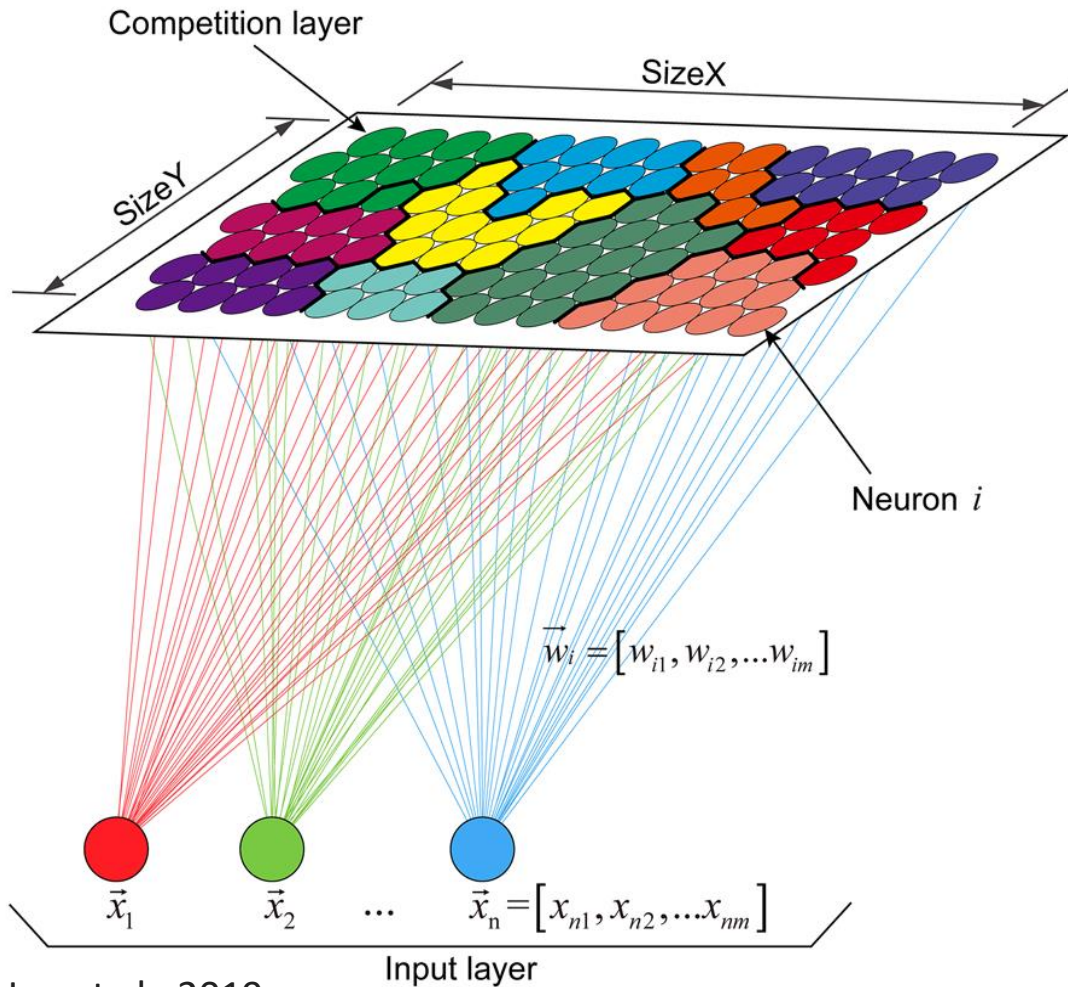
OUTPUT



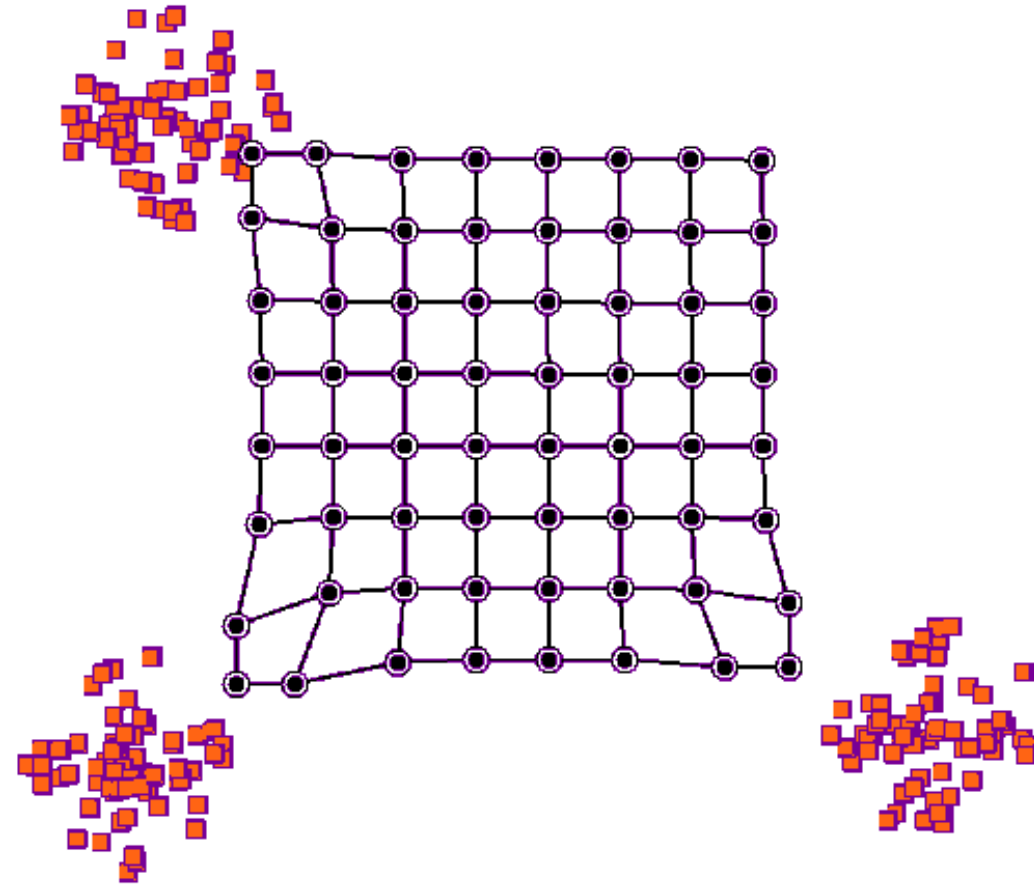
Obviate the need for hand-crafting features

Unsupervised machine learning: Learn features from primary data!

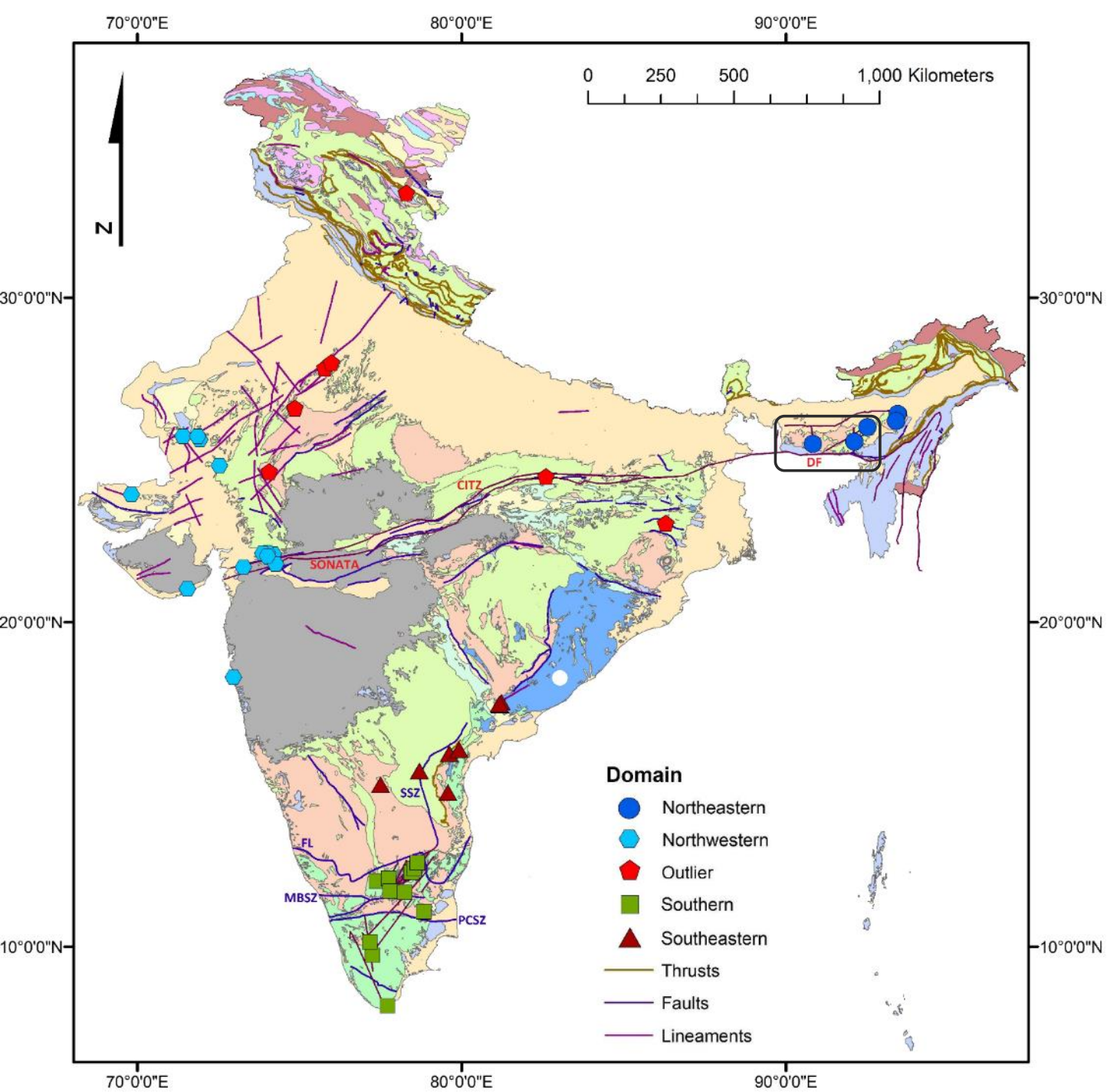
Self organising maps



Han et al., 2019



Chompinha, 2019



Study area

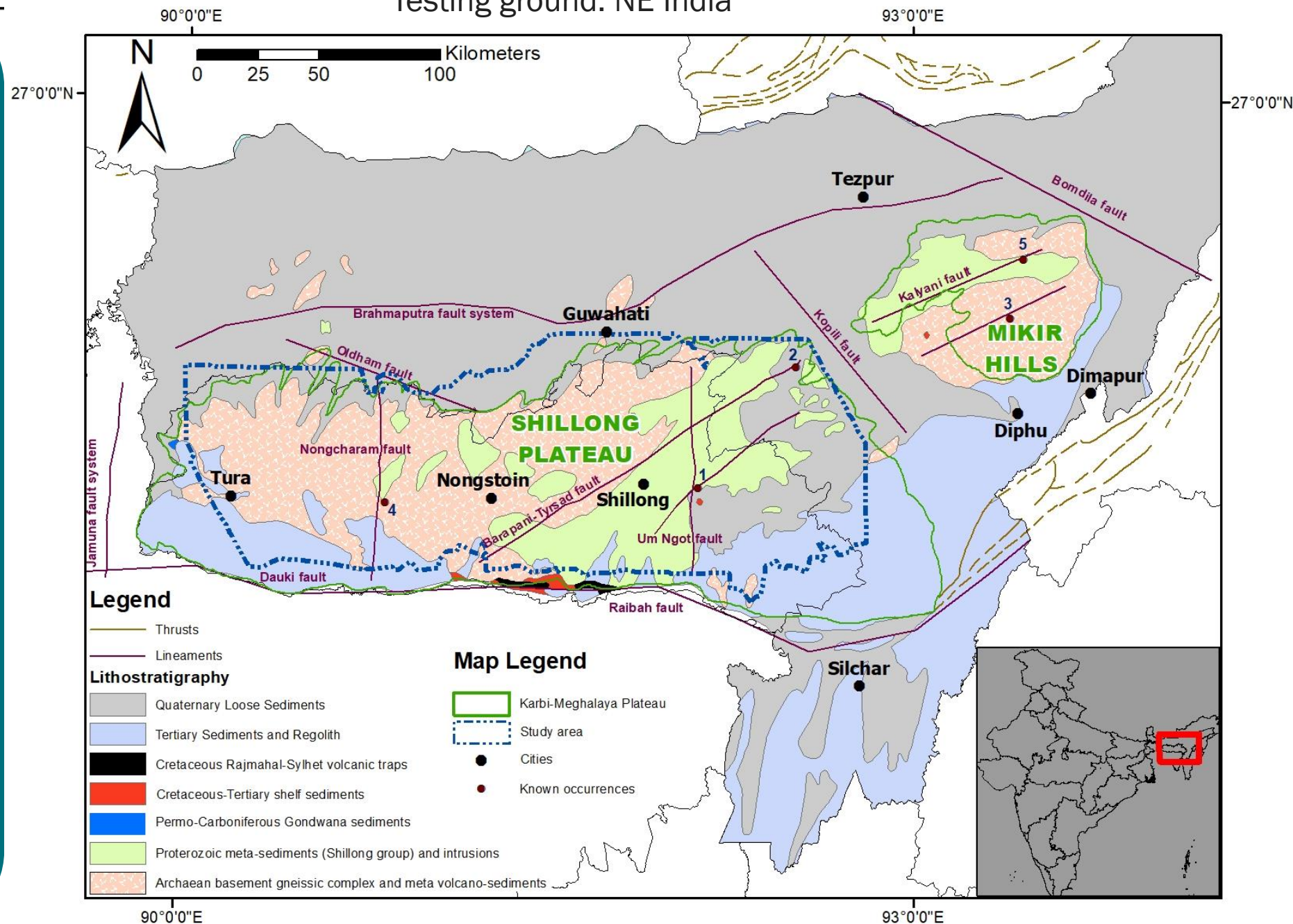


Case study : REE prospectivity mapping in NE India

Rationale

- Area consists of the second youngest and well-preserved kerguelen hotspot-related carbonatite province.
- Higher density of known occurrences in a smaller area.
- Well studied genesis
- Better coverage of geochemical data with decent geophysical data coverage over the province.
- Field knowledge

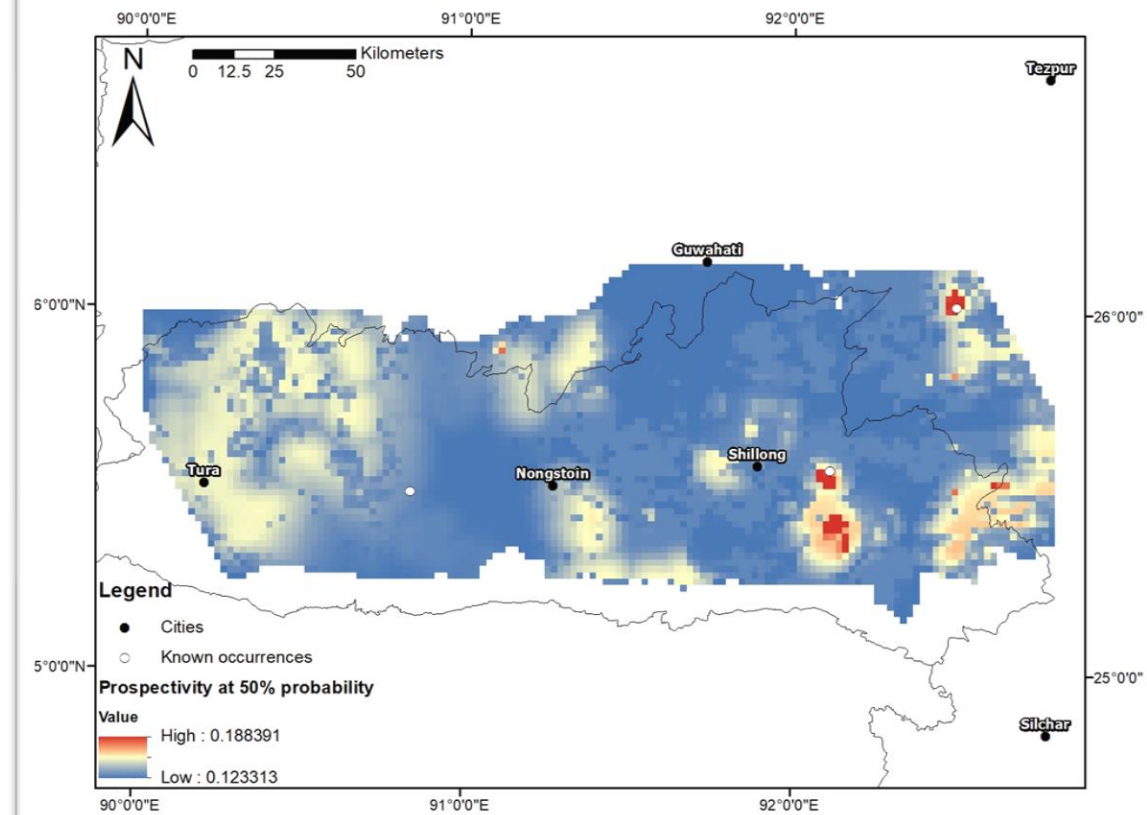
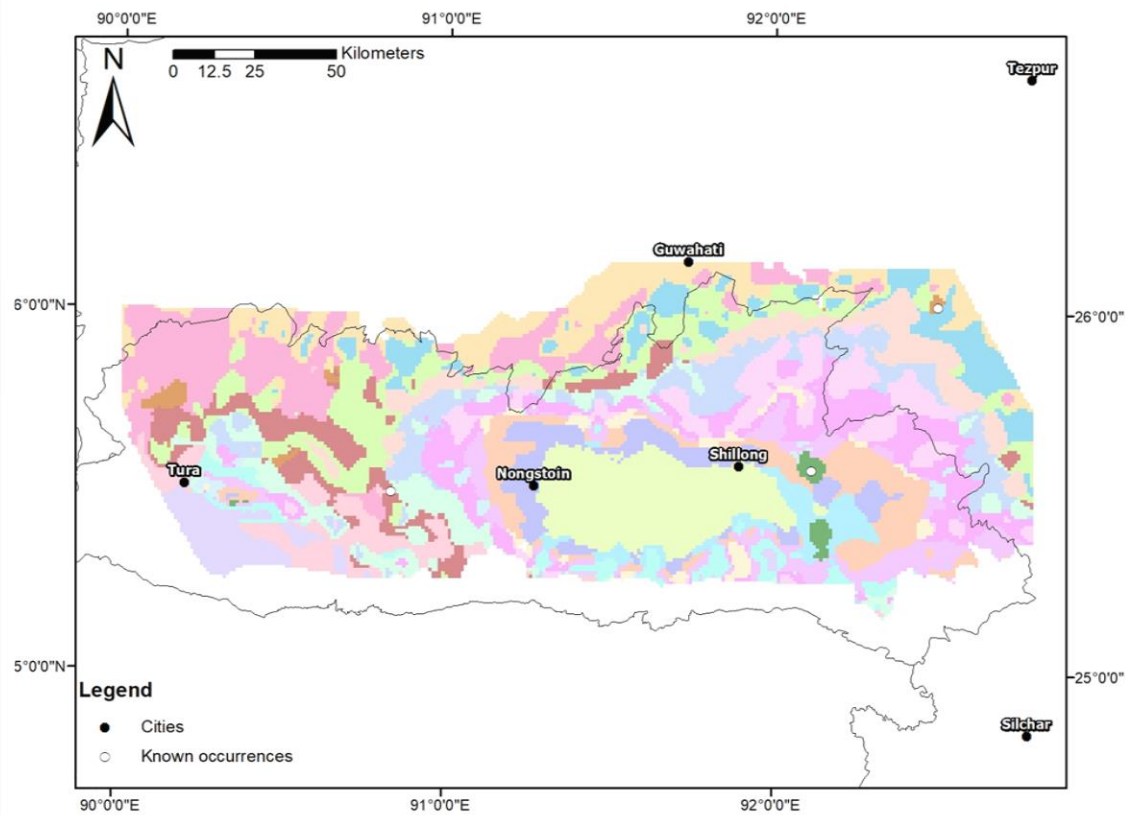
Testing ground: NE India



SOM Clusters



FIS Study



Gravity

RTP
Magnetics

Topography



To sum up...

Prospectivity models use input features that are hand-designed from primary data - typically using mineral systems approaches.

Manual feature extraction from interpreted geoscience data is subject to uncertainty

Unsupervised machine learning algorithms offer robust alternatives to traditional prospectivity modelling particularly in unexplored terrains geological knowledge is limited



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