



Mira Geoscience
20 years of modelling the earth

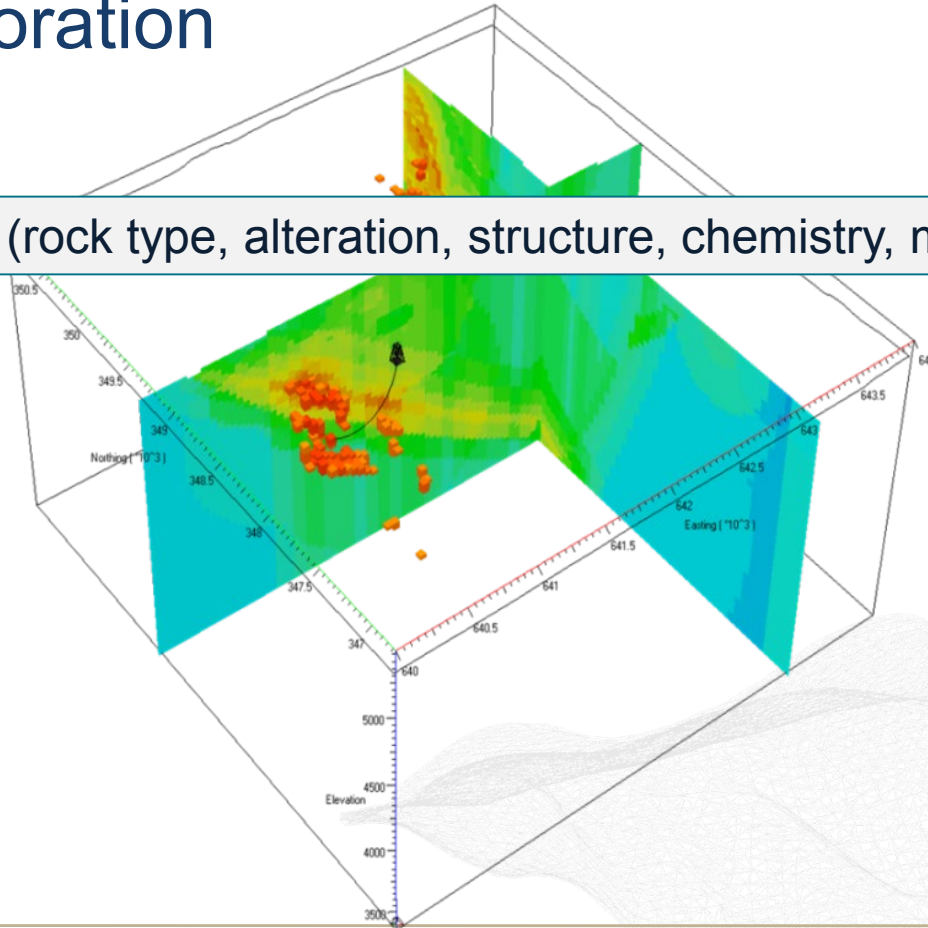
Advances and opportunities for AI in mining and geotechnical engineering

NATIONAL ACADEMY OF SCIENCES
SUBSURFACE DATA AND MACHINE
LEARNING MEETING – JUNE 2019

John McGaughey

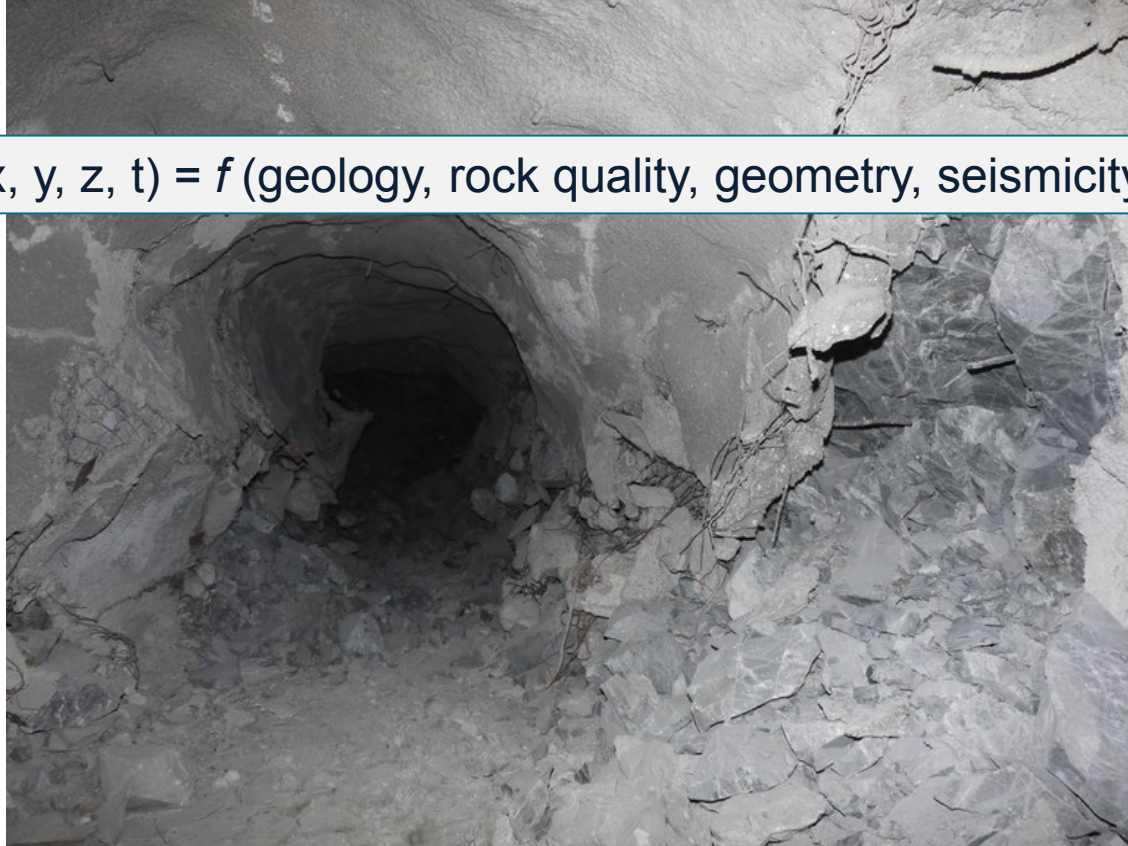
Mineral exploration

$\text{target}(x, y, z) = f(\text{rock type, alteration, structure, chemistry, mineralogy, ...})$



Geohazard

hazard (x, y, z, t) = f (geology, rock quality, geometry, seismicity, stress, ...)

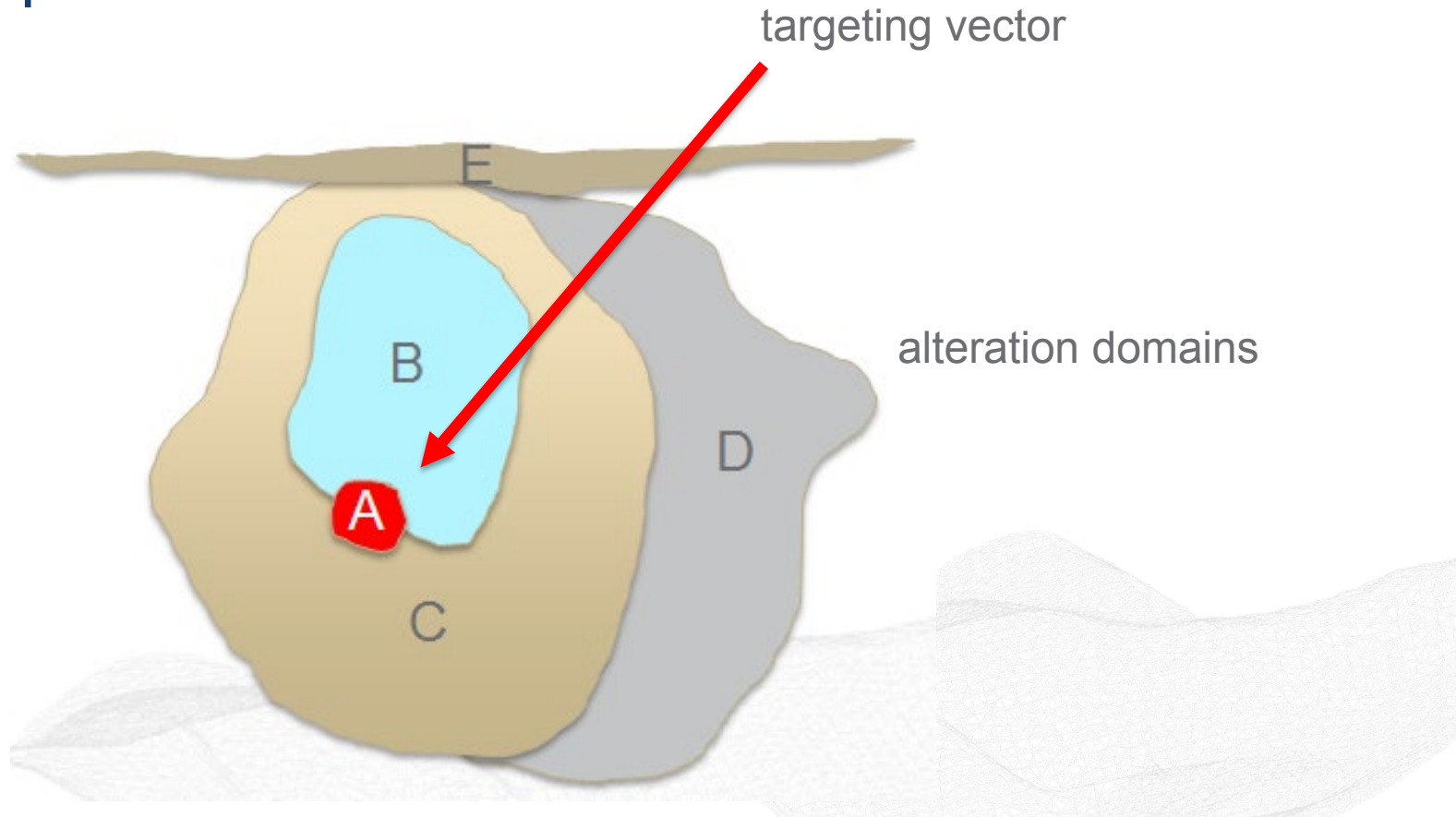


The AI challenge in mineral exploration

- potential benefits of AI in mineral exploration may be immense, yet its application is far from simple
- we must identify the location of an ore deposit at the core of a very complex, natural system—the result of millions of years of structural and hydrothermal alteration
- evidence of the deposit must be assembled from interpretation of subtle alteration effects extending kilometres from the target
- the challenge is in the problem set up, not the machine learning

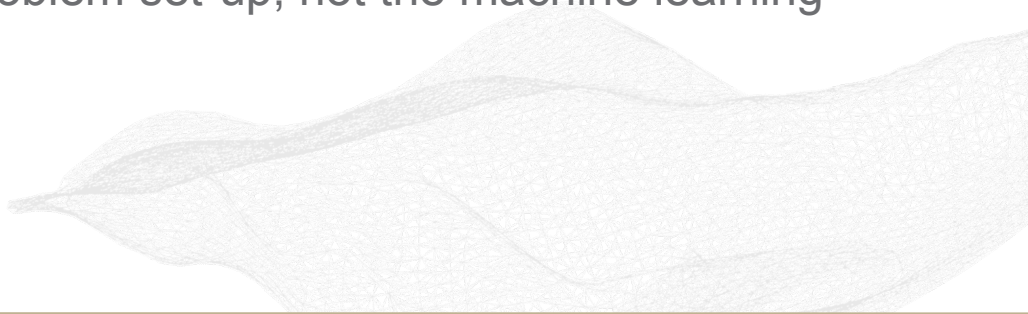


Conceptual framework

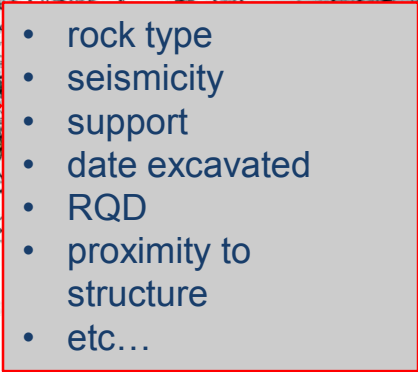


The AI challenge in geohazard assessment

- potential benefits of AI in geohazard assessment may be immense, yet its application is far from simple
- we must identify the probable location and time of a geohazard resulting from a very complex system with natural and engineered components
- evidence of the geohazard must be assembled from interpretation of numerous sparse, heterogeneous, time-dependent non-collocated data
- again, the challenge is in the problem set-up, not the machine learning

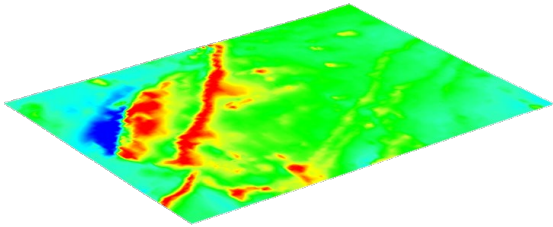


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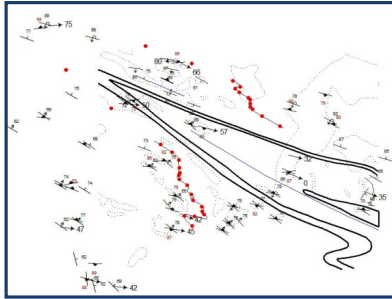


Data and models

geophysical data



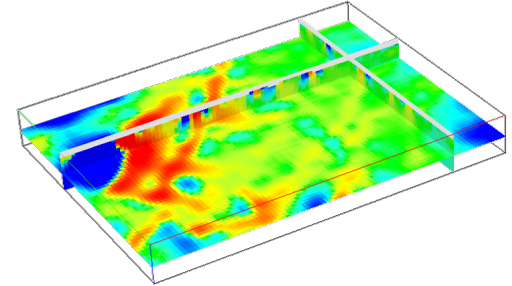
geological data



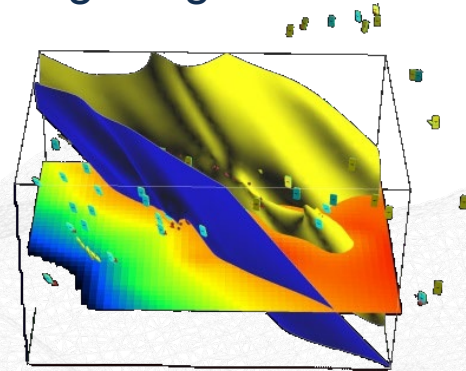
$$\phi_m(m) = \alpha_s \int_V w_s \left[w_r(z)(m - i) \right. \\ \left. \alpha_x \int_V w_x \left[\frac{\partial}{\partial x} (w_r(z)(i) \right. \right. \right. \\ \left. \left. \left. \Gamma \right] \right] \right]$$



geophysical model



geological model



inconsistent assumptions



$$s(\mathbf{x}) = \sum_{j=1}^{\mu} a_j K(\mathbf{x}, \mathbf{x}_j) + \sum_{k=1}^{\sigma} \\ + \sum_{l=1}^{\tau} e_l \left\{ t_{\mu+\sigma+l, \mathbf{x}} \frac{\partial K(\mathbf{x}, \mathbf{x}_l)}{\partial \mathbf{x}} \right\}$$

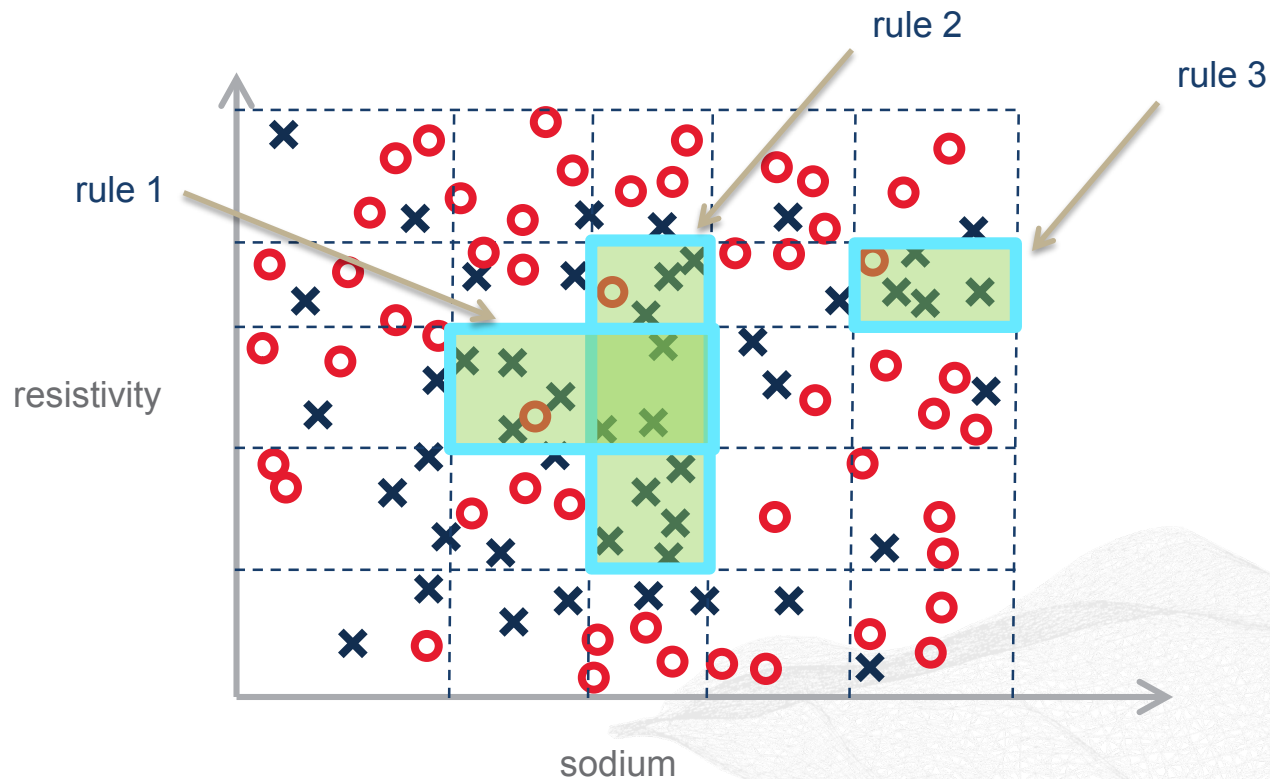


Data fusion table

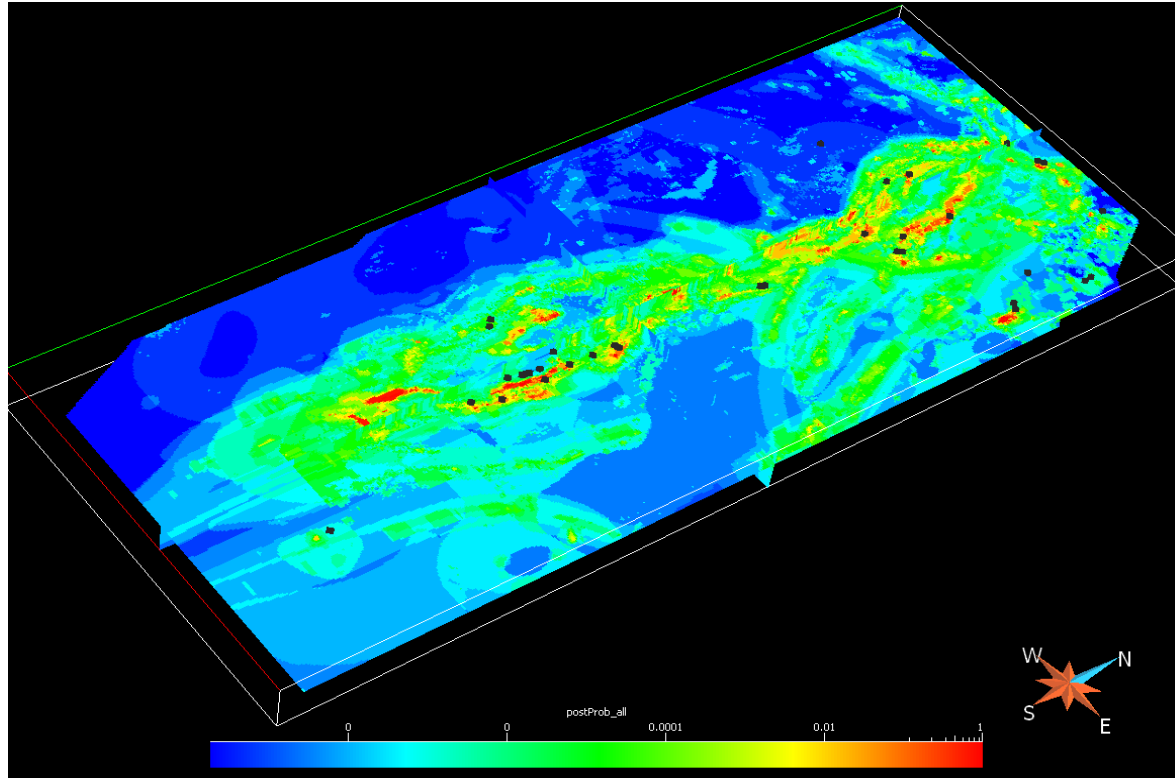
	rock mass				structure			seismicity			stress			hazard
	core diking				fault proximity			Es / Ep			deviatoric stress			
Observation 1														○
Observation 2														×
Observation 3														×
Observation 4														○
Observation 5														○
														○
														×
														○
														×
														○
														○
														×
														×
														×
														×
														×
Observation n														○



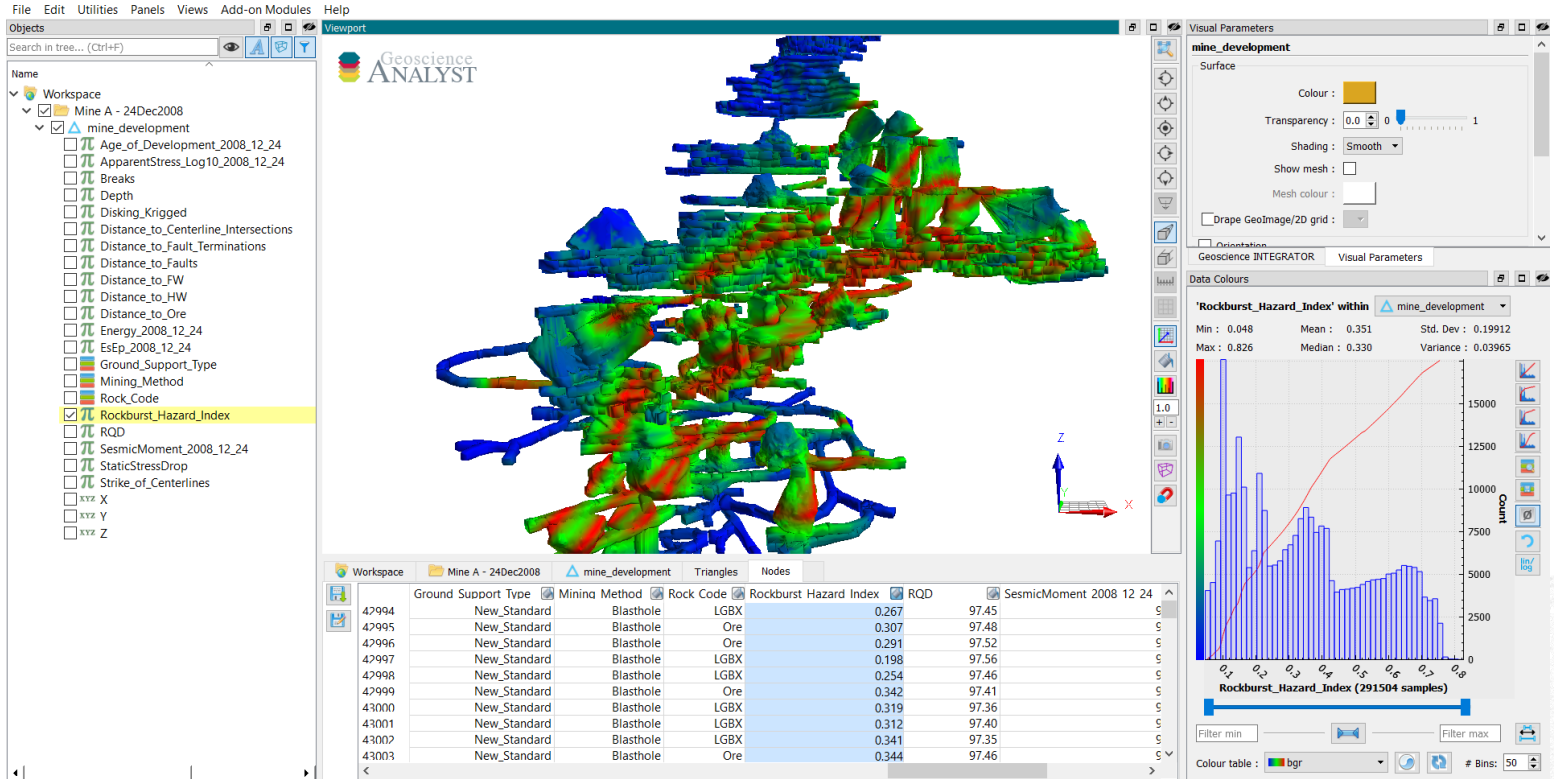
Machine learning



Exploration target probability model



Geohazard probability model

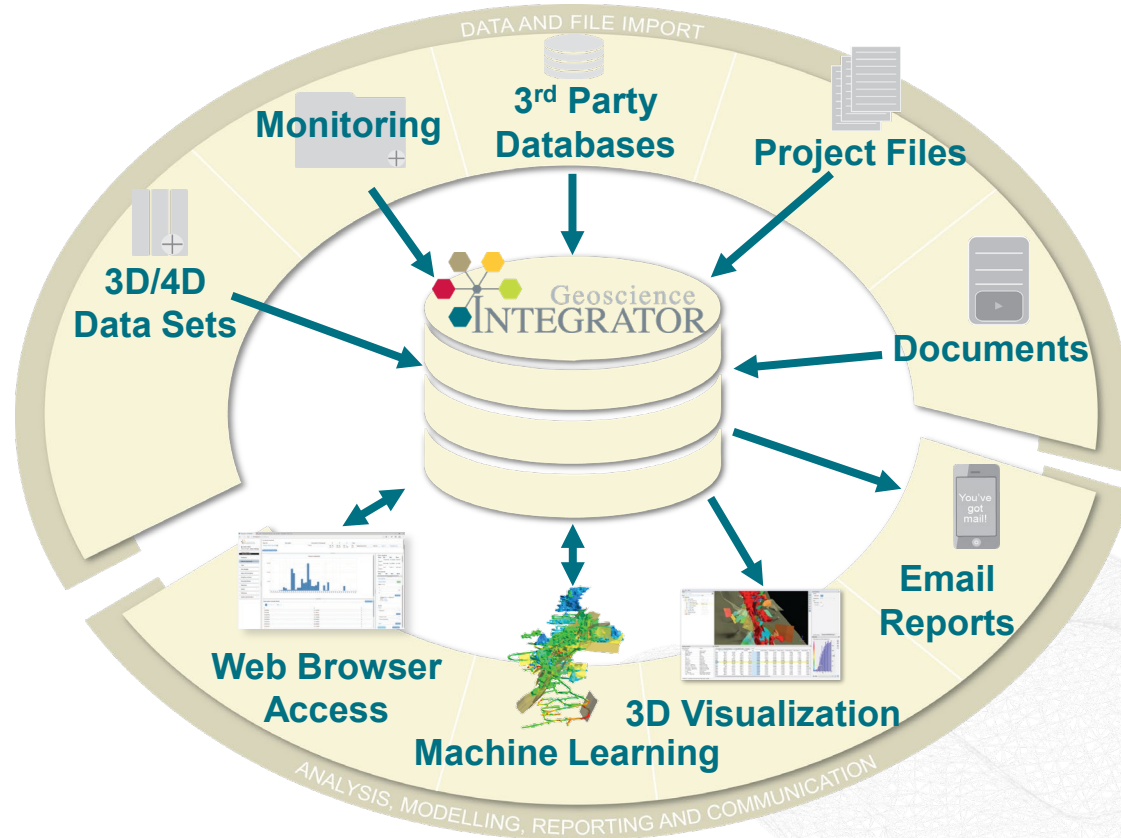


Solution requirements

- take the focus off the methods of AI as a discipline unto itself and put the focus on how the geoscience problem is set up for AI
- this is where deep domain knowledge and a domain-specific, supporting computational framework is required

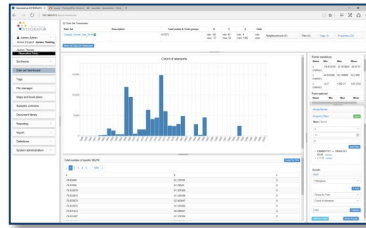


Geoscience INTEGRATOR



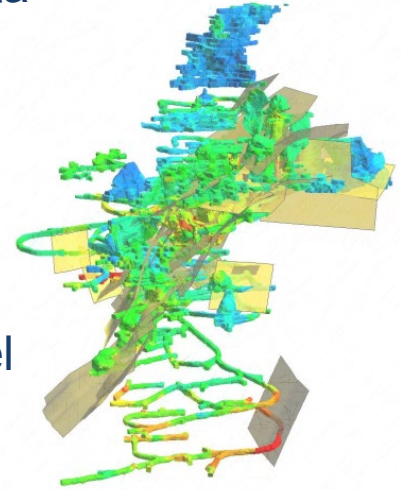


1 live connection to input data



2 spatial computation

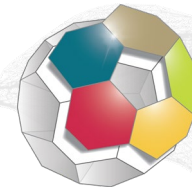
3 updated earth model



3D spatial modelling
engine on server

4 data fusion table

5 ML rules



machine learning

6 reporting



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Conclusion

$\text{target}(x, y, z, t) = f(\text{rock type, alteration, structure, chemistry, mineralogy, ...})$

- The targeting equation can be solved; practical application requires:
 - integrated multi-disciplinary 3D and 4D modelling
 - compilation of data and model into a “data fusion table”
 - connection to statistical and machine learning applications
 - integrated data management, model update, and analysis