

# The use of Machine Learning in Exploration

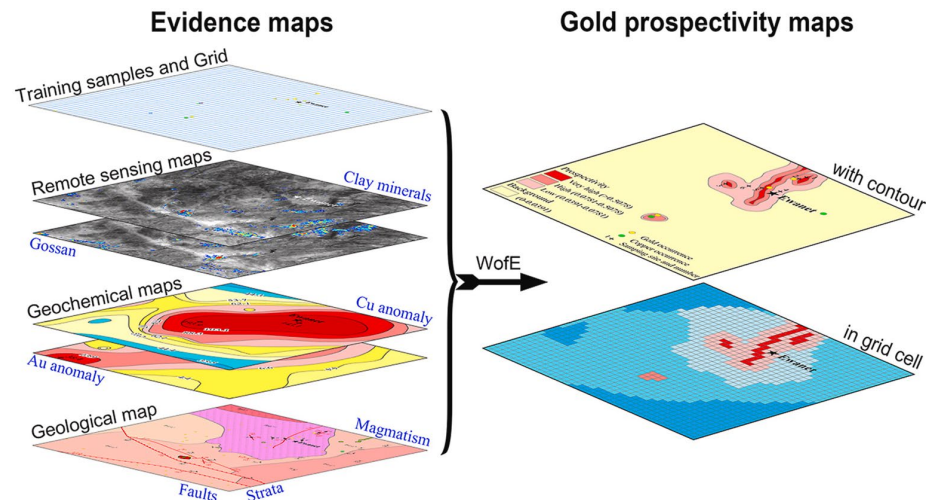
From greenfield to near mine

Tom Carmichael + Datarock Team

# Outline

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- Why Data Science and Machine Learning in Exploration?
- Where should we use ML (and maybe where we shouldn't use it)
- What can I do at the regional scale?
- What can I do at a camp scale?
- What can I do at a near-mine scale?
- *(How) can we move beyond the prospectivity map to provide concrete value in exploration and mining?*

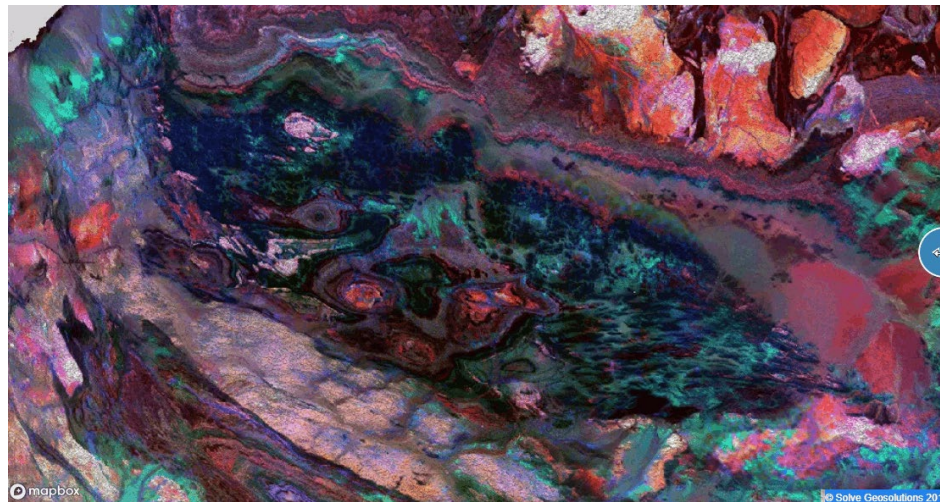


WOE (weights of Evidence) diagram from Fu et al 2021

# Why Data Science and ML in Exploration?

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- We collect a *lot* of data as an industry.
- The value of this data isn't always realised with traditional methods of geological analysis.
- Understanding of where ML provides value can add new techniques to the Exploration geologists toolkit



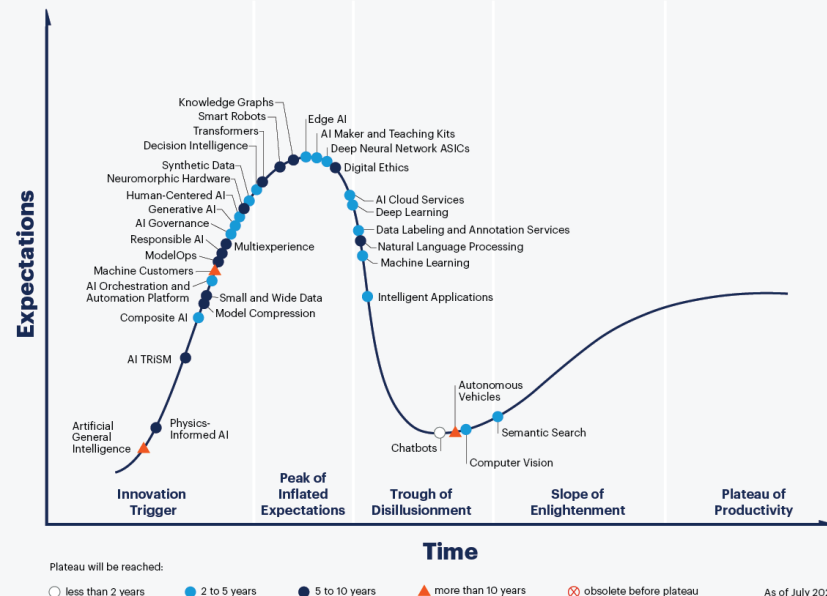
*Geological data that is suited for geological interpretation often needs to be manipulated to be more appropriate for ML purposes , particularly in the imagery space*

# Where should we use ML?

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- ML (and all techniques!) aren't a silver bullet - and applying them where they're not appropriate harms both sides of this work.
- *'When rules depend on too many factors and many of these rules overlap or need to be tuned very finely, it soon becomes difficult for a human to accurately code the rules. You can use ML to effectively solve this problem.'*

## Hype Cycle for Artificial Intelligence, 2021



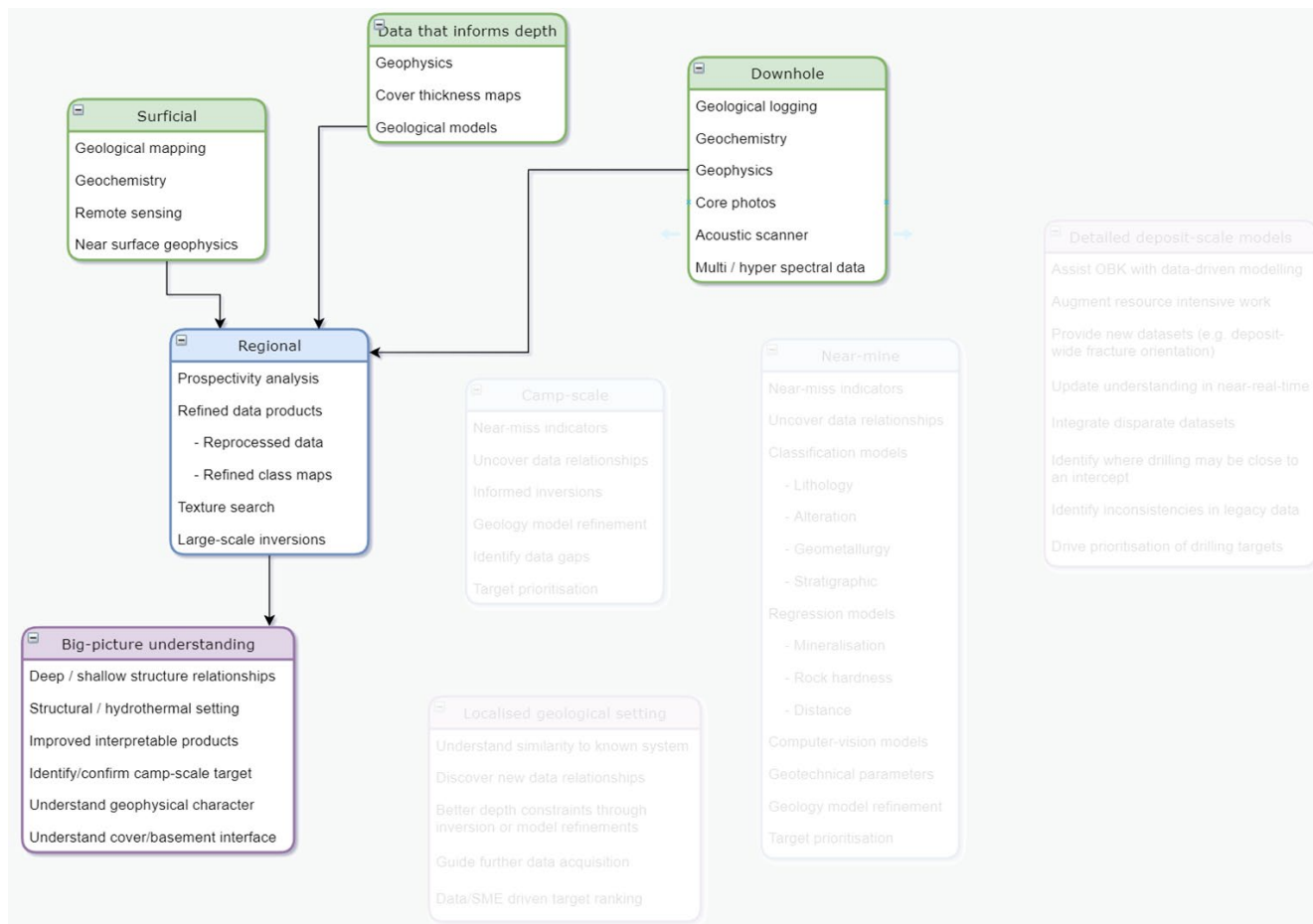
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# Different exploration phases - Different requirements

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# Greenfields Exploration

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- There are two broad approaches towards prospectivity - Knowledge Driven (*mineral Systems approach*) and Data Driven.
- A *minerals systems approach* works by combining theories of mineral formation are defined, then numerically and spatially quantified. (McCuaig et al 2010)
- The data driven approach maps a set of quantified features to known deposits and represents spatial areas relative to those known points
- Is a hybrid approach possible? (Januszczak 2021)

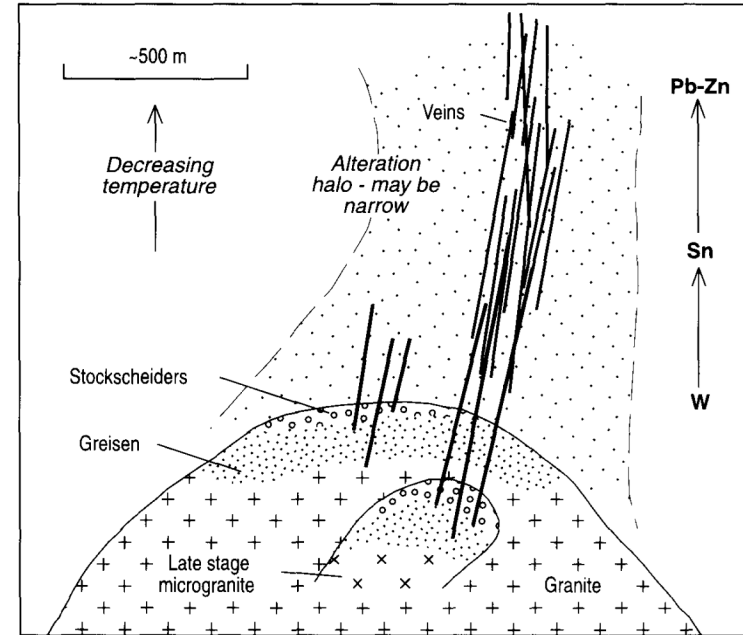
| Processes                  | Sub processes                       | Mappable Ingredient                                  | Predictor maps                            |
|----------------------------|-------------------------------------|--|---|
| Fluids, Metals And ligands | Magmatic-hydrothermal fluids        | Geochemistry of rocks                                | Proximity and elemental map               |
|                            | Magmatic                            | The presence of iron-rich intrusive/ extrusive rocks | Proximity of granitoid/ rhyolitoid rocks  |
|                            | Country rocks                       | The presence of iron-rich metal sedimentary rocks    | Proximity of limestone/ sedimentary rocks |
| Energy                     | Intrusive-volcanic complex          | The presence of iron-rich intrusive/extrusive rocks  | Proximity and airborne magnetic anomalies |
|                            | Hydrostatic head for oxidised fluid | Geochemistry of felsic rocks                         | Elemental map /                           |

*Examples of geological process and predictor relevant to some prospectivity maps from Sadeghi 2019.*

# Regional Exploration

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- Tin-tungsten deposits (in NW Tasmania) are typically associated with upper parts of evolved Devonian granite plutons where fluids from cooling granites have ponded and/or concentrated.
- Geophysical characteristics of the mineral system
  - Upper parts of low density granite bodies manifest as gravity lows
  - Low Fe-Ti oxide evolved granites tend to be magnetically 'quiet'
  - When exposed at surface, evolved prospective granites will give rise to strong radiometric responses due to high K, U and Th content

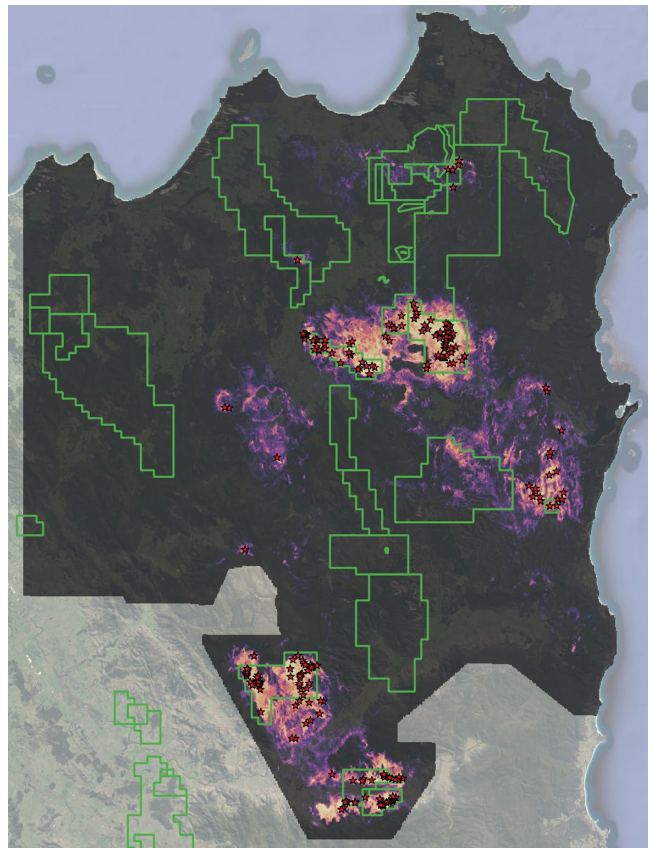
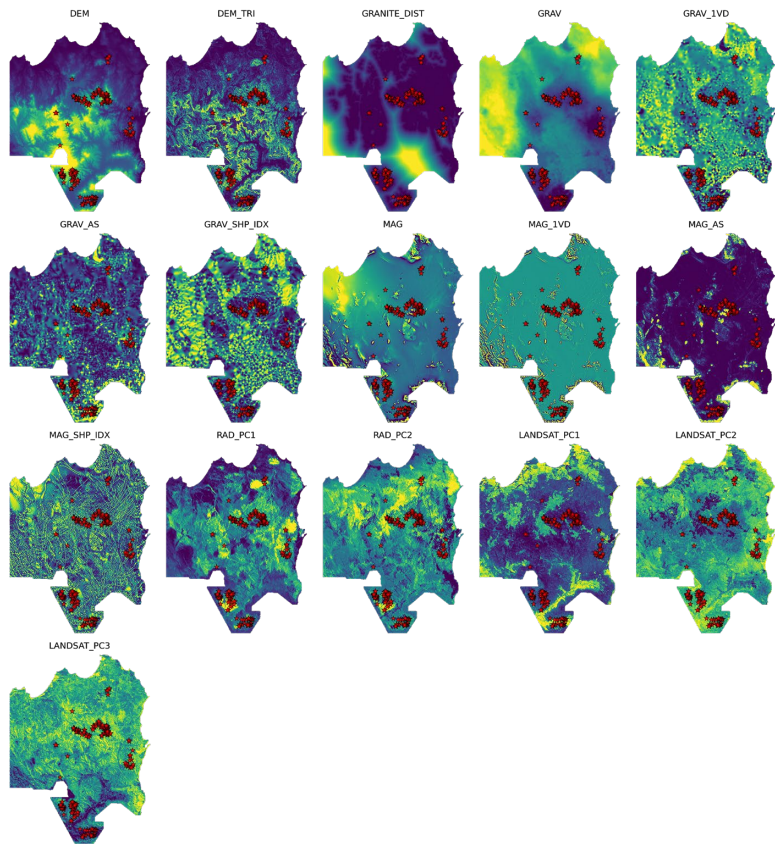


Source: [Blevin \(1998\)](#)



# Regional Exploration

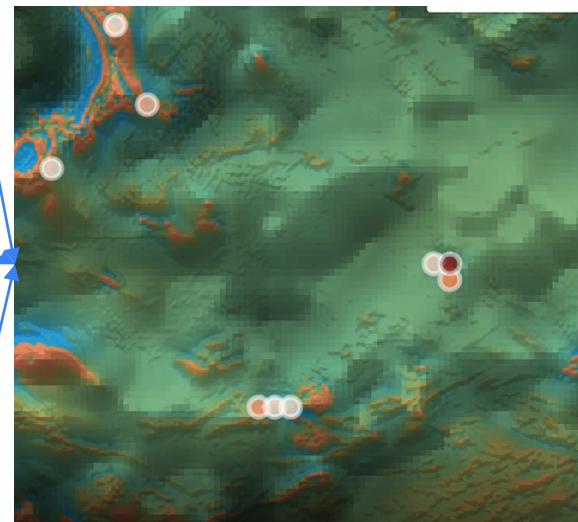
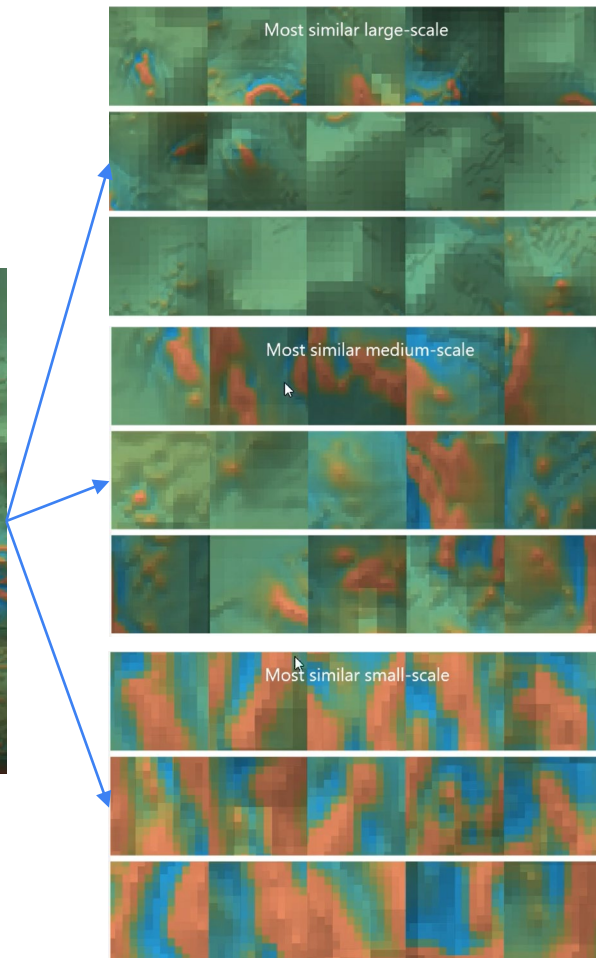
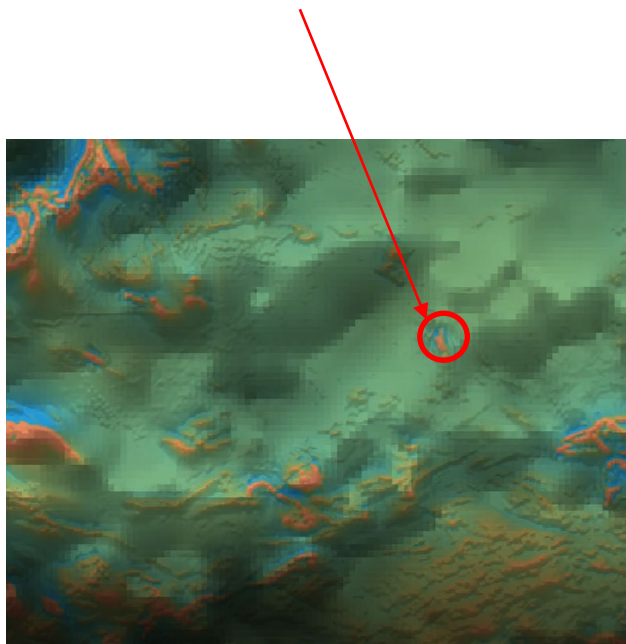
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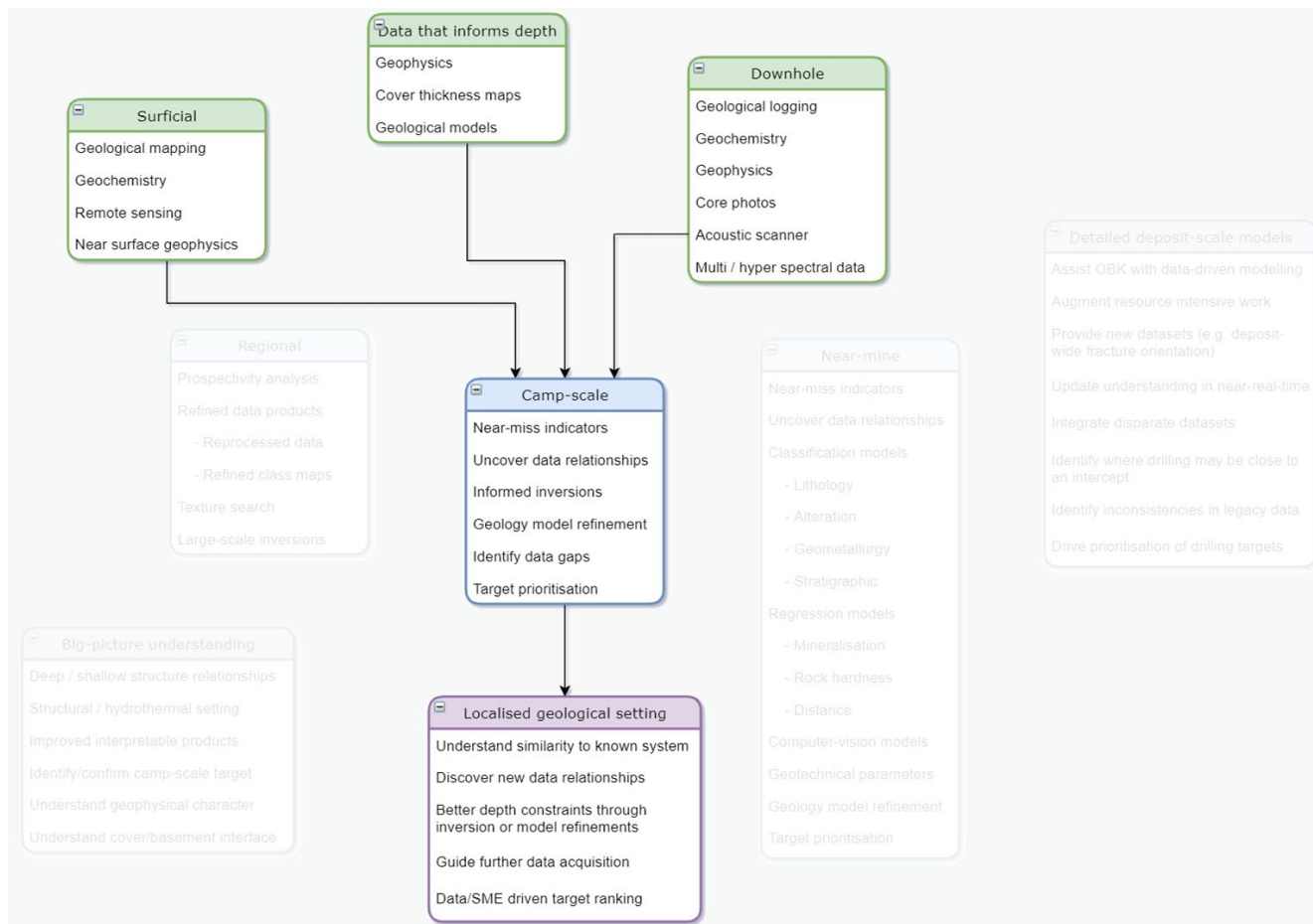
# Greenfields Exploration

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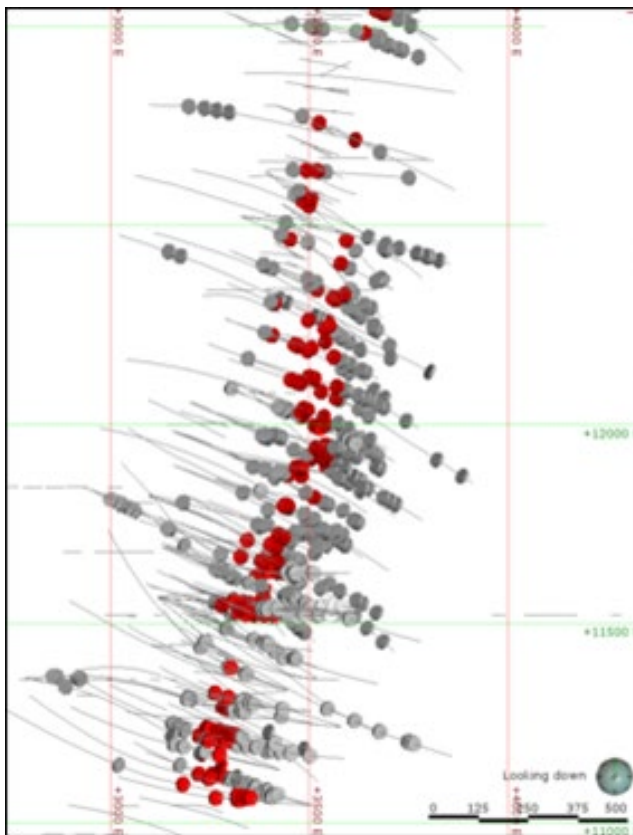
# Different exploration phases - Different requirements

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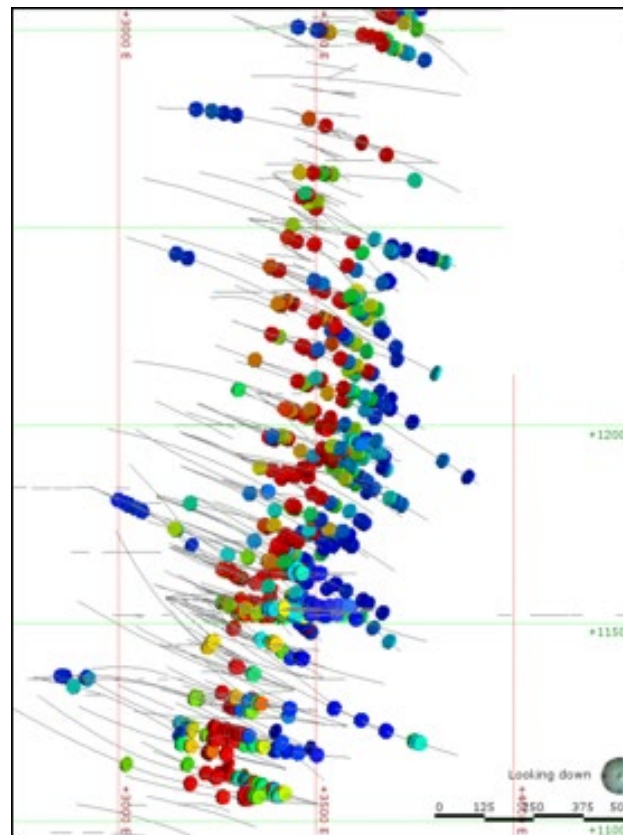


# Camp Scale Exploration

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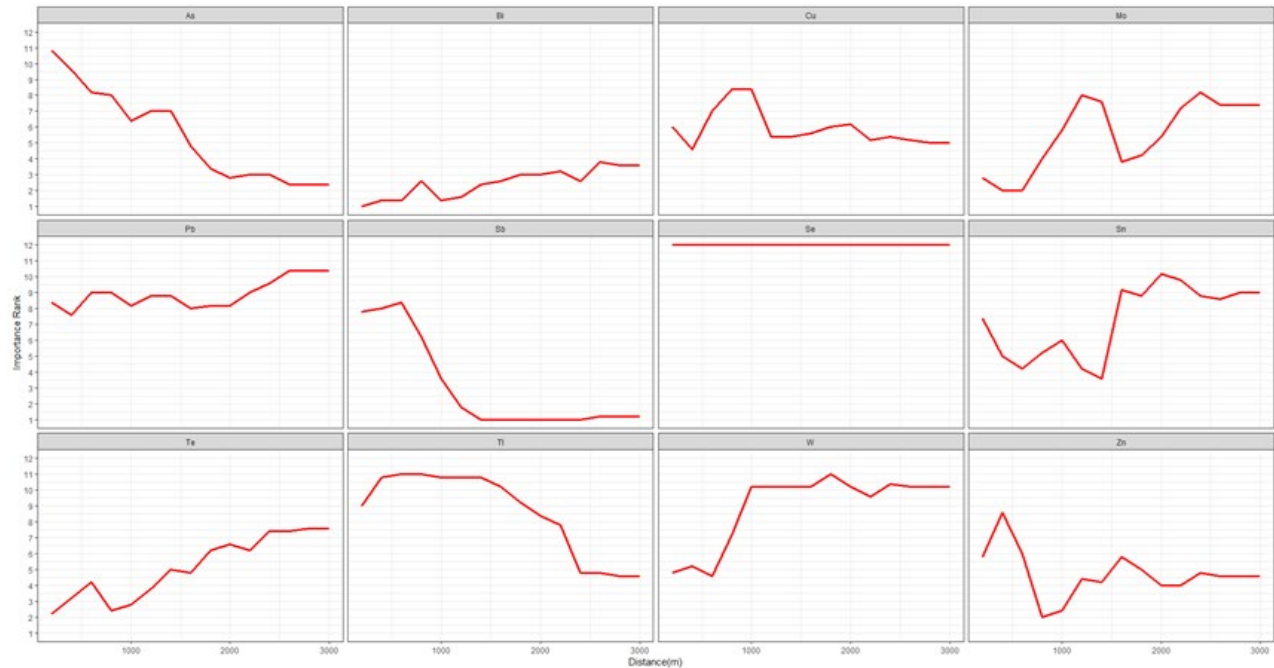


Classification of ore bearing unit

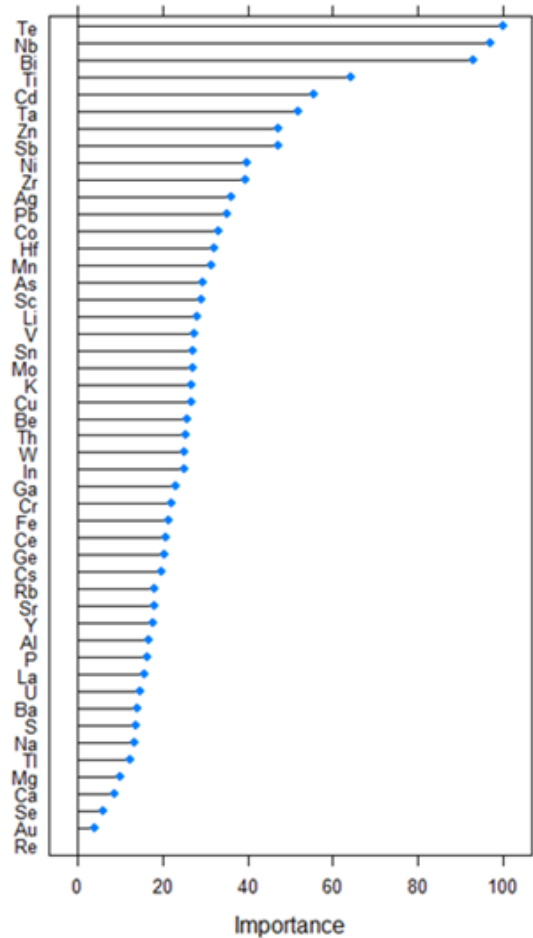


Probability of ore bearing unit

# Camp Scale Exploration

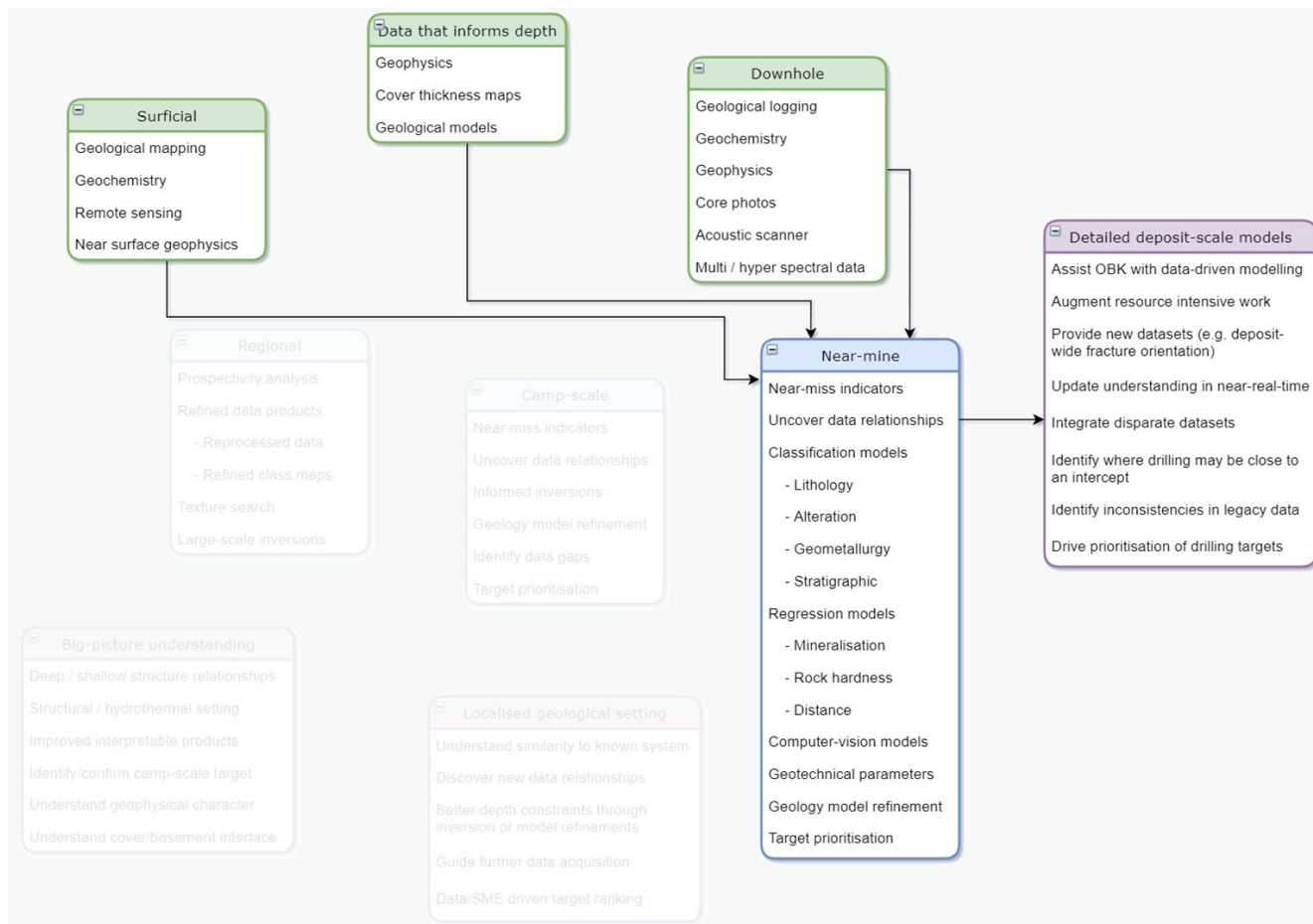


# Datarock.



# Different exploration phases - Different requirements

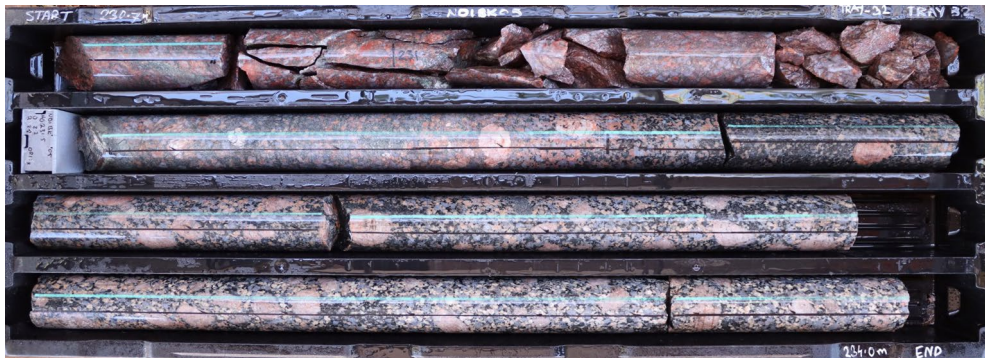
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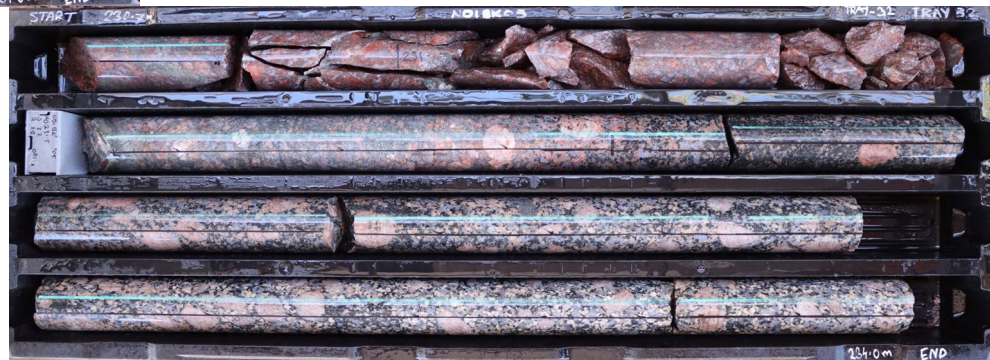
# Near Mine Exploration

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- Use OCR to identify writing on the core and use this in an intelligent way to determine the depth on the core.
- Depth register the image.
- Export + post process the required dataset (remove artefacts from writing, poor lighting in core sheds, etc)

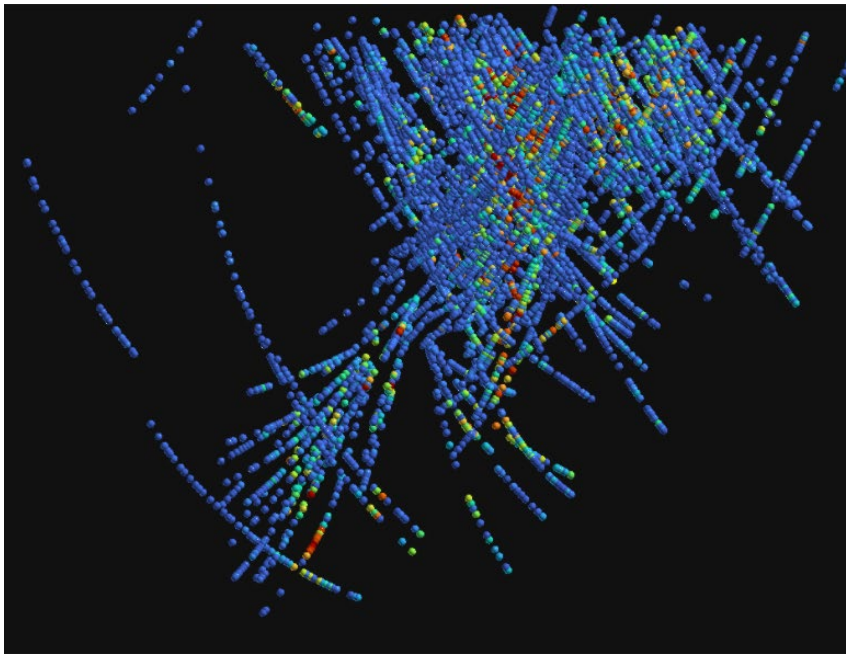
- Photo dewarping + identifying corebox location + masking
- Identify + mask the sections of the corebox that don't contain core.
- Identify + mask the section of the corebox that has coherent core.
- Identify + mask the section of the corebox that has *incoherent* core.



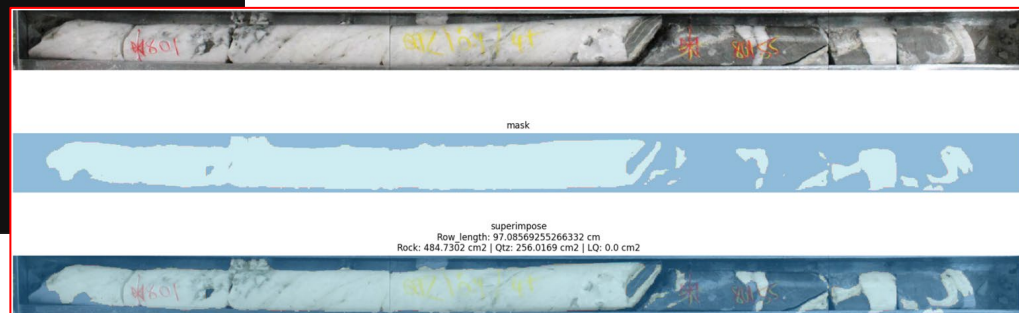
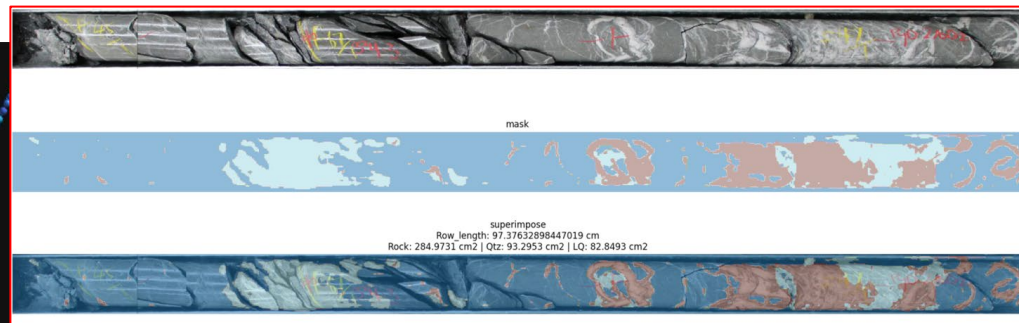


# Near Mine Exploration

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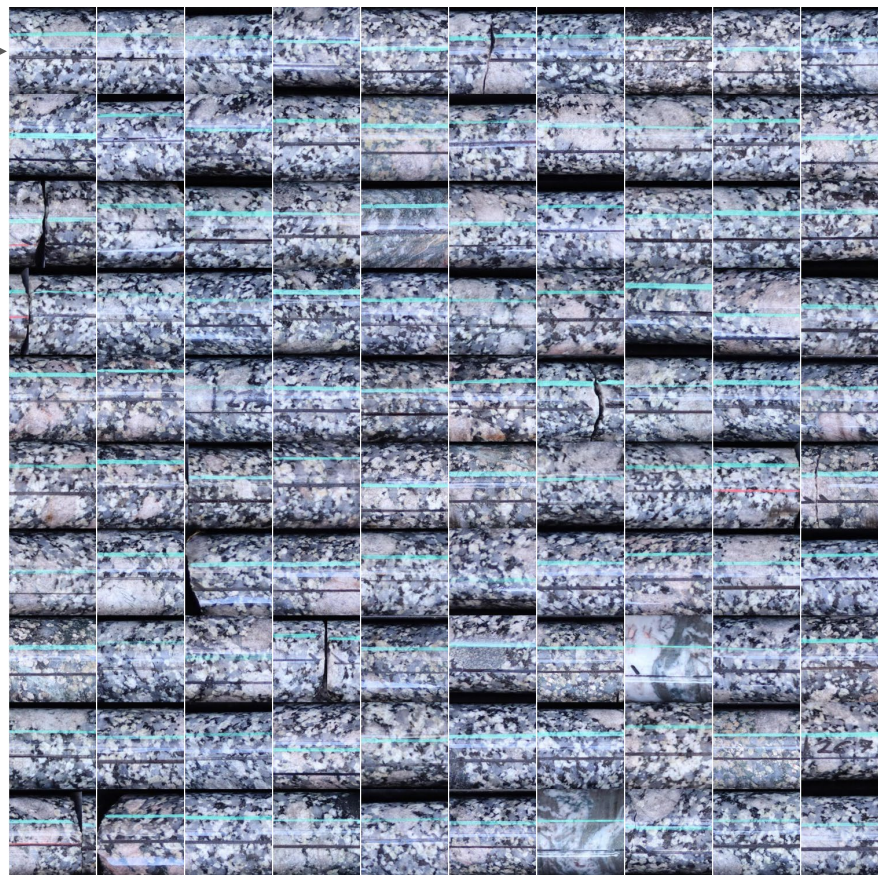


Vein area per  
metre



# Near Mine Exploration

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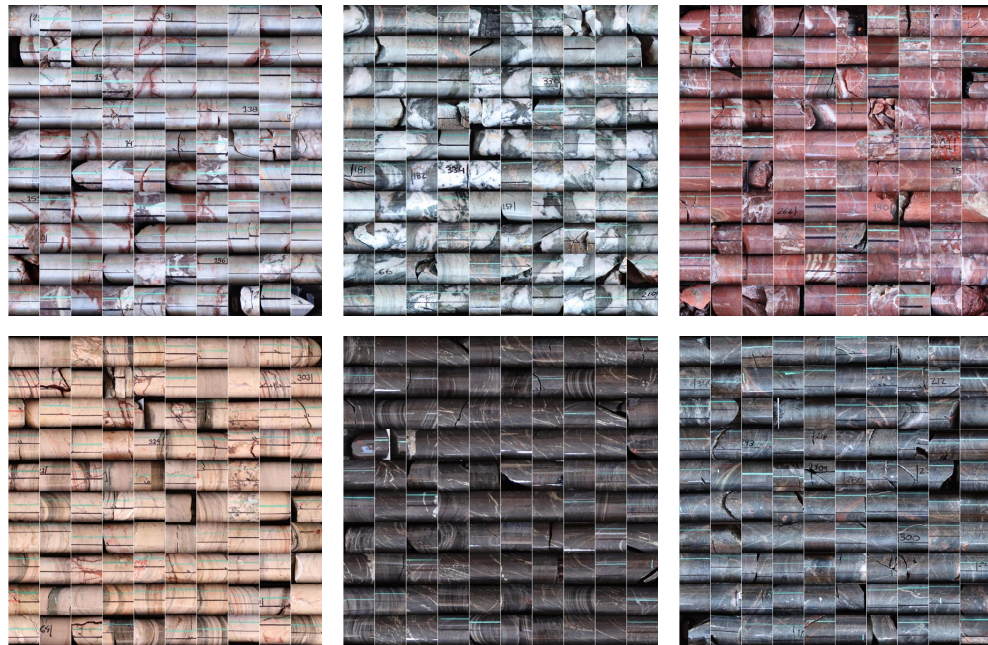


- Textural characteristics can be difficult to identify easily due to the vast amount of data available.
- Finding one or two examples can be easy (?) - then use ML to identify potential candidates of that texture in the remainder of the available dataset.



# Near Mine Exploration

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Data driven domains