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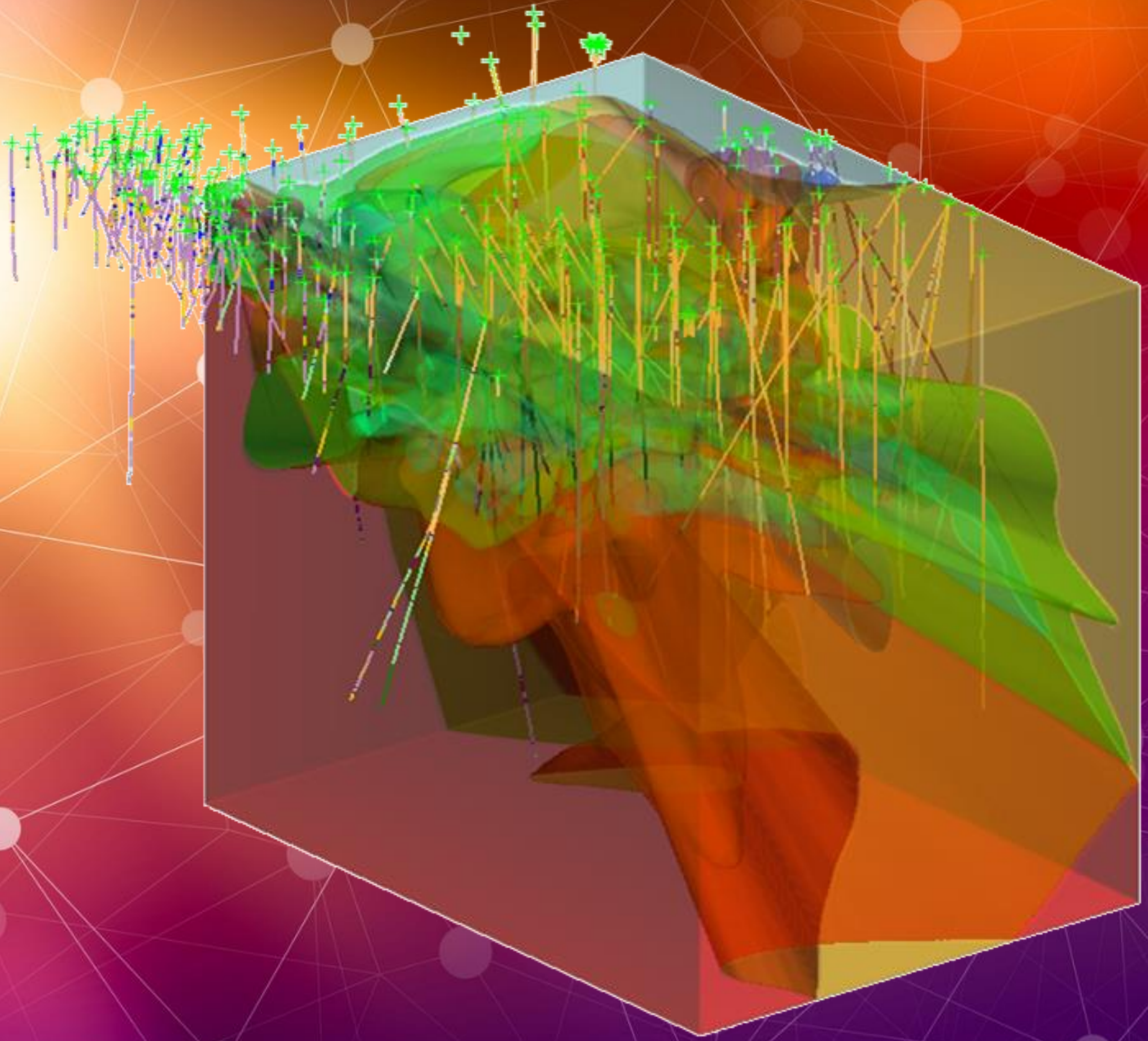

Machine Learning-Based Domaining of a Porphyry Copper-Gold Deposit

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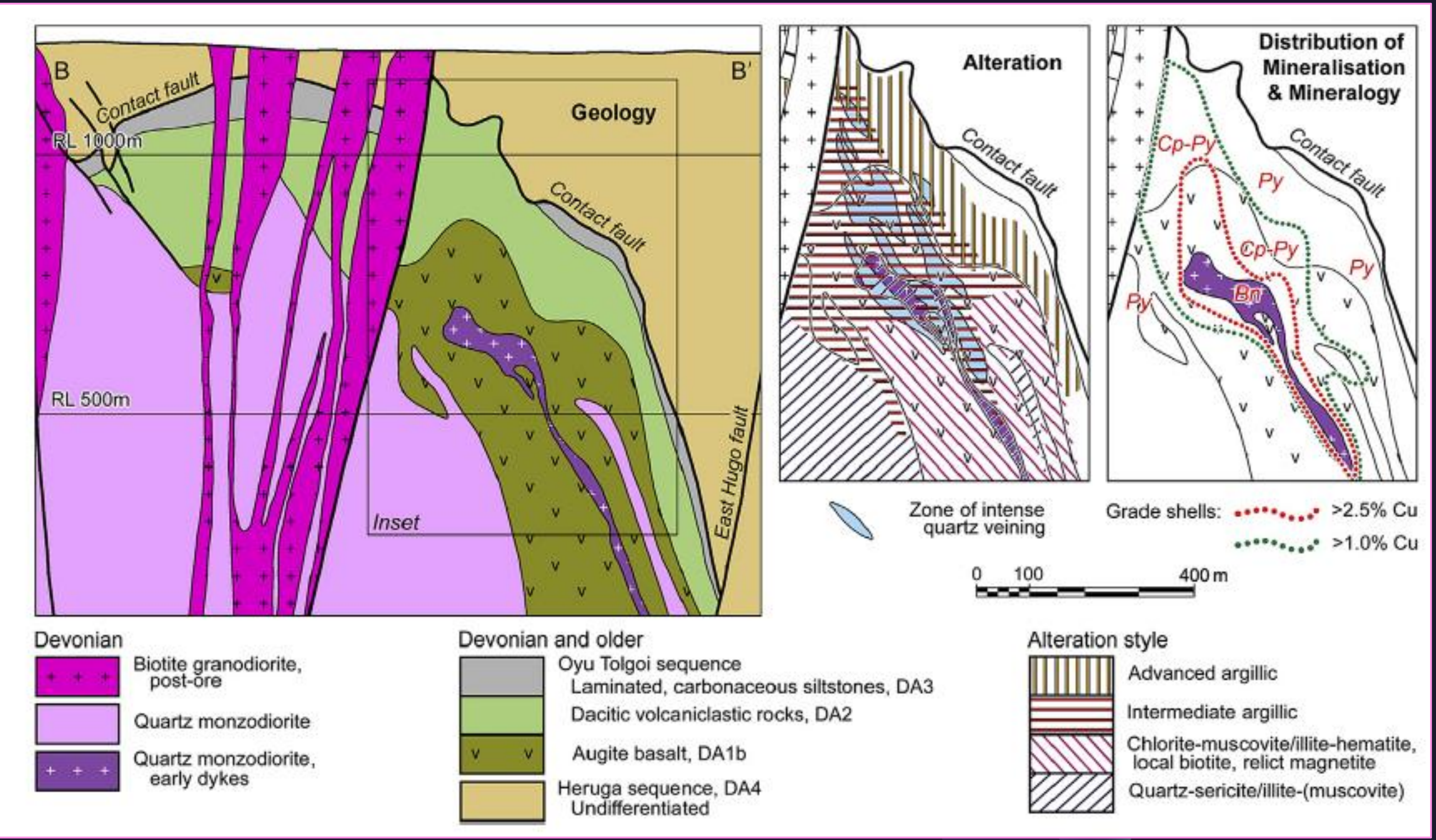
Geological background of the porphyry copper deposit



- Porphyry copper deposits are the main source of copper and other metals mined today to satisfy an ever-increasing global demand.
- Resource modelling of such deposits can be challenging as they usually present a complex geological environment, difficult to capture using conventional modelling tools.
- The porphyry deposit in this study contains economic grades of Cu, Au, Mo, and Ag, and is hosted by a basalt sequence, intruded by quartz monzonite, and disrupted and bound by faulting.
- Mineralisation consists of quartz-stockwork veining and alteration is typical of porphyry copper systems.

Figure from Porter, T.M., ***The geology, structure and mineralisation of the Oyu Tolgoi porphyry copper-gold-molybdenum deposits, Mongolia: A review***, Geoscience Frontiers (2015), http://dx.doi.org/10.1016/j.gsf.2015.08.003

The dataset

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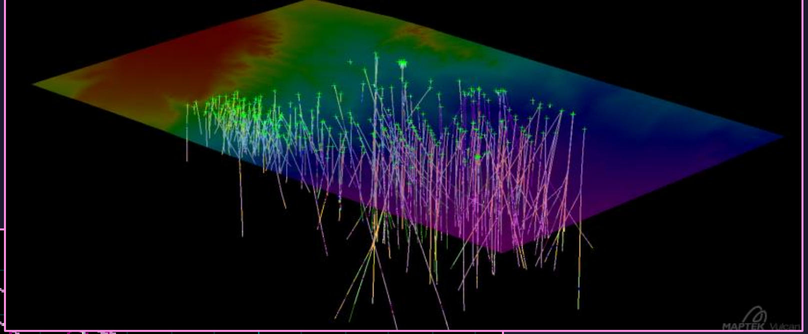

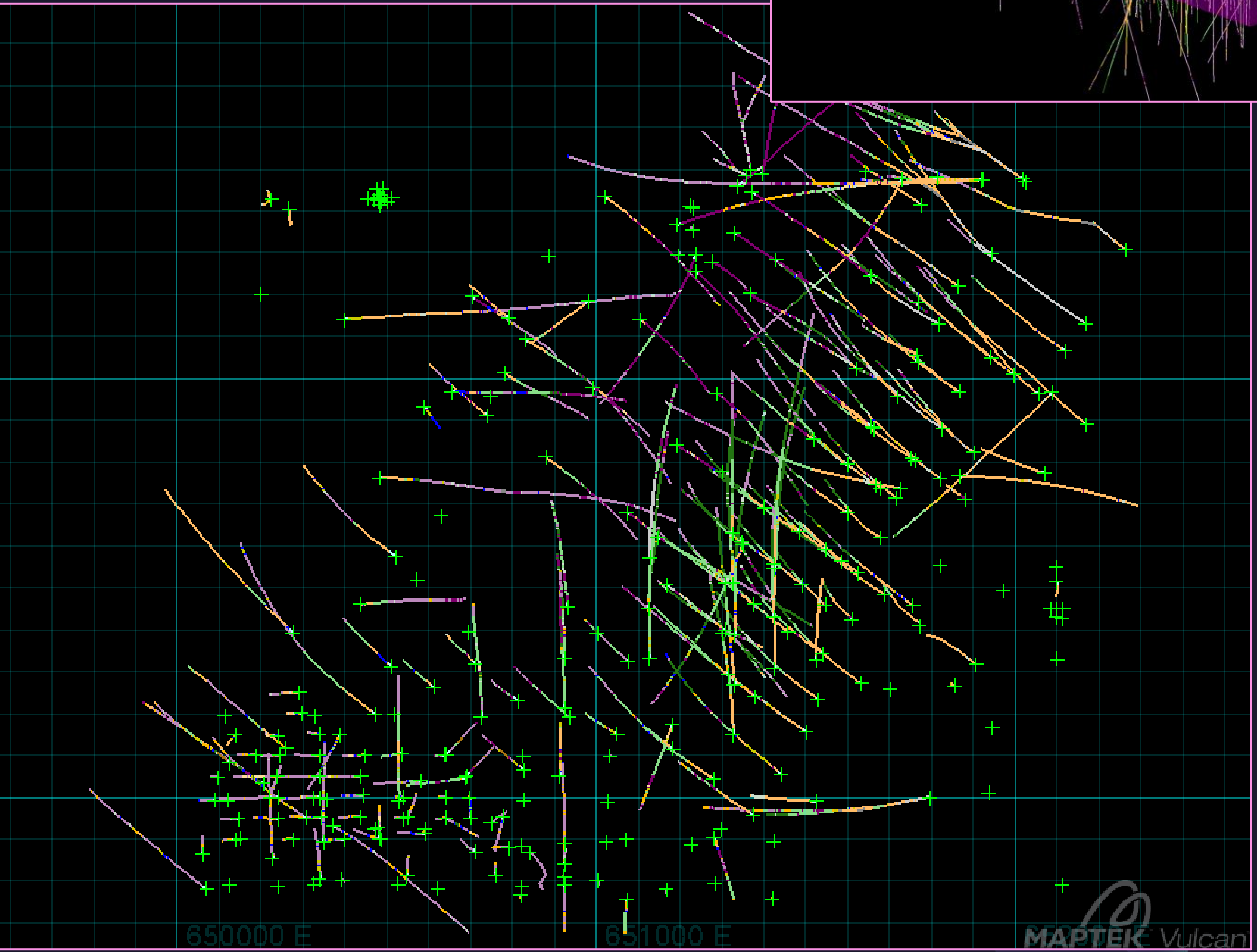

- Drill data included 7 files (collar, survey, assay, lithology, alteration, mineralisation and density).
- The assay table contained data for 13 elements, including economic grades of Cu, Au, Mo and Ag and potentially deleterious grades of As, F, S, and Fe.
- There were 360 drill holes totalling 178 km of drilling.
- The project topography surface.

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Domaining tools

The following software and modules were used in analysing and modelling domains in this study:

Maptek Vulcan:

- **Data Analyser**: an application used to perform statistical, spatial, and geostatistical analysis of raw samples, composites, in order to identify estimation domains.
- **Geology and grid modelling tools**: used to perform explicit modelling of geological boundaries and fault surfaces.
- **Block modelling tools**: used to perform implicit modelling of intrusions and grade estimation in different domains.

Maptek DomainMCF:

- a block model domaining system based on convolutional neural networks (machines) available as a cloud service.
- DomainMCF machines are trained using sample composites to learn the spatial distribution of geological variables (e.g., domain codes) and are applied on block models to estimate the value of these variables on each block.

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DomainMCF machines

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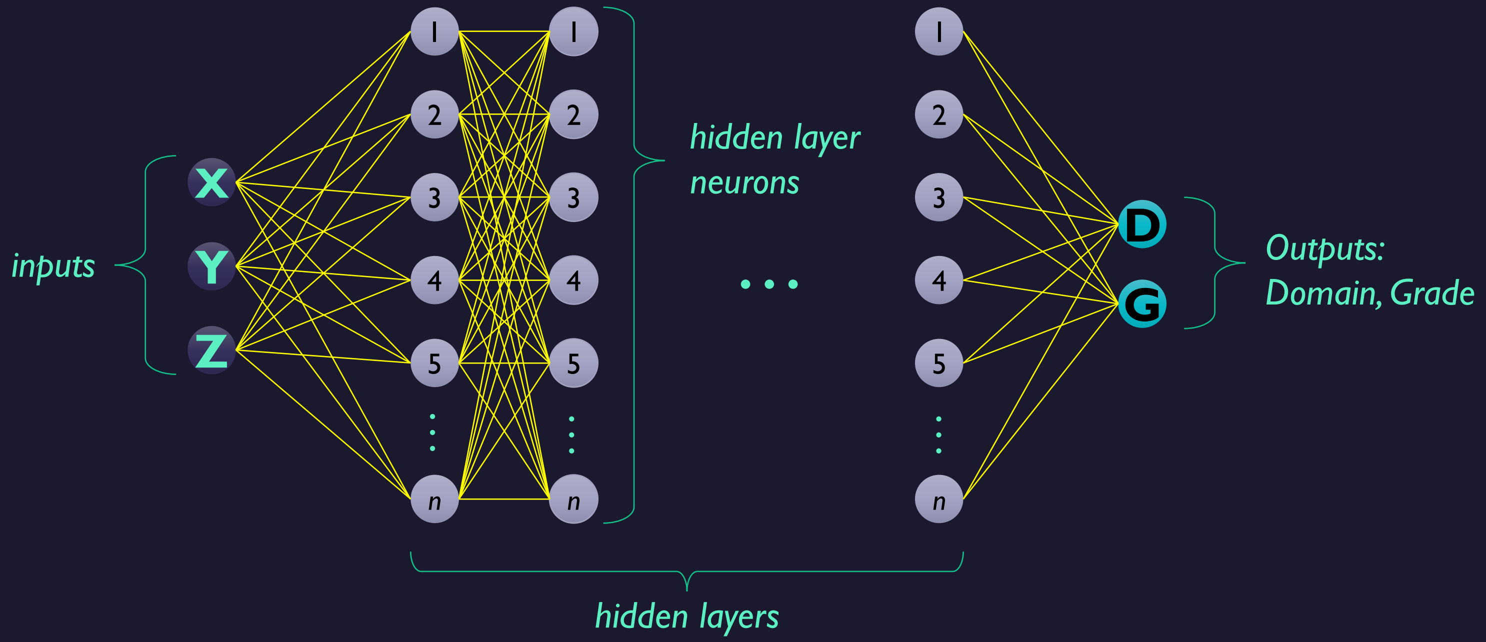

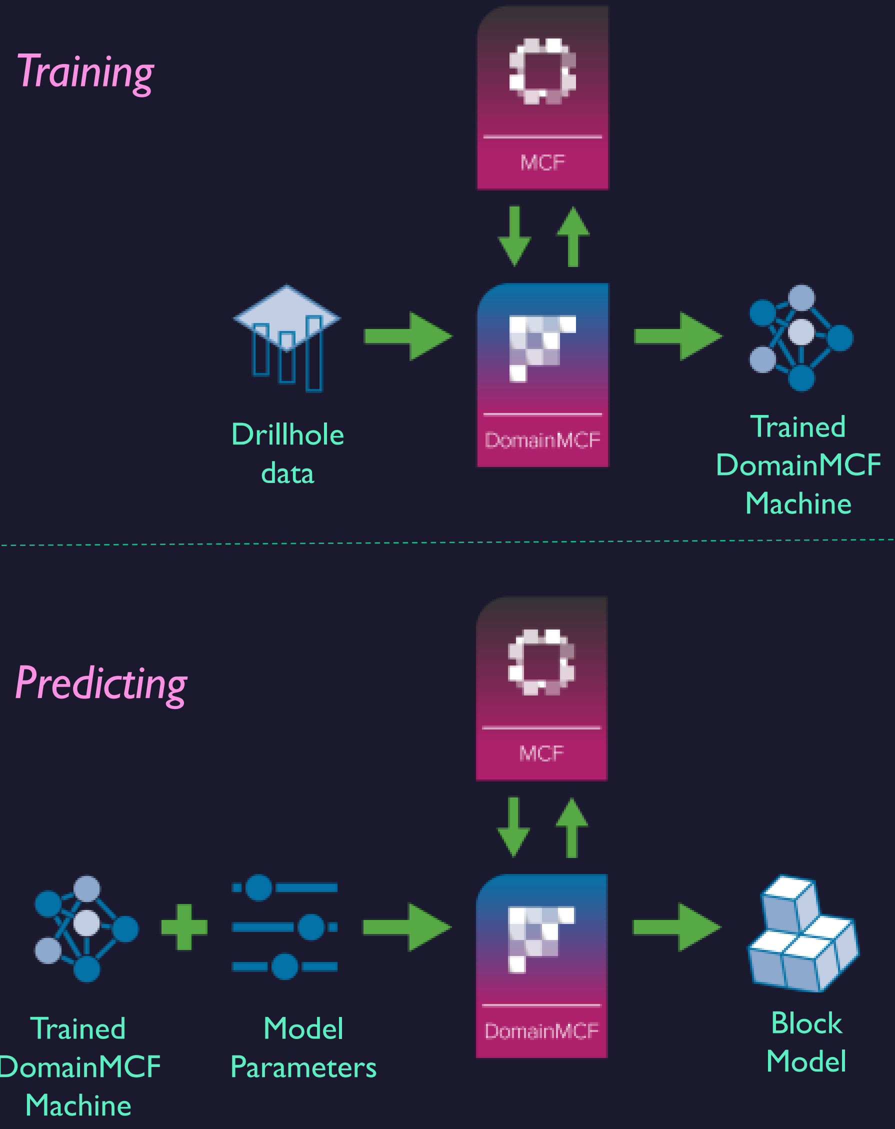

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Identifying domains

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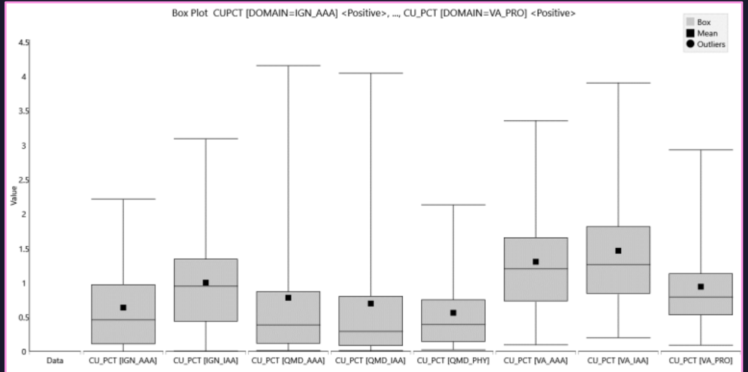
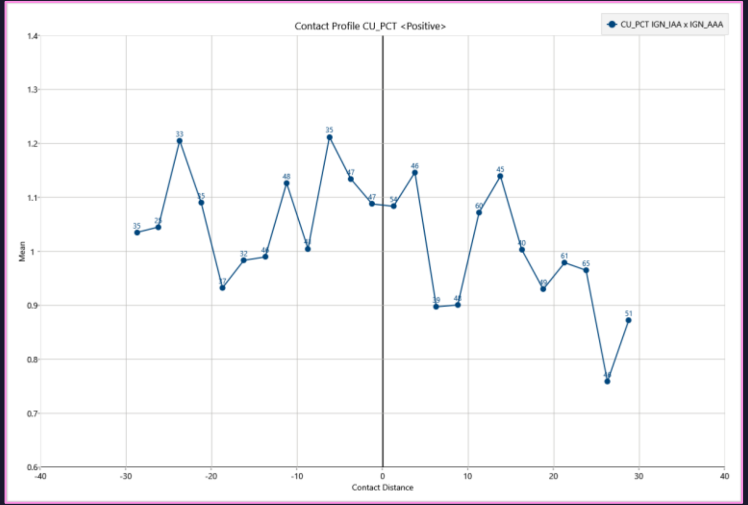


Data	CU_PCT [IGN_AAA]	CU_PCT [IGN_IAA]	CU_PCT [QMD_AAA]	CU_PCT [QMD_IAA]	CU_PCT [QMD_PHY]	CU_PCT [VA_AAA]	CU_PCT [VA_IAA]	CU_PCT [VA_PRO]
Number of samples	5.233	1.164	2.754	806	9.743	1.094	3.285	3.240
Max	7.270	6.290	21.500	8.940	9.010	6.770	17.400	6.980
97.5% quantile	2.200	3.073	4.125	4.021	2.120	3.333	3.879	2.910
Upper quartile	0.974	1.342	0.870	0.808	0.755	1.647	1.804	1.131
Median	0.459	0.943	0.382	0.289	0.395	1.198	1.258	0.787
Lower quartile	0.115	0.438	0.119	0.086	0.144	0.724	0.830	0.527
2.5% quantile	0.004	0.011	0.019	0.014	0.029	0.100	0.203	0.096
Min	0.001	0.004	0.001	0.005	0.000	0.005	0.002	0.005
Mean	0.637	0.999	0.779	0.692	0.558	1.298	1.459	0.939



- Statistical analysis of Cu and the other elements for each alteration type and each lithology code, including general statistics, histograms, cumulative frequency graphs, and box plots were generated to understand the effect of alteration and lithology to their distribution.
- Spatial analysis of grades was performed in combinations of alteration and lithology (zones) using swath plots to better understand the variability of grades within each considered zone and establish if some of them could be considered as estimation domains, if some could be combined, or if they should be split to more estimation domains.
- Contact profile analysis was also performed between neighboring domains to establish the transition of grades across their boundaries.
- The results of the initial statistical and spatial analysis lead to the following potential domains for estimation:

Domain	1	2	3	4	5	6	7	8
Lithology	IGN	IGN	QMD	QMD	QMD	VA	VA	VA
Alteration	AAA	IAA	AAA	IAA	PRO	AAA	IAA	PRO

- Once the domains were identified, composites were coded as to the domain.

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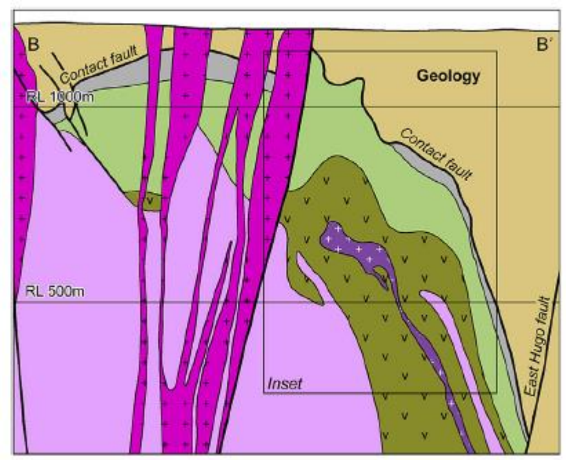
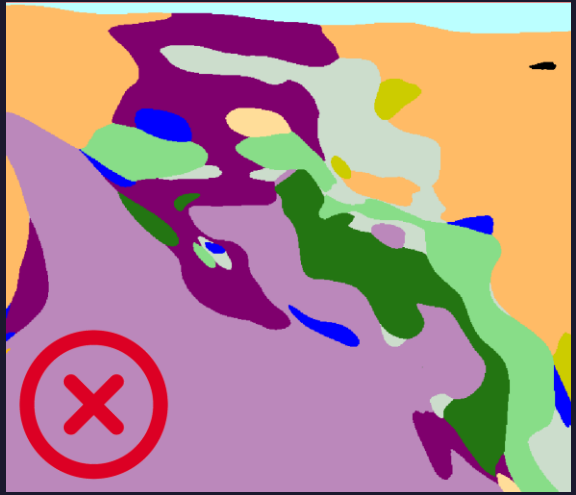
Geology-driven modelling procedure

(not just data-driven!)

Conceptual model of lithology



Direct (wrong!) model of lithology



First runs of DomainMCF directly on lithology or domain-coded composites proved that it would be impossible to reproduce the correct distribution of domains in one step, and that a more step-by-step procedure was necessary. The following procedure was adopted:

1. Generation of a block model of alteration by training a DomainMCF machine with the alteration information in the composites. (8 minutes)
2. Generation of a block model of main lithology types (HBX, HWS, IGN, QCO, QMD, VA) by training a DomainMCF machine with lithology information limited to only these types in the composites. (9 minutes)
3. Implicit modelling of intrusive lithologies (BIGD, BAD, AND, and RHY) in Maptek Vulcan. Intersection of these models with the block model in step 2 to overwrite lithology codes in the block model. (approx. 1 hour)
4. Modelling of the contact fault and CLAY floor using grid modelling and surface triangulations. (approx. 20 minutes excluding identification of contact fault intervals)
5. Consolidating all produced block models to a single block model and use of the imported alteration and lithology values with the contact fault and clay floor to derive the domain codes in the final block model. (approx. 1 hour)

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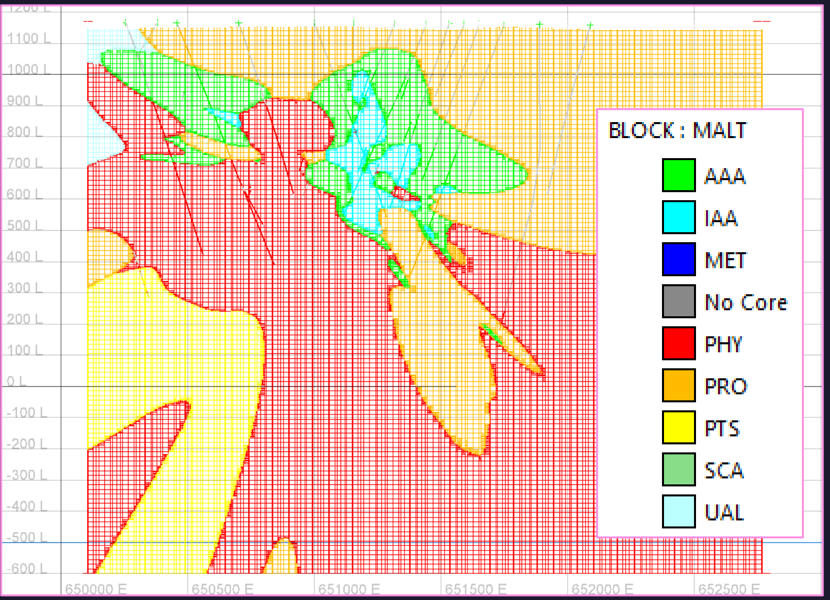
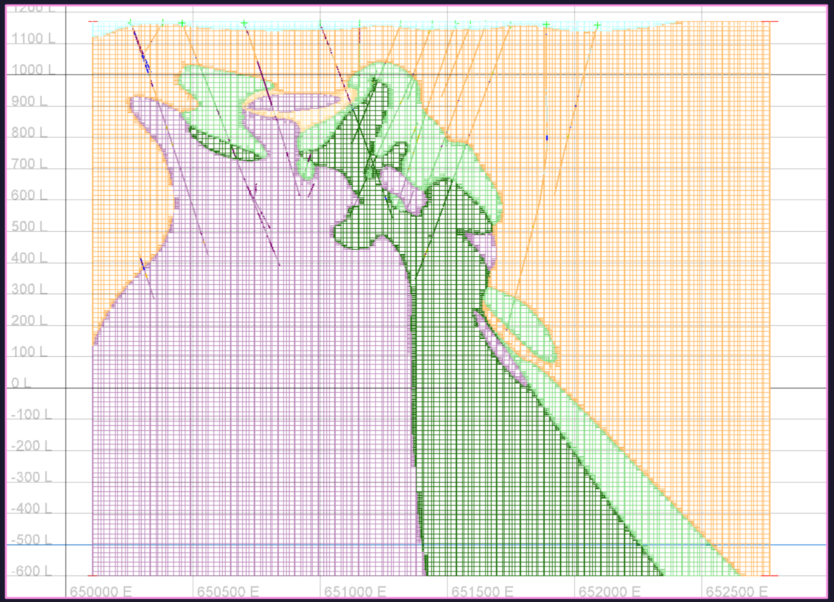
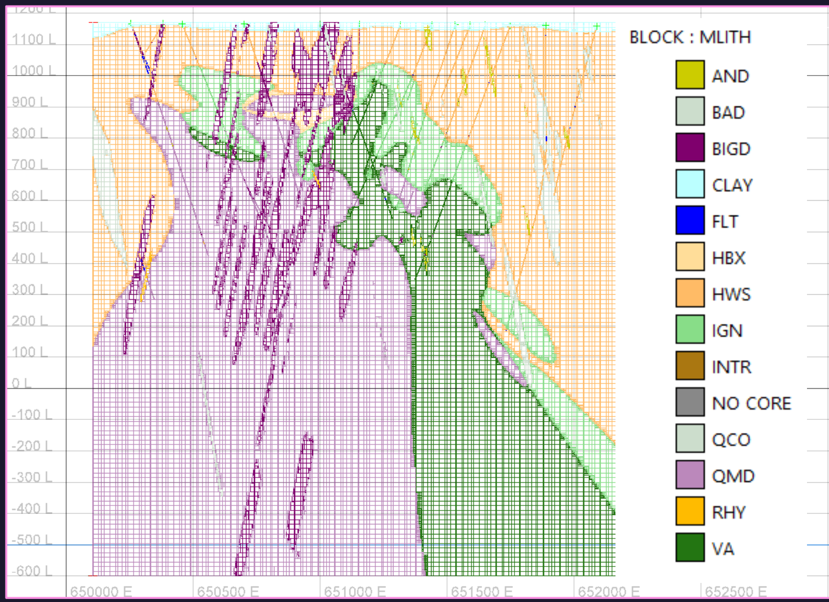
Step 1: DomainMCF modelling of alteration



Step 2: DomainMCF modelling of original lithologies



Step 3: Implicit modelling of intrusions



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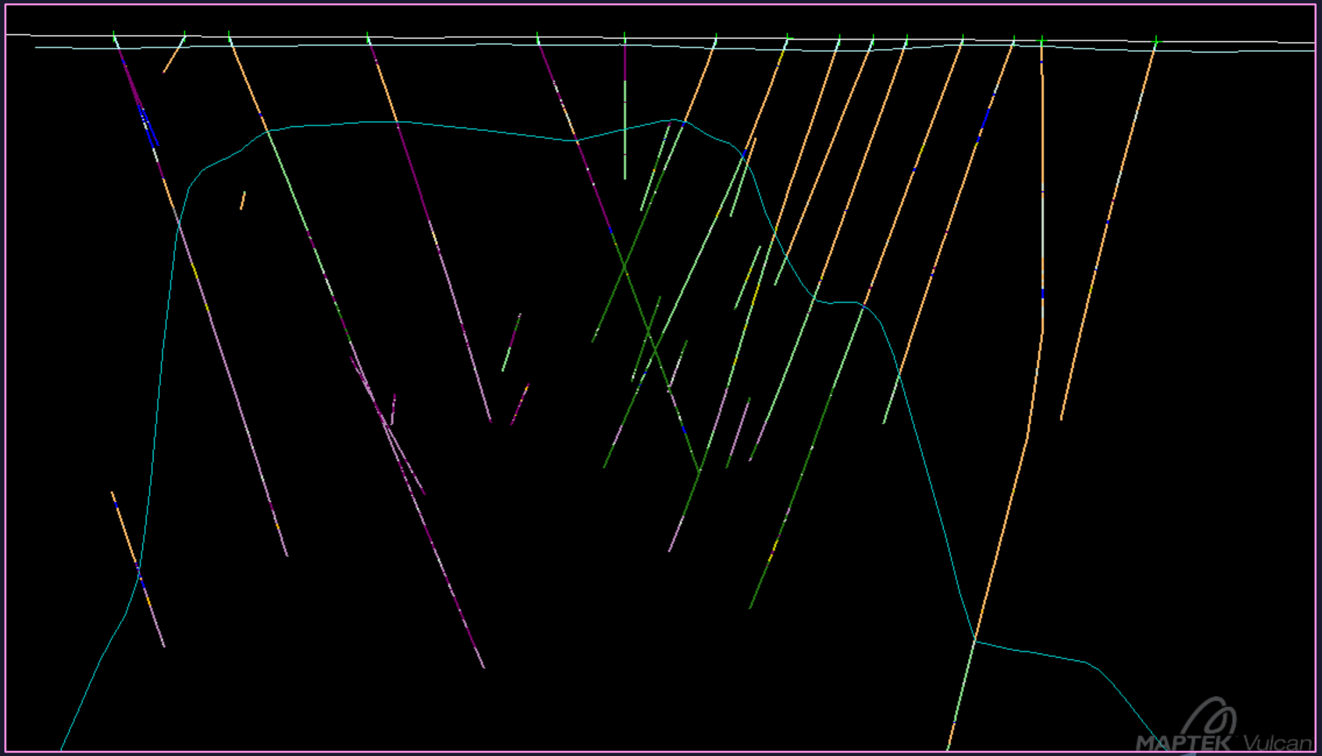
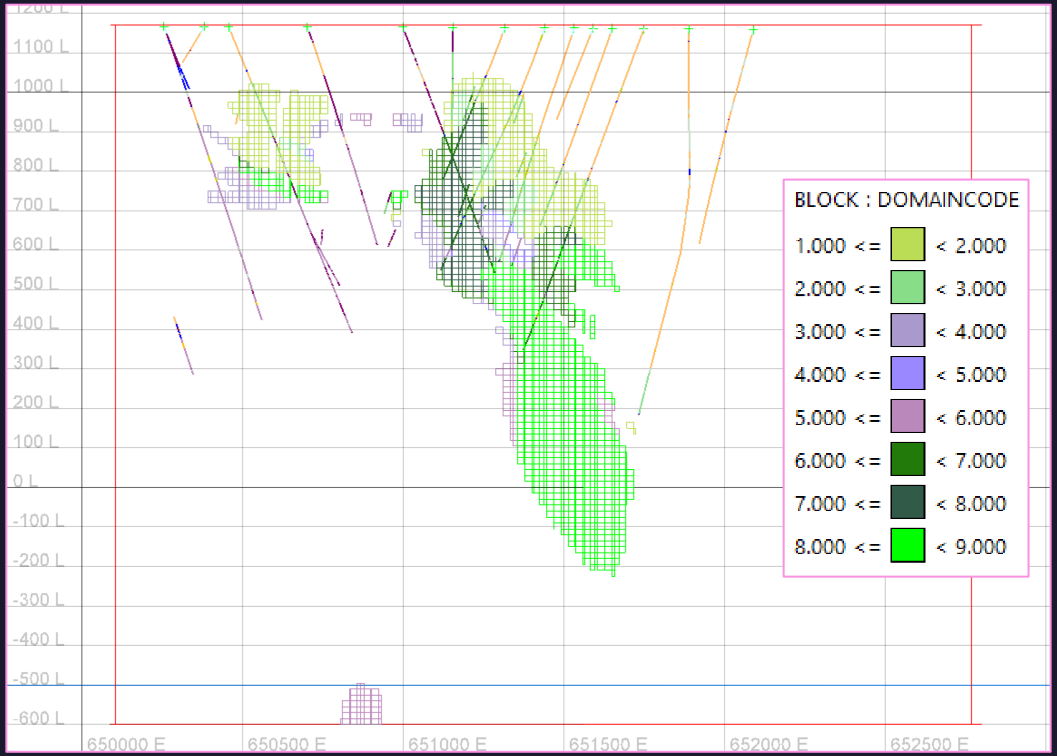
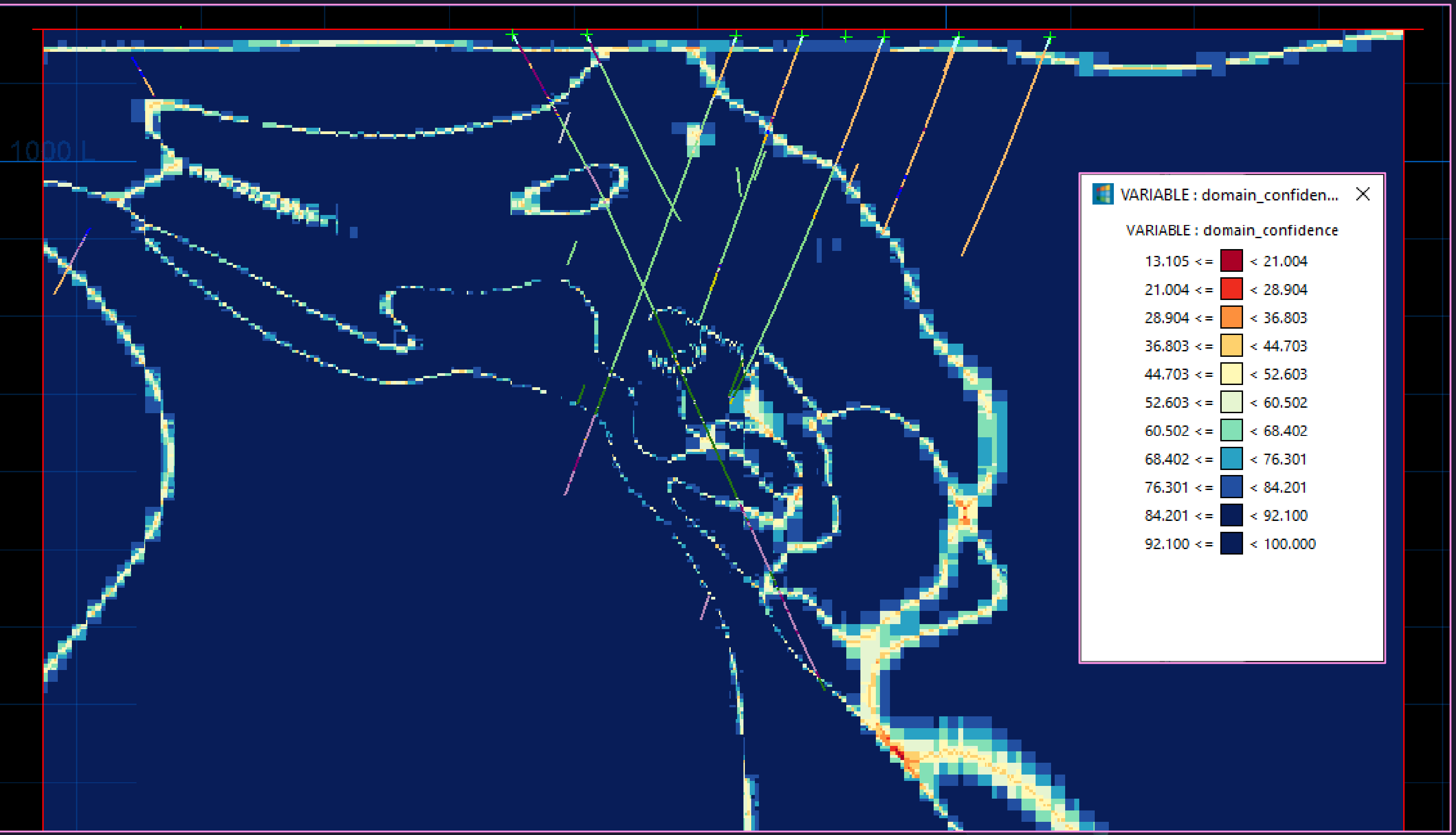
Step 4: Conventional modelling of clay floor and contact fault



Step 5: Final domain coding using all models



Domain boundary confidence values



- DomainMCF also produces a domain confidence value.
- This gives some measure of the system's certainty on the produced domain value at each location.
- Lower values seem to appear across the boundaries between different predicted domain values.
- Distance from training samples doesn't seem to affect the reported domain confidence values.

Density modelling using DomainMCF

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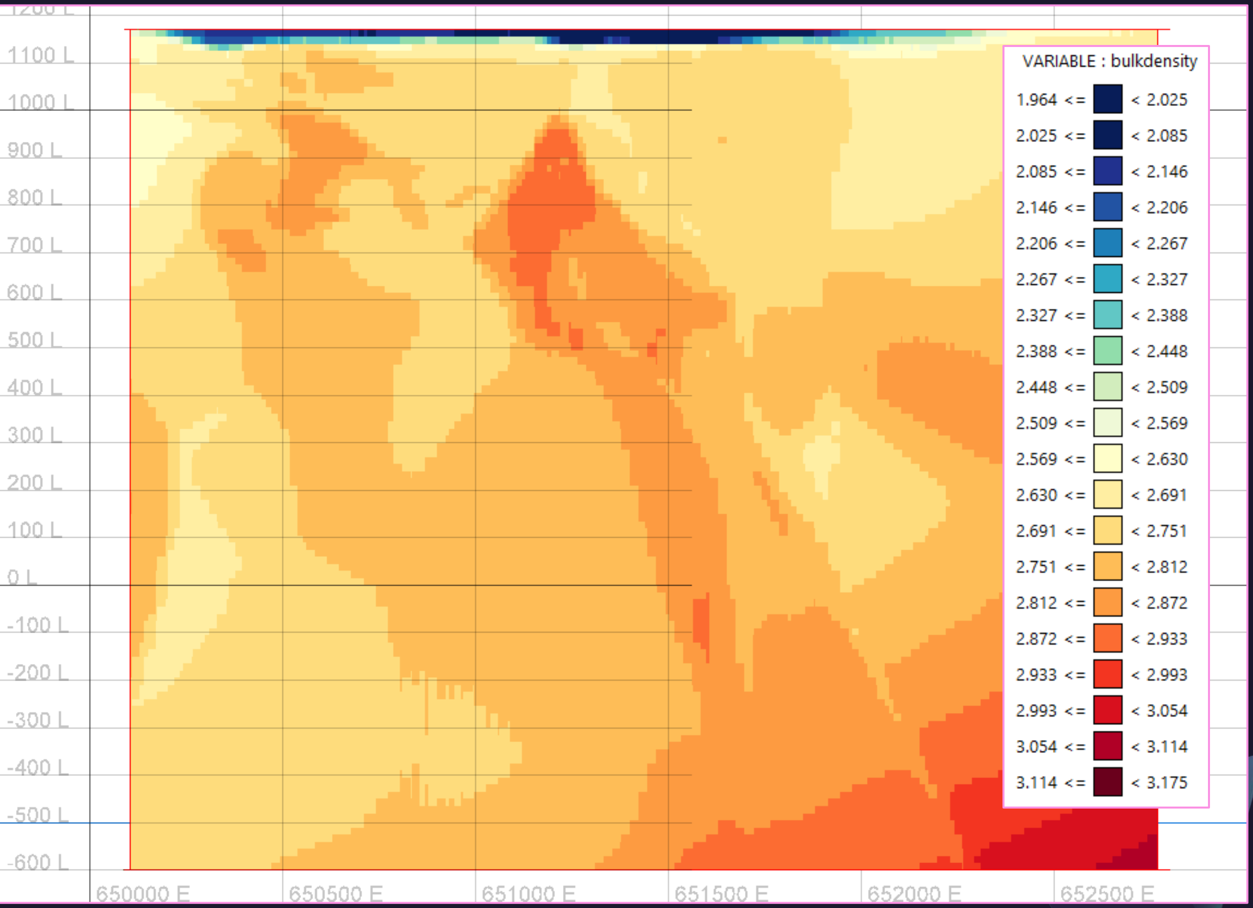
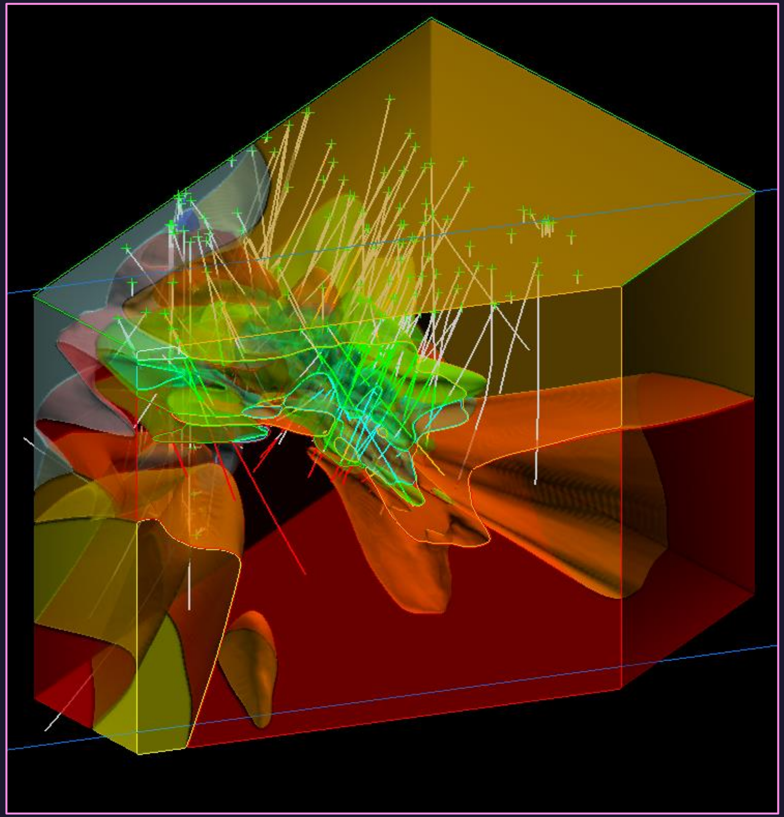


- The study continued with the estimation of grades using ordinary kriging and the classification of resources.
- DomainMCF was not used to produce grade estimates – however, it was applied to bulk density estimation using corresponding values in the composites.
- Composites were also coded as per lithology and alteration - a combination field was produced in the composites database (e.g., IGN_AAA).
- A DomainMCF machine was trained using the lithology-alteration combination field as domain output and the bulk density field as grade output, and XYZ coordinates as inputs (as in all cases).

Summary



- DomainMCF as most machine learning-based systems are data-driven and can produce results that match data in very little time.
- When dealing with a complex world, as the porphyry copper-gold deposit of this study, it is important to break down the modelling procedure and carefully choose the part of the data that will lead to a realistic model that follows applicable geological principles.
- Combining with other modelling approaches (such as conventional geological modelling and other existing implicit modelling techniques) might be more suitable in some cases.
- As a fast-developing technology, machine learning-based systems are expected to deliver a complete answer to geological modelling problems, once they become able to incorporate geological knowledge in their training and application process.

Thank You

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