Application of DomainMCF to Marble Quality Classification

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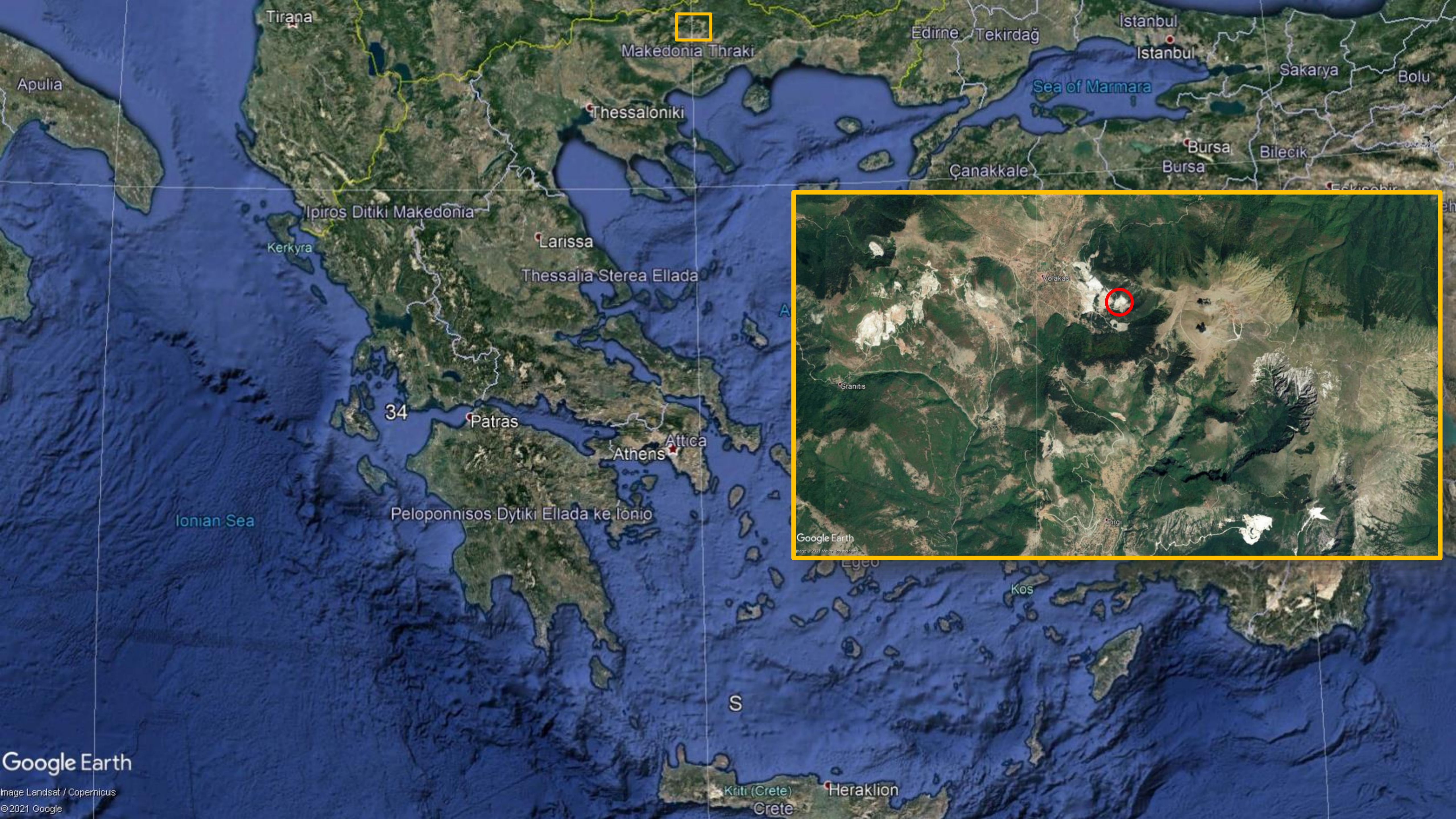
About this presentation

> Marble quality classification - description of the modelling problem
> Conventional classification method using inverse distance interpolation
> Some words on machine learning and artificial neural networks
> Application of DomainMCF to marble quality classification
> Conclusions

The Case of the Iktinos Hellas Volakas Quarry

- Iktinos Hellas SA has various marble quarries, mostly located in the Eastern Macedonia & Thrace area in NE Greece.
- The Volakas quarry is located NW of the city of Drama.
- Mount Volakas hosts a number of marble quarries.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Marble Quality Classification

- Marble quarry reserves are based on marble quality categories, almost unique for each quarry/deposit considered.
- These categories represent visual and physical aspects of marble such as colour, texture and fractures.
- Classification of marble to one of the categories is performed by experienced personnel and is based on samples much smaller in area than the blocks of marble which are potentially exploited.
- The use of standard estimation and modelling software tools in estimating marble quarry reserves poses a number of challenges, as the available information is mostly qualitative.

Marble Quality Parameters

In the case of the Volakas marble, the following parameters were identified and used to characterise the marble features that are significant to its quality classification:

- Lithology (dolomitic or calcite)
- Type (flower-like or diagonal-vein features)
- Background (presence of visible defects)
- Tectonic features at different observation scales (number of discontinuities per area unit)

Marble Type – Main Categories

Type L – flower like features

Type D – diagonal features

There are 4 more categories of marble type

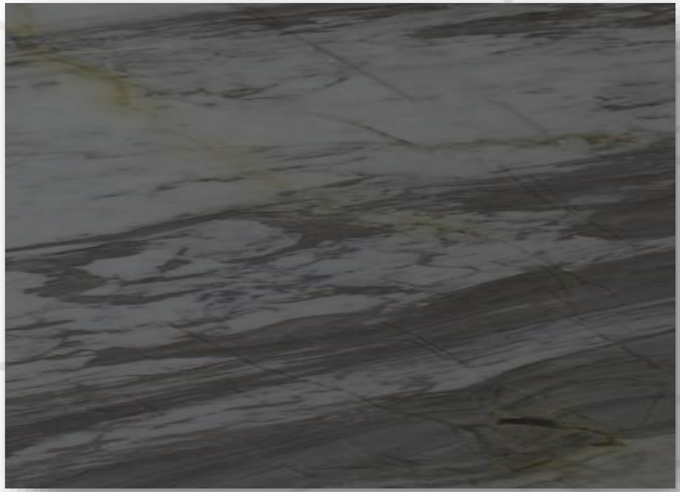
Marble Background

Background 1:
White background with homogenously distributed thin veins or flowers with no presence of calcite crystals and steins (yellow or red lines)

Background 2:
Slightly darker background with veins or flowers of varying thickness with some calcite crystals (glass)

Background 3:
Dark background with veins or flowers of varying thickness and many calcite crystals (glass) and steins (yellow or red lines)

Background 4:
Very dark background with veins or flowers of varying thickness with dense calcite crystals (glass) and steins (yellow or red lines)



Marble Tectonism

The presence of discontinuities in marble mass is measured at four different scales, leading to four parameters called TECTO1, 2, 3, 4.

Parameter	TECTO1	TECTO2	TECTO3	TECTO4
Scale	40/40	210/70	320/55	20/80

Parameter value	1	2	3	4
Discontinuities	0	1	2	3 or more

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Conventional Method of Classification

> As the available information is categorical, conventional estimation methods include the use of indicator kriging or some other interpolator of indicator values.

> Iktinos Hellas has been using Maptek Vulcan Quarry Modeller since 2014 and has implemented a methodology based on inverse distance interpolation of indicator values for the various marble parameters.

> In this process, each of the marble parameter values is associated with an indicator field that can be either 0 or 1, depending on whether the sample is classified to have the particular parameter value, e.g. if a sample is considered to be TYPE L, then the field L_PR = 1 and field D_PR = 0.

Conventional Classification Method Database Fields

- **Lithology**: CAL_PR, DOL_PR
- **Type**: L_PR, D_PR, K_PR, BL_PR, C_PR, M_PR
- **Background**: B1_PR, B2_PR, B3_PR, B4_PR
- **TECTO1**: T1_1, T1_2, T1_3, T1_4
- **TECTO2**: T2_1, T2_2, T2_3, T2_4
- **TECTO3**: T3_1, T3_2, T3_3, T3_4
- **TECTO4**: T4_1, T4_2, T4_3, T4_4

Example: DH=BL1, Interval=13-14
Lithology=DOL, Type=D,
Background=2, TECTO1=1,
TECTO2=1, TECTO3=1, TECTO4=1

Indicator Probability Fields:
DOL_PR=1, D_PR=1, B2_PR=1,
T1_1=1, T2_1=1, T3_1=1, T4_1=4

All other fields equal 0

Conventional Classification Method – Final Marble Quality Classification

- Interpolation of marble parameter indicator field values is normally performed using the inverse distance squared method as implemented by Maptek Vulcan Quarry Modeller software on the basis of a block model.

- The estimated volume is divided in blocks of the same size.

- Block dimensions are configured based on the marble volumes that are extracted separately at the given quarry.

- Samples are selected around each block using search ellipsoids which are oriented according to the geological features of the particular deposit.

- Each block receives a final marble classification by consolidating the interpolated indicator field values using a block model script.

Final Marble Quality Classification Script

```
**************************
* quality classification *
**************************

if (run1 eq 1 and run2 eq 1 and run3 eq 1 and run4 eq 1) then
    quality = "waste"
    if (litho eqs "dol" and (type eqs "l" or type eqs "d") and background eq 1 and ((tekto1 + tekto2 + tekto3 + tekto4) eq 4)) then
        quality = "a"
    endif

    if (litho eqs "dol" and (type eqs "l" or type eqs "d") and background eq 1 and ((tekto1 + tekto2 + tekto3 + tekto4) le 5) and quality nes "a") then
        quality = "ab1"
    endif

    if (litho eqs "dol" and (type eqs "l" or type eqs "d") and background eq 2 and ((tekto1 + tekto2 + tekto3 + tekto4) eq 4)) then
        quality = "ab2"
    endif

    if (litho eqs "dol" and (type eqs "l" or type eqs "d") and background eq 2 and ((tekto1 + tekto2 + tekto3 + tekto4) eq 5)) then
        quality = "b"
    endif
endif
```

DomainMCF

> DomainMCF, a machine learning based system developed by Maptek, was used to model the spatial distribution of marble quality characterisation parameters, and the resulting values were combined to produce a final marble quality classification.

> DomainMCF was made available as a cloud processing service through an early access program for individuals or companies who are interested in testing its capabilities and suitability in various modelling scenarios and geological settings.

> DomainMCF is based on artificial neural network (ANN) technology to model the spatial distribution of discrete domain values from a set of samples.

Artificial Neural Networks – Structure (1)

- ANN, such as those developed by DomainMCF, consist of multiple layers of ***processing elements*** (PEs) also known as ***neurons***.
- There are three types of layers and corresponding PEs – **input**, **hidden**, and **output**.
- PEs from one layer are connected to PEs in the next layer using weighted links, known as ***synapses***.
- PEs transfer the input signal to their outputs using an ***activation function*** that is different between the three types of layers.
- The number of input PEs is controlled by the way samples are presented to the ANN.

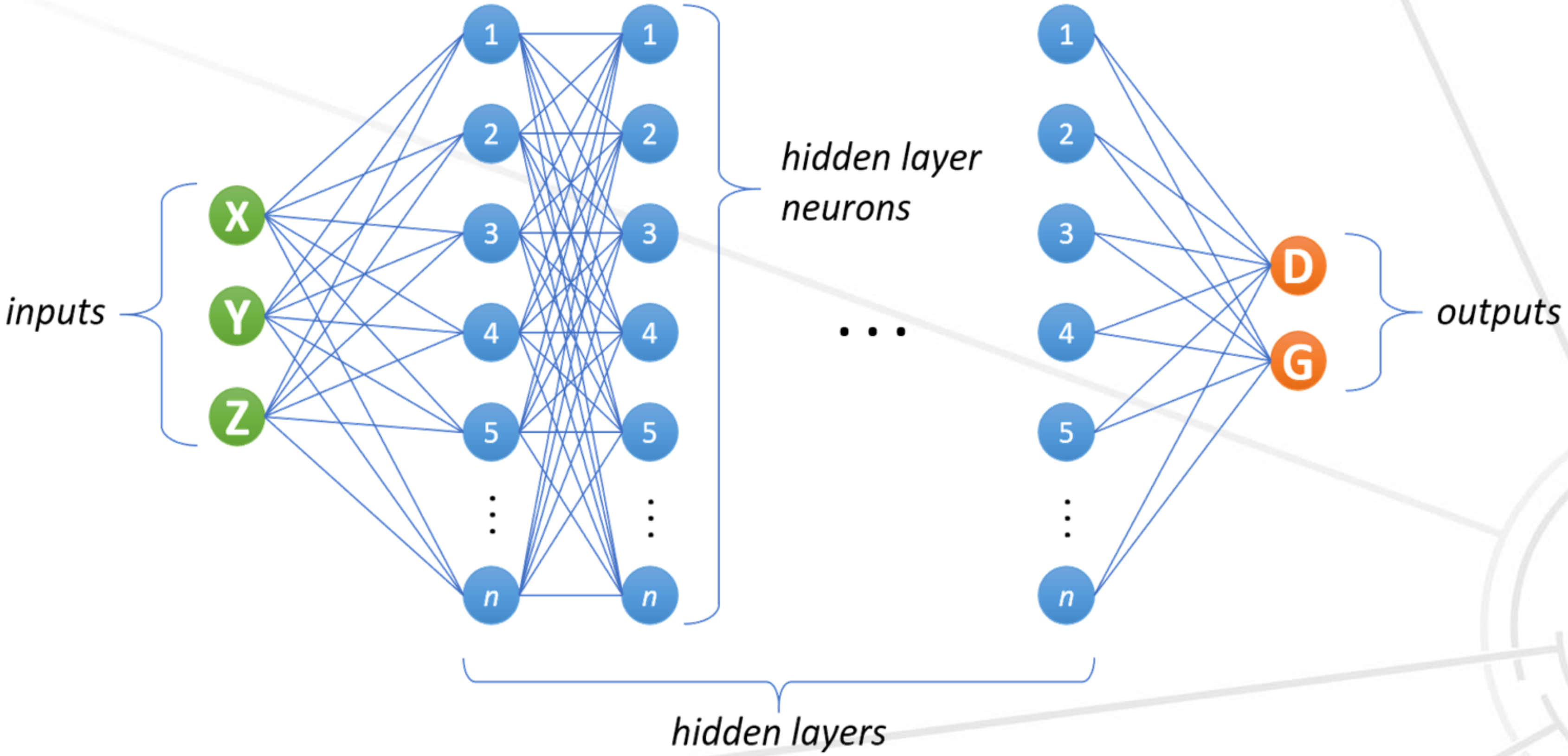
Artificial Neural Networks – Structure (2)

- The number of hidden layers and PEs per hidden layer can be fixed or controlled by an optimisation process that will find the best configuration according to some performance criterion.
- Typically, the number of network inputs and outputs and the complexity of the required mapping between them will lead to a different number of hidden layers/PEs.
- The number of PEs in the output layer is controlled by the number of variables to be modelled.

DomainMCF – ANN Configuration

- In the case of DomainMCF, sample X, Y, Z coordinates are used as inputs and the sample domain and, optionally, sample grade are used as the required outputs.
- When both sample domain and grade are used as outputs, the synaptic weights between PEs of successive hidden layers will be affected by both distributions during training, thus leading to some dependency between the learned mappings for each variable.
- Only the sets of links between the last hidden layer and each of the two output PEs remain independent of each other after ANN development is complete.

Architecture of an Artificial Neural Network used for Domain Modelling



Artificial Neural Networks - Learning

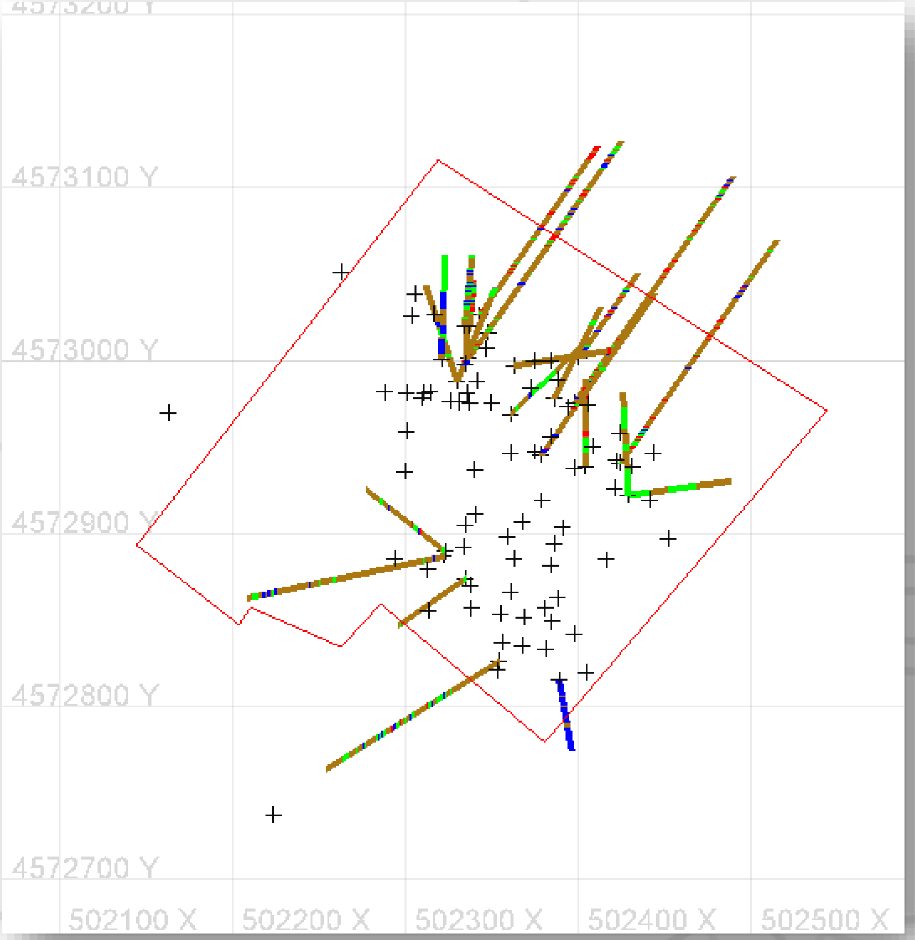
- Learning from examples is the main operation of any ANN.
- In general terms, learning means the ability of an ANN to improve its performance (defined with some measure) through an iterative process of adjusting its free parameters (weights, number of PEs, etc).
- The adjustment of an ANN’s free parameters is stimulated by a set of examples presented to the network during the application of a set of well-defined rules for improving its performance called a ***learning algorithm***.
- There are many different learning algorithms for ANNs, each with a different way of adjusting the synaptic weights of PEs and different way of measuring the ANN’s performance.
- Input and output sample values are commonly normalised to ensure their uniform treatment by the learning algorithm regardless of their original scale.

Data Requirements and Related Issues

- ANN development is data driven and thus largely dependent on the quantity of data.
- In the case of domain modelling, more samples will be required to produce a representative model in a more geologically complex scenario.
- A more complex ANN architecture with more PEs and hidden layers, allows a more complicated model to be generated (through development) but also requires more data.
- After development, the ANN can be used to get output values for any set of X, Y, Z coordinates presented at its input layer (e.g. block centroid coordinates), even outside of the sample coordinates range.
- However, outputs produced in areas outside of the range of examples introduced to the ANN during development, should be treated with caution and examined carefully as to their validity, as in any case of extrapolation by more conventional methods.

Case Study Data

- The quarry data used in this study consists of 95 drillholes and quarry face analyses, giving a total of 3570 1m samples.
- Most of the drillholes are vertical, but some are horizontal and intersect areas where underground quarrying is carried out or operations are planned for the near future.

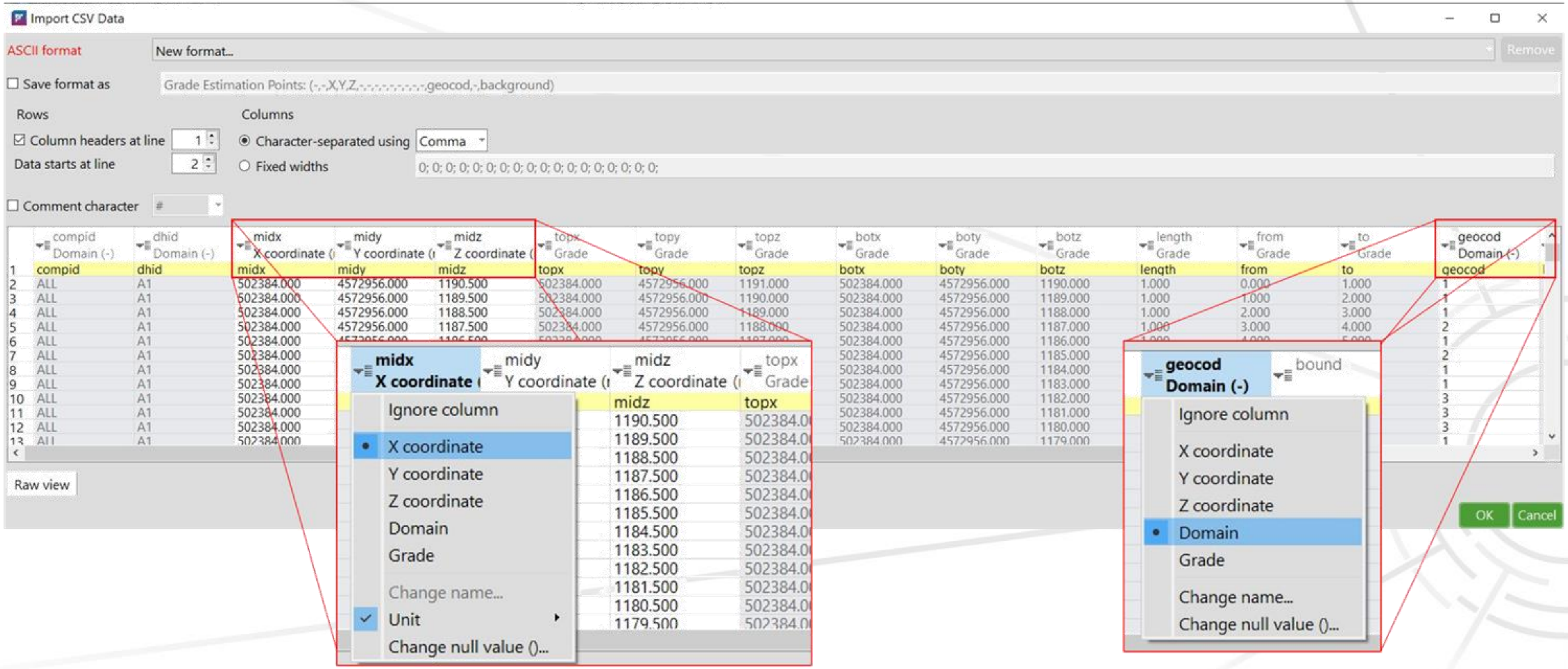


Training and Application Data for DomainMCF

- The sample data was composited in 7 separate CSV files, one for each of the marble quality parameters (lithology, type, background, tecto1, tecto2, tecto3, tecto4)
- Each file was used in a separate run of DomainMCF.
- A block model definition file was also provided to control the application area and locations for DomainMCF.
- The application area was also limited by an upper and lower triangulation surface.

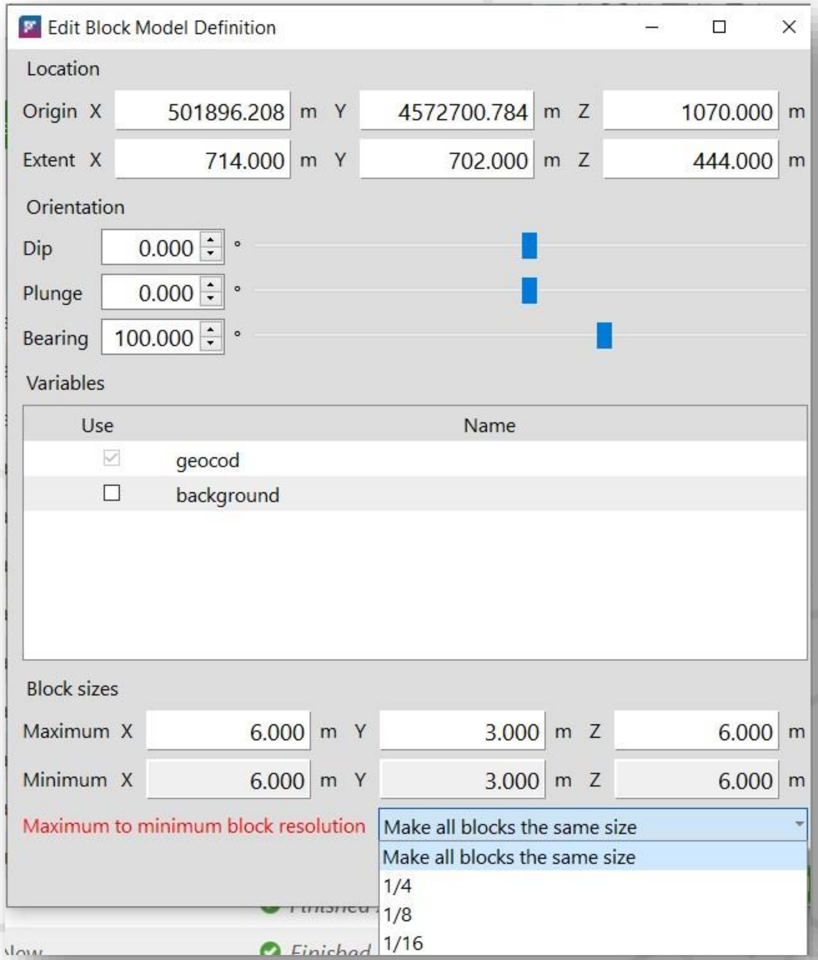
Selection of Inputs and Outputs

- For each CSV file containing the training samples, the network inputs and output fields were selected.
- DomainMCF would be trained to map the input values to the corresponding output(s).



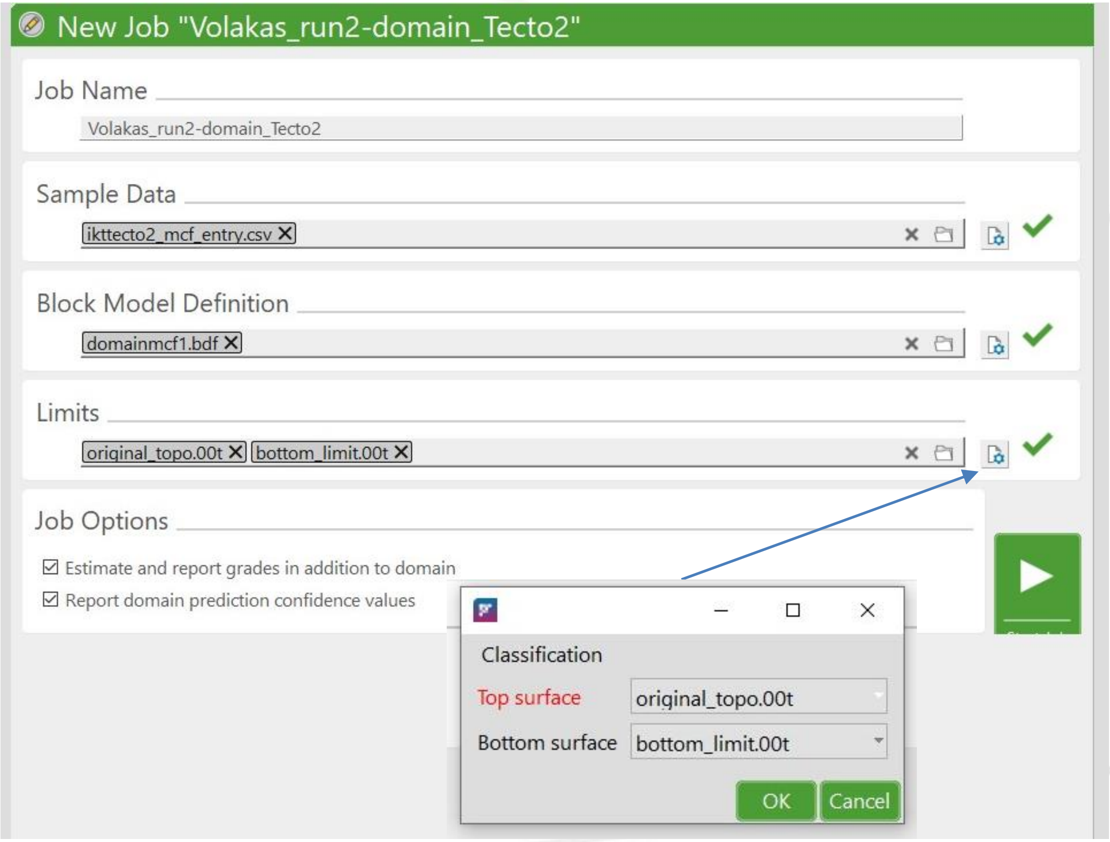
Block Model Definition

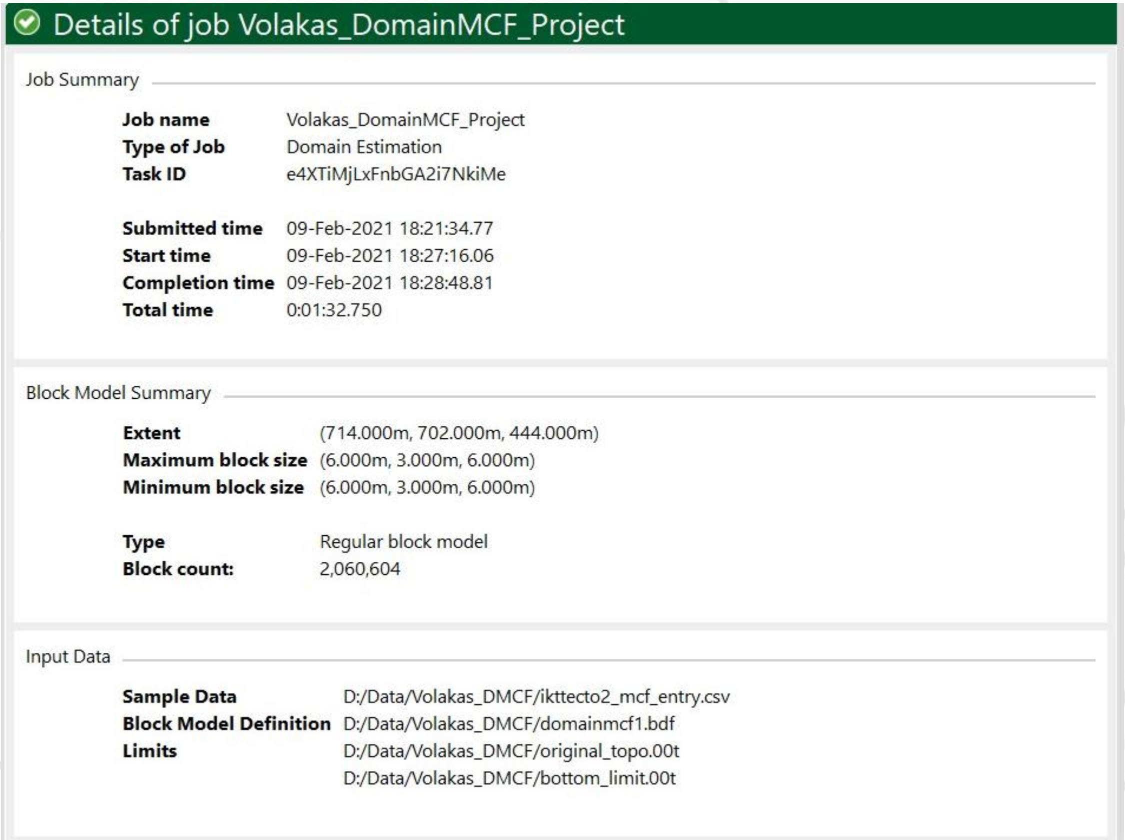
- The next step in the job setup is the selection of a block model definition file – a standard Vulcan file used to store the specifications of a block model.
- This can be a regular or a sub-blocked model.
- If a regular model is defined in the file selected, the user still has the option to subblock the model using one of the available ratios between maximum and minimum size.
- Block centroids are used by DomainMCF as inputs to control the locations of application, once training with the sample data is complete.



Surface Limits for DomainMCF Application

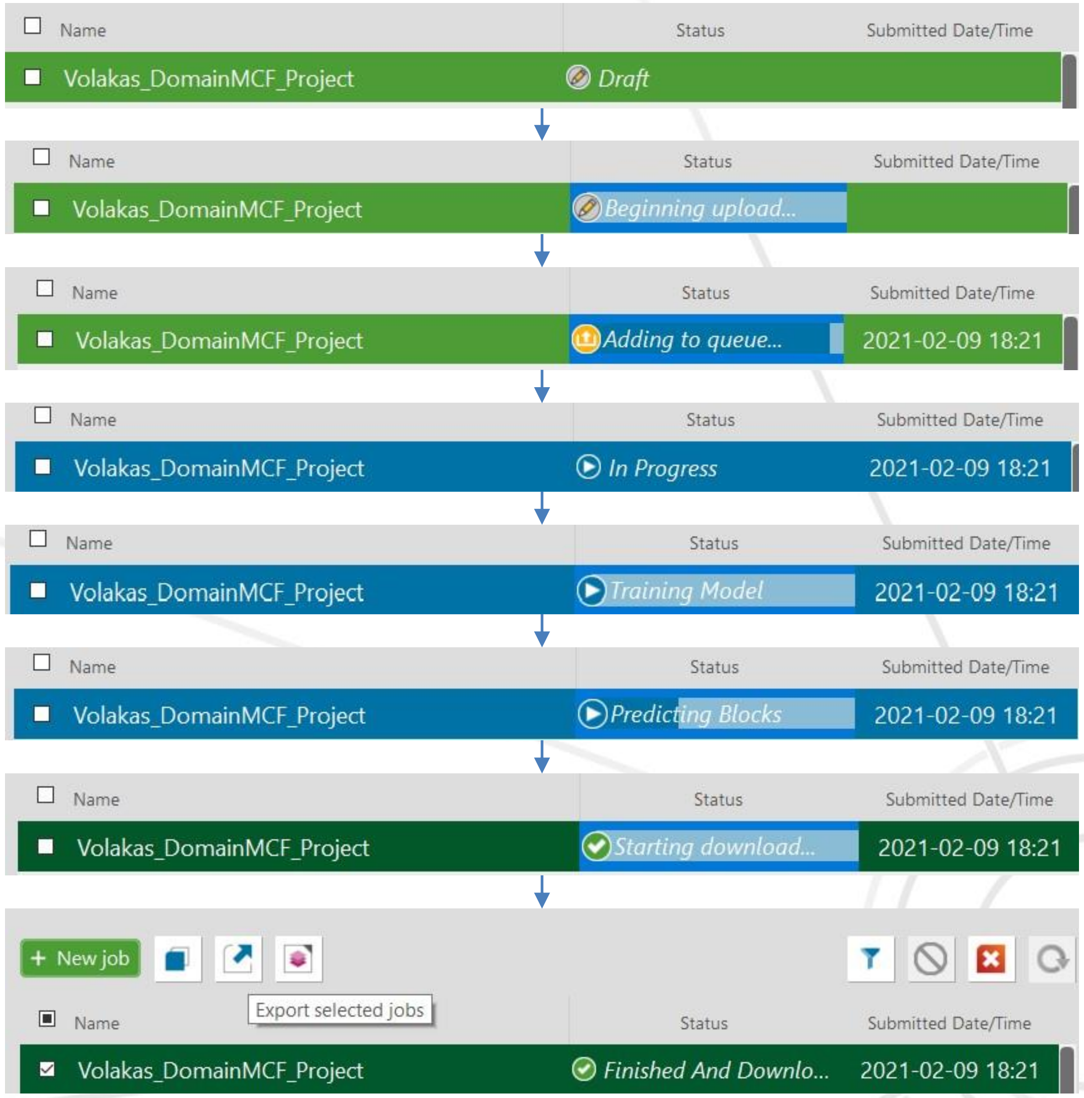
> The final step in the setup of the DomainMCF job, is to select the upper and lower surface boundaries that control the area of application.



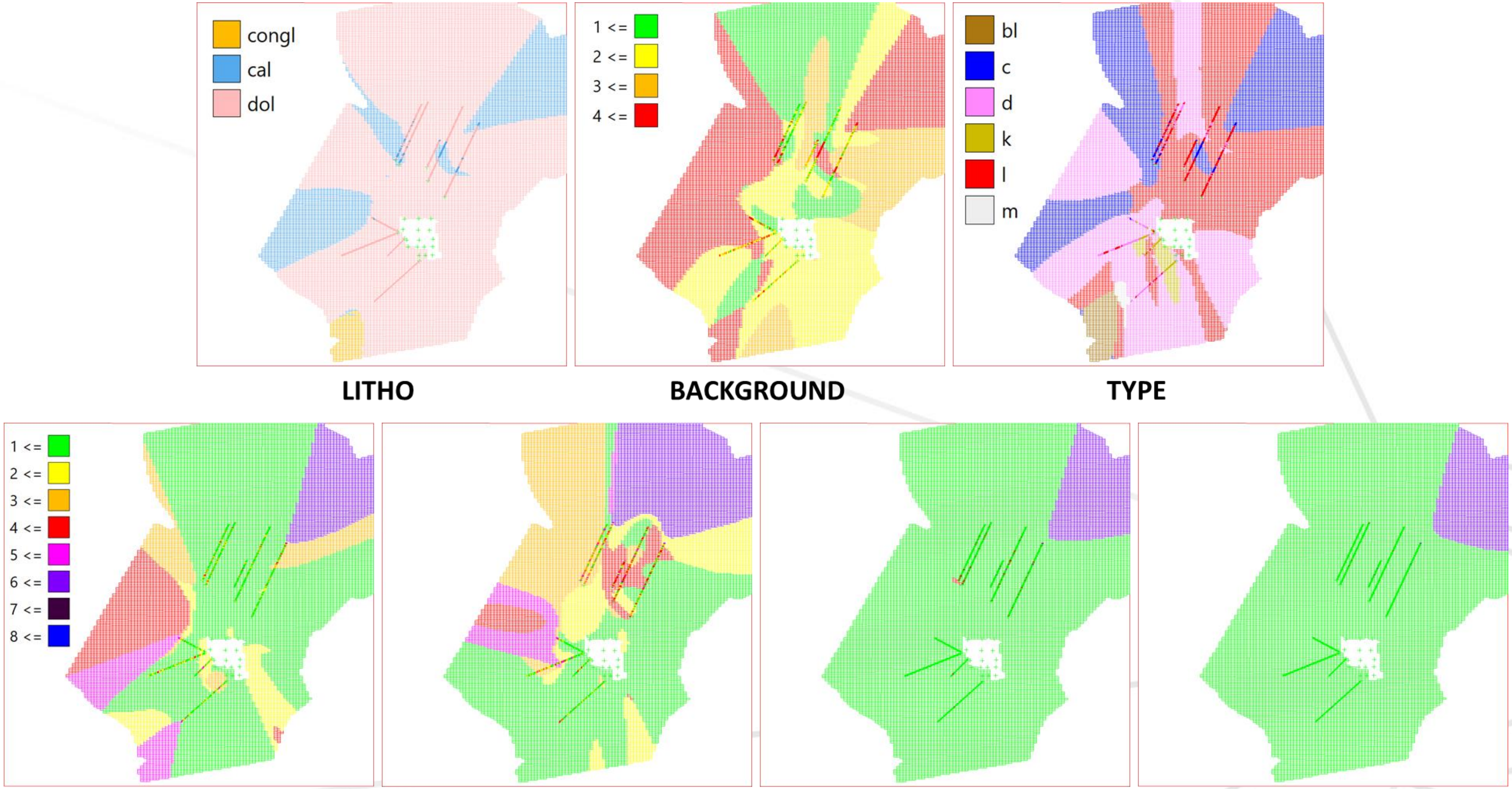


Running DomainMCF

- Once the setup was complete, DomainMCF was run.
- Running included uploading of the data, training using the sample data, application on the block model, and downloading of the block model.
- As the data and block model were limited (3570 samples and 2 million blocks), the whole process took less than 2 minutes for each run.
- The predicted values from the produced block models were exported and imported to a single block model that also contained classifications from the conventional system.



DomainMCF Marble Parameters Predictions



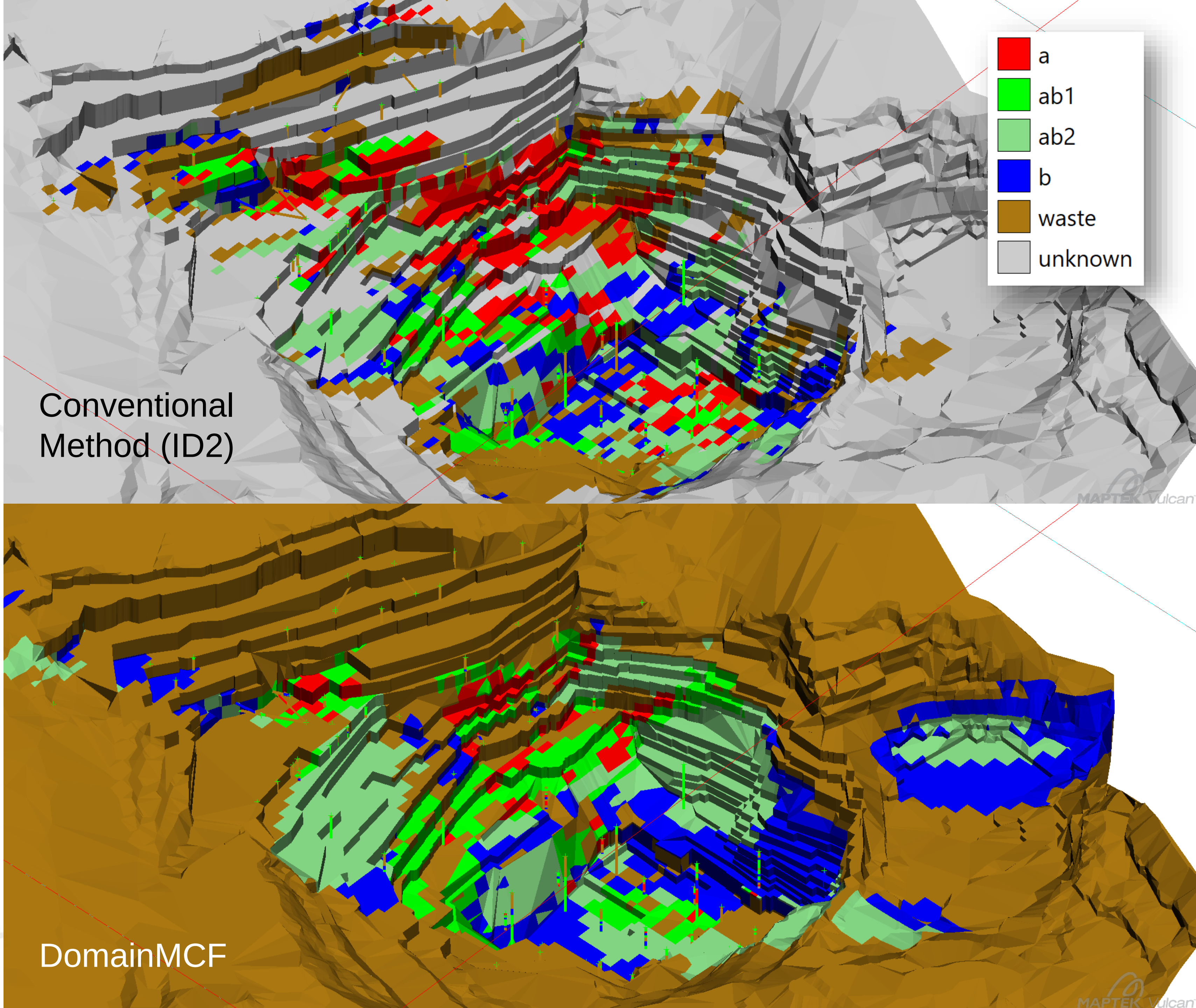
LITHO BACKGROUND TYPE

TECTO1 TECTO2 TECTO3 TECTO4

Comparison of Final Marble Quality Classifications

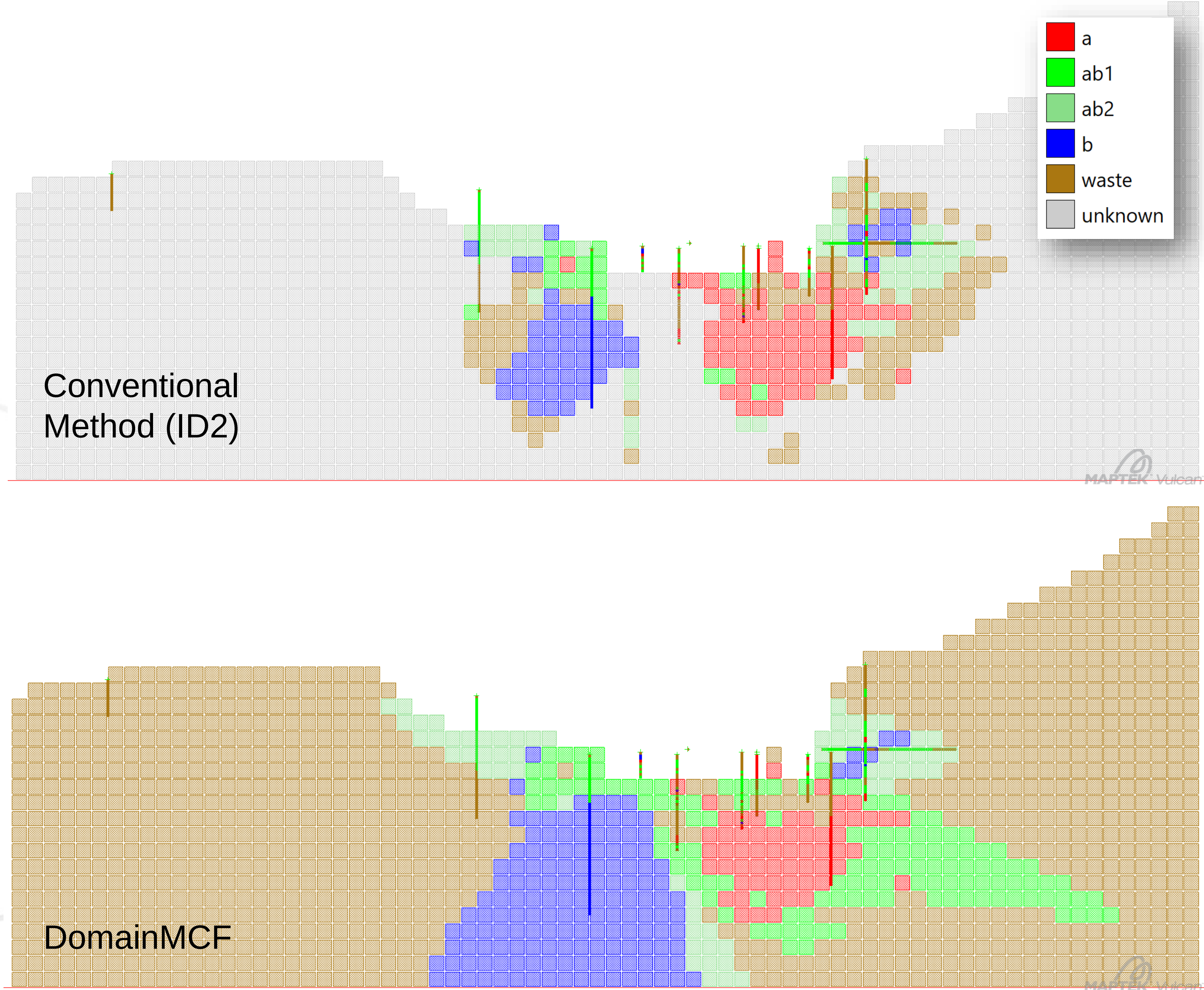
> A final marble quality classification was produced using the predicted marble parameters from DomainMCF and the same script used in the conventional method.

> DomainMCF classifications appear more uniform than those of the conventional method.



Comparison of Final Marble Quality Classifications

> The conventional method classifications were limited by search ellipsoids and minimum sample limits and so the comparison was focused only in blocks that were predicted by both methods.

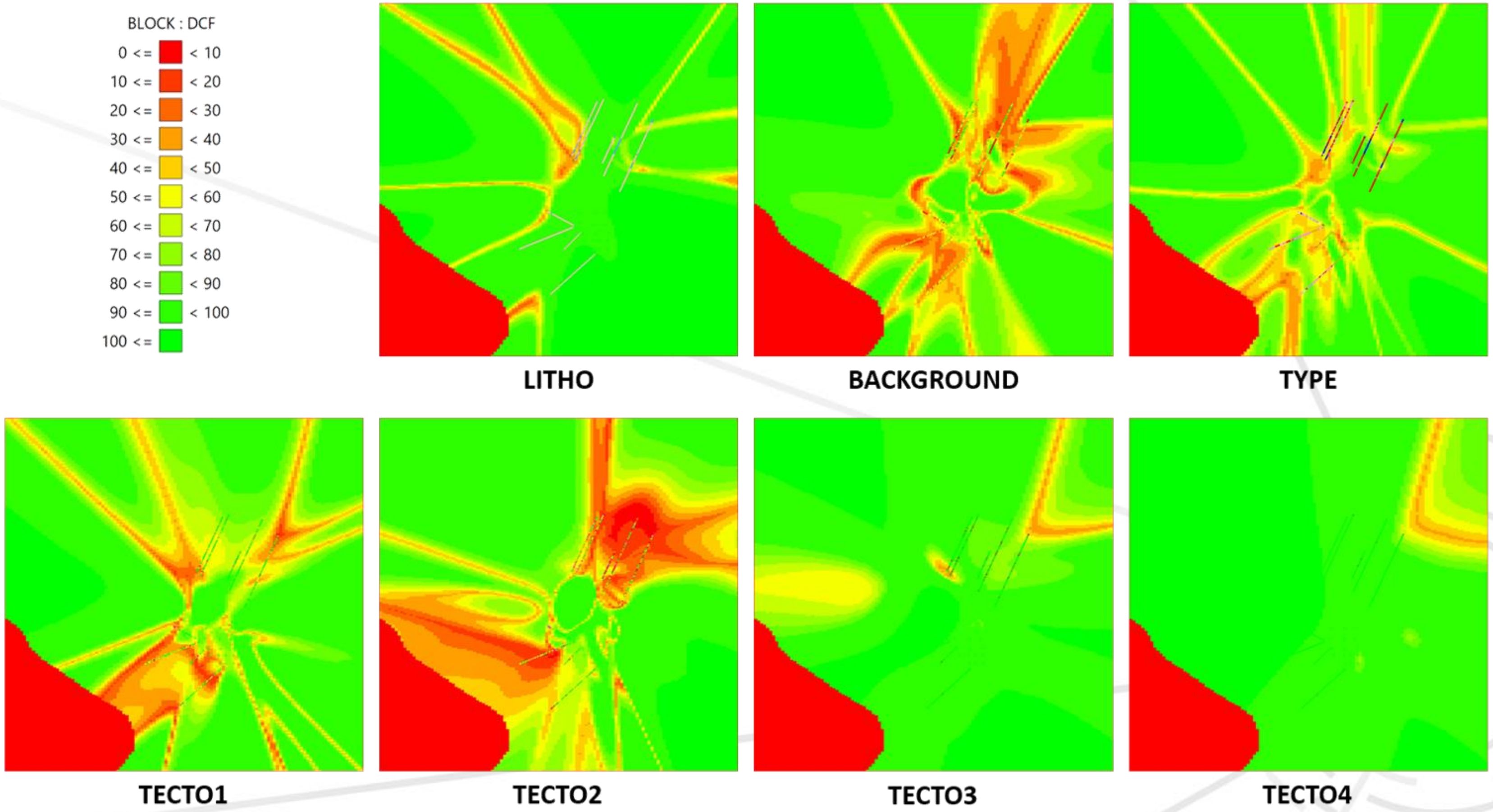


DomainMCF Confidence Levels

- In addition to the required outputs (domain, grade) in each of the block centroids presented to it, DomainMCF also produces a domain confidence value
- This is calculated during ANN development and gives some measure of the system's certainty on the produced domain value at each location.
- Domain confidence can be used to identify areas where it is more difficult to be certain about the predicted domain value, for example, areas where more sampling is required, or existing samples have higher local variability.
- As any other estimation or classification system, it is necessary to have tools to measure the local confidence of the results.

DomainMCF Confidence Levels

Horizontal section of DomainMCF confidence levels for each of the modelled marble parameters



Conclusions

DomainMCF Advantages

- Extremely quick way to produce marble classifications based on drillhole and other data.
- Produces more uniform marble classifications that are more reasonably distributed.
- Requires no structural analysis of the categorical parameters.
- Sampling pattern has no effect on the difficulty of the process.
- Reads from and writes to standard Vulcan file formats.

Future Work

- Ability to use anisotropy in predicting different marble parameters.
- Better understanding of confidence level values produced and how they can be associated to resource categories.
- More testing to investigate the influence of the grade field (when included as output) to domain predictions and vice versa.

*Thanks to **Iktinos Hellas SA** for their permission to use data from the Volakas marble quarry in this study.*

Thank you

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