# Spatial Declustering of Exploration Data in Marble Resource Estimation from Irregular Drilling Patterns

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2. Iktinos Hellas SA











#### Our study deposit

- 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.
- The provided dataset consists of 150 surface and underground exploration drillholes (vertical and horizontal) and 1899 production slabs giving a total of 3344 6m composite samples.

#### Drilling core samples

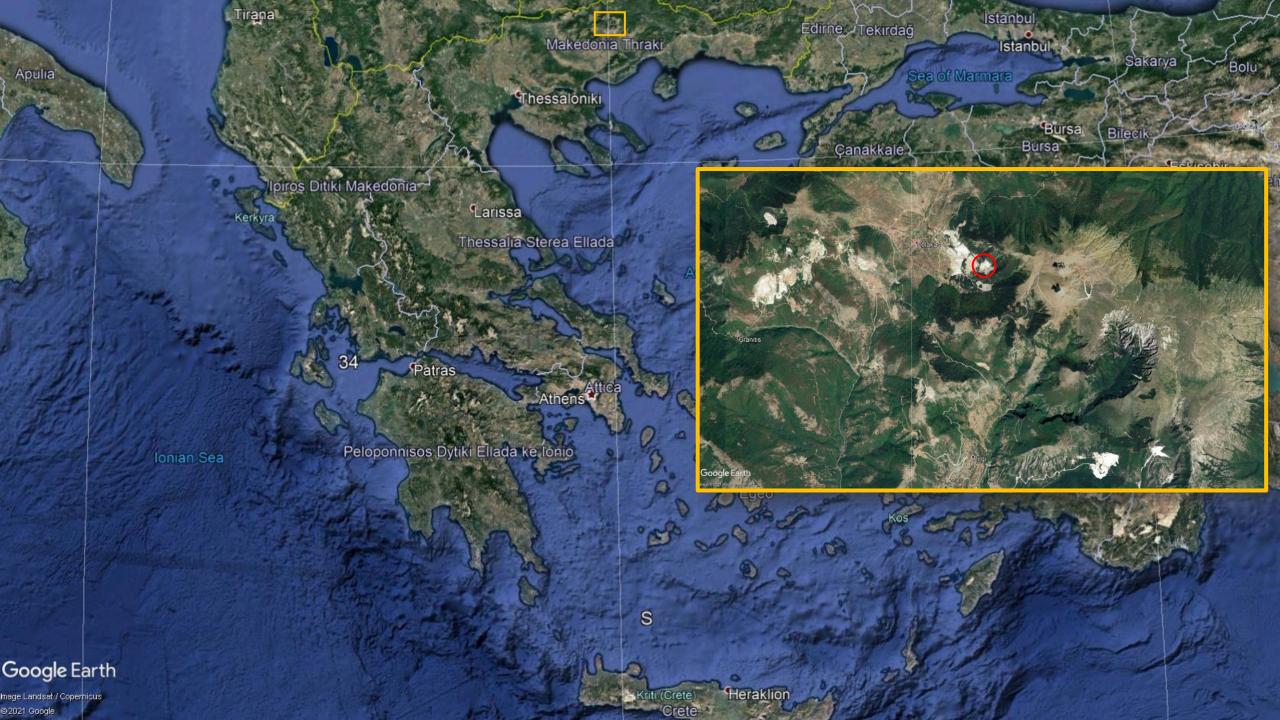


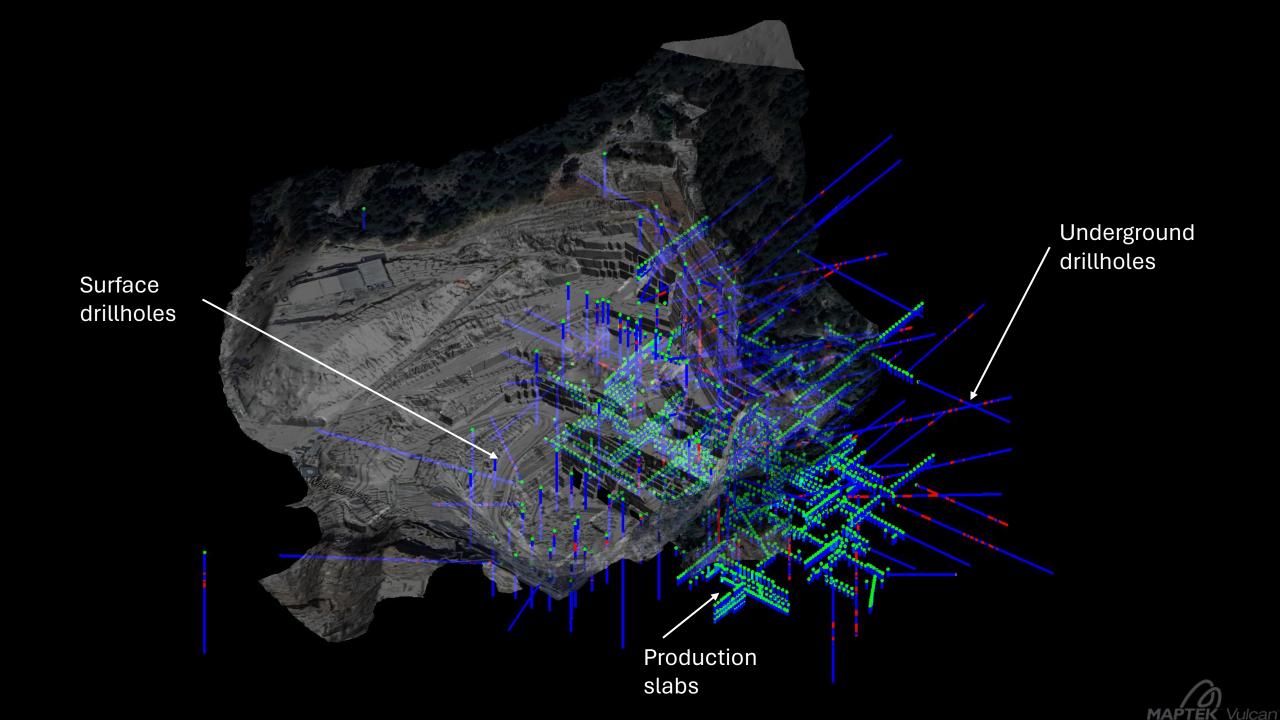
**Production slabs** 





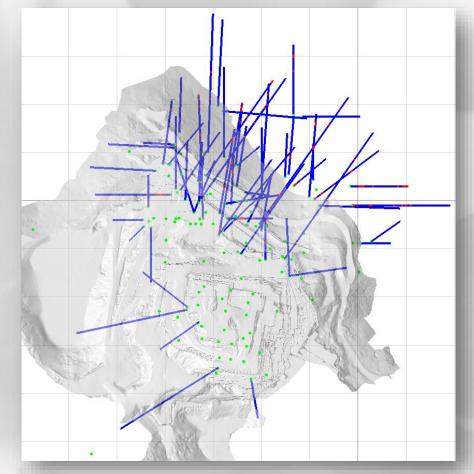






#### Irregular sampling = spatial clustering = bias

- Drilling campaigns in marble quarries tend to be highly irregular as to spatial density and drillhole orientation, as drilling is driven by the progress of extraction, and the need to expose good quality marble.
- This process introduces bias to resource estimation and can lead to overestimation of resources, if samples are not treated first for their spatial clustering.
- The clustered distribution of samples means that areas
  of good marble quality are potentially oversampled,
  while areas of poor quality have fewer to no samples
  leading to a sample distribution that is not
  representative of the resource that is to be estimated.









#### Sample characterisation

- Marble quarry resources 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.
- Each original 1m sample receives a final marble classification by consolidating the marble parameters using a script.
- This classification is then converted to indicator fields (with a value of 0 or 1), one for each marble quality category considered (e.g. A, AB, B, C, Waste, etc.), and the 1m samples are composited to 6m.

Type L – flower like features



Type D - diagonal features



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)



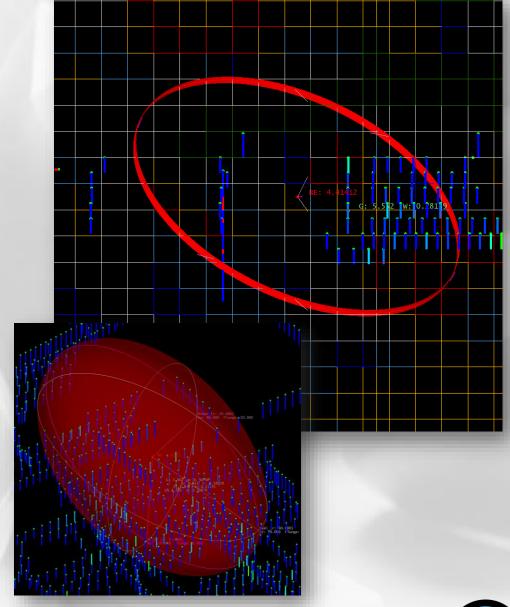






#### Resource estimation

- Interpolation of marble quality indicator values is normally performed using **ordinary kriging** on the basis of a **block model**.
- The estimated volume is divided into **blocks** of the same size.
- Block dimensions are configured based on the marble volumes (slabs) 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.



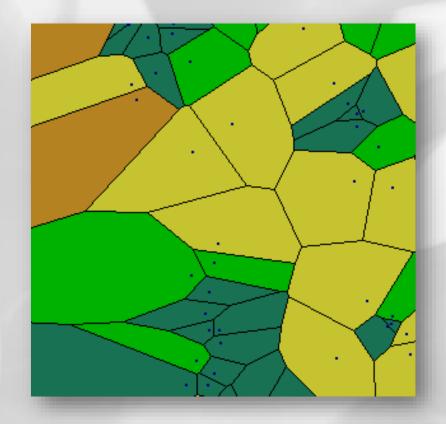






#### Declustering methods

- Cell declustering: it is the most common method applied in geostatistics. It is insensitive to the boundary locations and for this reason is seen as more robust than polygonal declustering.
- Polygonal declustering: it is based on the construction of polygons of influence around each of the sample data. These polygons of influence are described by all midpoints between each neighbouring sample data.
- Kriging weight declustering: kriging of the area of interest is performed and the weights applied to each conditioning data are summed and then standardised.

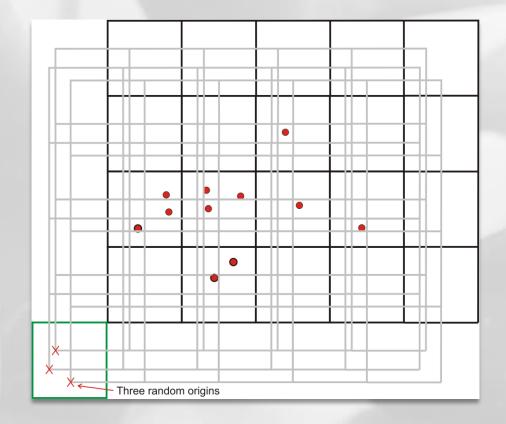






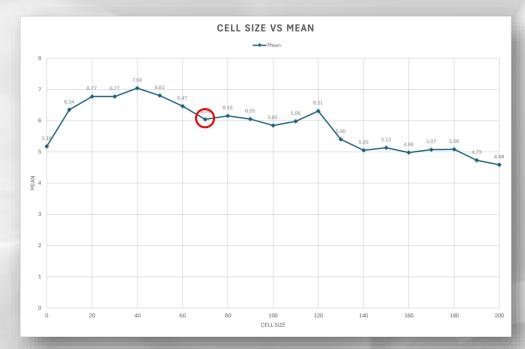
#### Cell declustering - principle

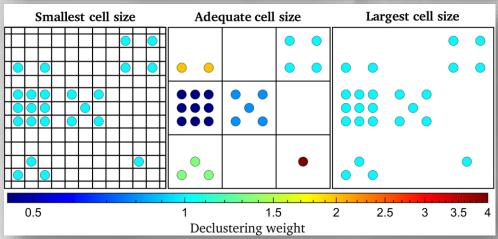
- The volume covered by the sample data is divided into 3D rectangular sections for declustering called cells.
- Each sample selected for declustering receives a weight inversely proportional to the number of samples that fall within the same cell.
- Therefore, closely spaced samples are assigned lower weights and sparse samples are assigned higher weights.
- The calculated global mean from cell declustering depends on the size of the cells.











#### Cell declustering – cell size

- If the cells are very small, then each sample will fall into its own group and all samples will receive equal weights.
- If the cells are as large as the global area, then all samples will fall into one group and will again receive equal weights.
- Somewhere between these two extremes is the appropriate cell size.
- A range of different cell sizes are examined and a graph of the declustered mean vs. cell size is produced to aid the selection of the cell size.





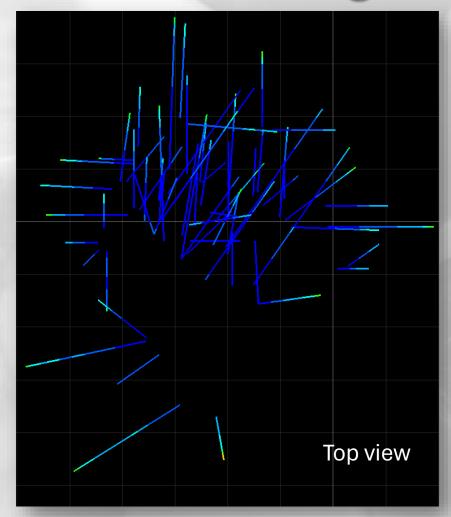
#### Declustering and anisotropy

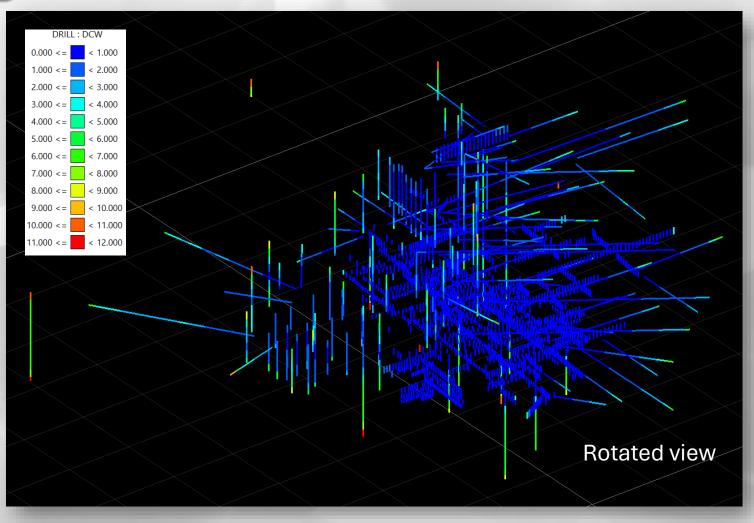
- Anisotropy in the data can be accounted for when calculating declustering weights.
- In the case of cell declustering, this is achieved using different aspect ratios between X, Y and Z directions, i.e. cells are 3D blocks of different size along X, Y and Z.
- The appropriate ratios might not be obvious (particularly for the Z axis) and experiment with multiple configurations is usually required.





#### Declustering weights







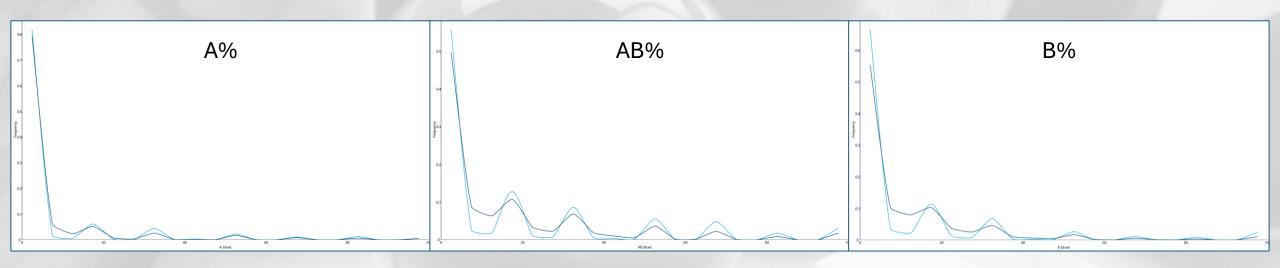




## Comparison statistics

clustered declustered

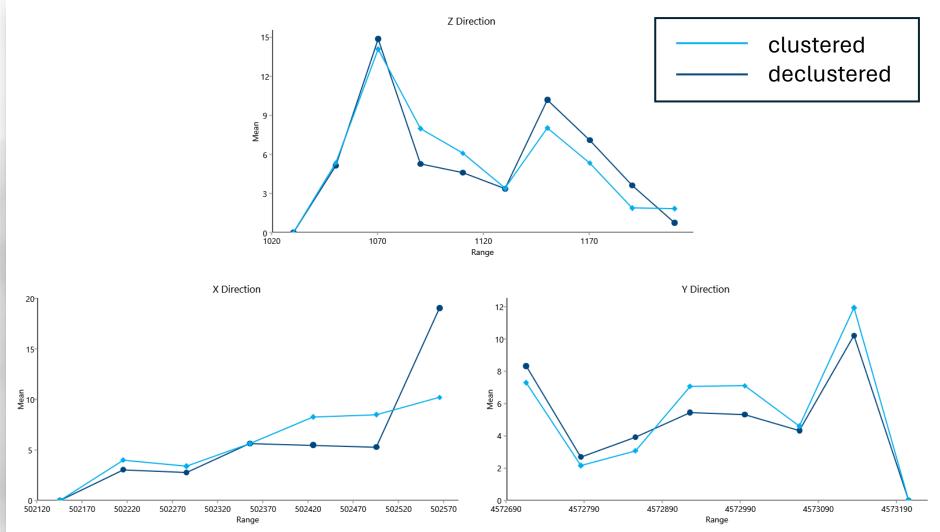
	A% clustered	A% declustered	AB% clustered	AB% declustered	B% clustered	B% declustered
Mean	6.11	5.18	17.14	14.35	10.71	10.11
Standard deviation	16.32	14.10	25.93	21.06	20.95	16.21
Variance	266.26	198.91	672.57	443.32	438.88	262.85
CV	2.67	2.72	1.51	1.47	1.96	1.60
Max	100.00	100.00	100.00	100.00	100.00	100.00
Min	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	3.32	3.90	1.66	2.02	2.67	2.77
Kurtosis	11.67	17.30	2.01	4.32	7.43	10.08
Range	100.00	100.00	100.00	100.00	100.00	100.00







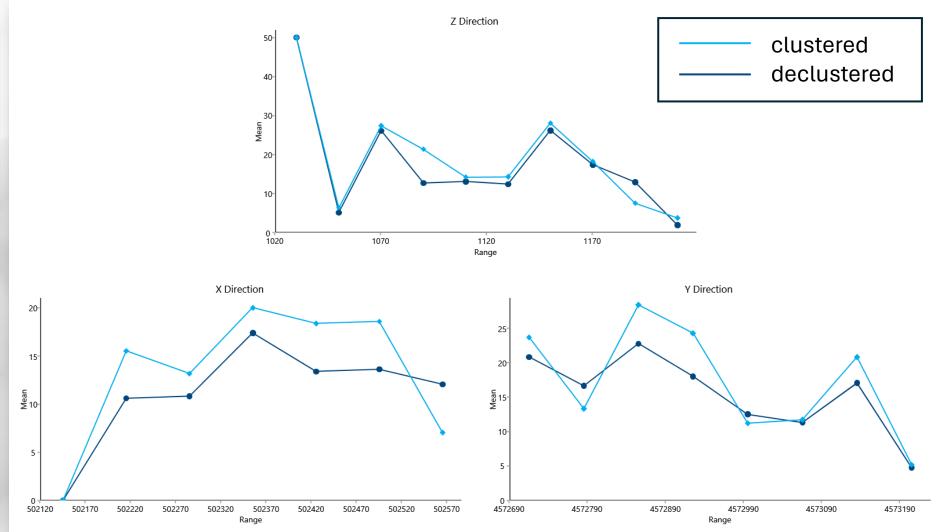
#### Spatial statistics – A%







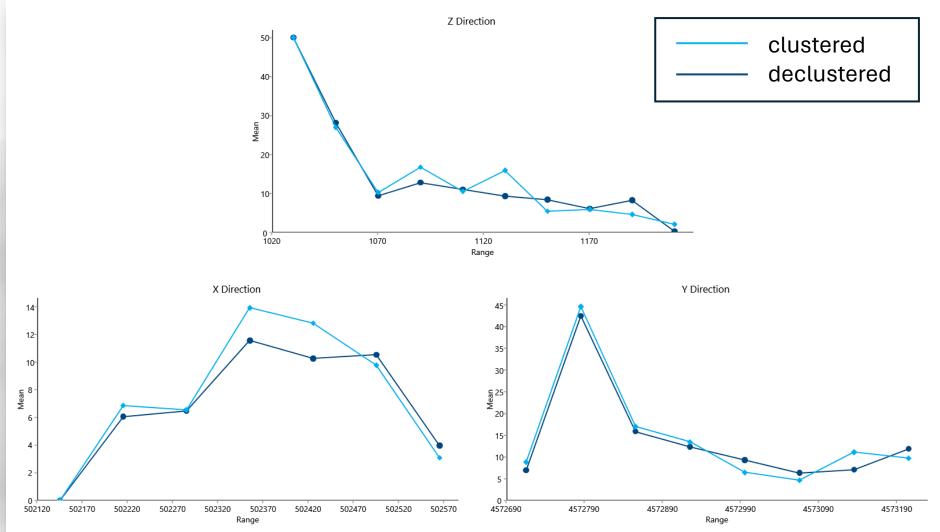
#### Spatial statistics – AB%







#### Spatial statistics – B%







## Resource estimation with declustering weights

- Declustering weights calculated with cell declustering are stored in the composite samples database.
- These weights are combined with ordinary kriging weights during block model estimation:
  - Without the application of declustered weights, the estimated grade is:

With the application of declustered weights, the estimated grade is:





#### Conclusions

- Preferential sampling commonly leads to sample distributions not representative of the underlying phenomenon.
- Declustering methods can be applied to address this issue.
- Cell declustering is one of the more robust methods available.
- Multiple tests might be necessary to decide the "optimum" cell size for the calculation of declustering weights.
- The effects of applying declustering weights to the original samples for resource estimation need to be carefully examined.







### Thank you for your attention!



