Deliverable code: EITRM109344

Deliverable number: D4.5

Deliverable name: A probabilistic map of variability of CRMs in the case study

Deliverable description: Starting from all information gathered, a probabilistic map of variability of CRMs in the case study was produced and reported in this Deliverable.
The Deliverable reports only the final estimation map, with associated estimation variance

Related Task: T4.5

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With the collaboration of: MYT, NTUA, DELFT, BRGM, ORANO

Confidentiality level: Confidential

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INCO-Piles 2020

International consortium to recover CRMs from stockpiles/tailings targeting RIS

Characterization of CRMs in the case study

Scientific Background

The recovery of metals, specifically critical raw materials (CRMs) from mining residues (stockpiles and tailings) is an important issue of EU research activity [1]. One of the crucial steps to have a comprehensive information about mining residues is the characterization, which means assessment of grade variability and the volume of piled materials.

Characterization and environmental assessment of mining residues is a difficult and challenging task for several reasons.

Firstly, the scarce availability of data and information: often there are not sufficient economic justifications for mining companies in sampling the stockpiles and landfills [2-3]. This is done just for checking the ore dressing process or when imposed by environmental legislation, and even when available, the quality of such sampling is often imprecise (with poor or missing georeferencing) [4-5].

The standard approach for resource characterization is based on a geostatistical modelling (an unbiased estimation with minimum error variance), which is possible when the materials of interest have a spatial distribution [6]. However, the spatial distribution of metal concentrations (grades) in a mining residue (for example tailings from processing plant) is artificial, meaning that the natural spatial variability of materials (e.g., metals) in the deposit, is not obeyed inside residues. While ore bodies have smooth and natural variability, mining residuals are formed by a highly artificial component (piled material belongs to the different process and are daily stocked in small areas by trucks). This is due to the mining process and to the interval time of piling materials [7]. In practice, the original variability of materials in a deposit changes due to: the specific part of the deposit mined during a given time interval (for example, richer zone of the deposit as possible premier excavations); the excavation methods and volumes size of the ore extracted; the strong homogenization of ore process because of crushing and milling; the definition of new products as the residues (tailings) because of metal separation; and the tailings disposal method which defines the localization of the new product sent to the tailings. This produces an “artificial” space-time variability of mining residue materials. For these reasons, a different analysis accounting for this artificial spatial variability must be established. Addition to this artificial effect, the lack of samples and difficulties in sampling from mining residues is another reason why the classical estimation methods cannot be easily adapted for mining tailings [8].

The Mytilineos bauxite residue is active since 2010 and materials are daily piled from the aluminium processing plant (around 2700 tons per day). Different groups of data were collected for the research including: processing exit samples (daily data of grades), Sentinel-2 images (to monitor the piling procedures and remote sensing studies), and in situ samples done by MYT and NTUA on 7th June 2021 (Figure 1).

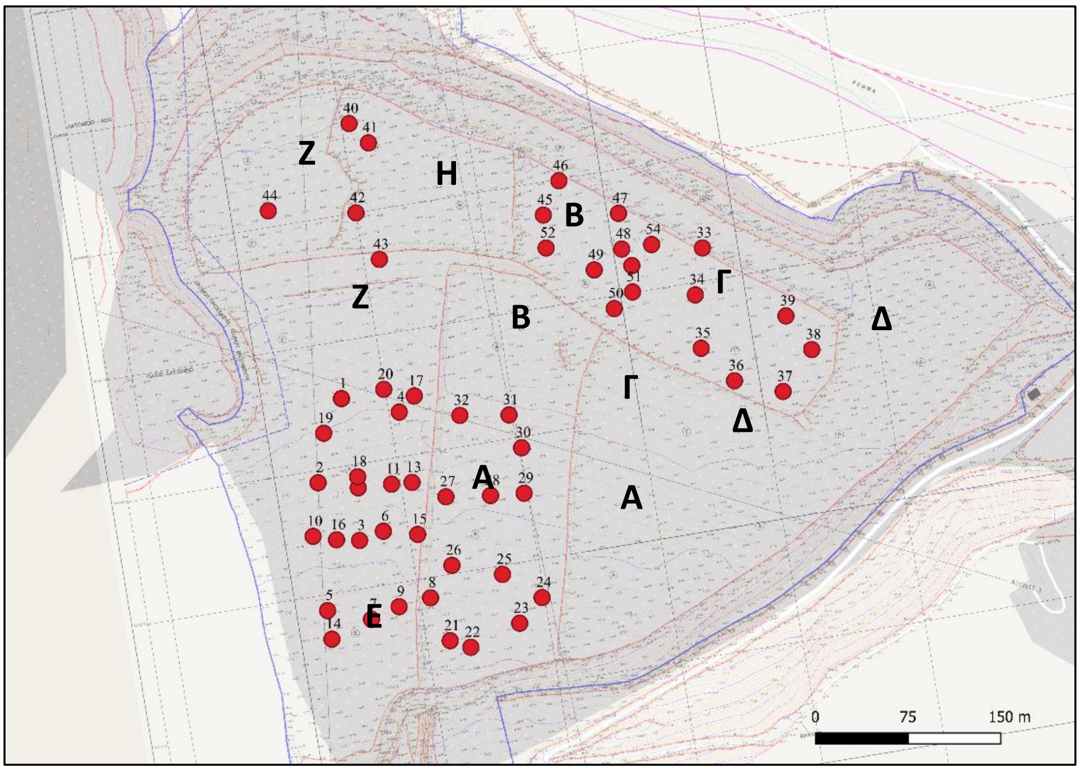


Figure 1. In situ samples on the topography maps showing the sample locations

Sampling could not be done in the area where the materials were piling at the date of sampling (eastern part of the residues in Figure 1, locations A -partially, Γ and Δ) and therefore, there was the traffic of trucks moving at the area.

Remote sensing data

Remote sensing data (RS) are used in this study to evaluate the possibility of integrating RS data with in situ samples. From Copernicus program, Sentinel-2A images are used in this work. The objective of using the satellite data for different targets:

- Following the piling procedures to highlight the active zones and filled areas. This information is used to sampling grid design, and monitoring the active layers at the time of sampling.
- Studying the possibility of integrating the Sentinel-2A images with in situ samples for mapping the major elements and CRM

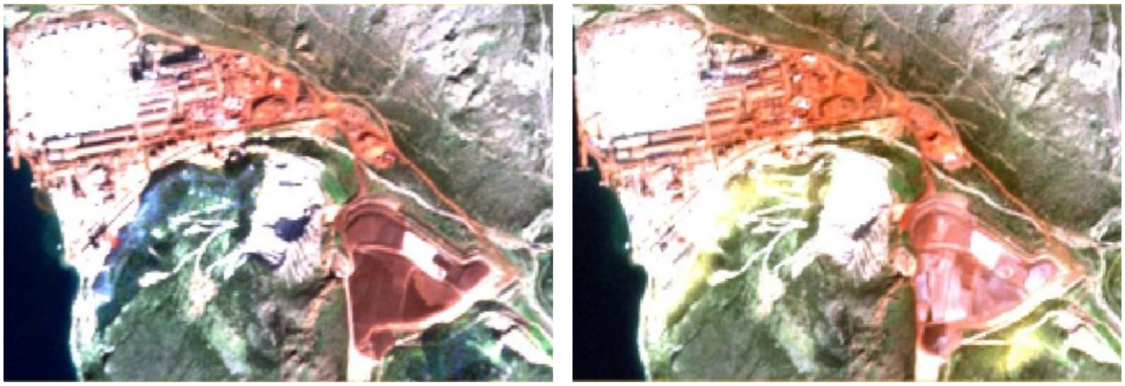


Figure 2. Sentinel-2A image showing the pilling areas in February (Left) and March (Right)

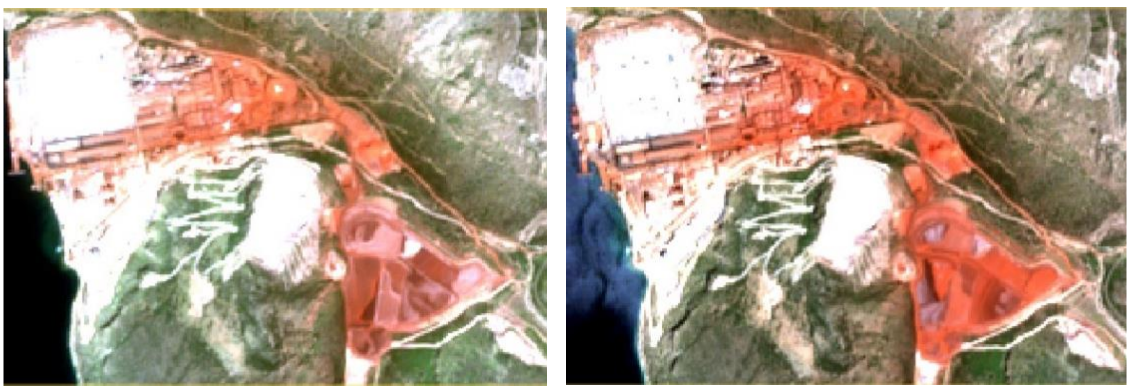


Figure 3. Sentinel-2A image showing the pilling areas in April (Left) and May (Right)

Figure 4. Sentinel-2A image showing the pilling areas in June (Left) and July (Right)

Data collection and Statistical analysis

Different groups of data are collected and studied regarding to the selected case study:

1) Daily dumping data

As a part of the standard management practices adopted by the mining company, daily information about piling operations is collected from the processing plant after performing filtering into piles. The daily dumping data include the tonnage of materials with their mean concentration value, and the area in which they were accumulated (Z, H, B, A, E, Γ, or Δ in Figure 1). however, the exact coordinates where trucks discharged the daily load of materials have not been recorded. This lack is quite common while discharging materials in mining residues and it is not a peculiarity of this case study. Therefore, to use this information, each daily reported concentration was considered as a point sample according to the piling direction and defined inside the recorded area of BR (each point is representative of one day due to the piling direction within the area of Z, H, B, A, E, Γ, or Δ). This step was performed in GIS as follows.

A topographic map was used as the base map to identify the seven piling areas. After georeferencing, the map was inserted in a Geographic Information System (GIS) software to identify the sample locations; through monitoring, the daily piling procedures were tracked.

2) Samples analysis from three different laboratories: BRGM, TU DELFT and ORANO

Three different tables were delivered to UNIBO to data analysis. From TU DELFT the table of X-ray Fluorescence analysis (XRF); from BRGM the table of REE and Li by ICP-MS, SEM/EDX analysis and finally, from ORANO, the table of XRF and ICP-MS analysis of the major and trace elements. Please refer to Deliverable D4.4 for all details about sampling analysis.

The advantage of analysing samples in different laboratories is the possibility of comparison between the analysis results. As an example, for Vanadium, the analysis results are compared with the daily dumping data from MYT:

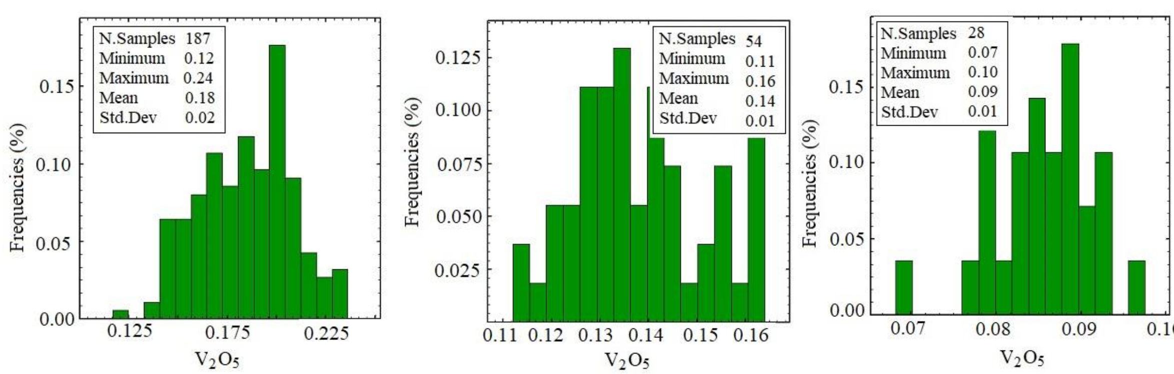


Figure 5. Histograms of data, referring to Vanadium: daily dumping data from MYT (Left), The XRF analysis from TU DELFT (middle) and ICP analysis from BRGM (Right)

The comparison of histograms has shown that the data obtained from XRF has the less variability (with the average of Vanadium= 0.14) in comparison with the daily dumping data (average of Vanadium = 0.18). The variability of Vanadium is still smaller in ICP-MS results for Vanadium (average = 0.09) in comparison to XRF results. Same histogram comparison for titanium can be found in Figure 6.

The reason is because of the solution steps at ICP-MS analysis, and most importantly, the volume and the number of samples, which are used in theses analysis.

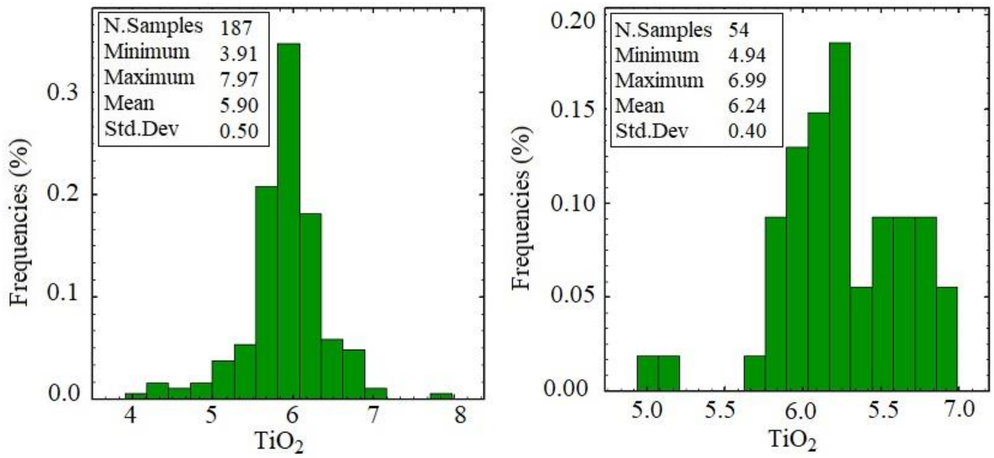
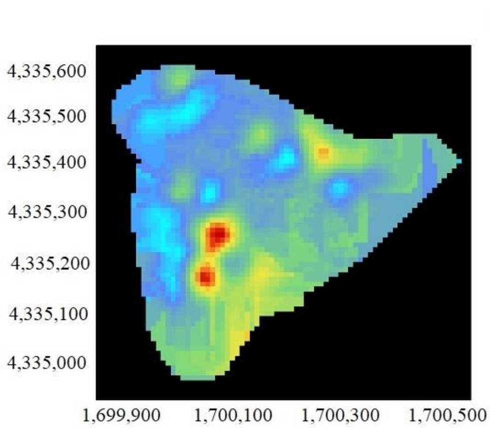


Figure 6. Histograms of data referring to Titanium: daily dumping data from MYT (Left) and the XRF analysis from TU DELFT (Right)

Statistical analysis is done for the selected elements (major and CRMs) which are chosen for mapping. The major elements of iron and aluminium are selected for mapping to have the general idea about the iron and aluminium variability in bauxite residues.
For trace and CRMs, the strategical elements are chosen for mapping such as Li, Cr, V, Ti and Sc

Probability maps and estimation variance

To map the major elements, the sample analysis from XRF are used because of higher number of samples. Maps are provided using Ordinary Kriging and in the case of high correlation coefficient between elements the Co-Kriging method is used [9]. The estimation variance map is provided for each map, identifying the uncertainty of estimation at points where there is no sample.



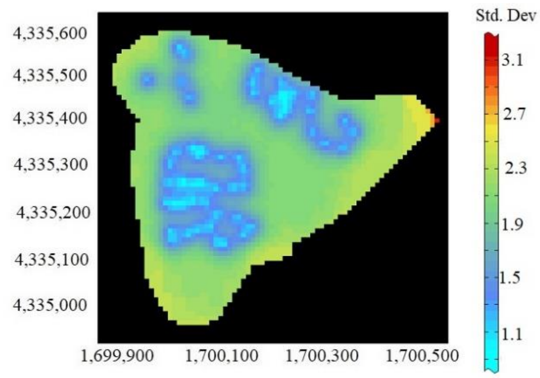
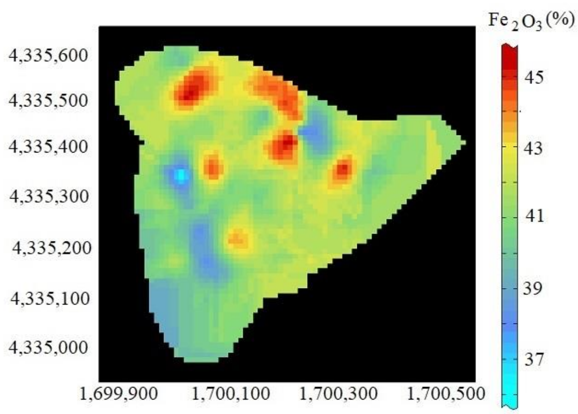


Figure 7. Map of Aluminium variability (wt%) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)



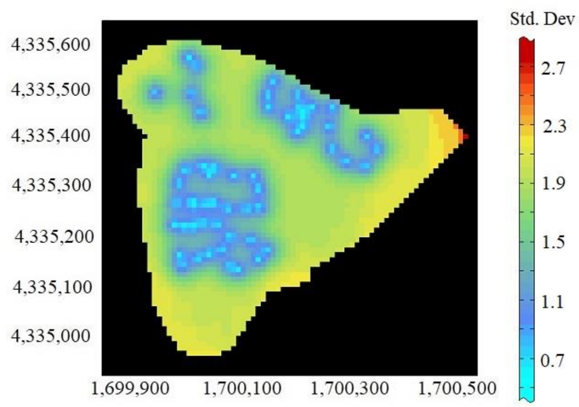


Figure 8. Map of Iron variability (wt%) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)

Probability maps for the selected CRMs

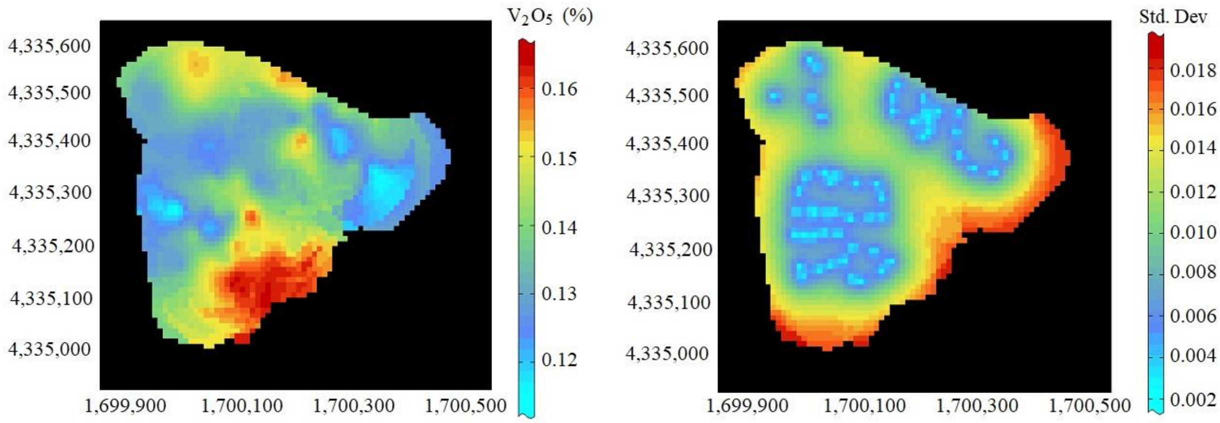


Figure 9. Map of Vanadium variability (wt%) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)

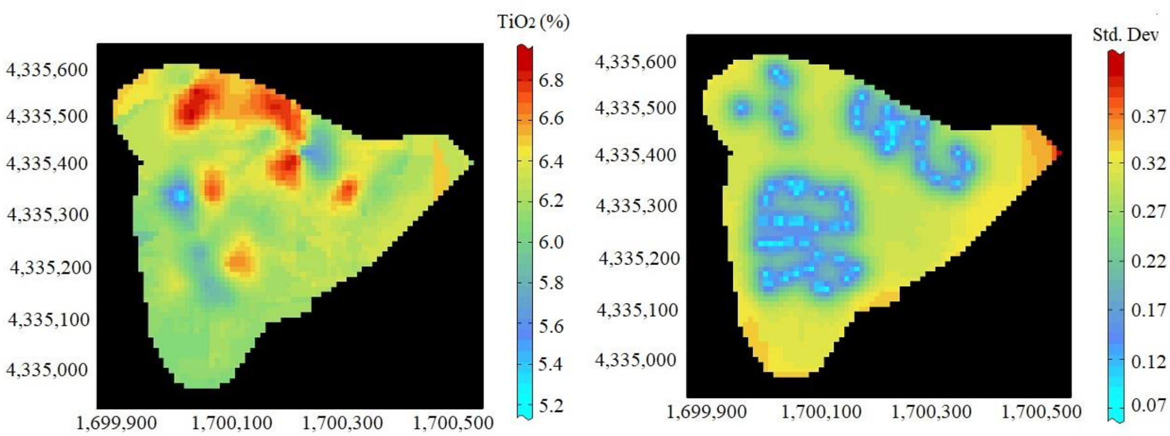


Figure 10. Map of Titanium variability (wt%) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)

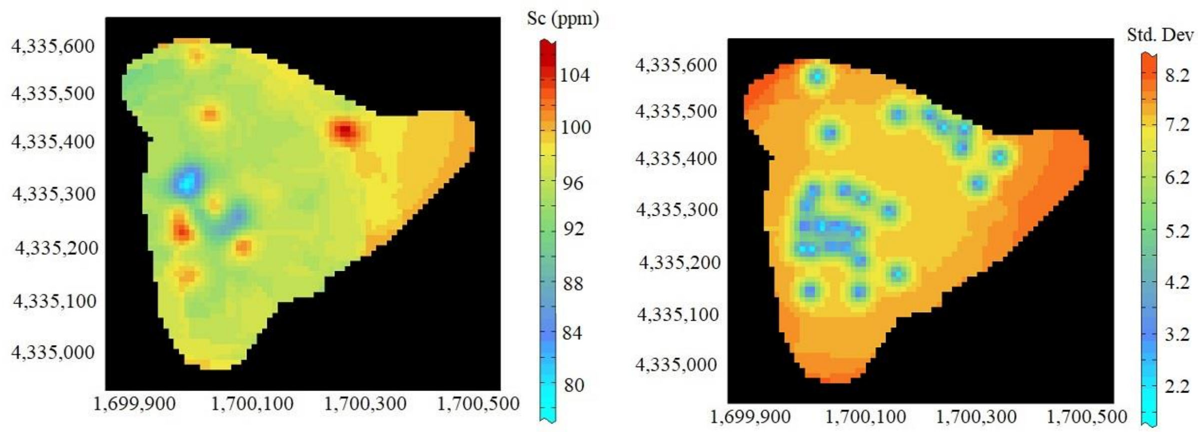


Figure 11. Map of Scandium variability (ppm) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)

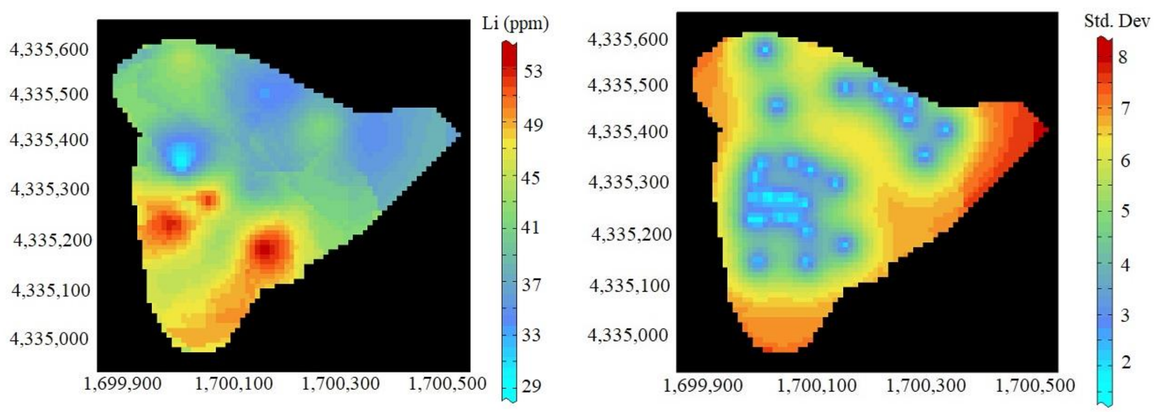


Figure 12. Map of lithium variability (ppm) within the Greece bauxite residues (Left) and the estimation precision (standard deviation) map (Right)

Conclusions

With the adopted techniques it has been possible to reconstruct the distribution of elements inside the tailing for the investigated layer. Results showed how, despite the materials are exit of a processing, some variability exist, which cause the presence of zones at higher or lower concentration. This can be due to the origin of the primary raw material before the process, or to different path of materials transformation. In all cases, characterization techniques can be further used to better map and quantify the presence of CRMs inside the target mining residues, for further analyses and studies.

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