

Uncovering Vertical Controls on Tin Mineralization through PCA and MAF Analysis: Toward Future Applications in Geometallurgy

Raharisolonjanahary Rindraniaina Sylvie*, Katsuaki Koike*, Vitor Ribeiro de Sá*, Mohamad Nur Heriawan**, Slamet Sugiharto***, Nur Rochman Nabawi*** and Anton Murtono***

*Graduate School of Engineering, Kyoto University, Katsura C1-2, Kyoto 615-8540, Japan.

**Faculty of Mining and Petroleum Engineering, Bandung Institute of Technology, Basic Science Center B Building, 4th Floor, Jalan Ganesha 10, Bandung 40132, Indonesia.

***PT Timah Jl. Medan Merdeka Tim. No.15, RT.6/RW.1, Gambir, Kecamatan Gambir, Kota Jakarta Pusat, Daerah Khusus Ibukota Jakarta 10110, Indonesia. Indonesia.

E-mail: raharisolonjanahary.sylvie.66x@st.kyoto-u.ac.jp; koike.katsuaki.5x@kyoto-u.ac.jp

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1. Introduction

Geometallurgical domain definition plays a crucial role in resource extraction and processing. Geological domains and geometallurgical domains can reduce metallurgical variability within a deposit by delineating units that share similar texture, mineralogy, and composition, which are expected to have similar metallurgical performance (Johnson and Murno, 2008; Tiu et al., 2023). Variability remains a challenge due to its intrinsic properties. However, few studies have been conducted on grouping and modelling the characteristics of complex ore.

This study aims to apply minimum/maximum autocorrelation factors (MAF) to data set from a tin deposit. MAF can yield categories that assemble data with similar characteristics. Decorrelation techniques, such as PCA (Principal Component Analysis)-MAF proposed by Switzer and Green (1985), have the flexibility to furnish tools to handle geological information. There are unique characteristics that we should consider as geometallurgical input data without considering the output, identifying and clarifying units such as Rock Quality Designation (RQD), tin grade, vein and having similar characteristics can help constrain the variability within a tin deposit.

2. Methods and materials

PCA-MAF is decorrelation methods including minimum/maximum autocorrelation factors and PCA.

The data used in this research are from Indonesia tin deposit composed of 25 inclined boreholes including grade, RQD, mineralization, vein percentage, and depth to examine vertical zoning patterns.

First, all variables were log-transformed to correct for skewness and normalized before analysis. After that, PCA was used to reduce dimensionality and identify the major components, while MAF analysis was applied to minimize spatial autocorrelation and isolate meaningful spatial structures. Finally, variogram analysis was conducted on PCA and MAF outputs to assess spatial

continuity.

The methodology is described in the flowchart in Fig. 1.

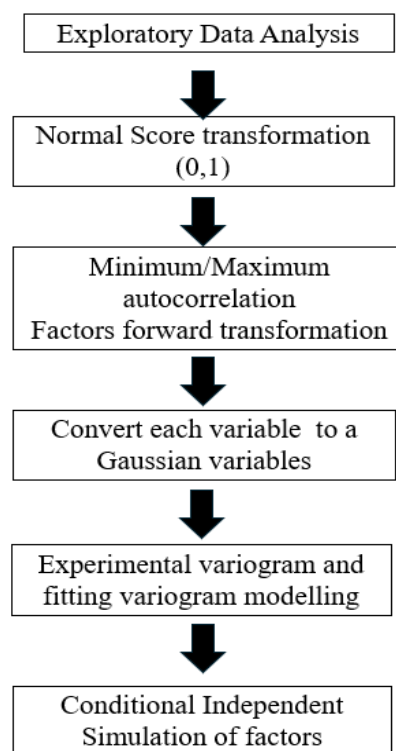


Figure 1. Flowchart of the methodology.

3. Results and Discussion

From Table 1, PC1 dominated mineralization and vein contribution from Sn indicated the structural control on the mineralization, and PC3 indicated independence of vein. PC1 and PC2 are used to build MAF due to it is correlation with Sn. The field orientation is based on in-situ measurements, with isotropy aligned along strike: N66° and dip: 53°NE.

Table 1. Result of PC (NS means Normal Score).

| Variable | PC1 | PC2 | PC3 |
|-------------------|-------------|--------------|-------------|
| NS Mineralisation | 0.85 | -0.14 | 0.03 |
| NS Sn | 0.55 | 0.34 | 0.72 |
| NS Vein | 0.71 | -0.31 | -0.48 |
| NS RQD | -0.18 | -0.88 | 0.44 |

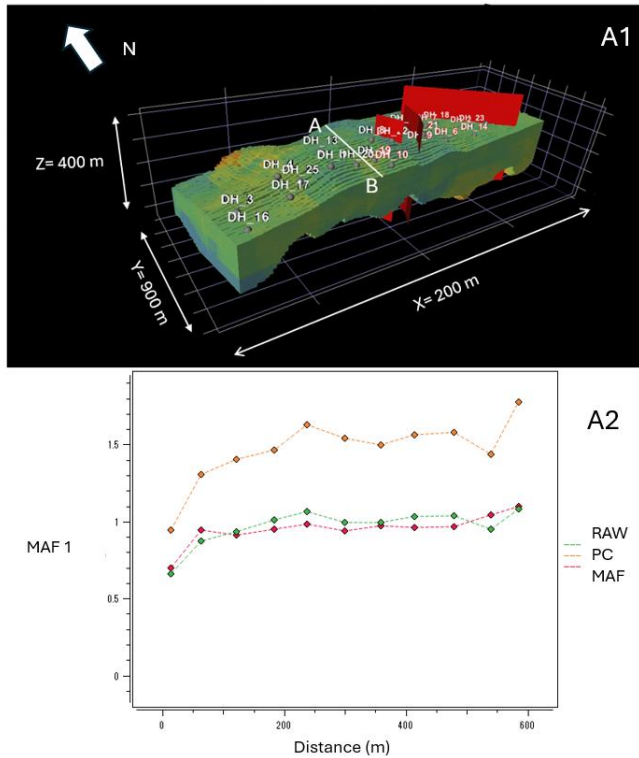


Figure 2. 3D representation of the MAF spatial distribution (A1) and plot variogram with raw (A2).

The MAF1 in Fig. 2 shows that the variogram increases gradually and smoothly with distance. The MAF1 captures strong spatial continuity better than raw and PC data. Based on the field research, it suggests a structural vertical trend reflecting lithological control. In the transition from variables to factors, Factor 1 (F1) exerts a strong influence on both Sn and RQD. These variables exhibit spatial inversion, making their detection and interpretation within the model challenging.

By aligning statistical output with lithology, tin grade, pyrite content, and RQD, we can pinpoint particularly important intervals. The enrichment of tin often coincides with sulfide mineralization and zones where the structural characteristics of the rock change.

Fig. 3 demonstrates the vertical distribution of Sn, pyrite, RQD and MAF attribute to representative borehole. Notably, high tin concentration aligns with increased pyrite content and specific MAF score intervals at approximately 50-120 and 200-250 m.

The downhole composite log provides the clearest visualization of geological reality with statistical analysis. The aligned scores with tin grade, pyrite, lithology, and RQD revealed key intervals. Tin enrichment coincided with sulfide occurrence and

structural variable zones. Vertical examination of the borehole data reveals that the mineral deposit is controlled by both the host rock lithology and depth.

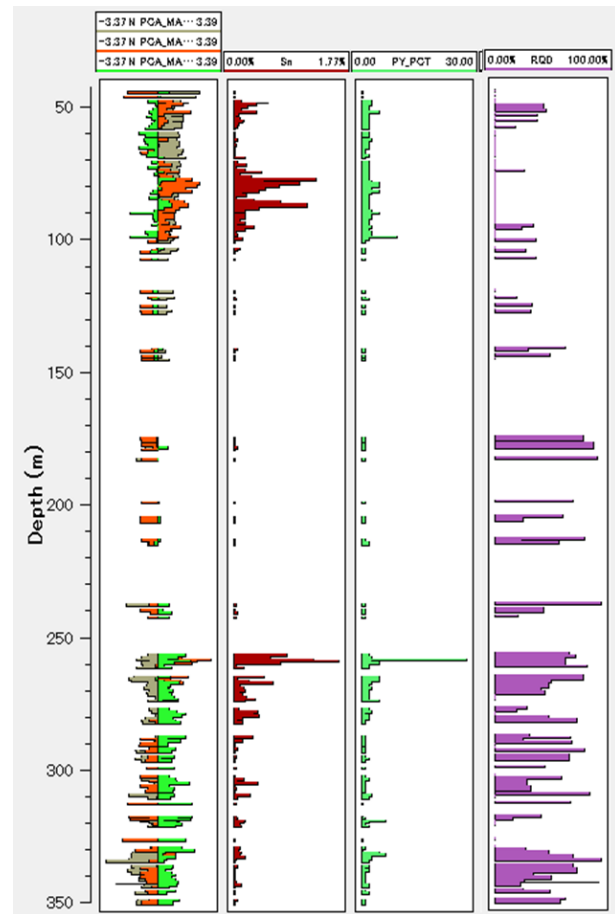


Figure 3. Representative sample of borehole composite log showing correlation with PCA-MAF, tin, RQD and mineralization.

4. Conclusion

PCA or MAF component could not fully explain tin distribution vertically, their integration with the borehole provides the clearest visualization of geological reality, with statistical analysis enabling the identification of key trends and the foundation for defining domains and guiding future geometallurgical models.

An additional dataset could help strengthen the model for predictive applications. This illustrates the challenge of operating in geometallurgical modeling and reinforces the practical value of multivariate methods in early geometallurgical investigations.

References

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