A geostatistical procedure for calculating joint roughness of large rock discontinuities

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ABSTRACT
3D scanning is usually used to obtain information about the surface of a given rock joint, but it is often impractical to scan a subsurface fault or rock joint due to the lack of access. The goal of this study is to reconstruct surface roughness of a large rock joint using limited and dispersed sample measurements. The process of predictions encompassed Kriging interpolation method along with variogram modelling. Five joint surfaces were reconstructed from 4, 7, 9, 11 and 13 samples distributed all over the surface. The results showed that the geostatistical procedure shows reasonable results when compared with the original surface. It was shown that the prediction approach is effective with nine samples that cover 54% of the whole area. This proposed method in this paper can characterize surface roughness while also addressing the scale dependence issue.

RÉSUMÉ
La numérisation 3D est souvent utilisée pour obtenir des informations sur la surface d'un joint rocheux donné. Mais il est souvent peu pratique de numériser un joint rocheux souterrain si c'est inaccessible. L'objectif de cette étude est de reconstruire la rugosité de surface d'un grand joint rocheux en utilisant des mesures d'échantillons limitées et dispersées. Le processus de prédiction englobe la méthode d'interpolation de Kriging ainsi que la modélisation des variogrammes. Cinq surfaces de joint ont été reconstruites à partir de 4, 7, 9, 11 et 13 échantillons répartis sur toute la surface. Les résultats ont montré que la procédure géostatistique donne des résultats assez précis par rapport à la surface originale. Il a été montré que l'approche de prédiction est efficace en utilisant neuf échantillons qui couvrent 54% de la surface totale. La méthode proposée dans cet article peut caractériser avec précision la rugosité de surface tout en abordant le problème de la dépendance d'échelle.

1 INTRODUCTION

The shear strength of rock discontinuities is proportional to the friction generated by contact between two surfaces during shear movement; thus, the roughness characteristics of discontinuity surfaces significantly affect the discontinuity shear behaviour (Jaeger., 1959). Hence, it is crucial to investigate the roughness characteristics of a joint surface. Over the last decades, many studies have focused on the characterization of the morphology of rock fractures. In 1973, Barton was the first to consider the effect of natural roughness on joint strength, introducing the term "joint roughness coefficient" JRC values (Barton., 1973). It was further developed by (Barton and Choubey, 1977) by specifying ten standard roughness profiles. This approach is adopted as the standard method for assessing joint roughness by the International Society for rock mechanics (ISRM., 1978). Because this approach relies on visual comparisons to estimate JRC values, the results may be subjective due to human bias (Wakabayashi and Fukushige., 1995; Hsiung et al., 1993). Among the significant advances, it is now possible to quantify the roughness of a joint rather precisely using laser profilometers or digital measuring devices.

The analysis of the collected data can then be conducted with different methods: statistical approaches (Wu and Ali., 1978);(Tse and Cruden., 1979);(Krahn and Morgenstern., 1979);(Dight and Chiu., 1981);(Maerz et al., 1990);(Reeves., 1985) have been used to quantify the roughness of rock joints using linear profiles. Recently researchers (Grasselli et al., 2002);(Lanaro., 2000);(Stout and Blunt., 2000) are using statistical parameters for quantifying 3-D rock profiles. Fractal approaches ((Lee et al., 1990) (Turk et al., 1987);(Carr and Wardner., 1987) have applied the concept of fractal dimension to rock joints.

Roughness characterization requires field measurements, with or without contact, which are often time-consuming and expensive to carry out, especially for measuring the roughness of a very large area. Numerous in situ technologies provide precise measurement at a variety of spatial scales. However, roughness measurement in inaccessible/partially exposed areas has not been studied yet. A major issue arises as how to accurately characterize the roughness of a subsurface discontinuity. A method is needed to reconstruct underneath discontinuity roughness from limited samples obtained from boreholes, or exposed surfaces.

(Gravel et al., 2015) initiated a project to find alternatives to large-scale direct shear tests conducted in the field. The objective was to transfer in-situ shear tests to the laboratory. A 50cm-by-50cm schist outcrop was scanned using a laser scanner profilometer, and a point

cloud of 3D coordinates defining the surface was acquired. These data served as a reference for this paper. We attempted to reconstruct the original surface from sparse topographic data using geostatistical techniques. The proposed method aims at characterizing the surface roughness while simultaneously resolving the issue of scale dependency.

2 METHODOLOGY

The initial stage in geostatistical analysis is to determine the spatial structure of each variable (in this case, the height of the surface points). The variogram was used to describe the continuity and variability of fracture surfaces between every data point. The variogram γ (h) is defined as follows (Matheron.,1963):

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [z(x_i + h) - z(x_i)] \quad [1]$$

Where, z(xi) = measurement taken at a location xi (in this case, z is the elevation of the surface point).
z(xi + h) = measurement taken at a location h distance away.
n(h) = number of data pairs h units apart in the direction of the vector.
h = lag distance.
γ(h) = variogram value.

The majority of variograms are defined by three parameters: the nugget effect, the sill, and the range.
-Nugget effect: is the micro-scale variation or measurement error.
-Sill: is the variance in the data.
-Range: is the distance (if any) at which data are no longer autocorrelated.

The experimental variogram cannot be used directly in structural analysis; it must be adjusted to a fitted function named the theoretical variogram. According to the literature, the spherical, exponential, and Gaussian models are three of the most often utilized variogram models.
These models were fitted to the experimental variograms using the weighted least square method, which has been proven to be the most effective and accurate way of fitting variogram models so far (Cressie., 1985). This approach reduces the weighted sum of squared residuals (RSS) of the experimental variogram data by optimizing many parameters, including the nugget effect, the sill, and the range of the experimental data. The theoretical variogram was selected based on the model with the lowest RSS value.

Geostatistical methods based on variograms are referred to as kriging. Kriging is an interpolation technique that generates the best linear unbiased estimate at each location using the spatial variability obtained from the variogram model (Cressie., 1990).

(Kumar and Remadevi., 2001) provided a comprehensive overview of the numerous uses of kriging in various fields, such as in the field of geotechnics (Burgess and Webster., 1980);(Vieira et al., 1981);(Berndtsson and Chen., 1994); in groundwater levels (Goovaerts., 2000); (Creutin and Obled., 1982); (Germann and Joss., 2001); in hydrology (Aboufirassi and Mariño., 1983); (Virdee and Kottegoda., 1984);(Kumar., 1996) and in atmospheric science (Bilonick., 1988);(Casado et al., 1994).

Kriging offers a wide and flexible variety of tools that provide estimates for un-sampled locations using the weighted average of neighboring field values (Isaaks and Srivastava., 1989).

A cross-validation technique was applied to verify the effectiveness of the prediction analysis approach,. One of the measured points was removed from the real data set in each iteration. Kriging analysis was done on the newly obtained data set and contour maps. The estimated values were compared to the true sample values that had been excluded from the sample data set at the start. A graphical plot was created to compare the actual and estimated values, , and error was determined as the root mean square of the differences between the estimated and true elevation values. The model is adjusted by the user based on these results, and then a second cross-validation is done, and so on.

Following this procedure for each predicted surface, surfaces were reconstructed by systematically dispersing (10cm by 10cm) samples, as shown in Figure 1. The roughness of the reconstructed surfaces is evaluated by (1) making a visual comparison to the original surface,(2) calculating Z2 for both x and y directions, and (3) analyzing the asperity's height distribution maps and frequency distribution histograms, as well as descriptive statistics, all of which are shown in Figures 2 to 5.

3 RESULTS AND DISCUSSION

The five surface roughness maps obtained by universal kriging interpolation are displayed in Figure 3. As expected, as the number of samples increases, the reconstructed surface tends to resemble the original surface.

The least accurate reconstructed surface is based on four samples with 24% coverage. However, the most accurate reconstructed surface is based on thirteen samples with 77% coverage. The surface based on a distribution of four windows has displayed the overall relief of the rock surface but not the macro-roughness of all surface, Then, as coverage increases, we capture more the macro-roughness, which is unsurprising given the high coverage.

We may assert that we obtained a surface quite comparable to the original fracture by using 9-sample distribution covering 54% of the whole surface. It is then confirmed by the height of statistical data. Figure 3 shows that the asperity height distributions are similar for the 9-sample reconstructed surface and the original surface: means of 41.44 vs. 41.3 mm and standard deviation of 6.94 mm vs. 7.19 mm.

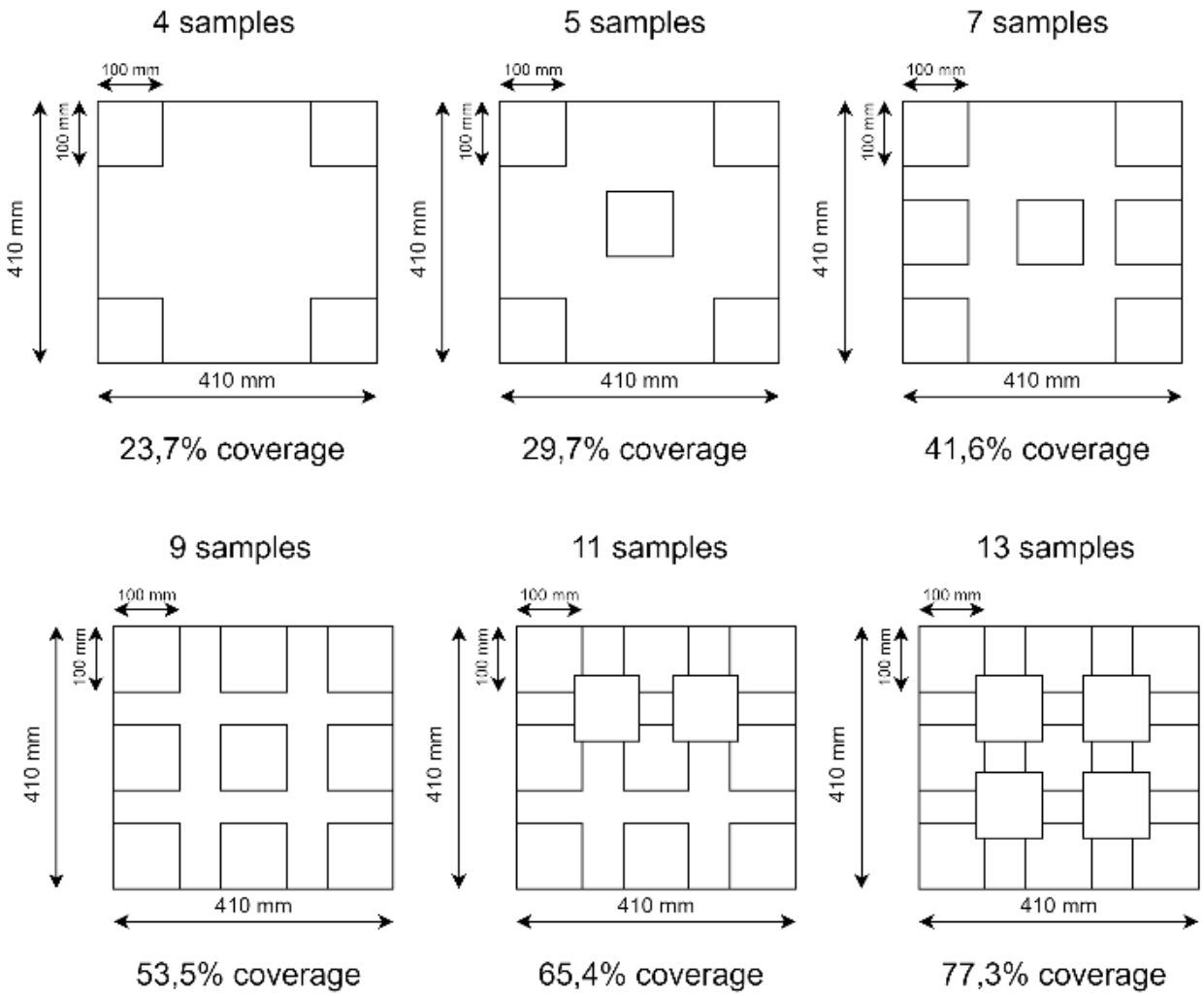
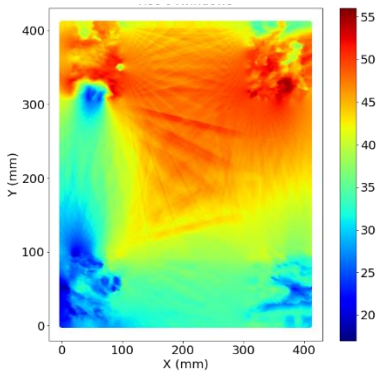


Figure 1. The distribution of 4, 5, 7, 9, 11, and 13 windows over each reconstructed surface.

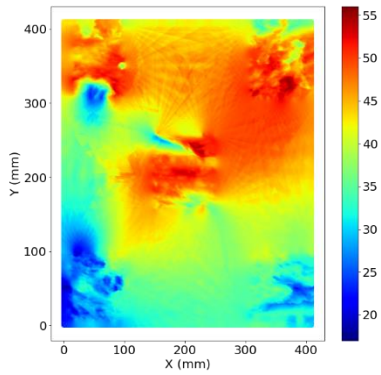
Tables 1 and 2 list the results of the descriptive statistics of Z2 values for x and y directions, which are also shown in the box plot in figures 4 and 5. Figure 4 shows that the average Z2 value in the X direction obtained by 4-sample and 13-sample reconstructed surface is 0.40 and 0.49, respectively,(an improvement of 18%). Figure 5 indicates that these values are 0.45 and 0.68 in the Y direction (an improvement of 34%).

This study suggests that it is possible to capture the roughness of an inaccessible surface by reconstructing its topographic surface using limited and dispersed samples. Still, this method's potential is limited by the coverage percentage, which depends on the number of samples and geometries. We should also point out that, since the weights of the kriging interpolator are dependent on the variogram model, kriging is very sensitive to variations in the variogram model's specification. Furthermore, suppose the number of sampled observations is small, and the data is restricted in geographical scope, or the data are not sufficiently spatially correlated. In that case, it is hard to construct a sample variogram, so, kriging may not be the ideal method for making predictions.

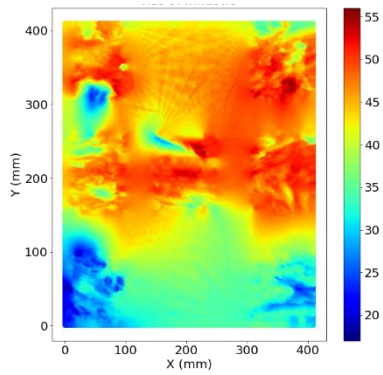
Finally, we suggest test this approach in an area with complex topography where the spatial autocorrelation of the variable of interest is only visible at a small scale.



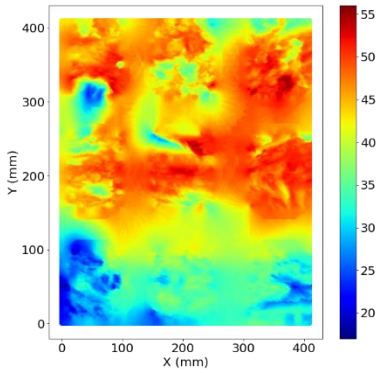
(a) 4 windows



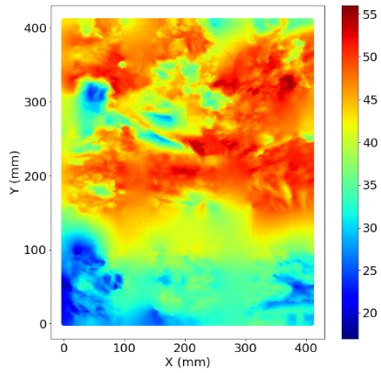
(b) 5 windows



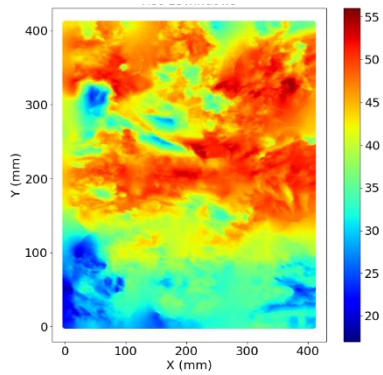
(c) 7 windows



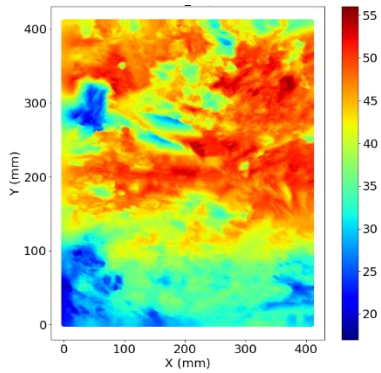
(a) 9 windows



(d) 11 windows



(e) 13 windows



(f) Original surface

Figure 2. 3D Surface topography of the reconstructed and original rock fractures.

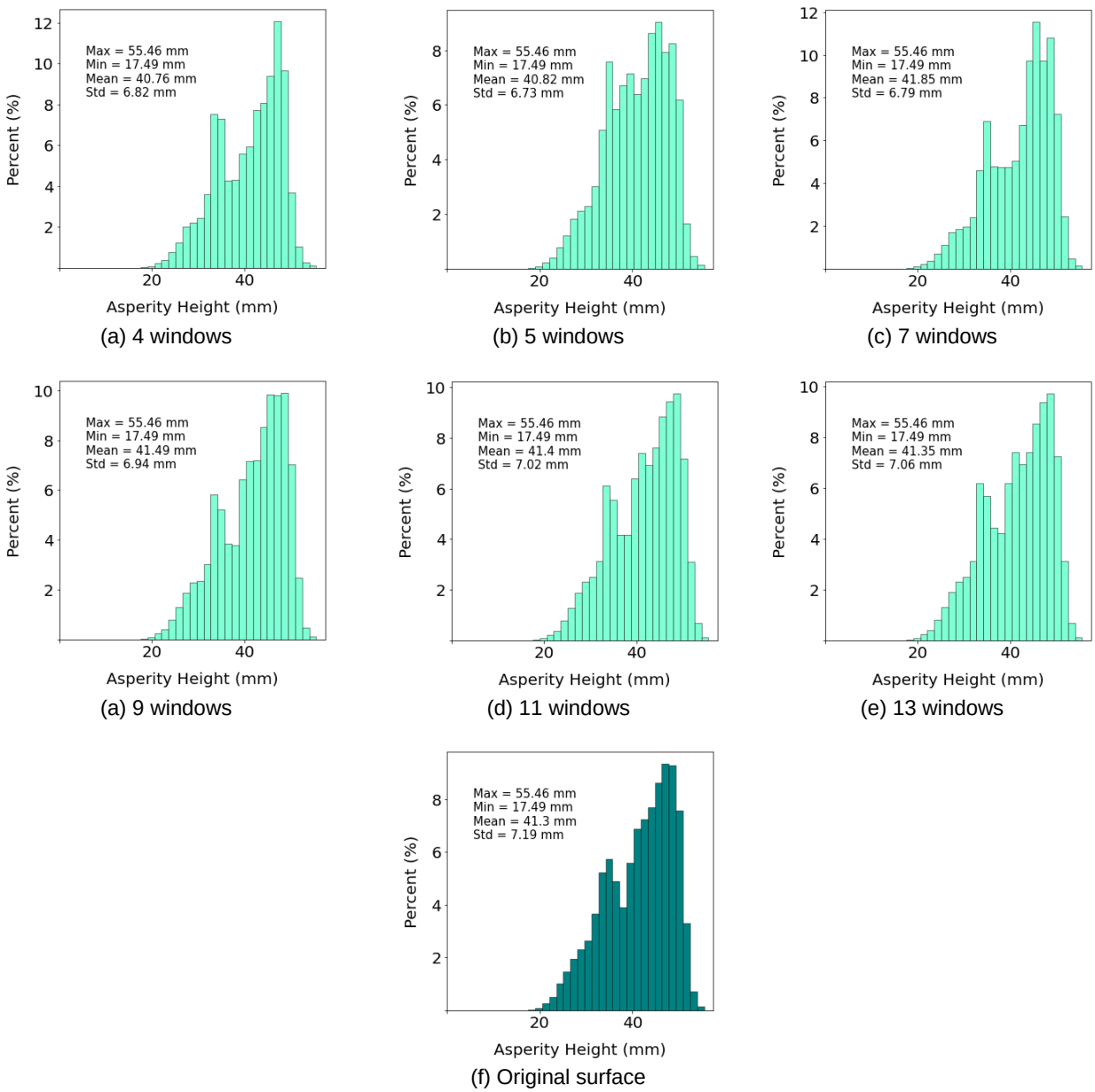


Figure *3*. Height distribution of the asperities for each reconstructed surface

Table 1. Summary of the statistical results Z2 (X direction)

Surface	Z2 (x direction)			
	Min	Max	Mean	Std
4W	0.24	0.71	0.40	0.11
5W	0.22	0.73	0.43	0.11
7W	0.22	0.73	0.44	0.12
9W	0.20	0.83	0.44	0.14
11W	0.19	0.86	0.46	0.15
13W	0.27	0.86	0.49	0.13
Original Surface	0.29	1.65	0.53	0.16

Table *2*. Summary of the statistical results Z2 (Y direction)

Surface	Z2 (y direction)			
	Min	Max	Mean	Std
4W	0.21	0.82	0.45	0.14
5W	0.21	0.89	0.52	0.15
7W	0.20	0.92	0.56	0.17
9W	0.24	0.97	0.59	0.20
11W	0.32	0.96	0.64	0.15
13W	0.37	0.97	0.68	0.14
Original Surface	0.40	1.42	0.77	0.16

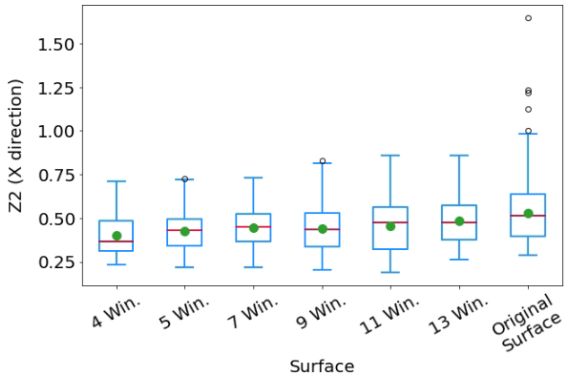


Figure 4. Box plot of Z2 values (X direction)

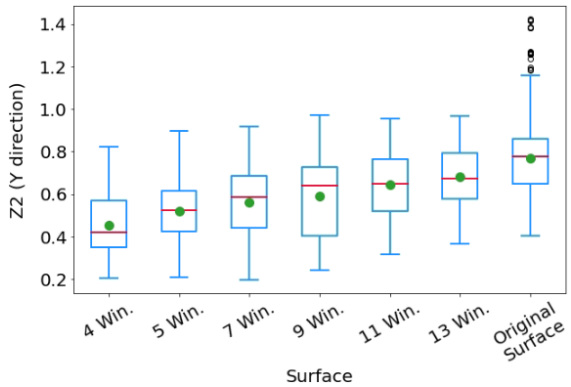


Figure 5. Box plot of Z2 values (Y direction)

4 CONCLUSIONS

When in situ rock joints are not accessible or fully exposed, it is often difficult to estimate roughness characteristics of full-scale rock joints. The geostatistical method can solve this problem by using the kriging interpolation technique to predict values at unsampled locations to obtain a reconstructed rock joint surface.

Kriging analysis was performed using spatial variability models, which provided reconstructed surfaces. The predictions were validated using the cross-validation technique. It was demonstrated that geostatistics could work effectively with 9 samples presenting 54% of the coverage of the whole surface. However, a sensitivity analysis to sample locations and sizes is currently performed to validate this technique and better understand its limits.

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