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GEOSTATISTICAL MODELING OF POROSITY FOR CO₂ STORAGE

ASSESSMENT IN A RESERVOIR

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Abstract

This study presents a geostatistical analysis of porosity in a reservoir, aiming to understand its spatial distribution within the study area and to evaluate its potential for CO₂ storage applications. Descriptive statistical analysis and histograms were used to assess the characteristics of data distribution and their suitability for geostatistical modeling. An experimental variogram was constructed and fitted with a spherical theoretical model to describe the spatial correlation structure. Ordinary kriging was applied to estimate porosity and to generate spatial distribution maps, while kriging variance and Gaussian sequential simulation were used to evaluate spatial uncertainty. The resulting porosity model was subsequently employed to simulate CO₂ storage under different injection configurations over a three-year period. The results indicate a well-defined spatial correlation structure, reliable porosity estimation, and a meaningful uncertainty analysis, providing a solid basis for reservoir evaluation and the feasibility of CO₂ storage.

Keywords: *geostatistics, porosity, variogram, ordinary kriging, Gaussian sequential simulation, CO₂ storage.*

1. Introduction

Geostatistical analysis of reservoir properties represents an essential tool for analyzing the spatial distribution of petrophysical parameters and for evaluating the storage capacity of geological formations. Porosity, as one of the main properties of reservoir rocks, reflects their ability to accumulate and store fluids and directly influences reserve estimation as well as the design of injection and production schemes.

Histograms and statistical indicators are used for the initial characterization of the data, enabling the analysis of value distribution and the identification of key statistical parameters such as mean, variance, minimum, and maximum. Variance plays a particularly important role in geostatistical analysis, as it serves as the basis for constructing the experimental variogram and for evaluating the spatial correlation structure of the data.

The experimental variogram is fitted with a theoretical model to determine the model parameters, such as the sill and range, which describe the sphere of influence of the measurements and the degree of spatial dependence. Subsequently, ordinary kriging is applied to estimate porosity in the studied area and to generate the corresponding maps, as well as to calculate the kriging variance, which expresses the uncertainty of the estimation.

To further analyze spatial uncertainty, sequential Gaussian simulation is performed by generating possible realizations of porosity and the corresponding variance maps. The obtained results are then used for CO₂ storage modeling in the studied reservoir, with the aim of evaluating its potential for practical appli-

cations in the fields of energy and environmental protection.

2. Materials and Methods

2.1 Data and Study Area

The data used in this study represent porosity measurements collected at sampling points identified as ST3. A total of 563 measurement points is available, which serve as the basis for the statistical and geo-statistical analysis of the reservoir. The data are distributed within a defined study area and represents real values of the petrophysical parameters of the formation.

Poroziteti i matur sipas puseve						
6						
x	m					
y	m					
z	m					
Porosity-St1						
Porosity-St2						
Porosity-St3						
1020	240	178.2	0.315	0.315	0.293	
1020	240	207.9	0.289	0.309	0.287	
1020	240	237.6	0.304	0.325	0.282	
480	1000	29.7	0.292	0.271	0.270	
480	1000	59.4	0.283	0.304	0.283	
480	1000	89.1	0.254	0.254	0.276	
480	1000	118.8	0.239	0.259	0.259	
0	80	148.5	0.344	0.303	0.324	
0	80	178.2	0.286	0.306	0.284	
1420	1600	207.9	0.295	0.315	0.293	
1420	1600	237.6	0.312	0.312	0.312	
800	220	89.1	0.301	0.281	0.259	
800	220	118.8	0.281	0.301	0.301	
800	220	207.9	0.324	0.283	0.282	
800	220	237.6	0.317	0.296	0.317	
800	220	267.3	0.272	0.251	0.294	
1680	120	59.4	0.269	0.290	0.269	
1680	120	89.1	0.299	0.319	0.341	
380	700	29.7	0.278	0.257	0.256	
380	700	59.4	0.266	0.286	0.308	
1380	2280	0.0	0.291	0.312	0.313	
1380	2280	59.4	0.335	0.294	0.315	
1380	2280	89.1	0.277	0.236	0.235	
1380	2280	118.8	0.310	0.289	0.332	
1380	2280	148.5	0.248	0.268	0.268	
1380	2280	237.6	0.304	0.304	0.304	
1380	2280	267.3	0.302	0.281	0.324	
1980	1020	29.7	0.263	0.263	0.241	
1980	1020	59.4	0.275	0.276	0.233	
880	680	178.2	0.279	0.320	0.299	
880	680	207.9	0.287	0.266	0.309	
880	680	237.6	0.305	0.304	0.325	
880	680	267.3	0.314	0.315	0.316	
620	1080	118.8	0.288	0.308	0.330	
620	1080	148.5	0.255	0.275	0.253	
620	1080	178.2	0.281	0.301	0.301	
1020	180	178.2	0.322	0.301	0.322	
1020	180	207.9	0.326	0.285	0.306	
1020	180	237.6	0.346	0.347	0.304	
1880	2300	29.7	0.225	0.224	0.245	

Figure 1: Porosity dataset

The study area is discretized into a three-dimensional grid for the purposes of spatial estimation and the generation of thematic maps. The grid dimensions and cell size are defined in accordance with the data density and the level of detail required for the analysis.

2.2 Statistical Analysis and Histogram Construction

In the initial phase, a statistical analysis of the data is carried out to evaluate their distribution and to identify the main statistical characteristics. Histograms are used as a graphical representation of the frequency distribution of porosity values, enabling a visual interpretation of central tendency, dispersion, and symmetry of the data.

For each dataset, statistical indicators such as mean, variance, minimum, maximum, median, and quartiles are calculated. Variance, as a measure of data dispersion around the mean, serves as an important

parameter for further geostatistical analysis and for the construction of the variogram.

2.3 Construction of the Experimental Variogram

To analyze the spatial correlation of the data, the experimental variogram is constructed. The variogram describes how the similarity of porosity values changes as a function of the distance between measurement points. It is calculated by analyzing pairs of points at different distances and along the main geological orientation directions.

In general, the experimental variogram is characterized by an increase in its value with increasing distance until reaching a stable value known as the sill, while the distance at which stabilization occurs is referred to as the range. The range represents the sphere of influence of a measurement and the distance beyond which values are no longer considered correlated.

2.4 Variogram Fitting and Theoretical Model

The experimental variogram is fitted with a theoretical model to obtain a continuous mathematical function that can be used in kriging calculations. In this study, a spherical model is applied, and the corresponding model parameters, such as sill, range, and nugget, are determined.

The model fitting is performed by achieving the best possible agreement between the experimental variogram and the theoretical model.

2.5 Ordinary Kriging and Kriging Variance

Spatial estimation of porosity is performed using the ordinary kriging method, in which the mean is assumed to be constant but unknown. The main condition of this method is that the sum of the kriging weights equals one, ensuring an unbiased estimate and minimizing the estimation error variance.

For each grid cell, the estimated porosity value and the kriging variance are calculated. The kriging variance represents the measure of estimation uncertainty and is used to assess the reliability of the results.

2.6 Sequential Gaussian Simulation

To more comprehensively evaluate spatial variability and uncertainty, sequential Gaussian simulation is applied. This method generates multiple realizations of the porosity distribution while honoring the variogram structure and the statistics of the original data.

The simulation results are used to construct variance maps and to perform a probabilistic analysis of porosity distribution within the reservoir.

3. Results

3.1 Statistical Analysis and Histograms

The statistical analysis of the porosity data includes the construction of histograms and the calculation of the main statistical indicators. The histogram represents the frequency distribution of porosity values and allows a visual assessment of the distribution shape, symmetry, and concentration of data around the mean value.

The dataset includes a total of 563 measurement points. The mean porosity value is 0.2886, while the variance is 0.0008196, indicating a relatively stable distribution of values. The maximum porosity value is 0.374, whereas the minimum value is approximately 0.183. The median is 0.288, while the lower and

upper quartiles are 0.271 and 0.308, respectively.

The histograms indicate an approximately normal distribution of the data, which justifies the application of geostatistical methods and Gaussian simulation in the subsequent analysis.

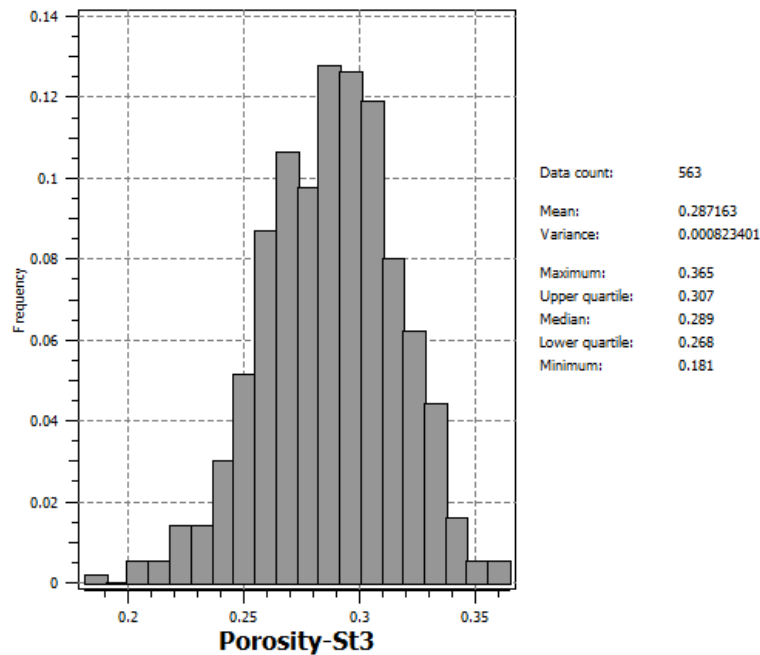


Figure 2: Histogram and descriptive statistical parameters of the ST3 porosity data

3.2 Experimental Variogram and Theoretical Model

The experimental variogram was constructed to analyze the spatial correlation structure of the porosity data. Its calculation was performed by considering the main orientation directions and the distance intervals between measurement points. The results indicate a progressive increase in variance with increasing distance, until reaching a stable value known as the sill of the variogram.

The variogram fitting was performed using a spherical theoretical model, which provides the best agreement with the experimental data. The model parameters describe the range of influence of the measurements and the degree of spatial dependence of porosity within the studied area.

The statistical analysis of the data indicates an approximately normal distribution of porosity, with a total of 563 measurement points. The mean value is 0.28862, the variance is 0.000819553, while the maximum value is 0.374 and the minimum value is 0.183. The median is 0.288, whereas the lower and upper quartiles are 0.271 and 0.308, respectively.

Variance represents an important indicator, as it serves as the basis for the construction and interpretation of the variogram and for the evaluation of the spatial correlation structure of the data.

$$Var[X] = E[(X - m)^2]$$

3.2.1 Construction of the Experimental Variogram

To determine the spatial correlation model of the data, which should reflect the spatial characteristics of the phenomenon under study, the regional geological orientation provides the main directions for variogram calculation. The experimental variogram is calculated using the following function:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{N(h)} [z(x_i) - z(x_j)]^2$$

Here, denotes the number of data point pairs separated by a distance .

To calculate the experimental variogram, both the direction and the lag distance for which the variogram function is to be estimated must be defined.

In general, the experimental variogram exhibits the following characteristics:

- It starts at or near zero for ;
- It increases with increasing lag distance ;
- It continues to increase or stabilizes beyond a certain value of .

The value at which the variogram stabilizes is referred to as the sill. The distance at which stabilization occurs is called the range. The range represents the distance beyond which and are no longer spatially correlated and can also be interpreted as the “sphere of influence” of a measurement.

When the measurements are no longer correlated, their covariance approaches zero and tends toward .

After grouping the data according to the corresponding directional angles, five directional variograms were obtained for the ST3 porosity data, along with one composite variogram. In this study, the experimental variogram was analyzed primarily along the vertical direction.

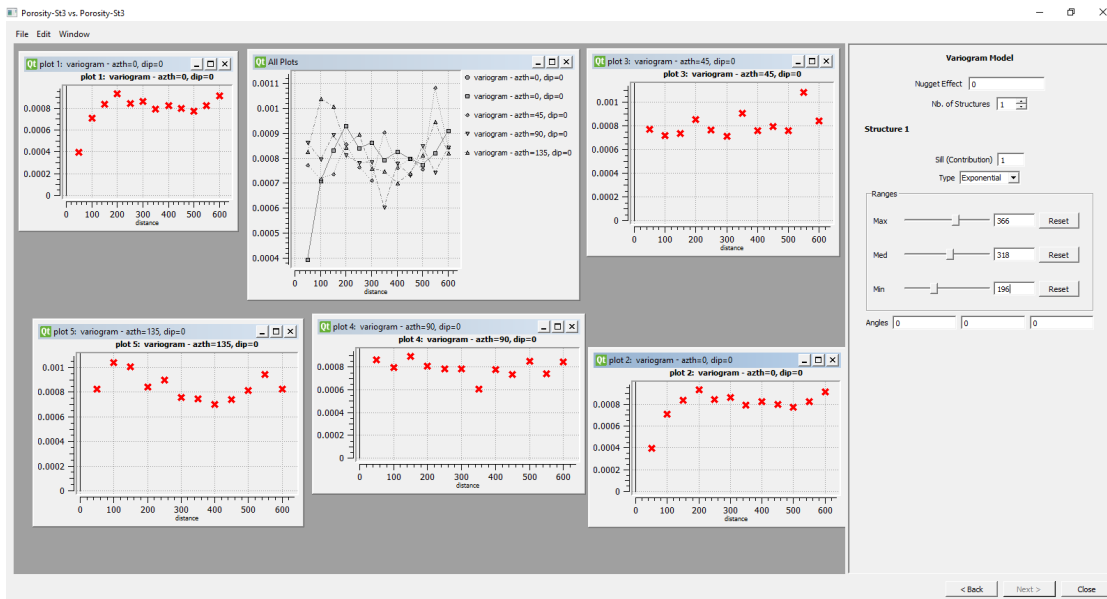


Figure 3: Experimental variogram and fitted spherical model

Spherical variogram model fitted to the experimental data (variance = 0.000819553).

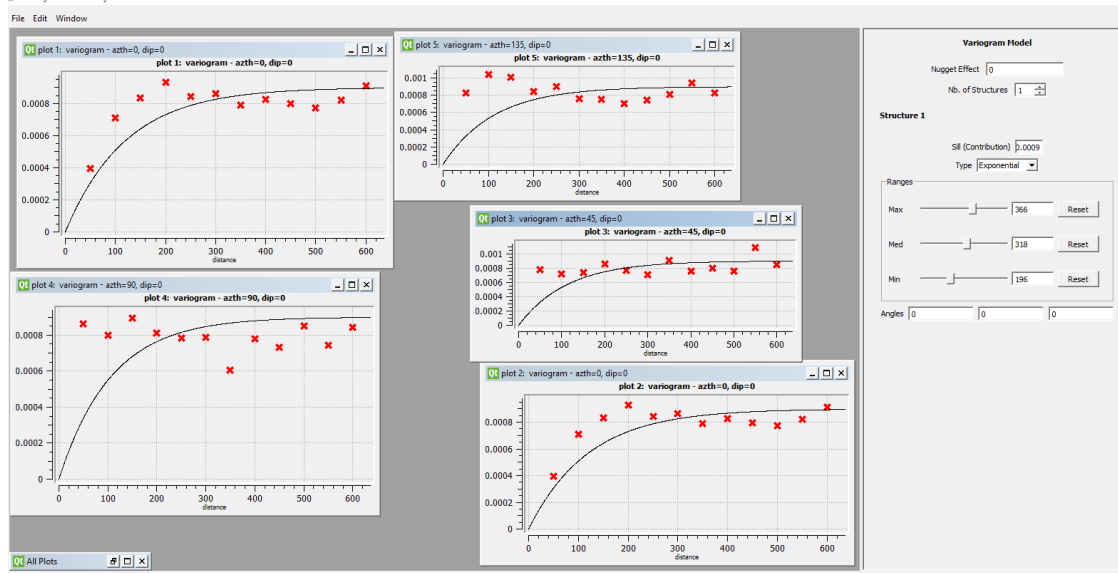


Figure 4: Fitted spherical variogram model

3.3 Estimation of Porosity Using Ordinary Kriging

3.3.1 Grid Construction

The geostatistical estimation of porosity was performed using the ST3 dataset and the ordinary kriging method. The data were initially mapped to analyze the spatial distribution of the measurement points. Subsequently, porosity was interpolated over the entire study area, and the corresponding map was generated.

Ordinary kriging is an estimation method in which the mean is assumed to be constant but unknown. The main condition of this method is that the sum of the kriging weights equals one, ensuring an unbiased estimate and minimizing the estimation error variance. In the case where only one neighboring point is used for estimation, the kriging variance equals twice the variogram value between the estimated point and the neighboring point.

For the estimation process, a three-dimensional grid was constructed to discretize the study area.

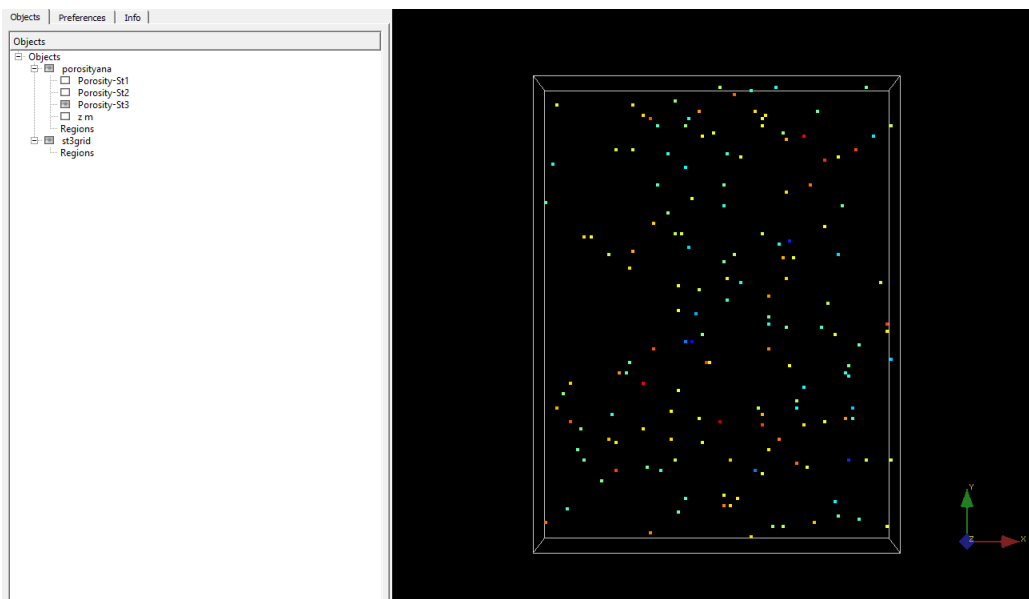
The grid dimensions are:

X = 100 cells, Y = 130 cells, Z = 14 cells.

The cell dimensions are:

$\Delta X = 19.8$ m, $\Delta Y = 19.8$ m, $\Delta Z = 14$ m.

This grid enables spatial representation of porosity and the generation of thematic maps.



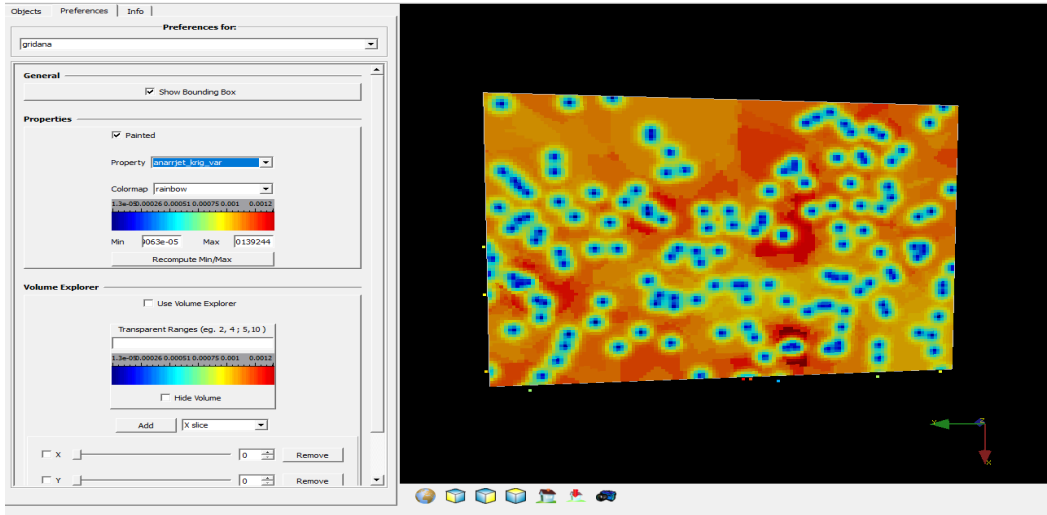


Figure 5: Spatial distribution of porosity estimated by ordinary kriging

The blue areas shown on the map indicate lower porosity values, whereas the orange and red areas represent higher porosity values within the reservoir. The practical significance of porosity lies in the fact that it reflects the storage capacity and fluid accumulation potential of the formation. Hydrocarbon reserves in a reservoir layer are directly proportional to porosity.

3.4 Kriging Variance

The kriging variance was calculated for each grid cell and represents the degree of uncertainty associated with the spatial estimation. Lower variance values are observed in areas close to the measurement points, whereas higher values occur in regions farther from the available data.

The grid used for the variance analysis has the following dimensions:

X = 40 cells, Y = 52 cells, Z = 14 cells.

The cell dimensions are:

$\Delta X = 49.5$ m, $\Delta Y = 49.6$ m, $\Delta Z = 14.85$ m.

This spatial distribution reflects the reliability of the kriging results and provides valuable information for risk analysis and for planning future data acquisition.

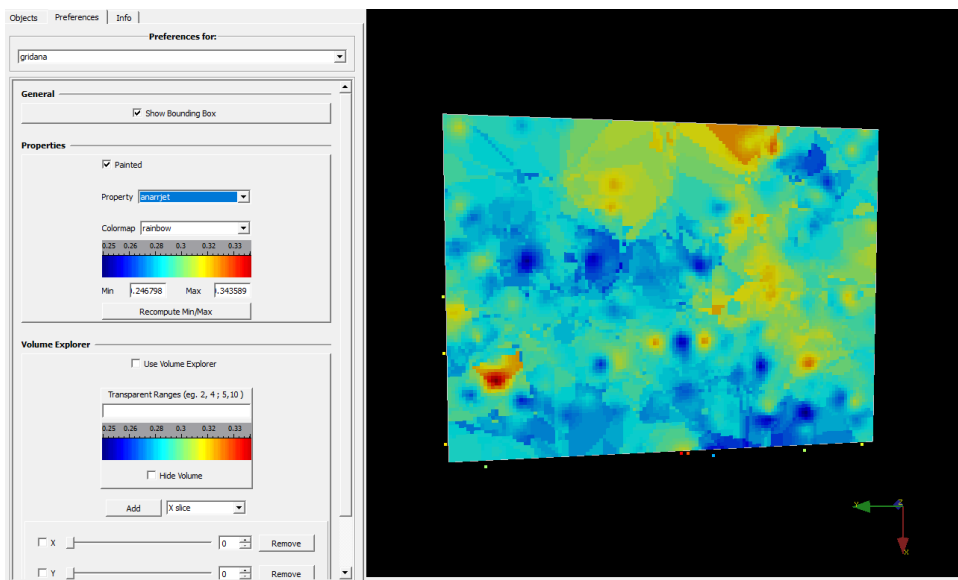


Figure 6: Spatial distribution of kriging variance

3.5 Sequential Gaussian Simulation

Sequential Gaussian simulation was applied to generate alternative realizations of the porosity distribution while preserving the statistical properties of the data and the variogram structure. The simulation results provide a more comprehensive representation of spatial variability and enable a probabilistic assessment of uncertainty.

The variance map obtained from the simulation highlights areas with higher variability and contributes to the evaluation of the reliability of the model.

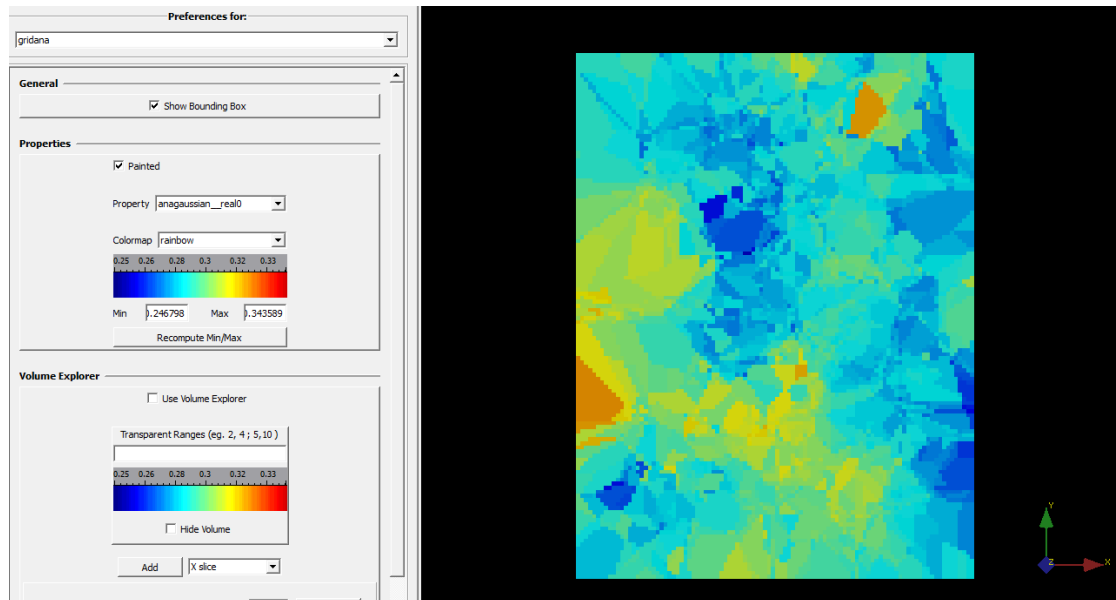


Figure 7: A realization of the sequential Gaussian simulation and the corresponding variance map

3.6 CO₂ Storage Modeling

For the reservoir defined by the contours of the study area derived from the geostatistical analysis ($2600 \times 2000 \times 270$ m) and using the porosity obtained from the geostatistical modeling, CO₂ storage simulations were performed for different injection well configurations. The simulations were carried out over a period of three years.

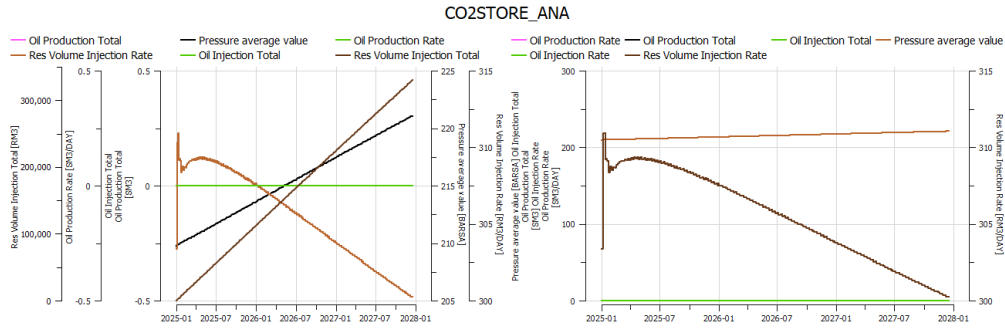


Figure 8: CO₂ storage simulation results

4. Discussion

The results of the statistical analysis indicate that the porosity data exhibit an approximately normal distribution, providing suitable conditions for the application of geostatistical methods and Gaussian simulation. The relatively low variance suggests a stable distribution of porosity values, although local heterogeneity remains present.

The experimental variogram and its fitting with a spherical model demonstrate the existence of a well-defined spatial correlation structure, confirming that porosity values are correlated within a certain range of influences. The derived variogram parameters form the basis for reliable porosity estimation using ordinary kriging.

The porosity map obtained from kriging highlights zones with higher storage potential and areas with lower values, reflecting the heterogeneous nature of the reservoir. The analysis of kriging variance shows that uncertainty increases with distance from the measurement points, emphasizing the importance of data density in improving the reliability of spatial estimation.

The results of the sequential Gaussian simulation provide a more comprehensive representation of spatial variability and enable a probabilistic assessment of uncertainty. This approach is particularly important for practical applications where risk evaluation and decision-making optimization are required.

The CO₂ storage modeling, based on the porosity distribution derived from the geostatistical analysis, demonstrates the potential of the reservoir for gas storage applications and contributes to the assessment of environmental and energy sustainability in the studied area.

5. Conclusions

In this study, a geostatistical analysis of porosity data for a defined reservoir was conducted, including histogram construction, experimental variogram modeling, fitting with a theoretical model, application of ordinary kriging, and sequential Gaussian simulation.

The results indicate that the data are suitable for geostatistical modeling and that the spatial correlation structure is stable and well-defined. Ordinary kriging enabled reliable porosity estimation and the generation of thematic maps, while kriging variance analysis and simulation provided valuable information on spatial uncertainty.

The CO₂ storage modeling showed that the studied reservoir has potential for practical gas storage applications, contributing to resource management and the reduction of environmental impact.

Future work may include the incorporation of additional data, more detailed anisotropy analysis, and the integration of other petrophysical parameters to improve modeling accuracy.

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