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Implications of statistical modelling of geological parameters in engineering applications

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Abstract

Geological modelling plays a critical role by improving subsurface characterization and supporting engineering decision-making. This study presents an integrated geostatistical modelling framework for spatial characterization of lithology, core recovery, rock quality designation (RQD) and percolation geoparameters at Bhama Askhed Irrigation Project site, Pune, India. Unlike conventional applications of geostatistical interpolation, the present work combines three-dimensional geological modelling, statistical validation, engineering performance assessment, and post-failure verification using Energy Dissipating Assembly (EDA) failure investigations by the Central Water and Power Research Station (CWPRS), Pune. Model performance was evaluated using correlation coefficient (R), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Ratio of Root Mean Square Error to Standard Deviation (RSR). The developed models exhibited satisfactory agreement between observed and predicted data with low residual errors and acceptable performance indices. Solid model residuals for the interpolated model are substantially less: 6.15, 8.29, 13.07 and -9.60 for lithology, recovery, RQD and percolation, respectively, thus indicating reasonable model fit. Statistical comparison of model-predicted parameters with the reserved data set also shows correlation coefficient greater than +0.70 indicates a strong uphill linear relationship between the observed and modelled data. The average correlation for lithology, core recovery, RQD and percolation was found to be 62.25%, 92.5%, 88.25% and 75.5%, respectively. The conducted tail channel erosion modelling can identify intensity of erosion-induced geological deterioration, enabling early recognition of vulnerable zones. The predicted weak zones showed consistency with field observations and post-failure investigations, highlighting the practical engineering applicability of the proposed framework. The study demonstrates that integrated geostatistical-geological modelling can, improve spatial prediction of geological parameters, produce missing spatial investigation data, support engineering design and risk assessment in infrastructure projects.

1. Introduction

Engineering geological models are requisite as per the Commission of the International Association for Engineering Geology and Environment (IAEG). These are the indispensable tools for engineering quality control and provide a reliable means of identifying critical geological issues [1]. Geological modelling can be synthesized, with either the knowledge-founded "Bulk Attribution

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Method" [1,2,3,4,5,6] or the algorithm-based "Geostatistical Approach" [7-11]. The observed geological parameters (geoparameters) can be compared with the model-predicted parametric values to assess the modelling validity [3, 4,12]. Elkadi A. S. et al. [3] have demonstrated the applications of 3D-Geo-Scientific Information Systems (3D-GSIS) for predicting subsurface geology for engineering substructures. The subsurface geology model was generated using a 3-D subsurface tunnel geometrical model, geostatistical modelling and a 3-D grid/block model. MacCormack K. E. [8], has presented the results of the three-dimensional subsurface model obtained from the borehole data. RockWorks was utilized for modelling and creating the bedrock topography and stratigraphy thematic sections. Wakeley L. D. et al. [13,14] have presented the work by the U.S. Army Engineer Research and Development Centre (ERDC) and Project Delivery Team (PDT) for the generation of 3-D geologic conceptual foundation and abutment substratum models for Mosul Dam. Digital and historic non-digital data were geo-referenced using a geographic information system (GIS). Kessler et al. [5] have demonstrated that geological modelling can give a detailed definition of sub-surface conditions. The 'bulk attribution' by GSI3D and 'geostatistical kriging' by Environmental Visualization System-EVS) were presented for 3-D geological volumetric modelling. The geostatistical approach provided an insight into the natural geological complexity through discretization and spatial interpolation of sample data values. Gallerini G. [15], presented a methodology for organizing, integrating and interpolating borehole geology and seismic profiles, resistivity and other geophysical data for developing a 3-D geological model. The modelling methodology was supported by GIS and geo statistics. Marache A. et al. [9] have presented the concept for generating a city-scale 3-D geotechnical model using boreholes and geotechnical test data. The Bayesian statistics of mechanical characteristics in the alluvial terraces and geostatistical kriging tools have helped in the improvement of the lithological and geotechnical information. Wycisk P. et al. [6] have discussed the conceptual process for generating the structural geological model. The 3-D modelling, using geostatistical interpolations and constructive cross-section-based interpolations, were compared to check their suitability for hydrogeological modelling requirements.

Sinan Akiska et al. [10], have discussed the application of 3-D modelling in the mining for the mineralogical, structural and geological elements in subsurface environments for the ore zone(s) detection. The study presents a 3-D modelling application for subsurface using available borehole data, using RockWorks software. Abdollahisharif J. et al. [16], have demonstrated a novel approach for rock mass characterization for the Khersan Dam area. Using the kriging interpolation technique, the RQD and lugeon/ percolation block models were generated for the diaphragm construction. The literature highlights the engineering geological models help in the identification of project-specific, critical geological parameters and associated conditions [17]. The geomodelling software can integrate a variety of subsoil investigation data into a geodatabase, using a data management system. Using geostatistical interpolation techniques, the geodatabase can be utilized for the synthesis of three three-dimensional (3-D) geological models. It helps in predicting the distribution of properties for the regions of sparse data and also analyzing and interpreting the geology [18].

Existing studies on three-dimensional geological modelling have predominantly focused on visualization of subsurface conditions, mineral resource estimation, groundwater investigations and geological interpretation. However, limited research has attempted to integrate geostatistical geological modelling with engineering validation, and post-failure investigations. Furthermore, the engineering applicability of such models in identifying vulnerable foundation zones with geological complexities and supporting remedial decisions has not been adequately demonstrated. The study demonstrates the holistic approach of integrating stage-wise acquired exploration data and its collective interpretation to overcome limitations in conventional method for the large projects. Reinterpretation of created models in context with post failures investigation presents the opportunity to revisit the modelling process, its feasibility, potential and modelling implications for future engineering projects. The present study extends conventional geological modelling by:

- Developing three-dimensional geological model's geoparameters for site characterization.
- Evaluating spatial continuity and variability through variogram analysis.
- Assessing model performance and reliability through geostatistical performance indicators.

- Examining sensitivity assessment of model performance to input data quantity and its spatial distribution, model resolution and selected algorithm.
- Validating model predictions through field observations and comparing model-derived vulnerable zones with documented EDA failure investigations.
- To demonstrate the engineering applicability of geomodelling by identifying erosion-driven changes in the tail channel, quantifying the associated loss of geological material, and evaluating their implications for long-term dam safety.

The novelty of the study lies not in the individual interpolation algorithms themselves but in the development of an integrated geological-engineering validation and application framework for dam foundation investigations.

2. Methodology

To check the feasibility of statistical modelling for various geological parameters, a case study of the Bhama Askhed irrigation project, Pune, India, is considered. The Bhama Askhed irrigation project ($18^{0}15'$N,$73^{0}43'$E) is located on the river Bhama, Pune, Maharashtra (India). It is a 51.125m high and 1425m long earthen dam with a 55.5m long ogee side spillway. Geology at the project site consists of fractured and sheet jointed compact basalt, and other unsuitable rocks, prone to weathering and disintegration. During 2005, uplift accompanied by the spillway discharge forces uplifted and displaced thirteen concrete panels (7m x 11m x 0.30m) of flip bucket Energy Dissipating Assembly (EDA). This failure portion indicated high seepage through the spillway foundation stratum, with a rate of 10-15 liter/s. The excessive seepage through the spillway foundation and associated uplift pressure have led to structural failure of the EDA [19].

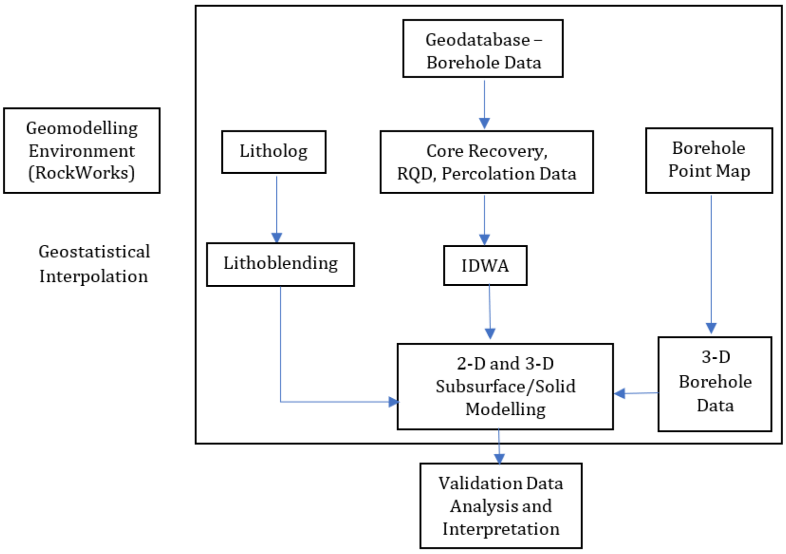


Fig. 1. Modelling process

The present study aims to check the implications of geostatistical modelling applications as a complementary tool to traditional geological understanding, for better site characterization and identification of geological complexities for the Bhama Askhed Irrigation Project, Pune, India. The present study is limited to statistical geo parameter modelling feasibility, process validation and its potential for dam site characterization to enhance spatial subsurface geological understanding. To achieve this objective, the included geomodelling methodological framework developed consists of following steps,

- Geodatabase generation - data evaluation, integration and standardization, through statistical pre-processing and variogram analysis - to control modelling quality
- Selection of an appropriate modelling algorithm and geomodelling using RockWorks software.

- Sensitivity analysis of modelling performance with input data quantity and its spatial distribution, model resolution and selected algorithm.
- Model validation using qualitative (optical correlation) and quantitative (statistical correlation) methods, using reserved independent borehole datasets.
- Model analysis, interpretation and check through engineering verification and applications using CWPRS post-failure observations.

Fig. 1 shows the process flow for modelling. The geological, geotechnical subsurface data was modelled in 3-D by interpolating the downhole interval data and point data into a solid model. In this study, solid modelling is implemented for geological parameters (geoparameters): lithology, core recovery, RQD (Rock Quality Designation), and percolation (Lugeon) values obtained from the field investigation data. The lithology indicates the suitable/unsuitable rock types at the project site. The core recovery indirectly indicates the physical condition of the rock. The RQD reveal the degree of jointing or rock mass fractures, whereas the Lugeon values measure the average hydraulic conductivity of rock masses. The estimation of the spatial variation of these geoparameters is done using generated geostatistical models. These geoparameters, along with the geological structure and site topography, play an important role in the selection of dam alignment, location of dam appurtenant structures, foundation and grouting depth, etc.

The concordance of the model-predicted data with the field data was checked using statistical parameters such as RMSE (Root Mean Square Error), Solid model residuals, Scatterplot correlation, etc. The statistical evaluation of the modelling results was also appended with the RSR (RMSE to Standard deviation Ratio) and the NSE (Nash-Sutcliffe Efficiency), as statistical measures for acceptable model performance. To assess the potential of statistical models to identify vulnerability in foundation substratum, the customized, thematic geomodels (Filtered Model) and Boolean models were prepared, using arithmetic operations to characterize the project site. The results of geomodelling were supplemented with EDA failure causes.

3. Statistical Data Assessment and Analysis

Prior to modelling, statistical data assessment were performed to evaluate data quality, variability and distribution characteristics. Parameters including mean, standard deviation, coefficient of variation and range were examined to ensure suitability of the data for spatial interpolation. The analysis confirmed that the geological parameters exhibited sufficient spatial variability for geomodelling applications while maintaining acceptable statistical consistency.

Table 1. Key histogram statistical parameters for observed data

Para-meter	Overall observed project data				Spillway and EDA Data			
	Mean	Standard Deviation	Std. Error	Coefficient of variation	Mean	Standard Deviation	Std. Error	Coefficient of variation
Lithology	7.842	4.827	0.261	0.616	7.038	4.840	0.541	0.688
Recovery	85.278	24.039	0.697	0.282	79.505	25.626	1.482	0.322
RQD	75.648	31.608	0.958	0.418	59.910	36.766	2.126	0.614
Percolation	1.456	3.7368	0.183	2.567	5.126	7.212	0.801	1.407

The project data was evaluated and analyzed to check its primary statistics such as histogram, variogram, standard deviation (SD), scattergrams, etc. However, for analysis of failure at the EDA section, more emphasis is given on analysis at the right dam abutment towards the spillway section. Table 1 shows the key histogram statistical parameters for the spillway and EDA data. The recovery and RQD% (quality rock mass) data at the spillway and EDS section show low mean values compared to the overall project; the Standard Deviation is quite high, indicating a wide spread of values above and below the mean value. The rock mass quality at the spillway and EDA section is poor compared to the overall quality at the project site. For recovery, RQD and percolation data show a high standard deviation. The comparatively high value for the coefficient of variation for percolation shows high dispersion. In addition, the values of the coefficient of variation for these parameters were also high compared to the overall project data, indicating a high degree of variation at the spillway section.

The variogram components indicate the data continuity, the degree of spatial autocorrelation and also help to characterize the geotechnical data. Variogram analysis captures the spatial relationships in the geological data and can reveal continuity, variability and directional anisotropy. The variogram model represents a generalized equation best fitting the observed data [20].

Table 2. Summary of variograms analysis for geoparameters

Variograms Status	Lithology	Recovery	RQD	Percolation
Optimal Variogram Model	Exponential With Nugget	Gaussian Without Nugget	Gaussian Without Nugget	Exponential With Nugget
Correlation Coefficient	1	0.99	1	0.99
Anisotropy Ratio	0.66	0.98	1	0.73
Nugget	0.003	0	0	0.86
Relative Sill	0.37	1.44	3.85	7.4
Major Axis Direction (degrees)	N138.4 0	N159.1 0.	N164.9 0.	N99.3 0.
Major Axis Range	82.5	20.84	20.93	38.91
Minor Axis Direction	N48.4 0.	N69.1 0.	N74.9 0.	N9.3 0.
Minor Axis Range	54.25	20.39	20.92	28.22

The method quantifies the similarity between data points with distance [20, 21]. The variogram provides the degree of spatial autocorrelation between the observed geological parameters and the model grid nodes [22]. The best-fit variogram model of observed Bhama Askhed data was created for the distance and directional relationships in the data. Table 2 presents the summary of variogram analysis for geoparameters. It indicates that lithology and percolation variograms show the best fit to the Exponential Models (representing an unpredictable, erratic dataset), which reach a sill asymptotically. Recovery and RQD variograms show best fit are the Gaussian Models (continuous phenomenon) characterized by parabolic behavior at the origin, then rising to sill values asymptotically. Statistically, a variogram with a low sill value shows lower variability of the data points [23]. Thus, geologically, a lower sill value indicates less variability within the data and also less variability of the corresponding geological subsurface. The lithology (0.37) had shown small sill values compared to recovery (1.44), RQD (3.85) and percolation (7.4). The overall variogram results highlight the variable nature of the geological formations with distances.

Although variogram analysis is generally associated with kriging-based geostatistical interpolation methods, in the present investigation it was primarily used to evaluate spatial continuity, anisotropy and correlation ranges of geological parameters. Variograms analysis in the present study was retained as a diagnostic tool to understand spatial structure and support model selection. Ordinary Kriging was examined during preliminary trials; however, because of limited data density in certain regions, irregular borehole spacing, local geological discontinuities and uncertainty in variogram fitting, the IDW-based interpolation generated more stable and geologically realistic predictions for engineering interpretation.

Scatterplot analysis represents the patterns in bivariate data. Scatterplots can show the mutual relationship between the geological parameters and the correlation among them. These statistical correlations can be used to approximately model/predict the non-data area for a specific geoparameter. The scatterplots also reveal data clusters, gaps, outliers and unusual features in data sets. Scatterplot analysis for site data indicates the following observations:

- Correlation between Recovery and RQD indicates a linear regression correlation coefficient = 0.86 strong uphill (positive) relationship.
- Correlation between Percolation (Lu) and RQD values indicates a linear regression correlation coefficient ≈ of 0.50, indicating a moderate downhill (negative) linear

relationship. This weak correlation may be the result of the unusual outlier values for Lugeon and RQD due to the jointed and fractured rocks and indicating non-uniformity of the region.

- Joints and Percolation relationship indicate a weak uphill (positive) linear relationship (correlation coefficient = 0.1< 0.30. indicating closed joints with increasing depth.
- Joints and RQD relationship show a weak correlation with correlation coefficient = 0.21< 0.30, indicating a weak downhill (negative) relationship which depends on joint spacing.

These scattergram correlations have also ascertained the mutual relationship between the geological parameters, similar to conventional understanding. Thus, indicating the correctness of data analysis.

4. Geomodelling

For modelling standard, UTM projection system, WGS-84 Datum, Zone- 43N was selected based on the site location. The survey stations and the coordinates of key locations such as Irrigation Cum Power Outlet (ICPO), spillway, available reference chainage marks established by the Irrigation Department on project site were used for georeferencing the site maps. The dam alignment and borehole data from available maps with chainage details were projected on a georeferenced base map to provide the required framework for spatial connectivity. The accuracy of georeferencing is verified with known on-ground benchmark locations. Table 3 shows different modelling combinations applied and the corresponding borehole data involved in the modelling.

The individual geomodels are prepared with data from the different stages of the site exploration and also with combinations of various data sets to check the effect of data quantity on modelling. However, for characterizing the geological setup of the site, Model IV, consisting of the entire available data, was used. The modelling combinations were performed with different modelling algorithms.

Table 3. Modelling combinations with number of borehole and extend of exploration

Geo-Modelling	Investigation phases	Alignment		Tail channel		Other U/s, D/s etc.	Total bore-holes (no.)	Total depth (m)
		MDL	Spill-way	Phase-I	Phase-II			
Model I	Bhama Askhed (BA), data - phase-1	15	2	--	--	13	30	611.51
Model II	Bhama Askhed, data - phase-2	18	3	3	--	--	24	634.02
Model III	Model I + Model II	33	5	3	--	13	54	1245.53
Model IV	Model III + (TL, COT, APPL, ICPO - phase-3)	33	5	3	23	24	88	1748.80

Abbreviations – Main Dam Line (MDL), Tail Channel (TL), Approach Channel (APPL), Irrigation cum Power Outlet (ICPO) Cut-off Trench (COT).

The extent of the solid model was selected to cover the study area along the dam alignment. The model node spacing, i.e., the node density of the interpolated model, represents the separation between nodes along each axis. X and Y spacing define the separation of the solid model nodes (horizontal resolution) in the selected map units (m). The model density needs to be optimized to represent the detail of the data being modelled. The selection of an appropriate density will ensure the proper data representation in the model without improper averaging out [24]. The required node resolution (density) for the model is selected by adjusting the spacing. The various 132 different combinations with the modelling data quantity and node spacing (5/5/1, 10/10/1 and 10/10/1.5) were compared based on RMSE values for selecting the literature suggested best-suited interpolation algorithm to give the optimum interpolation accuracy with the available data sets.

Table 4. Effect of model resolution, data quantity (Model I-IV) and algorithm on RMSE values

Parameter	Algori-thms	Model resolution (5/5/1)				Model resolution (10/10/1)				Model resolution (10/10/1.5)			
		Model				Model				Model			
		I	II	III	IV	I	II	III	IV	I	II	III	IV
Litho-logy	L.B.	4.2	4.1	4.4	4.4	4.3	4.2	4.3	4.2	2.5	3.4	3.4	3.2
	C.P.	4.1	4.2	4.2	4.1	4.1	4.2	4.2	4.1	2.8	3.3	3.2	3.2
Core Recovery	C.P.	17.6	9.4	13.7	13.4	17.1	9.4	13.4	13.4	14.8	11.8	13.2	13.6
	IDW-I	16.3	10.9	12.9	13.1	16.7	11.8	13.8	14.2	14.6	11.8	13.1	14
	IDW-A	16	9.6	12.6	12.6	15.8	9.7	12.9	13.1	14.4	11.8	13	13.6
RQD	C.P.	20.2	11.7	13.6	14.2	19.8	11.7	13.5	14.5	17.5	14.3	15	15.4
	IDW-I	19.2	12.9	13.8	14.7	19.6	13.5	14.3	15.6	17	13.6	14.5	15.8
	IDW-A	19	11.9	13	13.8	18.9	11.8	13	14.2	16.9	13.6	14.5	15.4
Percola-tion	C.P.	5.2	0.1	2.8	2.3	5	0.1	2.6	2.1	4.8	0.1	3.1	2.4
	IDW-I	4.7	0.1	2.5	2.1	3.3	0.1	2.2	1.8	3.2	0.1	2.7	2.2
	IDW-A	4.8	0.1	2.6	2.1	3.8	0.1	2.2	1.8	3.7	0.1	2.8	2.2

L.B. Lithoblending, C.P.-Closest Point, IDW-A- Inverse Distance Anisotropic Solid Modelling, IDW-I- Inverse Distance Isotropic Solid Modelling.

The sensitivity assessment undertaken by evaluating the influence of variations in model resolution, input data quantity/density and its spatial distribution and selected interpolation algorithm (Table 3,4) on model performance. The comparative analysis of models, demonstrated that model outputs are sensitive to;

- The model density i.e. node resolution or spacing affects modelling performance, however modelling resolution should be selected based on borehole spacing and sampling interval.
- The data distribution and density (Model I-IV): the lowest RMSE values were generally associated with datasets having more uniform spatial coverage. This observation indicates that data distribution exerts a greater influence on model reliability than merely increasing the number of boreholes.
- Selected interpolation algorithm: modelling performance measured as RMSE value sensitive to interpolation algorithm.

As a thumb rule, model X and Y-spacings are adjusted to half the average borehole spacing. Whereas the Z-spacing is adjusted close to the downhole sampling intervals. For Bhama Askhed, half of the average, the borehole spacing for the dam alignment is approximately 11.30m. Hence, the X and Y spacing was selected as 10m after optimization trials. The sampling interval in the Z-direction was selected as 1.5m based on logging and percolation test intervals. The optimum resolution with node density (x/y/z) of 10/10/1.5 is selected for final modelling. Table 5, shows the extent of the block Model for the project spanning the entire dam length.

Table 5. Dimensions and node spacing for 3D-block models

Extend	Minimum	Maximum	Spacing resolution	Nodes	Range (m)
X (Easting /Latitude)	365500	366300	10	81	800
Y (Northing/ Longitude)	2082600	2084100	10	151	1500
Z (Vertical/Depth)	560	680	1.5	88	120

The selection of an interpolation algorithm has the most influence on modelling complex models with limited data [8]. Hence, the geo parametric values were modelled with literature suggesting appropriate multiple algorithms and the best-fit models with the least RMSE, respecting the data type and the local geology, were adopted for final modelling.

4.1 Lithology Modelling Algorithm

The major rock observed in subsurface exploration at the dam site is compact basalt (81.5%), amygdaloidal basalt (15.6%), red tachylytic basalt and volcanic breccia (2.9%). Based on the weathering, infillings, hydrothermal alterations, and rock subtypes, these classes are further classified into finer subcategories for lithology modelling. All these types are uniquely identified and modelled.

Based on the literature findings, the Horizontal Lithoblending (LB) solid modelling algorithms and Closest Point (CP) solid modelling algorithms were preferred for the lithology modelling trial. Based on the accuracy of the estimated model (RMSE value) and capabilities to model the geological environment, the algorithms were selected for final modelling. LB solid modelling is the Nearest Neighbor algorithm with the search restricted to the horizontal XY plane surrounding the model node being calculated. This is the most recommended algorithm for the lithology modelling-based geological method [24]. The CP is another basic solid modelling algorithm for modelling lithology. For the CP algorithm, a voxel node value is equal to the value of the nearest data point, regardless of its distance from the point of the neighboring values. The CP algorithm produces the models with the least RMSE values for all three-trial resolutions except Model I (Table 6). For both CP and LB, the RMSE values gradually coincide with increasing data quantity. The CP gives a solid model with abrupt changes between nodes and material boundaries. In the LB method, the abruptness of "lithozones" around the borehole, ending abruptly with the zone from a neighboring borehole, can be minimized using random blending and the interpolation outliers' methodology [24]. Hence, for the realistic geological modelling output requirement, the Lithoblending algorithm was preferred with a little compromise with RMSE values achieved with the CP algorithm (Table 6).

4.2 Geological Parameters Modelling Algorithm

For geological site characterization, geological parameters, core recovery, RQD, and percolation from borehole data are modelled. For modelling these parameters, recommended algorithms from the literature are tried. The inverse distance weighted algorithm (IDW) estimates the unknown utilizing the distance and values to nearby known data points, with the assumption that each data point influences the resulting estimation up to a finite distance [25, 26]. The value of each of the data points is weighted according to the inverse of its distance from the voxel [27]. IDW is a versatile algorithm giving accurate results for wide-range scattered data in regular grids or irregularly spaced data [28, 29]. IDW suits both uniformly measured and densely distributed data points. It also preserves the local anomalies within the dataset. IDW is a local interpolator best suited for interpreting local anomalies as it uses only the proximal data points to produce estimates [22, 23].

Comparative study of literature suggested that the Closest Point (CP) algorithm, Inverse distance weighted (IDW) algorithms of isotropic and anisotropic are the most suited algorithms for modelling the geological parameters. However, the characteristics of geoparameters and the ability of the resulting model to geologically represent their spatial distribution have to be considered for selecting an appropriate algorithm. The bracketed element in Table 6. shows the selected modelling algorithm and their corresponding RMSE values.

Based on the interpretation from Table 6, The spatial distribution of data affects the output of the modelling algorithm. The Bhama Askhed data (Model-II- BA) is uniformly distributed over the left, middle and right abutment portions (0.4:0.2:0.4) with the highest average depth (26.42m) of boreholes. All three modelling algorithms, CP, IDWI and IDWA, have produced good output with the least RMSE values for core recovery, RQD and permeability for Model-II. All three modelling algorithms give high RMSE values for Model-I (Waki Data), though the data quantity (30 Boreholes) was higher than BA-data (24 Boreholes). However, the effect of data quantity on RMSE values is variable for each modelling algorithm. The Model-III gives reasonably fair RMSE results with all the modelling algorithms. However not selected for final modelling, as it does not include the tail channel and EDA data specifically required for the tail channel erosion study at Bhama Askhed. Hence, Model-IV (Model-III+ TL/COT-APPL-ICPO Data) was selected for final comprehensive modelling. The IDWA algorithm produces the models with the least RMSE for all three trial resolutions.

Table 6. Effect of interpolation algorithm, data quantity on RMSE values (10/10/1.5)

3D Solid Model	Algorithms	Model I	Model II	Model III	Model IV
Lithology	(H. Lithoblending)	2.49328	3.417	3.35996	(3.24771)
	Closest Point	2.78116	3.33866	3.20613	3.16986
Core Recovery	Closest Point	14.823	11.7945	13.17709	13.60661
	IDW-Isotropic	14.63824	11.80505	13.08026	13.95198
	(IDW-Anisotropic	14.35111	11.78992	12.96819	(13.59203)
RQD	Closest Point	17.51958	14.26384	14.97368	15.37547
	IDW-Isotropic	17.03725	13.63759	14.49818	15.83771
	(IDW-Anisotropic	16.94843	13.64143	14.49865	(15.37537)
Percolation	Closest Point	4.81732	0.1082	3.09146	2.43669
	IDW-Isotropic	3.19116	0.11179	2.70173	2.20826
	(IDW-Anisotropic)	3.66986	0.10928	2.76053	(2.23979)

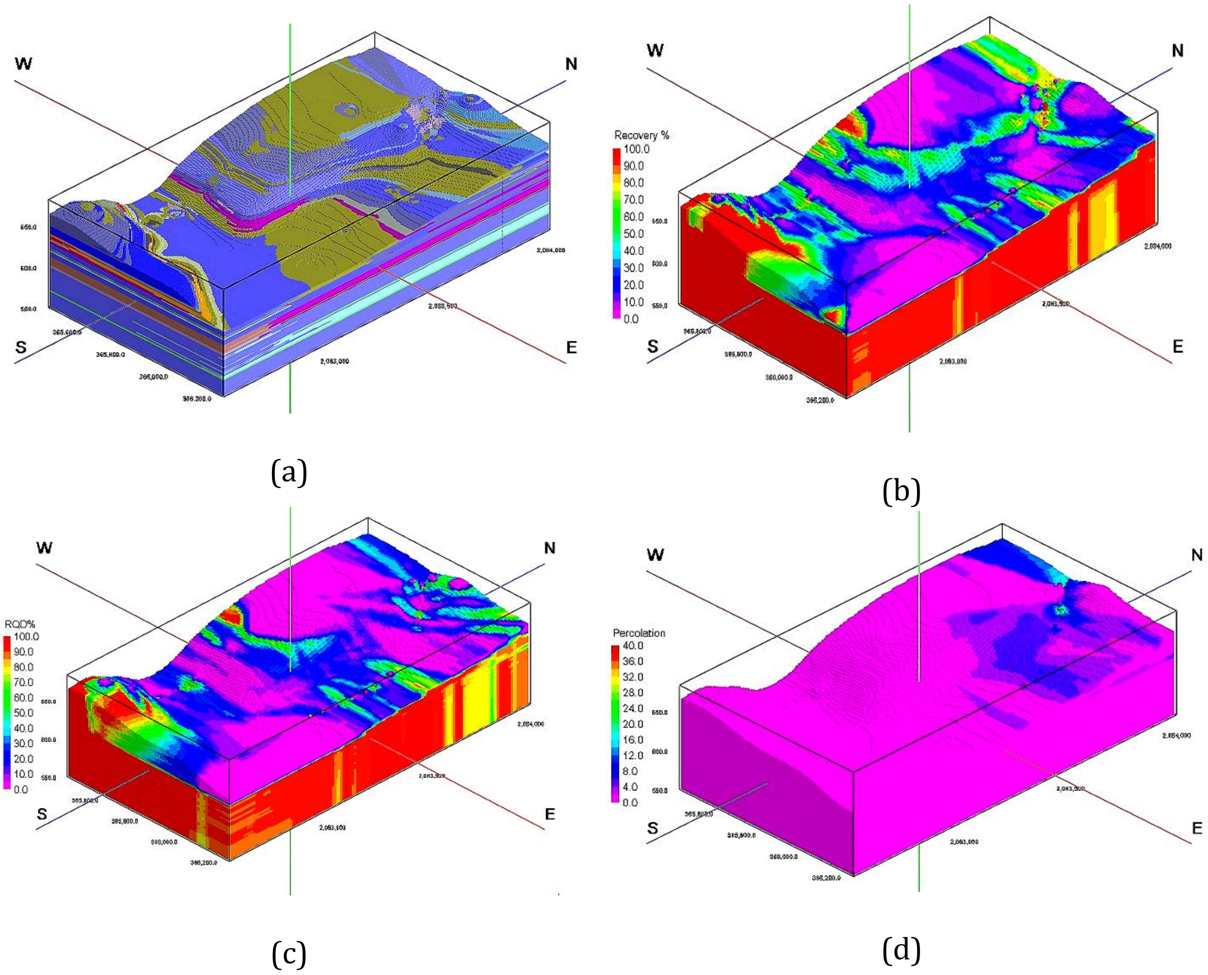


Fig. 2. (a) Lithology 3-D Block Model (3x vertical exaggeration), (b) Recovery 3-D Block Model (3x vertical exaggeration), (c) RQD 3-D Block Model(3x vertical exaggeration), and (d) Percolation 3-D Block Model (3x vertical exaggeration)

For the Bhama Askhed project site trial modelling, the neighbouring points were filtered by assigning node values. The equal horizontal and vertical weighting exponent (2) was used for both IDWI and IDWA to avoid weighting function ambiguity. Thus, data points are weighted according to the inverse of the square of their distance from the node in both directions. The equal weighting exponent value was selected to avoid directional bias in the absence of a detailed investigation. The directional search in the method improves the interpolation of values lying between data point clusters and is also suitable for modelling drill-hole data within anisotropic geologic settings.

For the Bhama Askhed project, consulting firms collected the geological data during different phases (Phase-1,2,3). The limited data-based model with the least RMSE may not represent the true geological conditions of the field. Thus, for representative geological characterization of the project site, the integrated diverse data from all the agencies (Model IV) have been used for comprehensive modelling [4, 6, 8, 11, 15]. The solid modelling, especially Recovery and RQD modelling, gives higher RMSE values. There is no absolute good or bad RMSE threshold, as it is defined based on dependent variables. The high RMSE can be due to the presence of a small number of high error predictions (outliers). (The range of values is 0-100 for both recovery and RQD, whereas for percolation it is 0-56.27). The model with a comparatively smaller RMSE can be chosen as the better modelling option. For modelling the geological parameters inverse distance weighted anisotropic algorithm was selected for modelling geoparameters with the additional advantage of reducing "bull's eyes" around the sampling point with localized highs, over the Inverse-Distance Isotropic method.

Permeability Modelling, the modelled Lugeon test data from 67 exploratory boreholes/drill holes (DH) (BA Data-38 DH, Waki-29 DH) were used to study the permeability variation of the rock masses of the dam site. Fractured-rock permeability is anisotropic, as the fracture orientations govern the variation in both vertical and horizontal permeability. Hence, the changes in permeability were evaluated using the Inverse distance weighted (anisotropic) algorithm that uses statistics to predict and simulate the geostatistical laws. High Fidelity was applied so that the node values would better honor the control points [24, 27]. Figs. 2(a), (b), (c), and (d) show the lithology, recovery, RQD and percolation 3-D block models, respectively, for the project area with the base extrapolated up to the modelling depth.

Thus, in addition to statistical performance as RMSE comparison, geological realism was considered during algorithm selection. The modelling algorithm was selected based on its capability to honor borehole control points while maintaining geological continuity. The resulting models generated should be consistent with observed geological continuity maintaining acceptable prediction accuracy.

5. Geomodelling Validity

Verification of the accuracy of 3-D geological modelling is difficult, as it needs additional drilling for validation. However, the geomodelling validity can be checked through qualitative and quantitative methods [30]. For the study area, the accuracy of the modelling was quantified using the statistical correlation between actual and interpolated data and qualitative optical correlation.

Algorithm Reliability Assessment was checked through Model Performance Indicator. The adopted modelling algorithms were evaluated through cross-validation and residual analysis. Model performance was further assessed using RMSE, NSE and RSR statistics to ensure that interpolation uncertainties remained within acceptable engineering limits. These performance indicators were selected because RMSE quantifies prediction error, RSR standardizes RMSE relative to data variability, and NSE evaluates the predictive capability of the model relative to the observed variance. Model performance was evaluated using four statistical indicators:

- $RMSE = \sqrt{[\Sigma(O-P)^2/n]}$
  where O = observed values, and P = predicted values, n = total number of observations
- $NSE = 1 - [\Sigma(O-P)^2 / \Sigma(O-\bar{O})^2]$
  where $\bar{O}$ = mean observed value
- Ratio of RMSE to Standard Deviation (RSR): $RSR = RMSE / SD_{(observed)}$
- Solid model residuals = (Observed Value) – (Predicted Value)
- Correlation Coefficient (R): $R = Cov(O, P)/(\sigma_O.\sigma_P)$
  Where: Cov(O, P) = covariance between observed and predicted values, σ_o = standard deviation of observed values σ_p = standard deviation of predicted values

5.1 Statistical Correlation between Actual and Estimated Data.

Models were validated by examining the concordance of statistical parameters of the field data (observed investigation data) and the model-predicted (estimated) data with the following statistical tools,

- Comparison of statistical parameters for observed & predicted data.
- Solid model residuals
- Scatterplot correlation.
- Correlation of model-predicted data with reserved borehole data
- RMSE check as a measure of model performance

5.1.1 Comparison of Statistical Parameters

The Comparison of statistical parameters for observed & predicted data is done through frequency histograms statistics. This histogram comparison helps in model validation by checking the concordance between the interpolated results and field data [27]. The comparison of actual and predicted values of geoparameters obtained for frequency histograms is presented in Table 7.

Table 7. Frequency histograms results for observed and predicted parametric values

Parameter		Mean	Standard Deviation	Standard Error	Coefficient of variation
Lithology	Observed	7.84191	4.82722	0.26141	0.61557
	Predicted	8.07123	4.27037	0.24948	0.52909
Recovery	Observed	85.2782	24.03950	0.69680	0.28180
	Predicted	85.83999	20.06845	0.59939	0.23379
RQD	Observed	75.64790	31.60800	0.95820	0.41780
	Predicted	74.52439	28.30510	0.88453	0.37981
Percolation	Observed	1.45570	3.73677	0.18255	2.56698
	Predicted	1.69903	4.01413	0.19681	2.36260

The mean, standard error and coefficient of variation for estimated geotechnical parameters predicted through the model are almost comparable with the observed data. The standard deviation (SD) values for estimated geotechnical parameters are less than those for observed data. This indicates that the respective modelling algorithms used are proper estimators, resulting in the reasonable accuracy of estimation. Also, the lower coefficient of variation suggests more model stability and less variation between observed and predicted data.

5.1.2 Solid Model Residuals

The actual field locations XYZ (latitude, longitude and altitude) for the selected borehole were used to get the details of modelled values at the same points to calculate the difference between observed and modelled values. Solid model residuals, i.e., the difference between source data grade values (G values) and calculated grade values for the interpolated solid model, were compared.

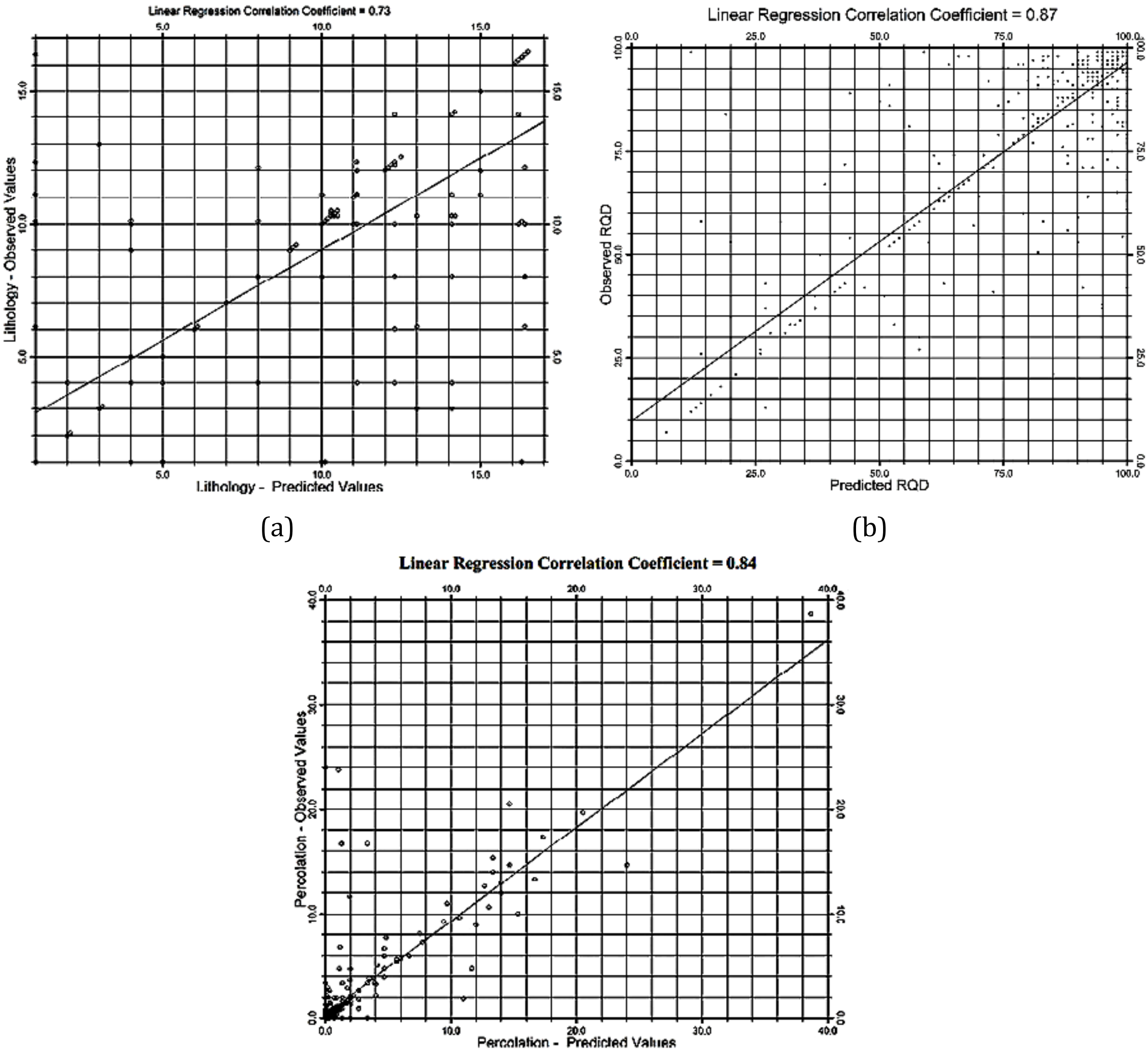
Table 8. Statistical characteristics of solid model residuals

Parameter	Mean	Standard Deviation	Standard Error	Coefficient of variation
Lithology Residual	0.52765	3.24771	0.18973	6.15511
Recovery% Residual	1.63819	13.59203	0.40596	8.29696
RQD% Residual	1.17619	15.37537	0.58448	13.07214
Percolation Residual	-0.23307	2.23979	0.10981	-9.60988

Table 8 shows the statistical parameters for solid model residuals representing the model's accuracy. Solid model residuals for the interpolated model are quite less 6.15, 8.29, 13.07 and -9.60 for lithology, recovery, RQD and percolation, respectively, indicating a reasonable model fit.

5.1.3 Scatterplot Correlation for Observed and Estimated Data

For perfect forecasting, the estimation errors should be symmetrically distributed, and linear regression of exact values on estimated values should be close to a 45° line [31]. A scatter diagram for observed versus computed node values was compared to compute the correlation coefficient. The following Figs. 3(a), 3(b), and 3(c) show the correlation scattergrams for lithology, RQD and percolation, respectively. Correlation scattergrams indicate a good correlation between original (Observed) data and predicted values. It is 73% for lithology, 87% for RQD, and 84% for percolation. The model predicted and observed values are in close agreement, and the prediction error indicates satisfactory interpolation results.



(a) (b)

(c)

Fig. 3. (a) Lithology Correlation Scattergrams, (b) RQD Correlation Scattergrams, and (c) Percolation Correlation Scattergrams

5.1.4 Correlation of Model-Predicted Data with Reserved Boreholes Data

The reserved boreholes not processed in modelling and the modelled geologic data at that location could be correlated for modelling validity [13,14]. Out of the randomly selected deepest boreholes of the region, four boreholes were excluded from the modelling process. The XYZ locations of these reserved boreholes and their respective data intervals same as observed in core logs, were used to get the modelled values exactly at that point using the models. The extracted data is then compared with the observed core log data to check the validity of the model and its ability to produce the data for the non-data area. Table 9 Summary of correlation between the modelled data and reserved borehole data (DH-105, DH-108, DH-I(3), DH-TL 14) not processed in modelling.

The Correlation Coefficient greater than +0.70 indicates a strong uphill (positive) linear relationship between the observed and modelled data. The average correlation for recovery, RQD and percolation is 92.5%, 88.25% and 75.5%, respectively, which shows good validity. While for lithology it is 62.25%, indicating a weak correlation, this may be because of their specific topographical location of (Boreholes DH-105 and DH-108) in the V-shaped river gorge. For the rest of the other randomly selected deepest boreholes, the modelled data shows good validity.

Table 9. Correlation between the modelled and reserved borehole data

Borehole	Statistical Parameter	Lithology	Recovery%	RQD%	Percolation
DH-105	Correlation Coefficient	0.330	0.90	0.94	0.75
	RMSE	5.769	7.600	6.470	0.091
DH-108	Correlation Coefficient	0.40	0.90	0.85	0.44
	RMSE	5.019	8.546	12.060	0.076
DH-I (3)	Correlation Coefficient	0.76	0.96	0.8	0.97
	RMSE	3.750	5.661	13.152	0.359
DH-TL (14)	Correlation Coefficient	1.0	0.94	0.94	0.86
	RMSE	--	8.929	8.739	1.205
Average percentage correlation		62.25	92.5	88.25	75.5

The average correlation obtained for lithology, recovery, RQD and percolation was 62.25%, 92.5%, 88.25% and 75.5%, respectively. According to commonly accepted interpretation criteria (>0.90 Very Strong, 0.70–0.90 Strong, 0.50–0.70 Moderate, <0.50 Weak) lithology exhibits a moderate positive correlation, while recovery, RQD and percolation demonstrate strong positive correlations. The relatively lower lithology correlation (Moderate agreement") is attributed to complex lithological transitions and the topographic constraints associated with the V-shaped river gorge.

5.1.5 Root Mean Square Error (RMSE) As A Measure of Model Performance

In geosciences, RMSE is a standard statistical system of measurement to verify the model's performance. [32]. As shown in Table 9, the percolation model gives the most precise model with RMSE values close to zero, while lithology, recovery and RQD modelling give mostly single-digit but higher RMSE values compared to the percolation model. The high RMSE can be due to the small number of high error predictions, i.e., outliers of residuals [24]. Consequently, RMSE is sensitive to an extreme deviation from the mean, i.e., outlier values [33, 34].

A statistical evaluation of the modelling results was appended with the RSR, i.e., RMSE to observations Standard deviation Ratio, and the NSE (Nash-Sutcliffe Efficiency), statistical measures. Singh et al. [35] suggested RSR for standardizing model RMSE. An RSR value closer to 0.5 or less than 0.5 is an acceptable indicator of low RMSE, indicating a good model simulation. NSE determines the relative magnitude of the residual variance compared to the observed data variance. NSE values between zero (0) and one (1) are acceptable levels of model performance [36, 37, 38]. For all the modelled geoparameters RSR value is around 0.5, also NSE is between 0 to 1, indicating a dependable model simulation. Table 10 indicates performance summary containing Correlation (R), RMSE, NSE and RSR values for Lithology, Recovery, RQD and Percolation. The combined statistical indicators demonstrate satisfactory predictive capability of the developed models

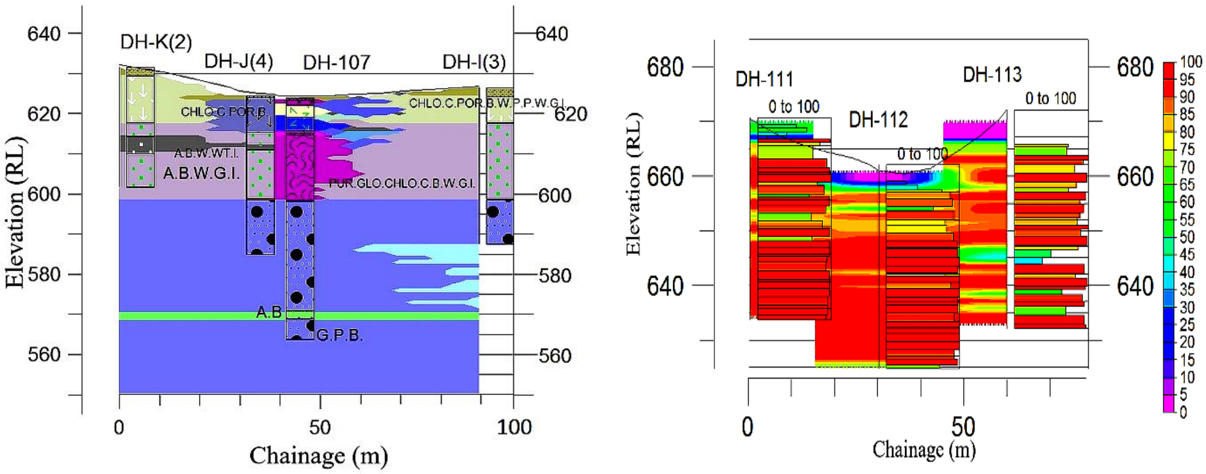
Table 10. Performance summary for generated geomodels

Parameter	RMSE	RSR	NSE
Lithology	3.24771	0.67	0.55
Recovery%	13.5920	0.57	0.68
RQD% Residual	15.37537	0.49	0.76
Percolation	2.23979	0.60	0.64

5.2 Optical Correlation Between the Borehole Data and Modelled Cross-Section

The cross-section obtained from the geomodel can be compared with the conventional (expert) cross-section generated using the same input data [39]. The thematic 3-D model cross-sections were compared with actual borehole log data to visually correlate them. Fig. 4(b) shows that the RQD% cross-sections match substantially with the respective model cross-section. The modelled values depict considerably well qualitative optical correlation well with similar value trends to the observed borehole data. Fig. 4(a) shows the optical correlation for the deepest boreholes (DH-107) lithology and block model lithology with cross-section between DH-K (2) and DH-I (3).

The slight deviations in optical correlations for both lithology and RQD are primarily due to the participation of adjoining borehole data in the modelling process. The statistical interpolation process includes the data from adjoining boreholes, giving a more comprehensive model as compared to the traditional cross-section between the boreholes (expert cross-section). For a conventional geological cross-section, it's very tedious to consider the effect of adjoining data sets. Overall, optical correlation concludes that the models predict the anticipated geology and also respect observed project data to a significant extent. The visual agreement between borehole logs and model-generated cross-sections indicates that the interpolation procedures preserve both geological continuity and local heterogeneity. This optical validation complements the statistical validation and provides confidence in the engineering applicability of the developed geomodels.



(a) (b)

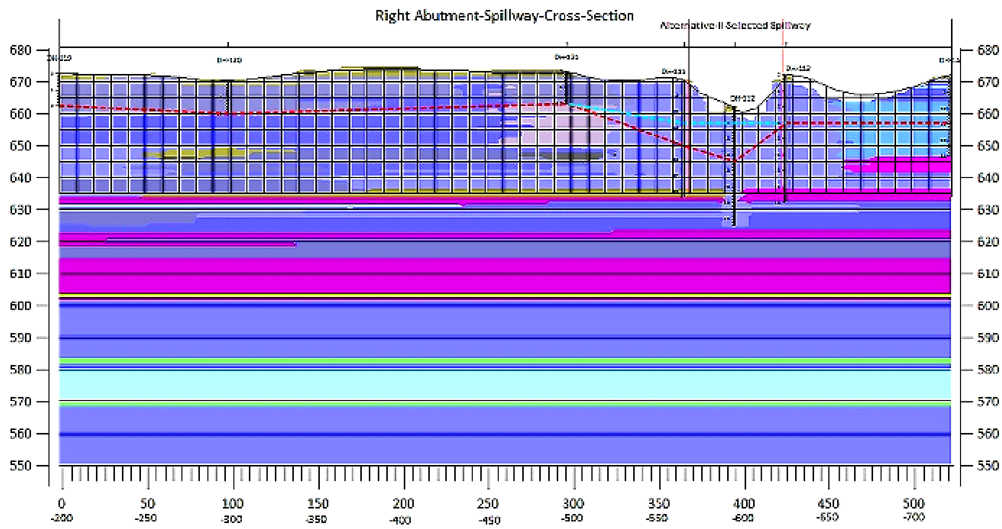
Fig. 4. (a) Optical correlation between the borehole lithology and the lithology model cross-section between DH-K (2) and DH-I (3), (b). Optical correlation between the expert and modelled cross-section for RQD along the spillway section

6. Geomodelling Analysis

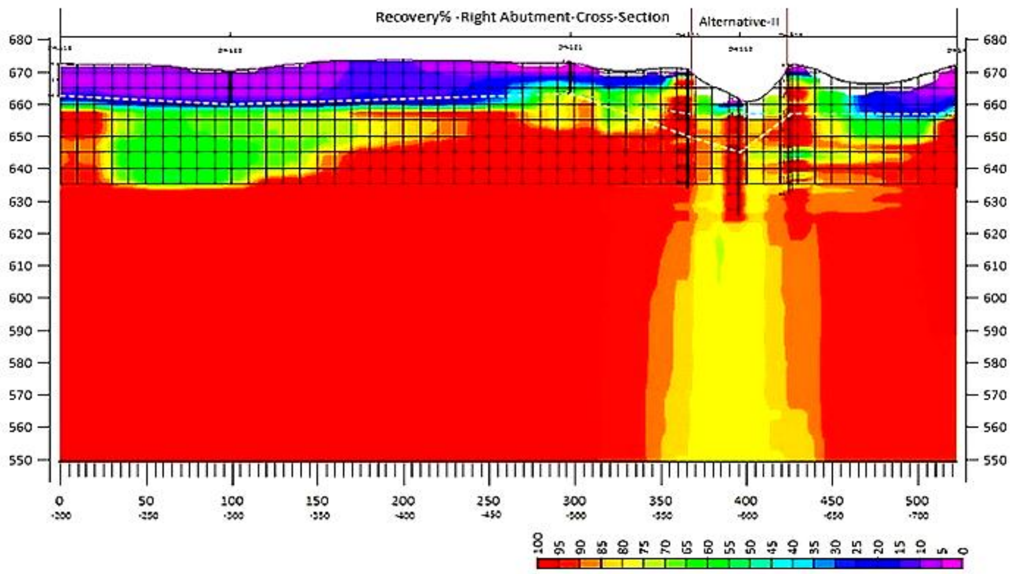
User defined cross sections, thematic- filtered and Boolean models were developed and analyzed along the area of interest from the generated 3D geomodels. Figs. 5(a), 5(b), 5(c) and 5(d) show the spatial distribution of geoparameters viz. lithology recovery, percolation and fracture zone along the selected sections (MDL/Tail Channel). The model analysis can reveal the geological scenario of the substratum, with location and lateral extent of unfavorable lithology (Lithology Model), rock status (Recovery and RQD Model), and permeable zones (Percolation Model). The spatial locations of these unfavorable geoparameters can be expressed as chainage (CH) and elevations (RL) along the required section. These cross sections along the desired investigation direction will be helpful for important foundation decisions such as foundation depth, COT depth, grouting depth, etc. Right abutment end is with spillway at Ch. 565 to -625m. The identified critical areas of right abutment are marked with the presence of unfavorable geoparameters and problematic lithology.

Table 11. Variation of geoparameters along the right abutment.

<table>
<tr><th rowspan="2">Location</th><th rowspan="2">Geo-parameter</th><th rowspan="2">Values</th><th rowspan="2">Chainage (m)</th><th rowspan="2">Elevation (m)</th><th colspan="2">Grouting RL(m)</th></tr>
<tr><th>Selected</th><th>proposed</th></tr>
<tr><td rowspan="6">Right Abutment (CH. -200 to -720m) Spillway</td><td>Recovery</td><td>55-70%</td><td>-600 to -700</td><td>645</td><td>655</td><td>645</td></tr>
<tr><td rowspan="2">RQD</td><td>35-45%</td><td>-570 to -625</td><td>620</td><td rowspan="3">640</td><td rowspan="3">620</td></tr>
<tr><td>35-45%</td><td>-625 to -720</td><td>635</td></tr>
<tr><td rowspan="2">Fracture</td><td rowspan="2">Fracture zone</td><td>-595</td><td>625</td></tr>
<tr><td>-570</td><td>648</td><td>640</td><td>645</td></tr>
<tr><td>Percolation</td><td>2.5 to 3.5 Lu</td><td>-560 to -710</td><td>600</td><td>640</td><td>620</td></tr>
</table>



(a)



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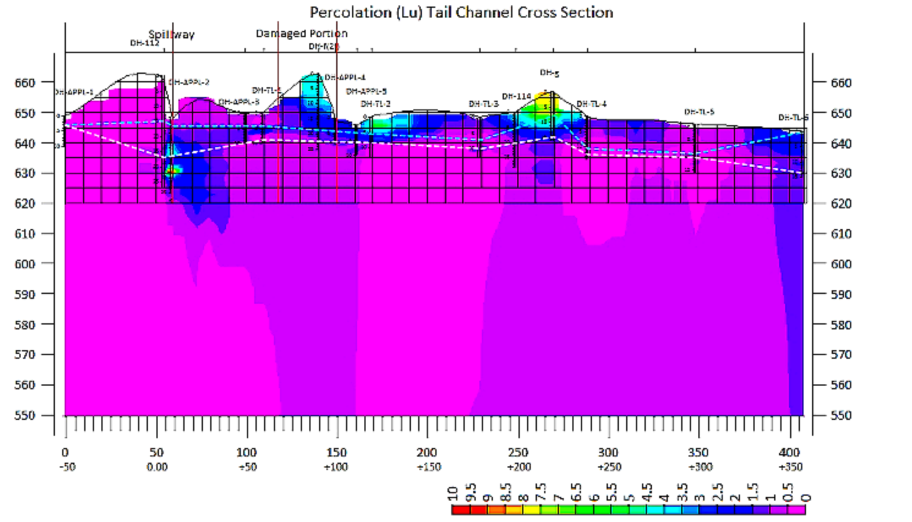

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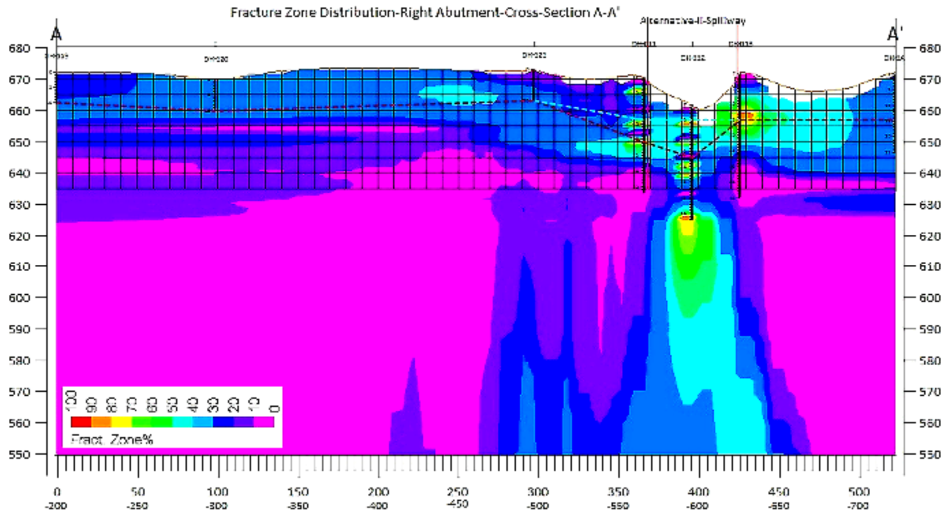


(d)

Fig. 5. (a) Modelled lithology cross-section for right abutment (legend same as Fig.4a, 6), (b) Modelled recovery cross-section along right abutment, (c) Modelled percolation cross section along the tail channel, and (d) Modelled fracture zone cross section along the right abutment

Table 11. Shows variation of these geoparameters along the right abutment. The area has low Recovery (55-70%), RQD (35-45%), and Percolation (>3Lu). It is also marked with two critical fracture zones below the executed grouting zone. To assess the potential of statistical geomodels to identify venerability in foundation substratum the customized Thematic Geomodel (Filtered Model) and Boolean Models were prepared from a solid geomodel using arithmetic operations. The Boolean models constrained with permissible geo parametric limits have helped to identify the spatial distribution of a combination of unfavorable geological properties. Using the overlapping Boolean model, the specific areas of concern marked by limiting values of geoparameters were identified. The results of geomodelling were used for site characterization and the analysis of EDA failure causes.

6.1 Thematic Geomodel

The respective solid geomodels were filtered for a specific required query based on parameter grade (G) values. The application was to segregate the occurrence of specific unfavorable or favorable lithology/recovery/RQD or percolation required to be considered critically during engineering applications.

The spatial occurrence of potential problematic rocks for engineering applications was analysed using generated thematic lithology models. Fig. 6 represents the lithology model filtered out to display the spatial extent of unfavorable lithology. From this model, lithology types, their spatial distribution, top surface elevations and the thicknesses can be identified. The location of unfavorable lithology concerning the existing foundation and grouting levels, along the dam alignment, can be checked to verify the adequacy of the executed dam foundation. At the spillway location, there are isolated pockets of unfavorable lithology, which can be secured with effective grouting. The exposed EDA failure portion pointed out the presence of weathered hydrothermally altered volcanic breccia and jointed basalt. The geomodel study also confirms the occurrence of unsuitable material immediately below the grouted levels at the spillway and tail channel section. Table 12 represents the details of unfavorable lithology in the approach, spillway and tail channel section identified based on the generated lithology thematic geomodel.

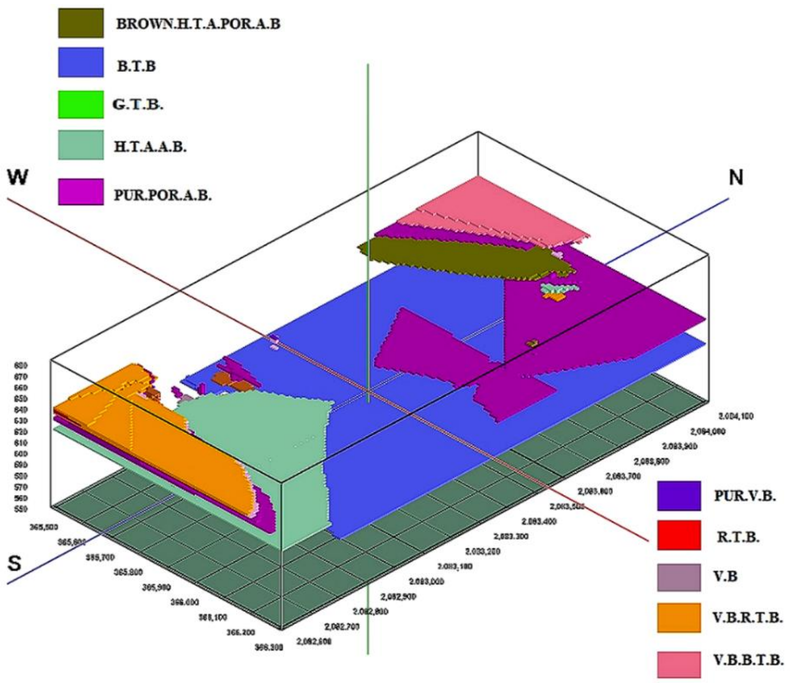


Fig. 6. Spatial extent of unfavourable lithology type

BROWN. H.T.A.POR.A.B.	*Brown Hydrothermally Altered Porphyritic Amygdaloidal Basalt*
B.T.B.	*Black Tachylytic Basalt / Black Tachylyte*
G.T.B.	*Green Tachylytic Basalt / Green Tachylyte*
H.T.A.A.B.	*Hydrothermally Altered Amygdaloidal Basalt*
PUR.POR. A.B.	*Purple, porphyritic Amygdaloidal Basalt*
PUR.V.B.	*Purple Volcanic Breccia*
R.T.B.	*Red Tachylytic Basalt*
V.B.R.T.B.	*Volcanic Breccia with Red Tachylytic Basalt.*
V.B.B.T.B.	*Volcanic Breccia with Black Tachylytic Basalt.*

Table 12. Unfavorable lithology in the Approach, Spillway and Tail Channel Section

Geologically unsuitable Lithology	Elevation (m)	Chainage (m)	Thickness (m)	Location
V.B.R.T.B.	645m	-10m to -50m	3m	Approach Channel
	640 to 645m	+210 to +220	1.5m	EDA
	640m to 645m	+50 to +70m	1.5m	Damaged EDA
	635m to 640m	+120 to +130	1.5m	EDA
BROWN. H.T.A.POR.A.B.	635m	00 to +110m	3m	EDA
	635m	-350 to -610m	2.5m	Spillway
Weathered Compact Porphyritic Basalt.	630m	+110 to +320m	1m to 9m	Tail Channel
	630m	-365 to -435m	1.5m	Spillway
Pink Volcanic Breccia.	635	-600 to -700	1.5m	Spillway

6.2 Boolean Models

The input geomodels having the same model dimensions and node spacing and with specific grade values (G-values) at the corresponding nodes can be arithmetically operated (added/ subtracted/ multiplied or divided) to create new output Boolean models to check the required combined geo parametric conditions. Boolean models can be used to obtain focus area for engineering considerations, with desirable or undesirable characteristics. For determining intersecting area(s) with a specific characteristic, Boolean models were established with the help of arithmetic operations on thematic geomodels. The solid models were converted to a Boolean (true/false) - type solid model. For this modelling, the threshold (limiting) values of the respective recovery, RQD and percolation were assigned to each solid model as grade value limits (G-values). These solid models were arithmetically operated to get the desired Boolean Models for enhanced geological understanding and detailed geological modelling analysis.

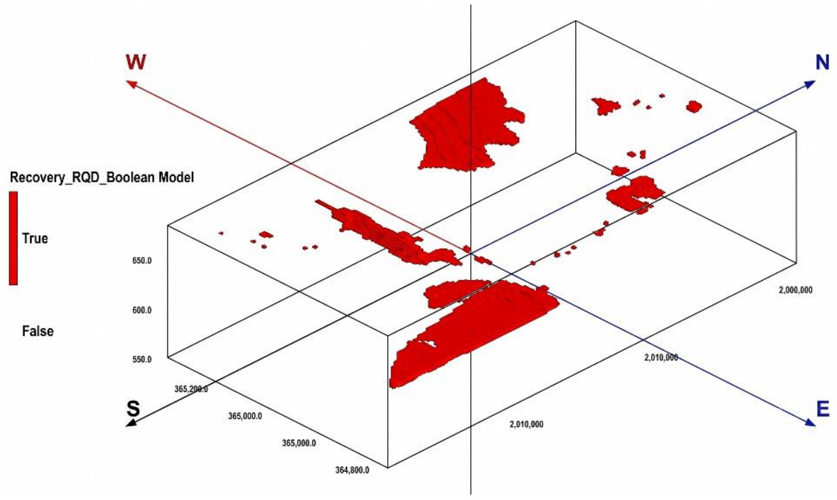
- Recovery Boolean with recovery < 50%, RQD Boolean with RQD< 50%. Similarly, the percolation Boolean model (value of "1" for Lu>3, value of "0" below 3Lu) was created.
- Combined Recovery _RQD_Boolean Model: Core Recovery alone is not the best indicator of core quality; hence, another parameter of RQD for rock mass is also considered. (Recovery Boolean with recovery < 50% poor rock) x (RQD Boolean with RQD< 50% partial recovery) = Recovery _RQD_Boolean Model. The resulting model will fulfil the required limits set for both RQD and Recovery values < 50%, Fig. 7(b).
- Similarly, other required models, such as Combined RQD_Lithology Boolean Models (unfavourable RQD and lithology type), can also be created
- Combined Recovery_RQD_Percolation_Boolean Models: The multiplication operation was applied for the generated Boolean model (RQD_Recovery_boolean.mod) and the percolation_boolean.mod. To get the required Recovery_ RQD_Percolation_Boolean Model. The value "1" indicates unfavourable levels above the cut-off grade for recovery, RQD and percolation. The "0" values indicate suitable levels.
- The Percolation_ Boolean model shows considerable area at the right abutment in the tail channel having percolation greater than 3Lu. These areas lying close to existing grout cut-off levels required grouting to be performed to reduce the seepage velocity, seepage losses, and subsequent erosion. The combined Recovery _ RQD_Percolation_Boolean Model, however, shows very little volume falling under the combined limit of recovery, RQD and percolation. Fig. 7(b) indicates there was a small area with low recovery and RQD values, which have open joints leading to high percolation values.
- Boolean models for subsurface fracture zones: The interval database (I-Data) was created for "Fracture Zones " from bore hole fracture data and entered values of "1" for downhole intervals with fracture zones and values of "0" for intact intervals.
- Combine model for low RQD, Fracture zone and Percolation Boolean Models: Low RQD, fracture zones and high percolation values were overlapped to identify the potential weaker section that required grouting.
- The Fracture Zone_ Percolation _Boolean Model: (Fracture Zone) x (Percolation _boolean.mod) = Fracture Zone_ Percolation _Boolean Model. Fig. 9(a) shows the area at the right abutment near the spillway section and in the tail channel with overlapping fracture zones and high percolation areas. These are the areas which require grouting to be performed.
- Combined Fractured loss zone_Boolean Model: Fig. 8 represents the schematic representation of the arithmetic operation involved in the process for creating this model. (Fracture Zone_ Percolation _Boolean Model) x (RQD Boolean G-less than 50%) = Fractured_water loss zone_Boolean Model

The solid model volumetrics and identified grouting depth can suggest the quantum of treatment required. Volumetric analysis of Boolean models is represented in Table 13. Water loss (I-Data-interval) data obtained from borehole drilling is also used for creating a model. The Fractured_water loss zone_Boolean Model encircled area at right abutment near spillway section and in tail channel is with overlapping fracture zones, high percolation greater than 3Lu and low

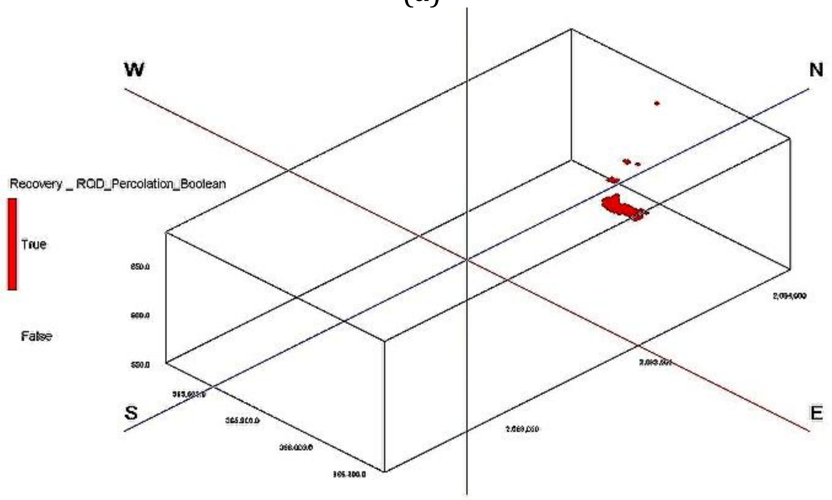
RQD areas. This spillway area (solid model volume = 750 m^3) has the highest possibility of water loss, which needs to be treated by grouting. The analysis from geomodels identifies the weaker problematic lithology (Fig. 6), low recovery_ low RQD values (Fig. 7b), a fracture zone with high percolation values (> 3Lu) coupled with water loss zones (Fig. 9a) and a Fractured zone with water loss (Fig. 9b).

Table 13. Boolean Model Volume Details

Model	Volume m^3	Remark
Recovery _RQD _Boolean Model	717150	Recovery & RQD less than 50%
Recovery_RQD_Percolation _Boolean Model	14100	Recovery & RQD lesser than 50% with Percolation greater than 3Lu
Fractured_water loss zone _Boolean Model	750	Fracture zones with Recovery & RQD lesser than 50% with Percolation greater than 3Lu



(a)



(b)

Fig. 7(a). Recovery_ Boolean Model ND (b). Recovery_ RQD_Percolation_ Boolean Model

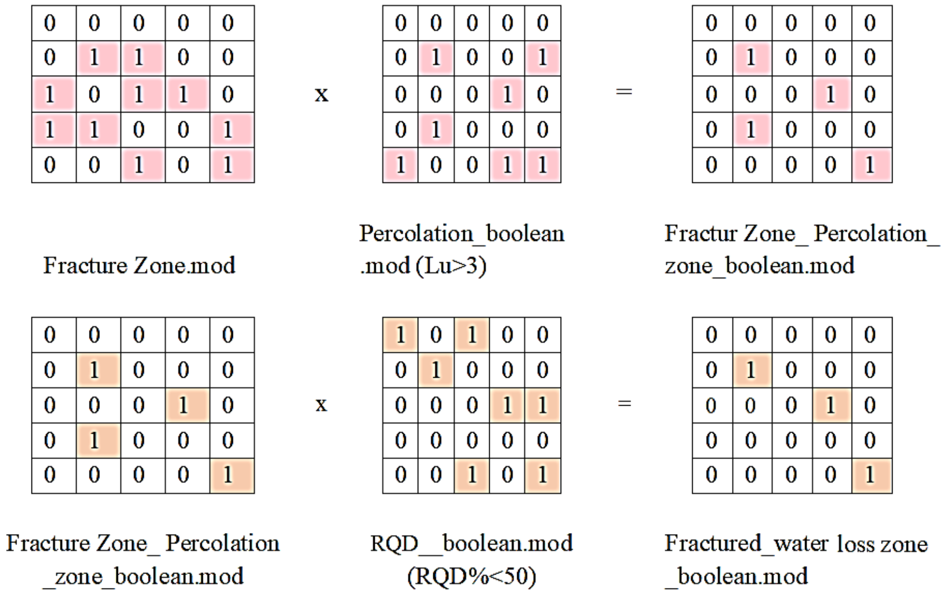


Fig. 8. Schematic arithmetic operations for fracture zone with 100% water loss

6.3 Analysis of Tail Channel Erosion

The analysis indicates that the rocks exposed at the tail channel location of dam site are vesicular, zeolitic, mixed Red Tachylytic or Red Tachylytic Basalt. These rocks having less resistance to erosion; and can be eroded very fast. The reduced level (RLs) profile levelling data (2015) over the 351 m length of tail channel, ahead of EDA portion was compared with design/executed RLs-1997 and RLs-2005 to check the tail channel erosion due to existence of weak rocks. Volumetric calculations based on the prepared Grid Models quantified the amount of erosion. Table 14 shows the estimated quantity of tail channel erosion over the time. Tail Channel Erosion Analysis has confirmed the process of erosion is continue in the tail channel area. The tail channel erosion needs to control else it will expedite the weathering and consequent seepage through exposed Tachylytic formation. The qualitative analysis of tail channel contour map shows gradual progression of erosion towards the spillway section [36].

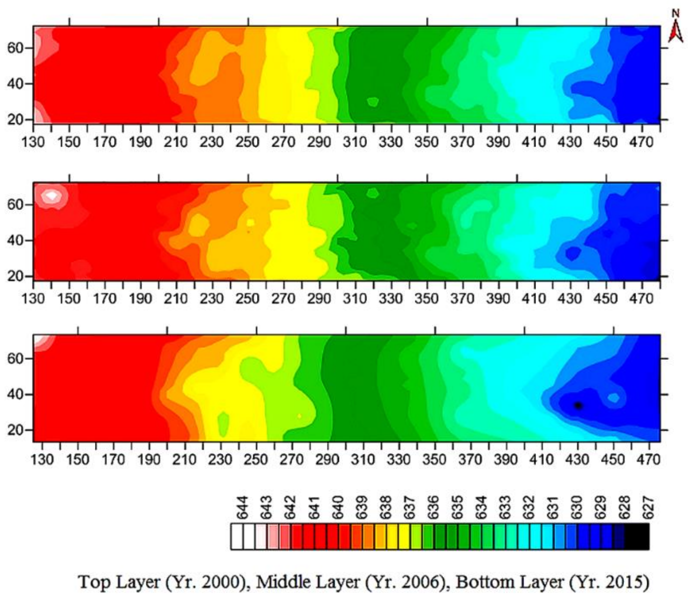


Fig. 9. Elevation map for temporal tail channel Erosion (EDA end RL. 125m to RL. 475m)

Table 14. Quantity of tail channel erosion

	Yr. 2000-2006	Yr. 2006-2015	Yr. 2000-2015
Net Volume of erosion	9866.44 m^3	3340.28 m^3	12885.79 m^3

7. Engineering verification and Implications of Geomodelling

After 2005, the EDA portion failure, Central Water and Power Research Station (CWPRS), Pune, carried out an investigation [19] to identify the causes of failure. The nuclear logging techniques and tracer tests were used to trace the seepage path to the damaged portion of the tailrace channel, and Calliper logging was also undertaken to determine the extent of joints and fractures in the boreholes at the Bhama Askhed Dam.

An important aspect of the present investigation is the comparison of geomodel predictions with independent post-failure investigations carried out by CWPRS. The geomodel identified unfavorable lithology, low recovery zones, poor RQD values, high percolation regions and fractured water-loss zones near the spillway and EDA section. These locations correspond closely with the seepage pathways, fracture zones and problematic geological conditions reported by CWPRS during failure investigations. The findings from Recovery_RQD_Percolation_Boolean Model, fractured_water loss zone_Boolean Model also justify the possible post-failure excessive seepage (10-15 litre/s) through the spillway foundation at the EDA portion [19]. Such agreement provides independent engineering verification of the developed modelling framework and demonstrates its capability to identify vulnerable foundation zones.

Based on the modelling analysis, the decisions about optimization of foundation levels, excavation depth, grouting depth, extent of grouting at specific locations according to geo parametric criteria can be checked. The developed geomodels provide practical support for engineering decision-making including, assessment of vulnerable foundation zones, Identification of high seepage zones, Verification of existing treatment measures, Prioritization of supplementary site investigations.

Beyond conventional geological visualization, the present study demonstrates that integrated geomodelling can serve as a predictive engineering tool for identifying erosion-driven geological deterioration, seepage pathways and foundation vulnerability. The successful correlation of geomodel predictions with tail channel erosion patterns and CWPRS post-failure observations establishes a practical framework for dam foundation risk assessment and preventive maintenance planning. The implication of developed geomodels and cross sections for dam site characterization is elaborated by the authors separately [36-38]. This shows the probable applications of geomodelling for engineering applications. Therefore, geomodelling should be considered a decision-support tool complementing conventional geological interpretation rather than replacing engineering judgment

8. Conclusion

The present study demonstrates that three-dimensional geomodelling integrated with statistical validation and engineering verification can significantly improve geological characterization of dam foundations. Unlike conventional geomodelling applications that primarily focus on visualization, the proposed framework establishes direct engineering relevance through assessment of lithology, recovery, RQD, permeability and fracture-zone behavior.

The principal contribution of this study is not the use of individual interpolation algorithms themselves, but the development of an integrated geological-engineering validation framework combining 3D geostatistical modelling, independent statistical validation, and verification against documented dam performance observations.

The intent of geomodelling is the site characterization for placing the project in the context of its surrounding geology. 3-D Geomodelling can enhance spatial understanding of site geology, assisting in better project decisions. This will help in identifying potential situations during engineering applications. 3-D spatial models allow the integrated, comprehensive representation of the subsurface geology with spatial geoparametric variations. The dissected geomodels permit the preparation of distinguished cross-sections characterized by typical geotechnical or geological conditions. Thus, enhancing the understanding of site geology. For the developed substratum models, there are lower values of standard deviations, coefficient of variation for observed and predicted data, suggesting reasonable accuracy of estimation (Table 6). Also, the solid model residuals for the interpolated model are quite less, 6.15, 8.29, 13.07 and -9.60 for lithology, recovery, RQD and percolation, respectively, indicating a reasonable model fit. (Table 7) A statistical comparison of model-predicted parameters with the reserved data set shows a correlation coefficient greater than +0.70, indicating a strong uphill (positive) linear relationship between the observed and modelled data. "The validation results indicate moderate correlation for lithology (62.25%) and strong correlations for recovery (92.5%), RQD (88.25%) and percolation (75.5%)."(Table 9)

As validated through statistical parameters such as standard deviation, coefficient variation (Table 6,7), correlation coefficient (Table 8), RMSE (Table 6,9) and also the RSR (about 0.5), NSE (0 to 1) (Table 10) indicates that Statistical Modelling methods can produce dependable model simulation. The optical correlation technique also highlights reasonable optical similarities. Thus, statistical modelling of geoparameters provides a dependable geological site characterization. These models can complement the conventional geological cross-section-driven approach. As witnessed by the correlation between the modelled and reserve borehole data (Table 9), the geostatistical interpolation can extend the limited investigation project data. Thus, the non-data or limited data area can be modelled approximately, for the specific parameter, using statistical modelling with suitable checks and validation.

Geomodels can disclose the parametric anomalies and their spatial locations over project areas, which can be investigated for confirmation. The pinpointed questionable locations with higher anomalies obtained from geomodels can help to optimize the site investigation needs. Such critical locations can be avoided or suitably treated. Through investigation can be carried out for selecting these for important structure locations. The modelling results can also be used for selecting suitable assessment methods, quality and optimization of further geotechnical investigation needed.

Comparison of geomodel predictions with CWPRS post-failure investigations confirmed the presence of vulnerable geological conditions near the spillway and EDA sections. This independent verification highlights the practical applicability of the developed geomodelling framework for foundation assessment, risk identification and decision support in large hydraulic infrastructure projects. Vulnerable zones identified through geostatistical modelling correspond closely with seepage-prone and structurally weak zones reported during post-failure investigations conducted by CWPRS. The spatial coincidence provides independent engineering verification of the developed models. The present investigation demonstrates that integrated geological geomodelling can effectively support engineering site characterization and risk assessment. The study successfully combines three-dimensional geological modelling, statistical validation, sensitivity assessment and engineering verification. Validation using independent datasets, resistivity surveys, and CWPRS EDA failure investigations confirms the reliability of the developed models. The proposed framework provides a practical methodology for predicting subsurface geological variability and identifying vulnerable foundation zones in large infrastructure projects. The principal contribution of the study lies in establishing an integrated geological-engineering validation approach rather than merely applying conventional interpolation algorithm

7.1 Limitations and Future Work

Even though 3-D models can be used as interactive exploration tools, it is important to know their limitations to represent the natural variability of geological systems. The reliability of the developed geomodels is influenced by borehole density, spatial distribution and the quality of available geological data and the spatial distribution of investigation points. Sparse data regions introduce interpolation uncertainty, particularly near lithological boundaries and structurally complex zones. Although the developed models demonstrated satisfactory performance, additional borehole information could further improve local-scale prediction accuracy.

The major constraints which influence the application of 3-D models are:

- The effect of data distribution - irregular data distribution or sparse data can lead to less significant regional models.
- Selection of interpolation method - The predicted value varies with the interpolation method. An extrapolative character of the prediction involves risk and uncertainty. Though the models can form the basis of relevant decision-making, appropriate precautions must be taken to ensure their correctness.
- The modelling validation considered for the research study is based on indirect measures through statistical parameters and Optical correlation. For direct validation of geomodels, site investigations can be carried out at model-suggested higher anomaly data locations. However, the high cost is involved in the investigation. In turn, the findings of the further investigation will help to validate and optimize the modelling performance.

Future investigations can also focus on, integration of machine learning and hybrid geostatistical techniques. Such developments would further enhance the reliability and engineering applicability of geological geomodelling for dam safety and infrastructure risk assessment.

References

[1] Aldiss DT, et al. Benefits of a 3D geological model for major tunnelling works: an example from Farringdon, east-central London, UK. Quarterly Journal of Engineering Geology and Hydrogeology. 2012;45:405-414. https://doi.org/10.1144/qjegh2011-066

[2] Turrini C, et al. Present-day 3D structural model of the Po Valley basin, Northern Italy. Marine and Petroleum Geology. 2014;56:266-289. https://doi.org/10.1016/j.marpetgeo.2014.02.006

[3] Elkadi AS, et al. 3D-GSIS geotechnical modelling of tunnel intersection in soft ground: The Second Heinenoord Tunnel, Netherlands. Tunnelling and Underground Space Technology. 2002;17:363-369. https://doi.org/10.1016/S0886-7798(02)00039-1

[4] Kaufmann O, et al. 3D geological modelling from boreholes, cross-sections and geological maps, application over former natural gas storages in coal mines. Computers & Geosciences. 2009;35:70-82. https://doi.org/10.1016/S0098-3004(08)00227-6

[5] Kessler H, et al. Unlocking the potential of digital 3D geological subsurface models for geotechnical engineers. In: 2nd International GSI3D Conference; 2008 Sep; Keyworth, United Kingdom. British Geological Survey; 2008.

[6] Wycisk P, et al. High-resolution 3D spatial modelling of complex geological structures for an environmental risk assessment of abundant mining and industrial mega sites. Computers & Geosciences. 2009;35. https://doi.org/10.1016/j.cageo.2007.09.001

[7] Ahmed AA. Using Lithologic Modelling Techniques for Aquifer Characterization and Groundwater Flow Modelling of Sohag Area, Egypt. GRMENA II. 2007:355-382.

[8] MacCormack KE. Viewing the subsurface in three dimensions: Initial results of modelling the Quaternary sedimentary infill of the Dundas Valley. Hamilton, Ontario. Geosphere. 2005 Aug;1(1):23-31. https://doi.org/10.1130/GES00007.1

[9] Marache A, et al. Geotechnical Modelling at the city scale using statistical and geostatistical tools: The Pessac case (France). Engineering Geology. 2009;107:67-76. https://doi.org/10.1016/j.enggeo.2009.04.003

[10] Sinan A, et al. Three-dimensional subsurface Modelling of mineralisation: a case study from the Handeresi (Turkey) Pb-Zn-Cu deposit. Turkish Journal of Earth Sciences. 2013;22:574-587.

[11] Sweetkind DS. Three-dimensional geologic Modelling of the Santa Rosa Plain, California. Geosphere. 2010 Jun;6(3):237-274. https://doi.org/10.1130/GES00513.S4

[12] MacCormack KE, et al. Using a multiple variogram approach to improve the accuracy of subsurface geological models. Can J Earth Sci. 2016;00:1-16.

[13] Wakeley LD, Kelley JR. Hydrogeology and 3-D Visualisation of Dam Foundations and Abutments. U.S. Army Engineer Research and Development Centre; 2007.

[14] Wakeley LD, Kelley JR. Geologic Conceptual Model of Mosul Dam. U.S. Army Engineer Research and Development Centre; 2007.

[15] Gallerini G, et al. 3-D Modelling using geognostic data: The case of the low valley of Foglia river (Italy). Computers & Geosciences. 2009;35:146-164. https://doi.org/10.1016/j.cageo.2007.09.012

[16] Abdollahisharif J. Using geostatistical simulation to determine optimal grout injection pressure in the dam foundation based on geomechanical characteristics. Bulletin of Engineering Geology and the Environment. 2018. https://doi.org/10.1007/s10064-018-1289-3

[17] Parry Baynes, et al. Engineering geological models: An introduction, IAEG commission 25. Bulletin of Engineering Geology and the Environment. 2014;73:707-707. https://doi.org/10.1007/s10064-014-0614-8
[18] Rajesh S, et al. A GIS/LIS Approach for Study on Suitability of Shallow Foundation at Southern Chennai, India. Geospatial World-2009. 2009.
[19] Kamble RK. Mapping seepage in the tailrace channel, Bhama-Askhed dam: a Case study. Bull Eng Geol Environ. 2011;70:643-649. https://doi.org/10.1007/s10064-011-0352-0
[20] Isaaks, Srivastava. An Introduction to Applied Geostatistics. New York: Oxford University Press; 1989.
[21] Senol O, et al. 3-D modelling system for ground engineering, International Institute for Aerospace Survey and Earth Sciences, Netherlands. Springer-Verlag Berlin Heidelberg; 2003.
[22] Johnston K, et al. Using the ArcGIS geostatistical analyst. ESRI; 2004. p. 300.
[23] Krajewski SA, Gibbs BL. Understanding Contouring: A practical guide to estimation and contouring using a computer and the Basics of using variograms. Gibbs Associates, Industrial Ergonomics, Inc.; 1996.
[24] RockWare Inc. RockWorks Case Studies and Technical Documents. RockWare; 2025 [Erişim tarihi: 19 Temmuz 2026]. Erişim adresi: https://www.rockware.com/support/rockworks-support/rockworks-downloads/rockworks-case-studies/
[25] Chaplot, et al. Accuracy of interpolation techniques for the derivation of digital elevation models about landform types and data density. Geomorphology. 2006;77:126-141. https://doi.org/10.1016/j.geomorph.2005.12.010
[26] Shahbeik S, et al. Comparison between ordinary kriging (OK) and inverse distance weighted (IDW) based on estimation error. Case study: dardevey iron ore deposit, NE Iran. Arabian Journal of Geosciences. 2014;7(9):3693-3704. https://doi.org/10.1007/s12517-013-0978-2
[27] Mojtaba R, Shahid. Three-dimensional Modelling of the permeability of the rock masses of Khersan dam using geostatistical methods. Specialty Journal of Architecture and Construction. 2016;2(3):21-42.
[28] Lam NS. Spatial interpolation methods. The American Cartographer. 1983;10:129-149. https://doi.org/10.1559/152304083783914958
[29] Li J, Heap A. A Review of Spatial Interpolation Methods for Environmental Scientists. Record 2008/23, Geoscience Australia, Canberra; 2008.
[30] Yasrebi AB, et al. Application of an inverse distance weighted anisotropic method (IDWAM) to estimate elemental distribution in Eastern Kahang Cu-Mo porphyry deposit, Central Iran. Int J Mining and Mineral Engineering. 2016;7(4):340-362. https://doi.org/10.1504/IJMME.2016.079995
[31] Saraç C, et al. Grade and reserve estimation of the Tulovasi borate deposit by block kriging. International Geology Review. 1996;38:832-837. https://doi.org/10.1080/00206819709465365
[32] MacCormack KE, et al. Evaluating the Impact of Data Quantity, Distribution and Algorithm Selection on the Accuracy of 3-D Subsurface Models Using Synthetic Grid Models of Varying Complexity. Journal of Geographical Systems. 2013 Jan;15(1):71-88. https://doi.org/10.1007/s10109-011-0160-x
[33] Pontius R, et al. Components of information for multiple resolution comparison between maps that share a real variable. Environmental Ecological Statistics. 2008;15:111-142. https://doi.org/10.1007/s10651-007-0043-y
[34] Willmott C, et al. On the use of dimensioned measures of the error to evaluate the performance of spatial interpolators. International Journal of Geographic Information Science. 2006;20:89-102. https://doi.org/10.1080/13658810500286976
[35] Singh J, et al. Hydrologic Modelling of the Iroquois River watershed using HSPF and SWAT. ISWS. CR. Champaign, Ill.: Illinois State Water Survey; 2004. Erişim adresi: www.sws.uiuc.edu/pubdoc/CR/ISWSCR2004-08.pdf.
[36] Aswar DS, Ullagaddi PB. Geological characterisation of the dam site. In: 1st International Conference on Sustainable Development in Civil and Electrical Engineering (SDCEE-2021); 2021 Dec. National Institute of Technology Kurukshetra: Society of Earth Scientists Book Series, Springer; 2021.
[37] Aswar DS, Ullagaddi PB. 3-D Geomodelling for Dam Site Characterization. In: Laishram B, Tawalare A, editörler. Recent Advancements in Civil Engineering. Lecture Notes in Civil Engineering, vol 172. Singapur: Springer; 2022. https://doi.org/10.1007/978-981-16-4396-5_71
[38] Aswar DS, Ullagaddi PB. Electrical resistivity investigation for the dam site. In: Gao XZ, Sethi S, Udgata SK, editörler. Intelligent Systems: Proceedings of ICMIB 2021. 1. baskı. Singapur: Springer Verlag; 2022. https://doi.org/10.1007/978-981-19-0901-6_32
[39] Flageollet JC, et al. The 3D structure of the Super Sauze earth flow: a first stage towards modelling its behaviour. Physics and Chemistry of the Earth. 2000;25(9):785-791.