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Research Article

An Integrated Geostatistical–Machine Learning Framework for Predicting Resurgence and Canaliculi in the Belo Monte Hydropower Dikes Using Borehole Data

Estrutura Integrada Geoestatística e Machine Learning para Prever Surgências e Canalículos nos Diques da Hidrelétrica Belo Monte Utilizando Dados de Sondagem

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Abstract: The Belo Monte Hydroelectric Complex, located on the Xingu River in Altamira, Pará, Brazil, includes two power plants: Pimental, built directly on the riverbed, and Belo Monte, which uses water diverted from an intermediate reservoir. This reservoir is contained by 28 dikes, mostly underlain by migmatite residual soils. During construction and early operation, tubular cavities known as canaliculi and associated resurgence processes were identified downstream of several dikes. However, the spatial controls governing these phenomena remain poorly understood in tropical lateritic environments. This study proposes an integrated geostatistical–machine learning framework for the spatial prediction of resurgence and canaliculi. Ordinary Kriging was applied to model the elevation of the Young Residual Soil (YRS) contact surface using approximately 450 borehole records. The model was subsequently extrapolated to downstream areas lacking direct subsurface data through Support Vector Machine (SVM) regression. A digital terrain model was combined with the modeled YRS contact to identify potential outcrop zones associated with resurgence. Spatial statistical indicators based on minimum-distance metrics were developed to quantify the correspondence between predicted outcrop areas and field-mapped occurrences. The results show strong spatial agreement between predicted YRS outcrop zones and mapped resurgence and canaliculi points across five representative dikes, with average shortest distance ranging from 4.4 to 50.6 m. Cross-validation indicated satisfactory predictive performance of the YRS digital model, with RMSE values between 4.16 and 9.56 m for kriging and between 3.36 and 10.65 m for SVM. The proposed framework provides a replicable and cost-effective predictive tool for dam safety management, supporting the definition of priority inspection corridors and early detection of anomalous resurgence and canaliculi behavior in tropical dam foundations.

Keywords: dam safety; support vector machine; ordinary kriging; spatial prediction; canaliculi

Resumo: O Complexo Hidrelétrico de Belo Monte, localizado no rio Xingu, em Altamira (PA), é composto pelas usinas Pimental e Belo Monte e por um reservatório intermediário contido por 28 diques, majoritariamente fundados sobre solos residuais de migmatito. Durante a construção e o início da operação, cavidades tubulares denominadas canalículos e processos de surgência foram identificados a jusante de diversos diques. Entretanto, os controles espaciais desses fenômenos ainda são pouco compreendidos em ambientes lateríticos tropicais. Este estudo propõe uma abordagem integrada de geoestatística e *machine learning* para a predição espacial de surgências e canalículos. A *Krigagem* Ordinária foi aplicada para modelar a elevação do contato do Solo Residual Jovem (SRJ) a partir de aproximadamente 450 sondagens. Em seguida, o modelo foi extrapolado para áreas a jusante sem dados diretos de subsolo por meio de regressão por *Support Vector Machine* (SVM). O modelo digital do terreno foi integrado ao modelo de contato do SRJ para identificar zonas potenciais de afloramento associadas às surgências. Indicadores estatísticos espaciais baseados em métricas de menor distância foram empregados para quantificar a correspondência entre áreas previstas e ocorrências mapeadas em campo. Os resultados indicam forte concordância espacial entre as zonas de afloramento do SRJ e os pontos de surgência e canalículos em cinco diques representativos, com menores distâncias médias variando de 4.4 a 50.6 m. A validação cruzada dos modelos de SRJ apresentou desempenho preditivo satisfatório (RMSE entre 4,16 e 9,56 m para *krigagem* e entre 3,36 e 10,65 m para SVM). A metodologia constitui ferramenta replicável e de baixo custo para apoio à segurança de barragens em ambientes tropicais.

Palavras-chave: Segurança de Barragens; MVS; krigagem ordinária; predição espacial; canalículo

1. Introduction

The occurrence of canaliculi in dam foundations represents a significant challenge to the safety of hydraulic structures in tropical environments, because their presence may enhance preferential flow conditions, as piping processes (Bjornberg et al., 1994). Despite their practical relevance, knowledge regarding their genesis, spatial distribution, and temporal evolution remains largely based on empirical observations and case studies, which limits a comprehensive understanding of their hydraulic and geotechnical behavior (Jury, 1989). In this context, although the literature reports advances in the geotechnical and geomorphological characterization of canaliculi, important gaps persist concerning the integration of subsurface data, spatial analyses, and predictive models capable of anticipating areas susceptible to resurgence associated with canaliculi.

1.1. Application of Geostatistical and Machine Learning Methods in Dams

The advancement of spatial analysis techniques and the increasing availability of geotechnical and topographic data have encouraged the use of geostatistics and machine learning–based methods in the assessment of dam behavior. (Namyslowska e Wynalek, 2017).

While geostatistics allows the explicit modeling of the spatial continuity of geotechnical variables, machine learning methods stand out for their ability to capture nonlinear relationships and complex patterns in spatiotemporal datasets (Chen et al., 2021). Recent studies indicate a trend toward hybrid approaches that integrate spatial dependence and predictive capability, thereby enhancing decision-support processes in dam safety (Leal-Villaseca et al., 2025).

However, systematic applications of these methodologies for the spatial prediction of processes associated with canaliculi and seepage remain incipient, particularly in tropical environments, which justifies the approach adopted in this study.

1.1.1. Geostatistical approaches for modeling and monitoring phenomena in dams

The earliest studies applying geostatistics to the analysis of dam behavior primarily employed kriging for the spatial and spatiotemporal interpolation of variables measured by monitoring systems, such as displacements and settlements, aiming to characterize the spatial distribution of these responses along the structure (Namyslowska e Wynalek, 2017).

A study at the Diama Dam on the Senegal River applied geostatistical techniques, particularly kriging, to characterize the hydrogeological setting of the delta's alluvial aquifer and assess the recovery potential of salinized areas. Using stratigraphic and piezometric data from a monitoring-well network, the authors showed that the thickness of the surficial clay layer controls the delineation of agriculturally suitable areas, highlighting the relevance of spatial modeling in hydrogeological assessments of hydraulic structures (Babacar e Denis, 1999).

Dai et al. (2016), they applied spatiotemporal modeling to dam deformation data for noise filtering, interpolation of unmonitored areas, and prediction of structural behavior. The authors showed that traditional point-based methods neglect spatial correlation and proposed the Spatiotemporal Kalman Filter (STKF), which integrates kriging-based spatial fields with recursive estimation, highlighting the value of integrated spatiotemporal approaches in geotechnical analyses of hydraulic structures.

Namyslowska e Wynalek (2017), they applied geostatistical methods to geodetic monitoring data to investigate spatial displacement patterns in hydraulic structures, demonstrating that kriging enables the representation of spatial continuity of observed variables from point-based measurements.

Despite their statistical robustness and interpretability, these methods exhibited limitations in representing nonlinear behaviors, which constrained their application in foundation geometric modeling associated with hydrogeotechnical processes such as seepage and canaliculi evolution (Leal-Villaseca et al., 2025).

1.1.2. Machine Learning Methods for modeling and monitoring phenomena in dams

From the year 2010 onward, numerous studies began to employ machine learning algorithms for the analysis of dam monitoring data, driven mainly by the increasing availability of long time series and by the need to represent nonlinear relationships among observed variables (Ruan et al., 2023).

Wang e Chai (2024) applied recurrent neural networks (RNNs) and their variants to forecast pore pressure time series in earth dam slopes. The authors demonstrated that recurrent networks can capture relevant temporal patterns solely from monitoring data, reinforcing the potential of these techniques as complementary tools to conventional methods for dam safety and slope stability analyses.

Hariri-Ardebili e Salazar (2020) investigated the use of soft computing techniques integrated with numerical simulations to reduce the computational cost of uncertainty analyses in dams. By evaluating variables related to materials, geometry, and reservoir level, the authors demonstrated that artificial neural networks achieved higher predictive accuracy, with errors below 1%, highlighting the potential of machine learning as a complement to traditional numerical models in structural reliability analyses.

Chen et al. (2021) proposed a dynamic early-warning model for dam deformations based on the fusion of spatiotemporal characteristics and deep learning techniques. The method integrates Proper Orthogonal Decomposition (POD), Deep Kernel Extreme Learning Machine (DKELM), and a cloud model, enabling the capture of spatial nonlinearities, randomness, and temporal uncertainties in deformation data.

Ruan et al. (2023) propose a proactive safety control model for tailings dams based on the integration of graph convolutional neural networks (GCN) and gated recurrent unit (GRU) networks, incorporating a temporal attention mechanism. The method achieved higher predictive accuracy and an enhanced capability to anticipate critical variations in safety parameters, highlighting the potential of graph-based deep learning for improving risk prevention and control in tailings dams.

1.1.3. Integration between Geostatistics and Machine Learning (Hybrid Models)

Gaussian Processes and traditional kriging are widely used in spatiotemporal modeling; however, they assume stationarity and data normality and entail high computational costs when applied to large datasets (Leal-Villaseca et al., 2025). More recent studies indicate a methodological convergence between geostatistics and machine learning, with the development of hybrid spatiotemporal models applied to the analysis of dam behavior.

Chen et al. (2021) showed that dam deformation exhibits strong spatiotemporal variability that is not captured by conventional point-based assessments. To address this, they proposed an integrated methodology combining spatiotemporal clustering with multioutput ensemble machine learning, incorporating correlations among adjacent dam regions, and demonstrated high predictive performance on real displacement data.

Leal-Villaseca et al. (2025) propose DeepKriging, a deep neural network–based approach that replaces the covariance function with spatiotemporal embedding layers. The method combines interpolation using DNNs with temporal forecasting using LSTM and ConvLSTM, enabling probabilistic estimates and improved computational efficiency. The results demonstrate that DeepKriging is suitable for complex and large-scale spatiotemporal processes.

1.2. Canaliculi

Canaliculi are natural tubular phenomena that develop predominantly in tropical soils, especially in lateritic residual soils, and exhibit high spatial heterogeneity. These phenomena have diameters ranging from millimeters to centimeters and may reach considerable lengths and depths, with vertical, subvertical, or horizontal orientations, as well as irregular, branched, and frequently interconnected geometries, occurring either empty or partially infilled. When present in dam foundations, canaliculi may act as preferential flow paths, significantly increasing the permeability of the medium and promoting seepage, fines transport, and internal erosion processes such as foundation piping, thereby constituting a critical factor for the stability and safety of hydraulic structures (Bjornberg et al., 1994).

1.2.1. About Canaliculus Genesis

Despite the practical relevance of canaliculi in the performance of foundations, the technical and scientific literature still presents significant gaps regarding their origin, evolution and impact on geotechnical works. The predominant hypotheses associate their genesis with leaching processes, biological action of termites and plant roots, and structural collapses in zones of intense laterization (Jury, 1989; Bignell, 2000)

The first hypothesis, related to the inherent properties of the material, attributes the formation of canaliculi to pedo-karstic erosion, a physical erosive process resulting from the dissolution of small rock fragments along minor joint intersections, which initiates the development of cavities. Another variation of this hypothesis links the phenomenon to intense soil laterization. In this context, the leaching of soluble elements promotes increased water infiltration, contributing to cavity formation (Jury, 1989).

The hypothesis of biological origin considers termite activity as a key mechanism in the development of canaliculi. Termites form complex biological systems, comprising species with diverse feeding and nesting behaviors. Along with earthworms, they are among the primary invertebrates responsible for ingesting and redistributing organic and mineral matter in tropical soils (Bignell; Eggleton, 2000). In the case of the Balbina Dam, the hypothesis that termites contributed to canaliculi formation by consuming root systems gained wide acceptance. Microscopic analyses of undisturbed samples from Balbina, as well as from the Samuel and Tucuruí dams, revealed the presence of organic remnants attributable to these organisms (Gutierrez, 1987).

A third hypothesis involves the vegetative life cycle. Over time, tree roots undergo chemical and structural degradation. After the death of a tree, its root cells begin to break down through autolysis. Simultaneously, bacterial and fungal activity decomposes plant tissues, leading to the formation of voids in the soil structure (Saha et al., 2023).

1.2.2. Presence of Canaliculi in Civil Engineering Structures

In Brazil, the first documented record of canaliculi occurrence in dam foundations dates back to 1957, during the construction of the Vereda Grande Dam in the state of Piauí (Barradas, 1985). Subsequently, at the Tucuruí Dam, canaliculi were identified in soils derived from weathered metabasites and diabases, with varying degrees of laterization, exhibiting predominantly subvertical orientations, decimetric diameters, and high permeability coefficients (**Figure 1**.c). In finer lateritized units, these cavities assumed entangled geometries and smaller diameters, associated with high water absorption rates, highlighting their hydraulic relevance at the foundation scale (Buosi; Cadman, 1985; Cruz, 2004).

Brazilian experience also records different treatment strategies associated with the presence of canaliculi. At the Tucuruí Dam, deepened and widened exploratory trenches were adopted to function as cutoff trenches, along with direct filling of canaliculi with cement grout and the installation of downstream filtering and drainage layers, aiming to reduce the erosive potential of concentrated flow (Cruz, 2004).

At the Balbina Dam, in the state of Amazonas, where a high incidence of canaliculi was observed in saprolitic soils and alluvial deposits (**Figure 1**.a), the solution consisted of grouting the residual soil using tube-à-manchette systems, combined with the construction of downstream relief wells, aiming at sealing the cavities, homogenizing foundation permeability, and reducing seepage discharges, with effectiveness confirmed by water loss tests conducted before and after the treatment (Mello et al., 1985; Gutierrez, 1987).

Figure 1. Illustration of the locations of Brazilian dams where canaliculi were identified

In the international context, the cases of Saddle Dam D at the Xe-Pian–Xe-Namnoy Hydropower Complex in Laos and the Comoé Dam in Burkina Faso clearly illustrate the consequences of canaliculi in lateritic foundations. In the former case, the failure that occurred in 2018 was associated with the high heterogeneity of the foundation, characterized by lateritic residual soils with interconnected canaliculi and preferential flow paths, resulting in permeabilities far exceeding design estimates and in the development of regressive internal erosion leading to embankment destabilization. At the Comoé Dam, although no total failure occurred, persistent seepage was observed since the first reservoir filling, evolving into resurgences and progressive subsidence, which required detailed investigations and the adoption of integrated mitigation solutions such as sheet pile cut-off walls and grouting techniques, highlighting the latent risk associated with canaliculated foundations (Chraibi; Nombré, 2017; Chraibi et al., 2020).

More recently, during the implementation of the Belo Monte Hydroelectric Complex in the Amazon region, canaliculi were again reported in residual migmatite soils used both as embankment material and as dam and dike foundations, occurring in high concentrations and exhibiting predominantly subvertical orientations (**Figure 1**.b). Exploratory excavations enabled the systematic identification of these features and the application of localized treatment measures, such as compressed air blasting to enhance cavity visibility and sealing by cement grout injection., illustrate on the **Figure 2** (Bandeira et al., 2018).

Figure 2. Treatments carried out in excavations with canaliculi

After completion of the works and reservoir impoundment, some of the instruments installed in the foundations of the dikes and dams exhibited rapid responses over a short time interval. In addition, seepage and the development of canaliculi were observed, particularly downstream of certain dikes (Bandeira; Silveira; Leite, 2017). Since then, the Norte Energia dam safety team has been monitoring the evolution of these phenomena and, when necessary, implementing mitigation measures such as drainage trenches and inverted filters, as illustrated in the **Figure 3** (Rodrigues et al., 2024).

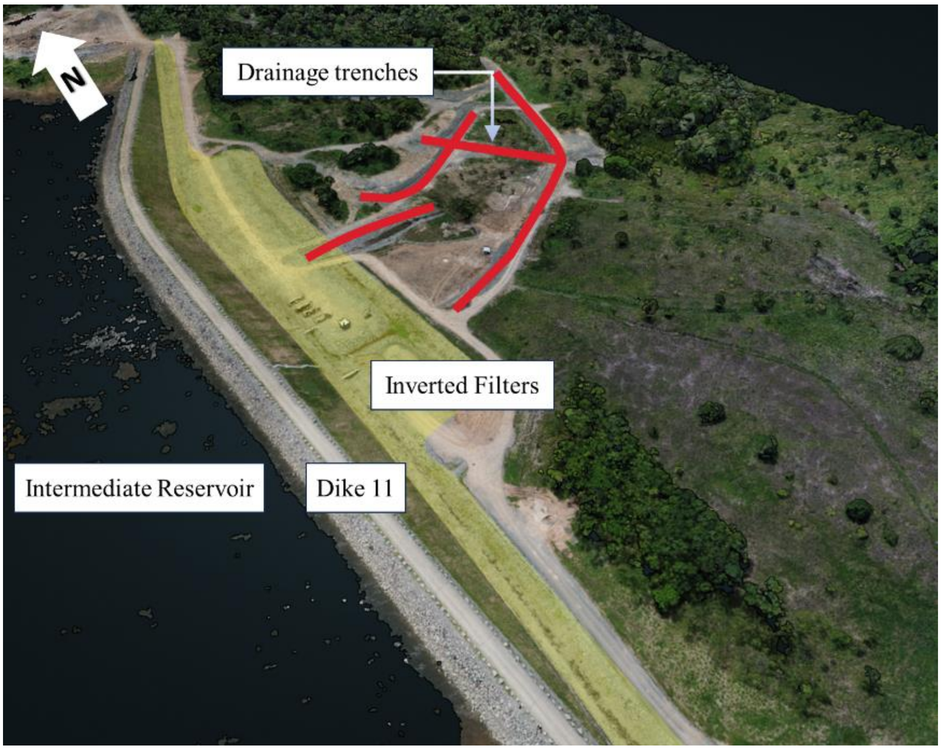


Figure 3. Drainage trenches and inverted filter locations

During the excavation of trenches intended to mitigate water seepage at different dikes and periods, field observations revealed a flow behavior pattern strongly associated with the local lithology. In many cases, seepage areas corresponded to zones where the contact between the surface soil and the Young Residual Soil (YRS) occurred at shallower depths, resembling an outcropping interface. This pattern was confirmed during the development of the geological foundation model of Dike 11, which was used to simulate water flow and to evaluate the effectiveness of the constructed trenches (Rodrigues et al., 2025). These results were fundamental to the development of a spatial prediction methodology for water seepage and canaliculi evolution, based on the integration of borehole data and digital terrain models obtained from pre-construction LiDAR aerial surveys.

Despite their technical relevance and the history of documented cases, scientific production on canaliculi in dam foundations has shown a significant decline in recent decades, particularly after the major hydropower projects implemented in Brazil between the 1970s and 1990s. The recent resurgence of this topic, driven by systematic observations at the Belo Monte Hydroelectric Complex, highlights a research gap related to the spatial and evolutionary understanding of these phenomena, as well as their integration with geological, geotechnical, and topographic data at the design scale.

In this context, the present study is justified by the need to advance the identification, characterization, and spatial prediction of canaliculi occurrence and their hydrological effects, considering the potential risk these phenomena pose to dam safety. The integration of borehole data, digital terrain models, and spatial modeling applied to the prediction of seepage and canaliculi evolution emerges as a promising approach to support preventive actions, optimize monitoring strategies, reduce costs, and contribute to the safe management of hydraulic structures in tropical environments.

2. Methodology For Spatial Prediction of Resurgence and Canaliculi at the Belo Monte Complex

The proposed methodology integrates geostatistics and machine learning for the spatial modeling of the contact between foundation geotechnical units and its relationship with the occurrence of resurgences and canaliculi. Initially, ordinary kriging was used to interpolate the elevation of the Young Residual Soil (YRS) contact from borehole data, with variogram model definition based exclusively on the statistical performance of the spatial contact model. Information on resurgences and canaliculi locations was not considered at this initial stage.

Subsequently, the contact model was extended to downstream areas without direct borehole coverage through the use of Support Vector Machine (SVM), whose parameters were defined by minimizing the prediction error of the YRS contact elevation, using boreholes previously excluded from modeling for independent validation. Occurrences of resurgences and canaliculi were incorporated only at a later stage for evaluative purposes.

The identification of areas potentially associated with resurgence occurrence was performed by overlapping the digital model of the YRS contact with the digital terrain surface model, allowing the estimation of zones where the contact approaches or intersects the topography, thereby characterizing potential outcropping areas.

Finally, spatial statistical analysis procedures were applied to evaluate the correspondence between the estimated YRS contact outcrop areas and field-mapped resurgence and canaliculi points. These analyses involved calculating the minimum distance between each individual occurrence and the YRS contact outcrop line, as well as determining the mean distance and its standard deviation. These indicators were used as objective metrics to examine the relative spatial distribution between the observed phenomena and the contact model, as detailed in the subsequent sections. **Figure 4** presents a flowchart summarizing the procedures adopted in the proposed methodology applied to all dikes of the Belo Monte Intermediate reservoir.

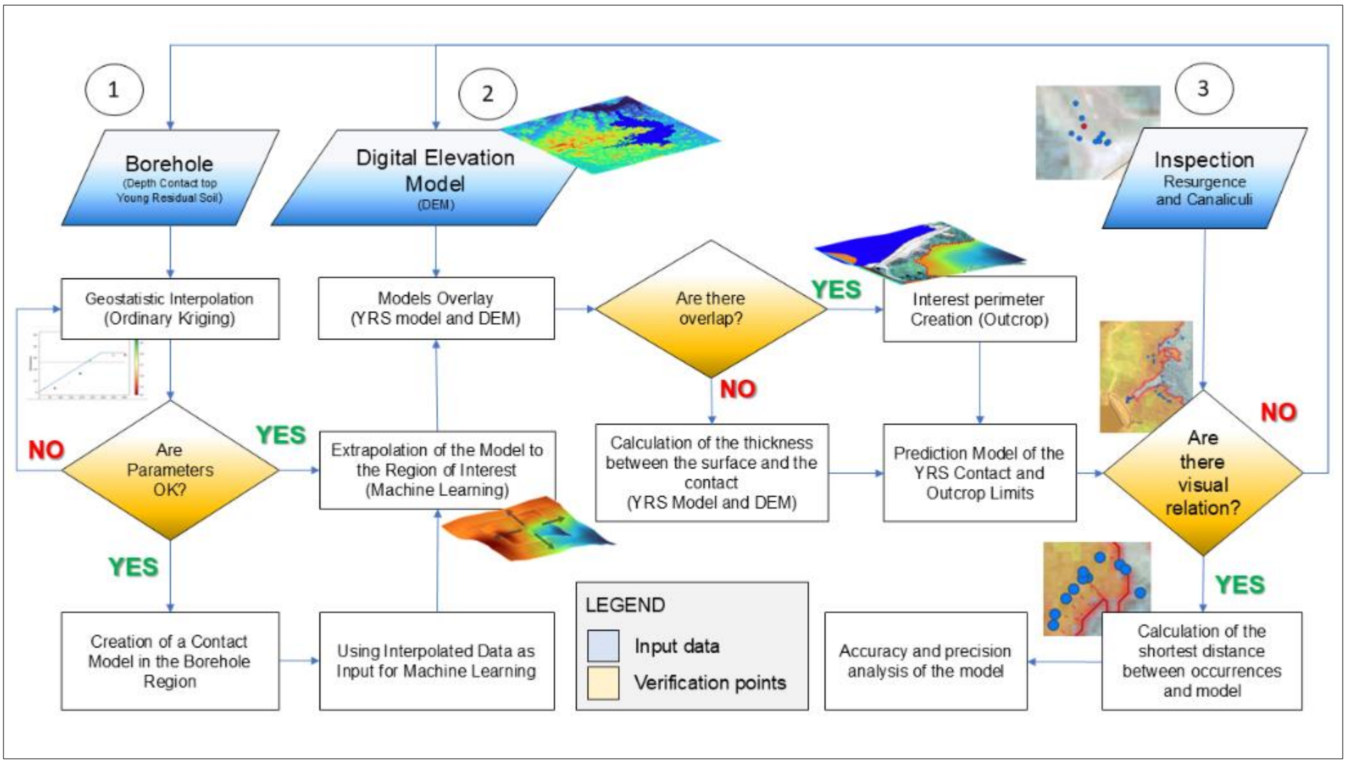


Figure 4. Flowchart of the developed methodology

2.1. *Input data Definition*

2.1.1. *Boreholes*

To identify patterns related to the resurgence and canaliculi phenomena, as well as the distribution of physical properties and lithological characteristics of the foundation soils, borehole data collected during the investigation phase were compiled to develop geotechnical models of the foundation. Approximately 450 analyzed boreholes were considered suitable for the analysis, specifically in the areas designated for dike construction. In parallel, field inspection records from 2020 to 2023 were gathered, documenting the locations and dates of observed resurgence and canaliculi occurrences downstream of the dikes. To identify reliable correlations between foundation characteristics and the occurrence of resurgence downstream of the dikes, it is essential to have a robust dataset comprising both subsurface investigation and field observation data.

During the analysis of borehole locations, it was observed that they were primarily concentrated in areas designated for dike construction, which is expected in foundation investigations for civil engineering projects. However, for the purposes of geological modeling, this spatial concentration presents a significant challenge. This is because the resurgence phenomena and the evolution of canaliculi, which have been more systematically monitored since 2020, often occur several meters downstream of the dikes, outside the original investigation zones. **Figure 5** illustrates the locations of the boreholes and the recorded incidents of resurgence and canaliculi for each dike presented in this work.

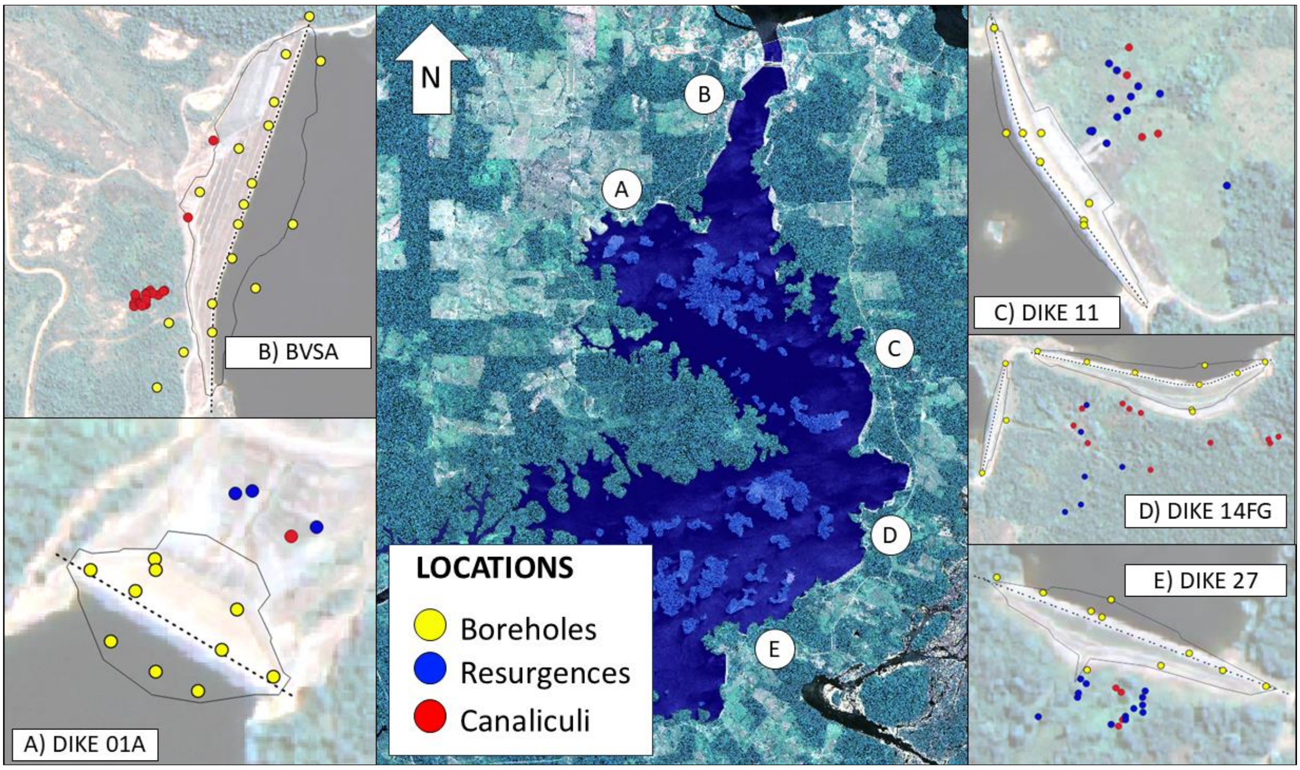


Figure 5. Illustration of the borehole locations and the resurgence and canaliculi occurrences for dikes presented in this work

The borehole dataset includes the lithological units identified along each borehole and the depths of contacts between distinct soil strata. In addition to its universal availability, this choice was supported by field observations, geological modeling, and numerical simulations, which indicated that areas where the contact point of the Young Residual Soil (YRS Top) lie closer to the surface tend to exhibit a higher incidence of resurgence and canaliculi (Rodrigues et al., 2025). Due to the high variability of surface soil types, a standardization was adopted: these upper lithological units were collectively classified as Superficial Soil (SS), followed by the under lithological unit Young Residual Soil derived from migmatite (YRS), as illustrated in **Figure 6**.

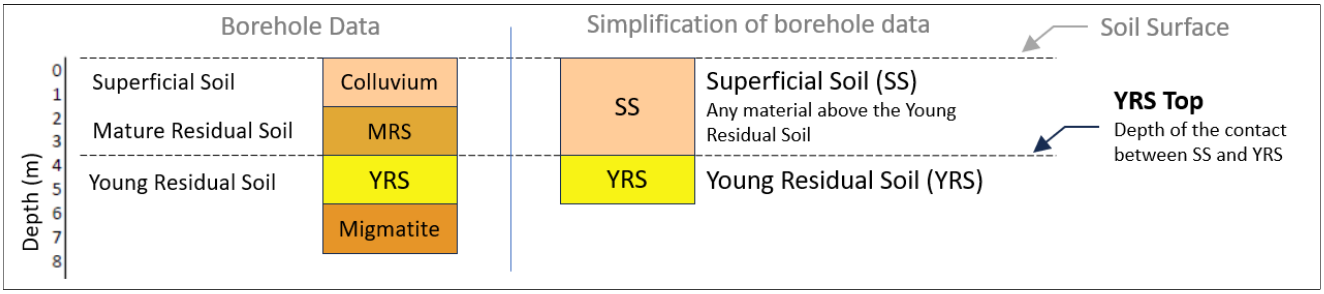


Figure 6. Illustration of the simplified (standardized) lithological profile of borehole data

Prior to geostatistical interpolation, the spatial autocorrelation of the YRS contact depth data was evaluated using Moran's I index as an exploratory diagnostic step (Moran, 1950). Although Moran's Index does not provide direct parameters for variogram modeling, from a geostatistical perspective the index may offer preliminary insights into the expected behavior of the variogram. The results (**Table 1**) indicated positive spatial autocorrelation for all analyzed dikes, with strong and statistically significant values for BVSA, 11 and 27, and weaker but still significant spatial structure for dikes 01A and 14FG. These results indicate that nearby boreholes tend to present similar contact depths, supporting the application of ordinary kriging for modeling the spatial continuity of the YRS contact. The variability observed among dikes also highlights the need for site-specific variogram modeling, rather than the adoption of a single regional model.

Table 1. Moran Index of Boreholes and quantity of incidences

Dike	Boreholes			Resurgence and Canaliculi Quantity
	Quantity	Moran Index	p-value	
01A	10	0.681	0.078	4
BVSA	18	0.917	0.001	23
11	17	0.811	0.001	17
14FG	13	0.117	0.022	17
27	16	0.740	0.001	17

2.1.2. Local Elevation Digital Model (DEM)

After developing the YRS Contact Model (Column 5 of Table 1), an overlay analysis was performed between the contact models and the topographic DEM. The DEM used in this study, referred to as the LiDAR DEM, was obtained through laser scanning of the intermediate reservoir region during the geotechnical investigation phase, as shown in **Figure 7**.

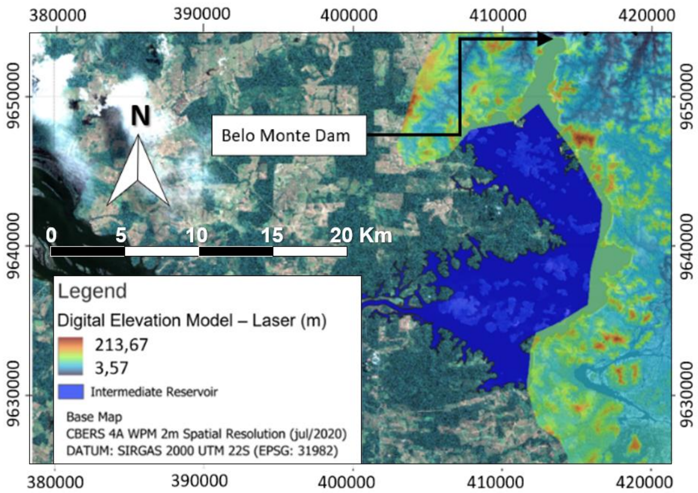


Figure 7. Illustration of the Digital Elevation Model of the Belo Monte Complex

2.2. Process Methods Definition (combined geostatistical and machine learning framework)

In this work, the SmartMap plugin, QGIS and Python program language was used to perform Ordinary Kriging (OK) and Support Vector Machine (SVM) methods (Qgis, 2024; Pereira, 2022).

2.2.1. Ordinary Kriging (OK)

Kriging is a geostatistical interpolation method that estimates values of a regionalized variable at unsampled locations based on the spatial dependence among observations. It is grounded in the theory of regionalized variables and uses the variogram (**Figure 8**) to describe spatial continuity, ensuring unbiased estimates with minimum variance (Yamamoto and Landim, 2013).

Among its variants, Ordinary Kriging (OK) is widely employed in geotechnical and geomorphological studies (Babacar and Denis, 1999). In this method, a locally constant and unknown mean is assumed, a hypothesis suitable for spatially continuous natural phenomena without a defined global trend, such as lithological contact surfaces. The estimate at each location results from a weighted linear combination of neighboring samples, whose weights are determined by the variogram model in order to minimize estimation error. The variogram quantifies the variation of semivariance as a function of the distance between sample pairs and constitutes the main element of spatial modeling. From the experimental variogram, a theoretical model is fitted, characterized by the following parameters (Yamamoto and Landim, 2013):

- **Variogram model:** theoretical function used to represent the spatial structure. The model defines the manner in which semivariance increases with distance.
- **Lag (h):** distance interval used to group point pairs in the calculation of the experimental variogram. It controls the spatial resolution of the analysis.
- **Maximum distance:** the largest distance considered in variogram construction and interpolation, ensuring that only point pairs with potential spatial correlation are used.
- **Nugget (C_0):** semivariance value near the origin, associated with measurement errors and variability at scales smaller than the sampling spacing.
- **Sill ($C_0 + C_1$):** semivariance plateau representing the total variance of the variable when spatial correlation no longer increases.
- **Range (a):** distance beyond which variable values no longer exhibit significant spatial correlation, defining the spatial scale of continuity of the phenomenon.

These parameters directly control the behavior of the kriging model, influencing the smoothness of interpolated surfaces, the radius of influence of samples, and the reliability of spatial estimates.

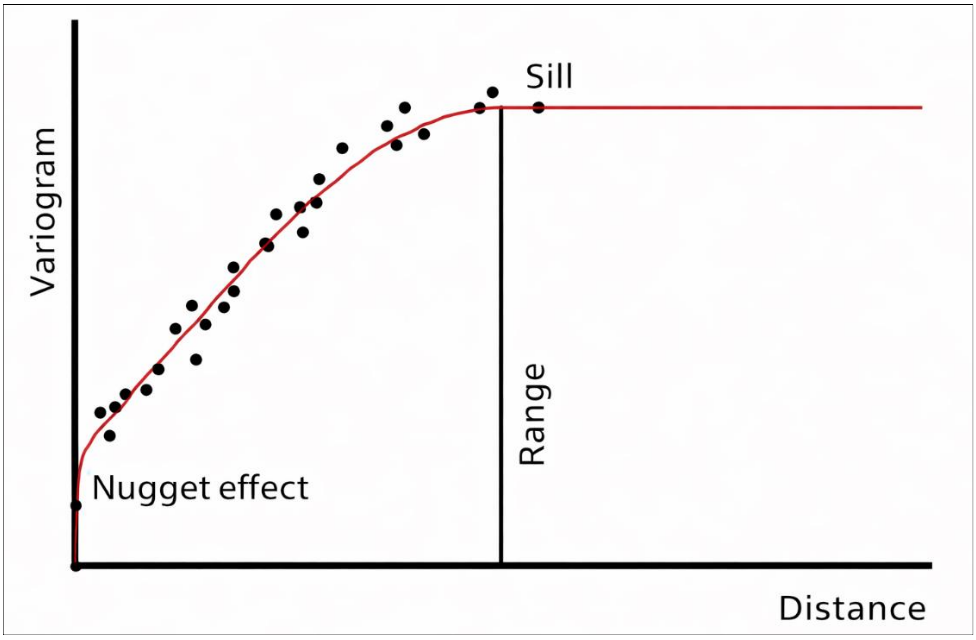


Figure 8. Illustration of the Variogram of Kriging method

Ordinary kriging performance was evaluated using leave-one-out cross-validation. Model accuracy was quantified by the root mean square error (RMSE) and the coefficient of determination (R^2), where lower RMSE and R^2 values closer to 1 indicate better predictive performance. Only cross-validation metrics were considered, as they provide an unbiased measure of model accuracy.

2.2.2. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning method grounded in convex optimization principles and statistical learning theory, widely employed in regression and classification problems due to its high generalization capability (Zhou, Zhang, and Wang, 2016). In its regression formulation, known as Support Vector Regression (SVR), the method estimates a function that represents the relationship between explanatory variables and a continuous response variable, while simultaneously controlling model complexity and relevant prediction errors (Cortes and Vapnik, 1995; Vapnik, 1995).

SVR is based on the concept of an ε-insensitive margin, defined by the parameter ε, within which deviations between observed and estimated values are not penalized, providing robustness to noise in the data (Smola and Schölkopf, 2004). The geometric principle of support vector regression, including the hyperplane, the margin, and the support vectors, is illustrated in the **Figure 9**.

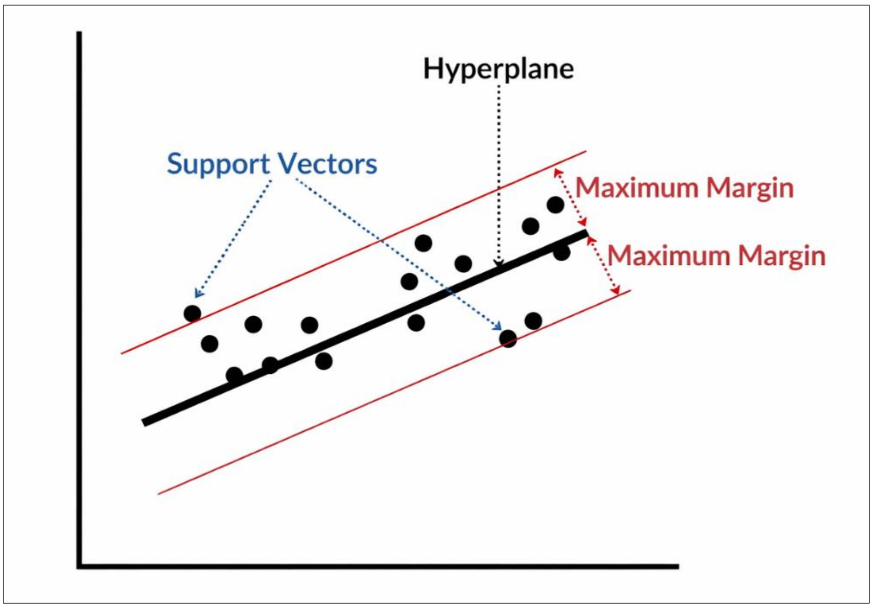


Figure 9. Illustration of the Support Vector Regression method

The performance of SVM models is commonly evaluated through cross-validation, using metrics such as the root mean square error (RMSE) and the coefficient of determination (R^2), which quantify predictive accuracy and the model generalization capability (Cortes and Vapnik, 1995; Vapnik, 1995).

2.2.3. Coupling between Geostatistics and Machine Learning

To extend the borehole data originally limited to the areas designated for dike construction (**Figure 10**.a) into the downstream zones, where resurgence and canaliculi were observed, two complementary methods were employed. Ordinary Kriging (OK) was applied to interpolate the lithological data between existing borehole locations **Figure 10**.b). In parallel, the Support Vector Machine (SVM) algorithm was used to extrapolate and classify the data into the downstream areas beyond the borehole coverage, as shown in **Figure 10**.c. Using the compiled lithological information, the final outcome was the generation of a digital elevation model (DEM) representing the contact surface of the Young Residual Soil (YRS), illustrated in **Figure 10**.d.

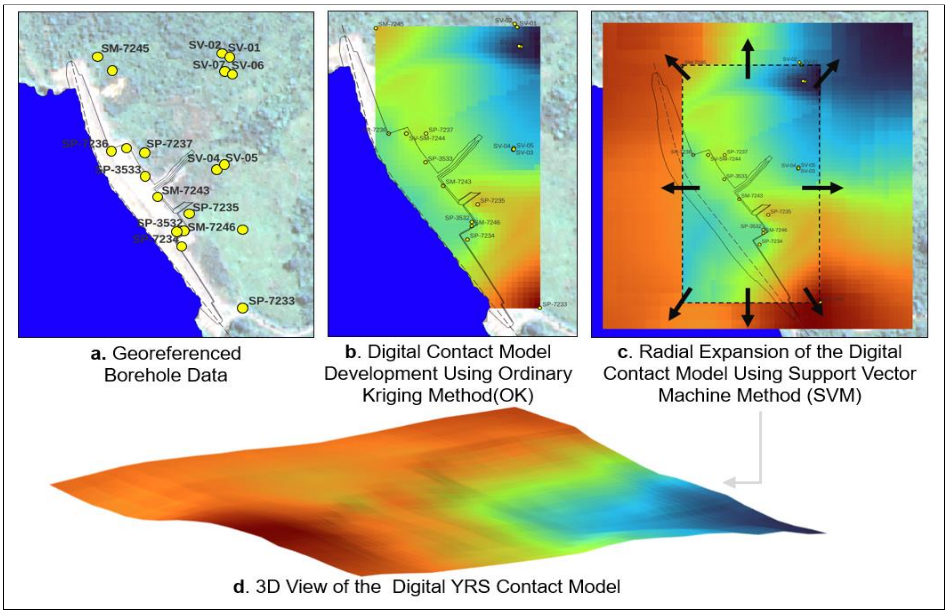


Figure 10. Illustration of the development of the YRS Contact Digital Model (YRS Contact DEM)

2.2.4. Standardization of Outcrop Estimation by Empirical Insights

Based on empirical analysis, which indicated a higher incidence of resurgence and canaliculi in areas where the YRS contact lies closer to the surface, a Digital Elevation Model (DEM) was also incorporated into the prediction methodology (**Figure 11**.a). By combining the two digital models (the YRS contact surface and the topographic surface) using Eq.(1), it was possible to standardize and automate the identification of outcrop zones of the YRS layer (**Figure 11**.c). This approach enabled the validation of observed correlations between resurgence events, canaliculi occurrence, and the spatial distribution of YRS outcrops (**Figure 11**.d).

$$\begin{gathered} \boldsymbol{IF}\ \left(Elevation_{YRS\,Model\,x,y} \leq Elevation_{DEM\,x,y}\right) \\ Elevation_{MDC\,SRJ\,x,y} \\ \boldsymbol{Otherwise}, location\ (x,y) = 0\ or\ NULL \end{gathered} \tag{1}$$

Where x and y are the UTM North and East georeferenced coordinates of the models, $Elevation_{YRS\,Model\,x,y}$ is the elevation of the contact of the young residual soil and $Elevation_{DEM\,x,y}$ is the elevation of the topographic surface of the digital elevation model.

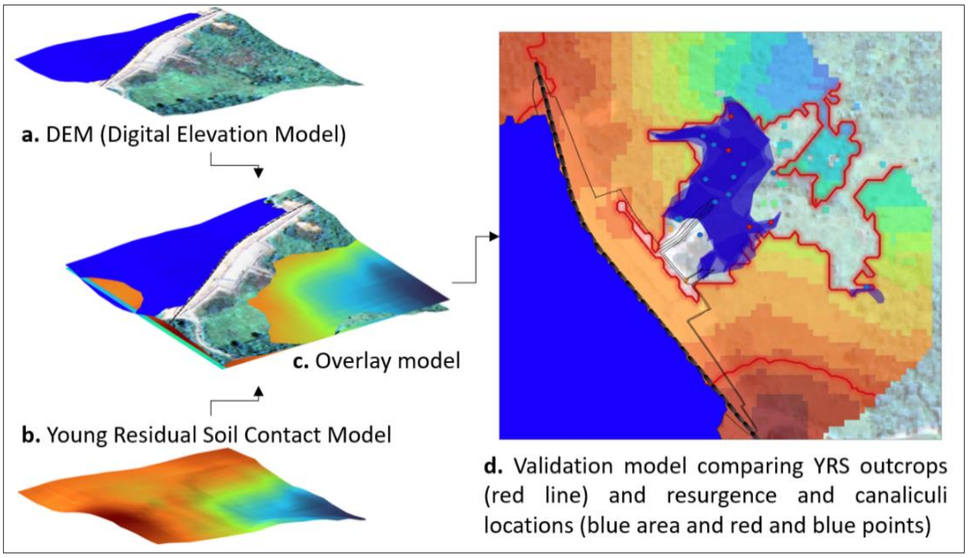


Figure 11. Models Overlay illustrations

1.2.5. Statistical Indicators of the Spatial Relationship Between Occurrences and the Contact Outcrop

To quantitatively assess the model predictive capability, a Python algorithm was developed to automatically calculate the shortest distance (SD_i) between each observed point (i) and the vectorized YRS DCM Boundary line (**Figure 12**). The Shortest Distance Average (SDA) and its standard deviation (sd_{SDA}) for each dike are then computed using Eq.(2) and Eq.(3) respectively.

$$SDA = \frac{1}{n}\sum_{i=1}^{n} SD_i \tag{2}$$

$$sd_{SDA} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(SD_i - SDA)^2} \tag{3}$$

- Shortest Distance Average (SDA): Values closer to zero indicate a strong spatial correspondence between the predicted YRS contact outcrop and the observed locations of resurgence and canaliculi.

- Standard deviation (sd_{SDA}): Lower values indicate that the spatial distribution of the predicted YRS contact outcrop closely aligns with the spatial pattern of resurgence and canaliculi occurrences, as illustrated in **Figure 13**.

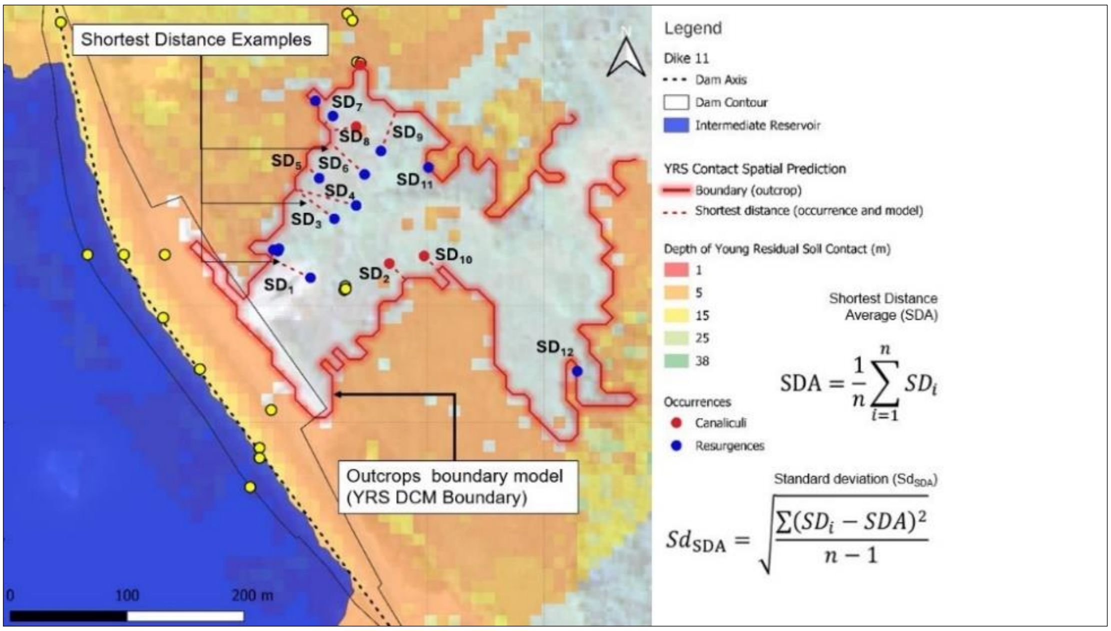


Figure 12. Shortest Distance (occurrence and model)

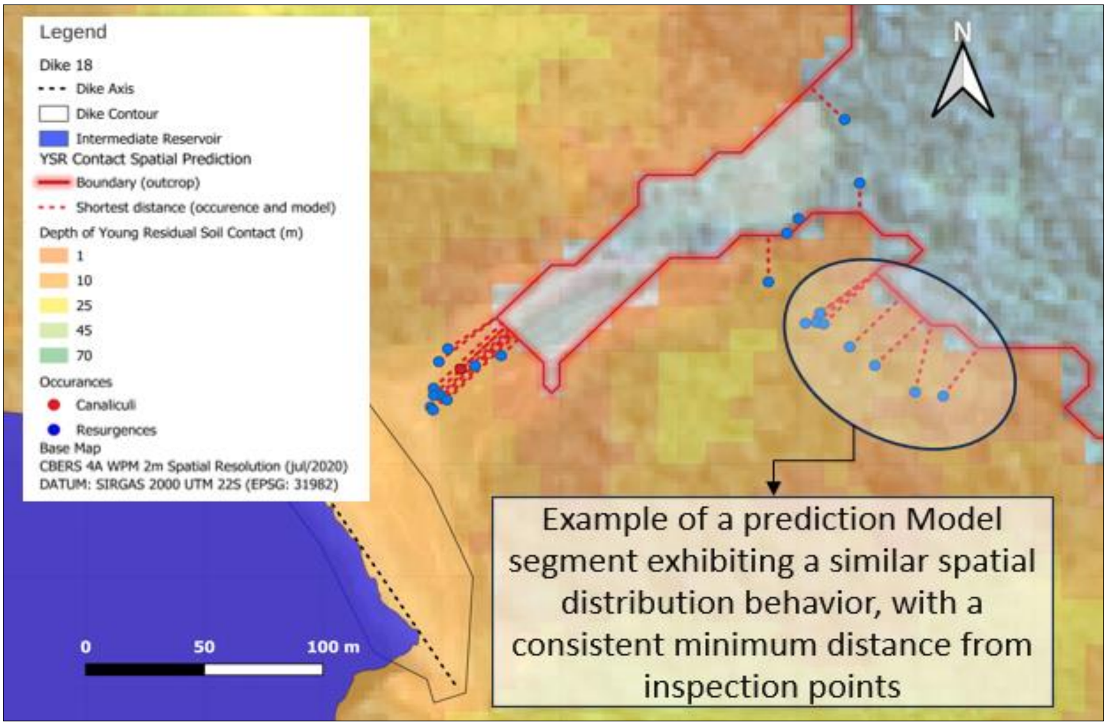


Figure 13. Illustration of the Statistical Indicators Representation for the Prediction Model

3. Results

3.1. Digital models of the Young Residual Soil (YRS) contact

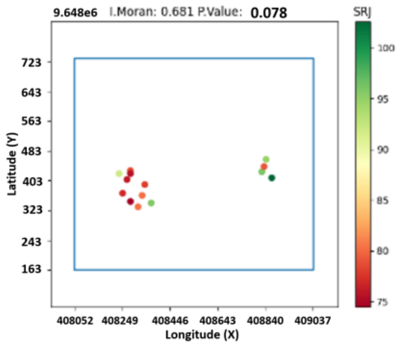
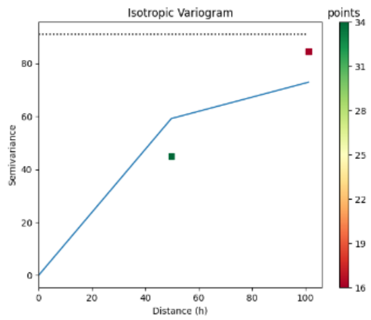
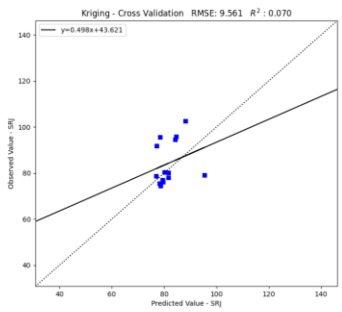
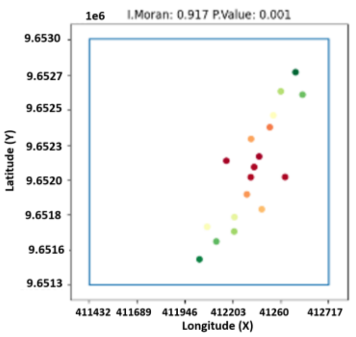
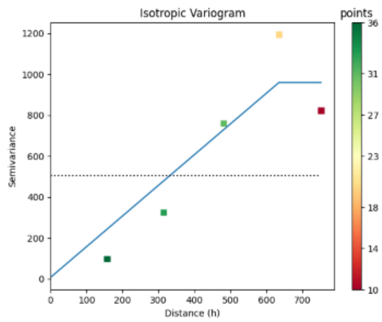
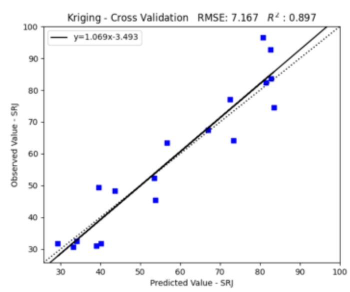
Considering the variation in data availability across the dikes and dams, tests were conducted by combining borehole data from adjacent dikes to optimize the variogram parameters for the initial YRS contact models using the Ordinary Kriging method. Due to the volume of results, this study highlights the spatial prediction models for five representative dikes: 01A, 11, 14FG, 27 and BVSA (Santo Antonio Dam).The **Table 2** presents the models and the corresponding calibration parameters for each YRS digital model developed using Ordinary Kriging (OK).

Table 2. Ordinary Kriging models and parameters of the Dikes

	Ordinary Kriging (OK)									SVM	
Dike	**Variogram model**	**Lag (m)**	**Max. distance (m)**	**Nugget**	**Sill**	**Range (m)**	**Neighbors**	**RMSE**	**R^2**	**RMSE**	**R^2**
01A	Exponential	70	150	0.00	76.76	101.08	7	9.56	0.07	5.58	0.63
BVSA	Linear to Sill	160	810	6.81	959.29	634.88	16	7.16	0.89	10.62	0.81
11	Linear to Sill	80	400	0.31	34.37	280.14	16	4.16	0.34	3.50	0.54
14FG	Linear to Sill	124	395	0.00	69.72	193.93	12	7.85	0.61	10.65	0.28
27	Gaussian	70	2043	8.48	129.41	635.52	30	4.64	0.76	3.36	0.89

Table 3 presents the locations of the boreholes, the fitted kriging variograms, and the cross-validation results based on RMSE.

Table 3. Boreholes Locations, Variogram (OK), Cross validation (OK RMSE Graph)

Dike Model	**Borehole locations and Moran Index**	**Variogram (OK)**	**Kriging – Cross Validation (RMSE)**
01A			
BVS A			

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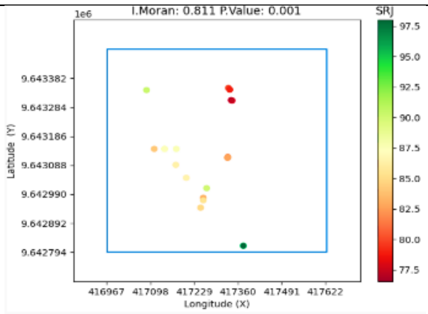
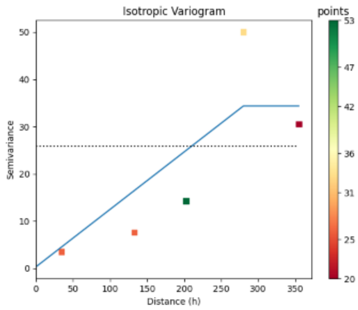
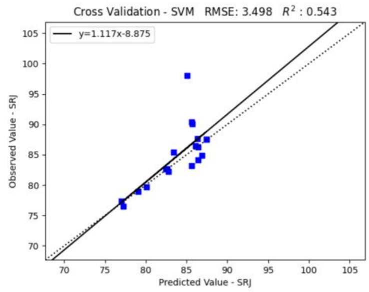
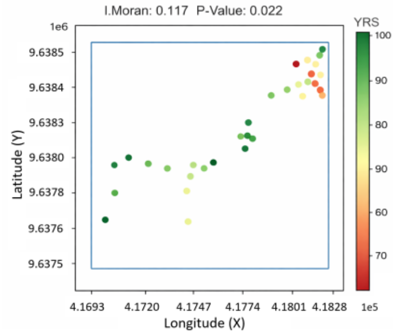
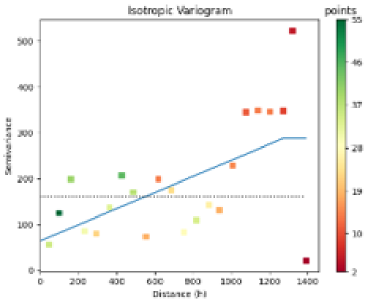
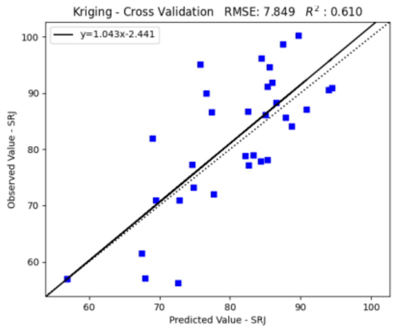
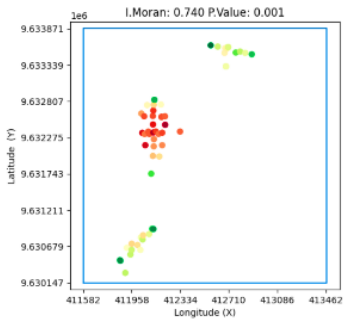
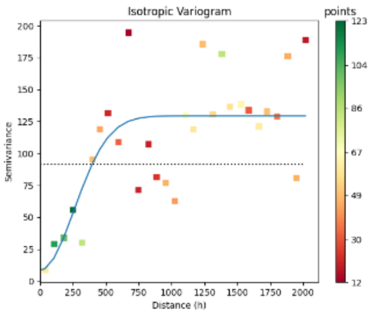
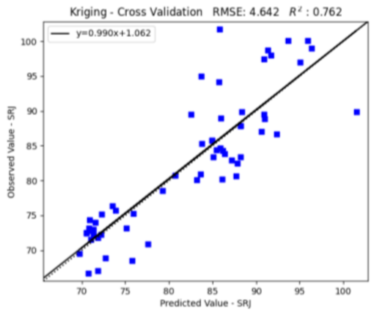
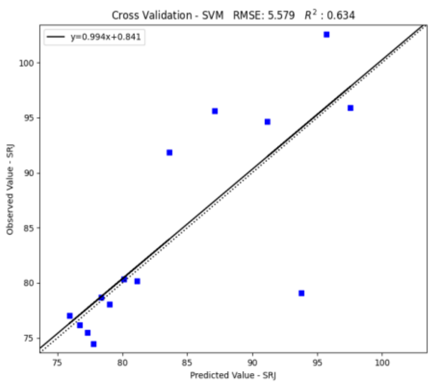
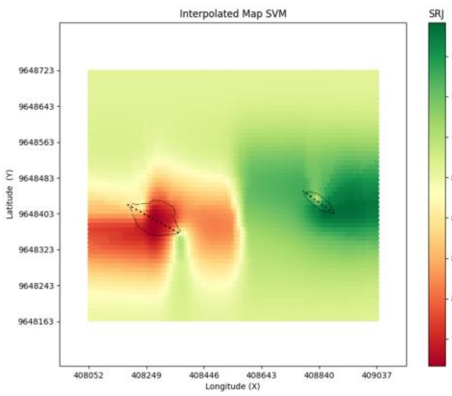
Continuation

Dike Model	Borehole locations and Moran Index	Variogram (OK)	Kriging – Cross Validation (RMSE)
11			
14FG			
27			

These models were subsequently extended to downstream regions, where resurgence and canaliculi were identified, using the SVM method. **Table 5** presents the results of cross-validation using the Root Mean Square Error (RMSE) to define the SVM hyperparameters and the digital model of the YRS contact surface, with the locations of the corresponding dams superimposed.

Table 4. Cross validation by RMSE (SVM) and Contact Digital Model.

Dike Model	SVM optimized Hyperparameters (RMSE)	YRS Digital Contact Model
01A		

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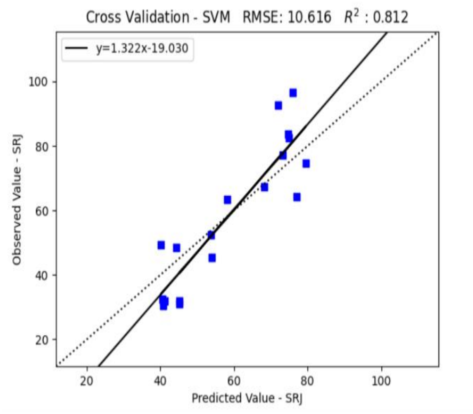
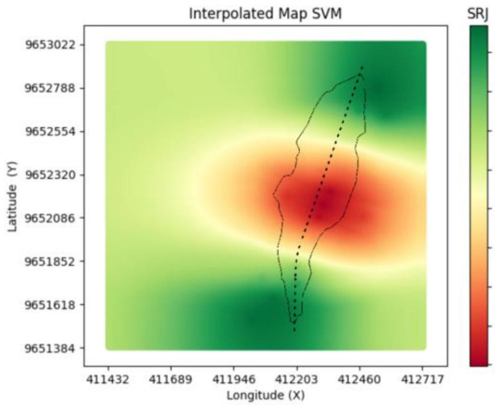
<table>
<tr><th>Dike Model</th><th>SVM optimized Hyperparameters (RMSE)</th><th>YRS Digital Contact Model</th></tr>
<tr><td>BVSA</td><td>
</td><td>
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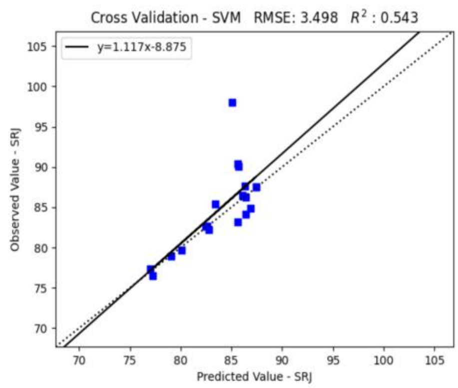
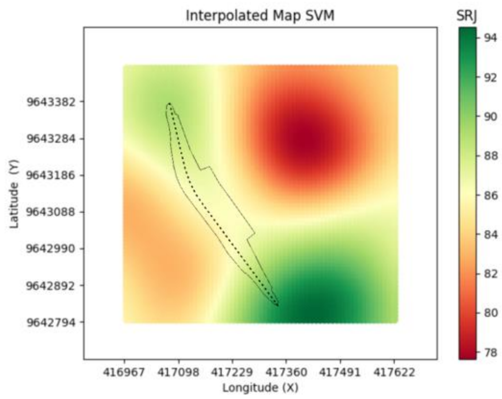
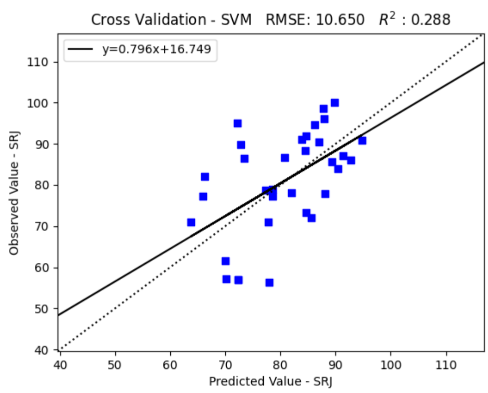
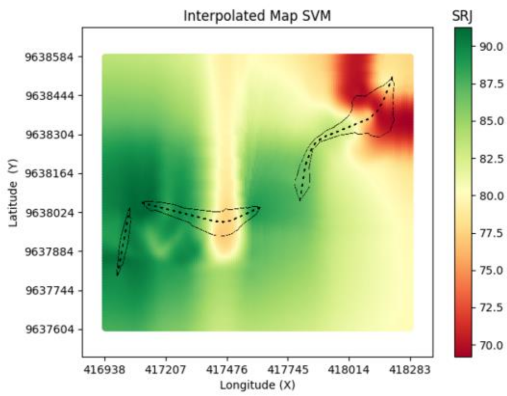
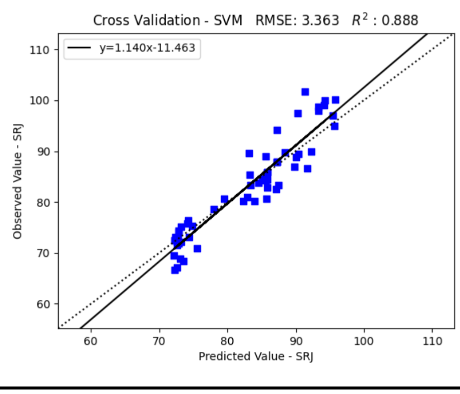
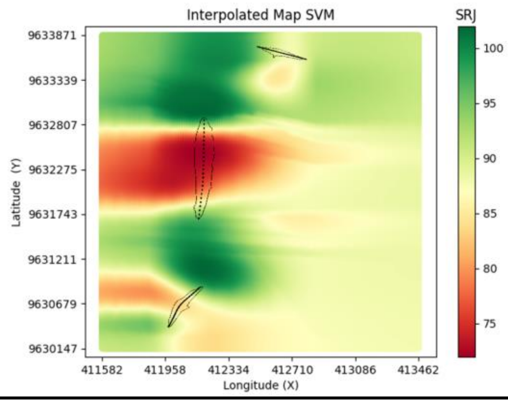
<tr><td>11</td><td>
</td><td>
</td></tr>
<tr><td>14FG</td><td>
</td><td>
</td></tr>
<tr><td>27</td><td>
</td><td>
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3.2. Mapping of Young Residual Soil outcrops and overlap with occurrence points

Following the methodology presented in **Figure 4**, georeferenced vectors representing the boundary of the YRS contact model (YRS DCM Boundary) were generated, delineating the areas where the contact outcrops. When this boundary was overlaid with inspection data, specifically the recorded locations of resurgence and canaliculi evolution, a notable spatial correlation between the predicted outcrop regions and the observed phenomena was identified, as illustrated in **Figure 14** through **Figure 18**.

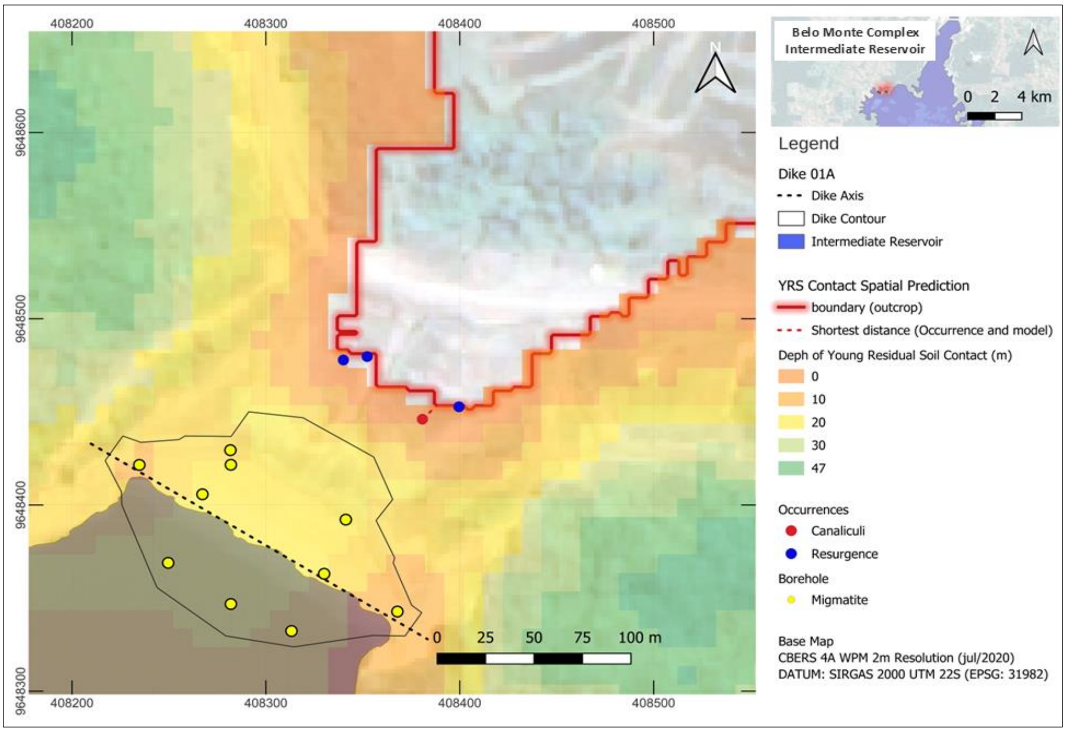

Figure 14. Dike 01A (Spatial Prediction Model)

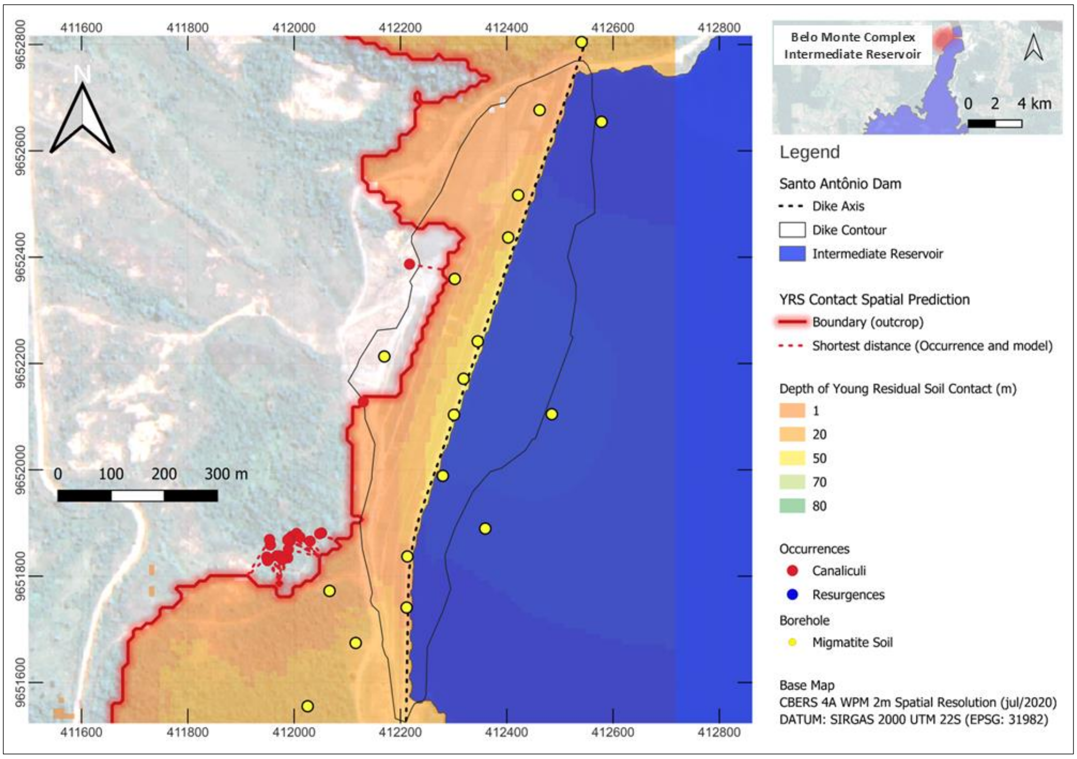

Figure 15. BVSA - Santo Antonio Dam (Spatial Prediction Model)

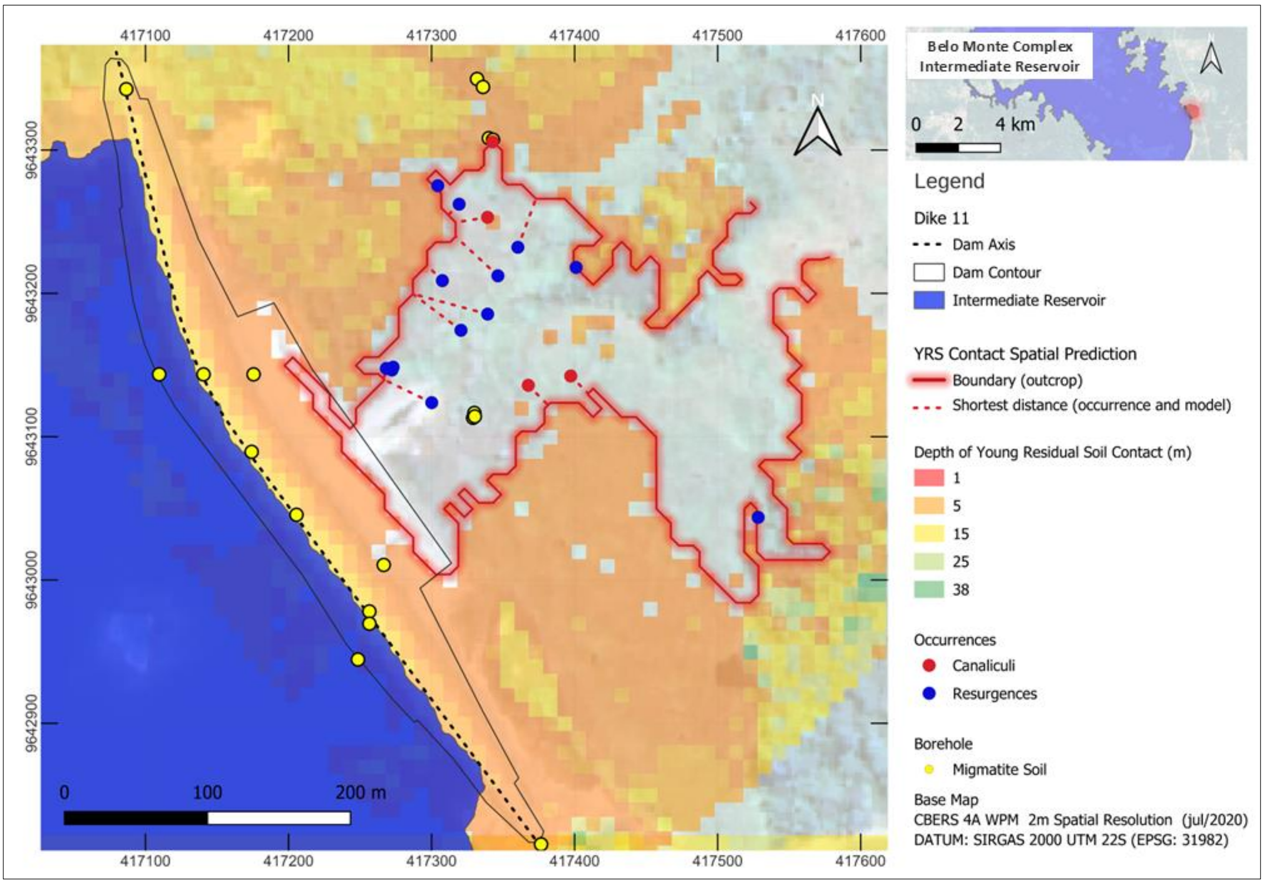

Figure 16. Dike 11 (Spatial Prediction Model)

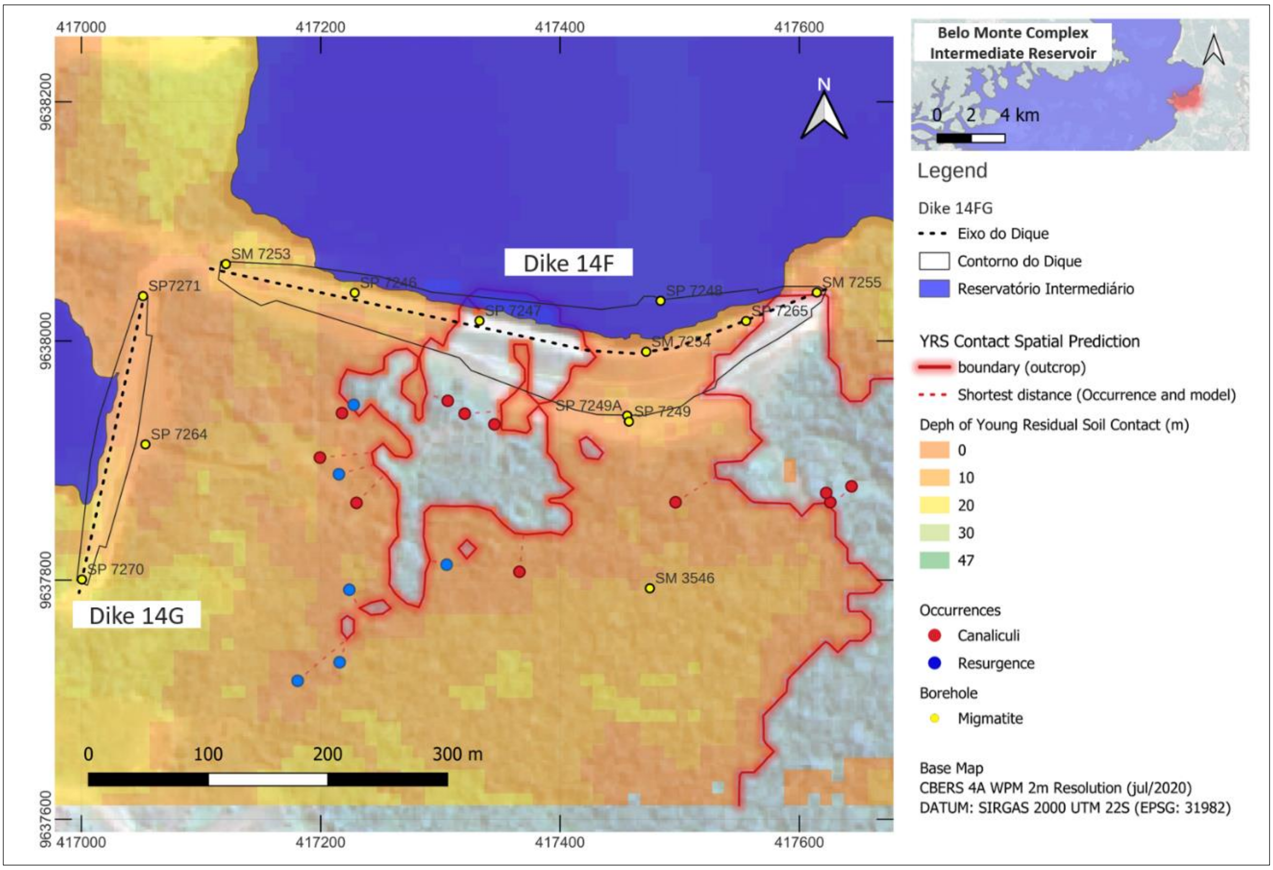

Figure 17. Dike 14FG (Spatial Prediction Model)

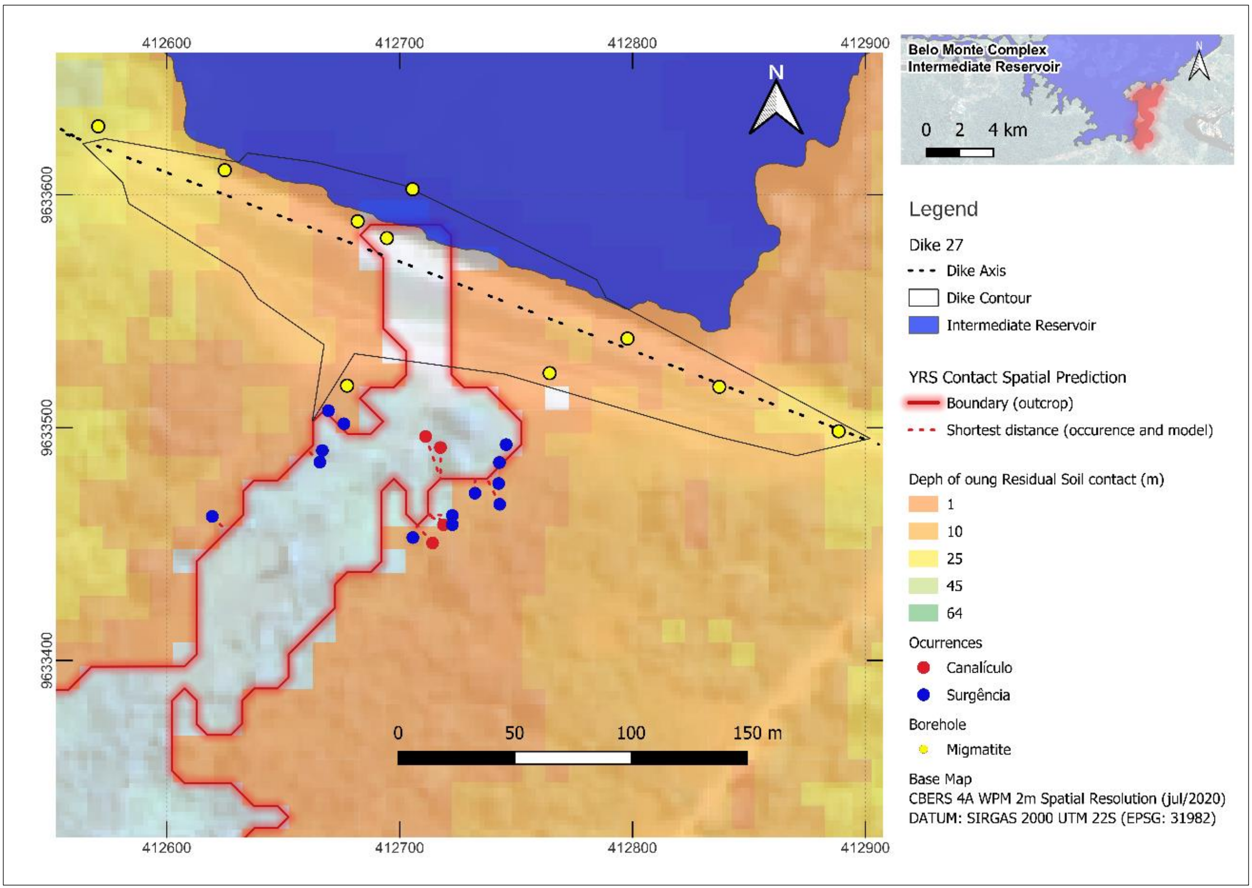

Figure 18. Dike 27 (Spatial Prediction Model)

3.3. Statistical Indicators of Occurrences and the Contact Outcrop

To quantify the proximity between the YRS Contact Boundary Line and the observed resurgence and canaliculi points, a Python algorithm was developed to calculate the shortest distance from each point to the boundary line for every dike. Subsequently, the average of these distances was computed for each dike, referred to as the average of Shortest Distance (MSD) along with the corresponding standard deviation values. The results are summarized in **Table 5** in meter.

Table 5. Statistical Indicators of the Intermediate Reservoir Dikes

Dike	Shortest Distance Average (SDA) [m]	Shortest Distance Deviation (sd_{SDA})
01A	4.44	4.40
27	7.71	4.78
11	19.04	16.91
14FG	24.55	16.15
BVSA	50.63	16.94

4. Discussion

The occurrence of canaliculi and associated resurgence processes in tropical dam foundations has been traditionally interpreted as the result of a complex interaction between pedogenetic evolution, biological activity, and hydraulic forcing. In this context, the results obtained for the Belo Monte Hydroelectric Complex provide important insights into how these processes manifest spatially and how they can be interpreted within a broader geomorphological and hydrogeological framework.

The strong spatial correspondence observed between resurgence and canaliculi occurrences and the modeled outcrop zones of the Young Residual Soil (YRS) contact indicates that these phenomena are not randomly distributed features of the foundation. Instead, they are structurally conditioned by the internal organization of the weathering profile. This finding is consistent with classical hypotheses that associate canaliculi genesis with advanced laterization and pedo-karstic processes, in which differential leaching of soluble elements and the progressive degradation of primary rock fabric promote the development of preferential void networks (Jury, 1989).

From a geomorphological perspective, the YRS contact represents a transition zone marked by contrasts in texture, structure, and hydraulic conductivity. Such contrasts are known to favor subsurface flow concentration and the redirection of percolating water along stratigraphic discontinuities. The results of this study suggest that where this contact approaches the surface or intersects the local topography, hydraulic gradients increase locally, enhancing the activation and enlargement of preexisting tubular voids. This mechanism provides a conceptual explanation for the recurrent association between shallow YRS contact depths and the emergence of resurgences downstream of the dikes.

The laboratory characterization of the canaliculi infilling material further supports this interpretation. The similarity between the infilling material and the surrounding soil matrix, combined with the lower content of iron oxide–hydroxide concretions and the presence of organic remnants, is consistent with a genesis dominated by in situ soil reorganization rather than by external sediment input (Fernandes et al., 2025). This observation aligns with studies that emphasize the role of root systems and biological activity in initiating voids, which are subsequently enlarged by hydraulic erosion once preferential flow paths are established (Bignell; Eggleton, 2000; Saha et al., 2023). The identification of dendritic geometries, associated with root interactions, reinforces the interpretation of canaliculi as features that evolve progressively within the pedological framework.

When compared with classical Brazilian case studies, such as Tucuruí and Balbina, the Belo Monte case exhibits both similarities and distinctive characteristics. In all these cases, canaliculi occur in highly weathered residual soils and act as preferential flow paths, significantly increasing foundation permeability. However, in Tucuruí, where the depth to competent bedrock was relatively shallow, extensive excavation and direct treatment of canaliculated horizons were feasible, effectively removing the most problematic zones. In Belo Monte, the greater thickness of the residual soil mantle and the depth of the rock surface precluded such an approach over large areas, resulting in a fundamentally different engineering response.

This constraint places Belo Monte closer to cases such as Balbina and international examples in lateritic environments, where mitigation strategies focused on controlling hydraulic gradients and homogenizing permeability rather than eliminating the phenomenon itself. The international failures and incidents reported for lateritic foundations, such as at the Xe-Pian–Xe-Namnoy and Comoé dams, further illustrate the consequences of underestimating the spatial organization and connectivity of canaliculated networks. In this regard, the Belo Monte experience highlights the importance of understanding canaliculi not as isolated phenomena, but as manifestations of a spatially structured subsurface system.

The hydraulic conductivity results obtained in this study provide an additional link between the observed spatial patterns and the theoretical framework. The higher permeability values measured at the interface between the superficial soil and the YRS corroborate classical seepage theory, which predicts that flow tends to concentrate along stratigraphic contrasts and zones of reduced structural resistance (Cedergren, 1937).

Taken together, these findings reinforce the interpretation that canaliculi evolution in tropical residual soils is governed by a combination of pedological inheritance and hydrological activation. The spatial models developed in this study should therefore be understood not merely as predictive tools, but as representations of underlying geomorphological controls. By translating borehole-based stratigraphic information and surface topography into spatial patterns of susceptibility, the approach adopted here provides a framework for linking empirical observations to process-based understanding.

In this sense, the contribution of the Belo Monte case extends beyond site-specific analysis. It demonstrates that the integration of subsurface stratigraphy, geomorphological context, and spatial modeling offers a viable pathway for bridging the gap between descriptive case studies and a more systematic interpretation of canaliculi-related processes in tropical environments. Such integration is essential for advancing both the scientific understanding of these phenomena and their practical management in dam safety contexts.

5. Conclusion

This study demonstrated that the integrated application of Ordinary Kriging and Support Vector Machines (SVM), in combination with digital terrain models and empirical observations, constitutes a robust strategy for the spatial prediction of resurgence and canaliculi in containment dikes.

The proposed methodology not only validated the field records of the Belo Monte team but also proved capable of transforming empirical observations into a systematic predictive tool. The developed protocol can be replicated in other hydroelectric projects, supporting dam safety teams in the early detection of anomalies while reducing time, costs, and inspection efforts through the creation of corridors representing areas with higher likelihood of resurgence and canaliculi occurrence. These corridors are generated from the YRS contact outcrop line and extended both upstream and downstream by a distance equal to the average shortest distance defined for each dike. This work contributes to advancing dam safety management practices, reinforcing the importance of multidisciplinary approaches that integrate geotechnics, geology, and data science in the understanding and mitigation of complex processes such as canaliculi evolution and resurgence occurrence.

Another important aspect not addressed in this study was the temporal modeling of resurgence and canaliculi phenomena. Due to the semiannual frequency of inspections, it was not possible to establish a relationship considered valid for spatiotemporal modeling of these phenomena. Although multivariate analyses were performed considering reservoir level, piezometers, and flow meters, the results were not satisfactory. Therefore, the study focused exclusively on deepening the understanding of the spatial relationship between occurrence points and the geological conditions of the foundation of the Belo Monte intermediate reservoir dike complex. This situation led to recommendations for improving and optimizing data collection during inspections by increasing their frequency and adopting equipment that facilitates the standardized and digital acquisition of large volumes of data, such as the use of drones with high-resolution and thermal cameras.

Possible future developments currently underway, but not completed within the timeframe of this project, include the development of a routine capable of dynamically and automatically updating the outcrop model upon the insertion of new borehole data. At present, the model, implemented in the Belo Monte production system (INPI Software Registration BR512024003843-4), allows the updating of statistical indicators (average shortest distance and standard deviation) through the incorporation of new resurgence and canaliculi occurrences during subsequent inspections. A similar situation applies to the spatiotemporal prediction of these phenomena. New data are currently being collected by the Belo Monte team and may be used not only to refine the spatial models but also to establish accurate spatiotemporal relationships, enabling the development of spatiotemporal prediction models.

Authors' Contributions: Conception E. J SILVA JUNIOR, R. L. RODRIGUES, D. O. FERNANDES, A. E. LIMBERGER and L. REGINATO; Research, E. J SILVA JUNIOR, R. L. RODRIGUES, D. O. FERNANDES, A. E. LIMBERGER and L. REGINATO; Methodology, E. J SILVA JUNIOR, C. G. NOGUEIRA, J. P. FRIGO; Software, E. J SILVA JUNIOR; Validation, R. L. RODRIGUES, D. O. FERNANDES, C. G. NOGUEIRA, E. D. KRAJEWSKI; Data preparation, E. J. SILVA JUNIOR; Article writing, E. J SILVA JUNIOR, R. L. RODRIGUES, D. O. FERNANDES, A. E. LIMBERGER; Review by, R. L. RODRIGUES, D. O. FERNANDES, A. E. LIMBERGER, L. REGINATO, C. G. NOGUEIRA, J. P. FRIGO, E. D. KRAJEWSKI. supervision by R. L. RODRIGUES. All authors have read and agreed with the published version of the manuscript.

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Conflict of Interest: The authors declare no conflict of interest.

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