Journal of Geomine (2026), 4(2), 102-114
DOI: 10.22077/jgm.2026.10907.1071

Data-driven ensemble strategies for enhancing ore grade estimation accuracy

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Received: 2026 Jan. 28, Revised: 2026 Jul. 12, Accepted: 2026 Aug. 19, Published: 2026 Sept. 20

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ABSTRACT

Accurate ore grade estimation is critical for effective mine planning, resource evaluation, and economic feasibility in mineral deposits. Traditional geostatistical methods such as ordinary kriging (OK) and inverse distance weighting (IDW) provide robust spatial predictions but struggle to handle non-stationary and highly heterogeneous ore bodies. Machine learning algorithms (MLAs), including artificial neural networks (ANNs) and support vector regression (SVR), offer flexibility in capturing nonlinear relationships but may suffer from overfitting and unstable uncertainty quantification. This study introduces a hybrid ensemble framework that integrates geostatistical and machine learning models for enhanced ZnS grade estimation in the Gushfil Pb–Zn deposit, Irankuh district, Iran. A total of 518 composite drill-core samples taken from layer No. 3 of the deposit were analyzed, and five base learners (OK, IDW, kNN, ANN, and SVR) were implemented. Three ensemble strategies (Basic Ensemble Method (BEM), Generalized Ensemble Method (GEM), and Locally Weighted Ensemble Method (LEM)) were evaluated. The results show that individual models, particularly OK and SVR, provide competitive predictive performance (R = 0.60 and 0.58, respectively). However, the adoption of ensemble strategies leads to a further improvement in prediction accuracy, resulting in the best overall performance among the evaluated methods. The LEM approach achieved the highest correlation coefficient (R = 0.66) and the lowest mean squared error (MSE = 0.015) by adaptively weighting base learners according to local performance. These findings demonstrate that hybrid ensemble frameworks effectively combine spatial structure and nonlinear modeling, offering a robust and reproducible approach for ore grade estimation in complex and heterogeneous deposits.

KEYWORDS

Ore grade estimation, hybrid ensemble learning, kriging, artificial neural network, support vector regression

I. INTRODUCTION

Precise estimation of ore grade serves as a fundamental aspect of mineral resource evaluation, as it has a direct influence on mine design, production planning, and the long-term economic sustainability of mining operations (DOMINY, NOPPÉ, and ANNELS 2002). Despite the remarkable progress of geostatistics and computational modeling over the past several decades, predicting ore grades remains a considerable challenge. The limited spatial coverage of sampling, complex geological structures, and inherent uncertainty of subsurface mineralization often lead to estimation errors that can propagate through the entire mine planning process (De Souza, Costa, and Koppe 2004; Lindi et al. 2024). These uncertainties are particularly critical during feasibility studies and strategic planning, where even small deviations in grade predictions can lead to substantial financial and operational consequences.

Traditional spatial interpolation techniques (such as ordinary kriging and inverse distance weighting (IDW)) have remained the dominant tools for grade estimation because of their solid theoretical basis and ability to quantify spatial uncertainty (Calder and Cressie 2009; Olea 2018). Ordinary kriging, in particular, offers an explicit measure of estimation variance and has therefore become a benchmark for reporting mineral resources under various international standards (Yamamoto 2000). Nevertheless, these geostatistical approaches rely on key assumptions, including second-order stationarity and well-defined variogram models, which may not hold in deposits characterized by abrupt lithological transitions or strongly non-Gaussian grade distributions (M.J-C. Wadoux, Brus, and Heuvelink 2018; Piao and Park 2023). Under such conditions, model misspecification can lead to biased predictions and reduced reliability (Todini and Ferraresi 1996; Piao and Park 2023).

The advent of data-driven techniques has introduced new opportunities to overcome these limitations. Machine learning algorithms (MLAs) such as Artificial neural networks (ANNs) and support vector regression

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(SVR) have shown considerable proficiency in modeling complex nonlinear relationships between geological characteristics and mineral grades. (Mahboob, Celik, and Genc 2022; Battalgazy et al. 2023; Maniteja et al. 2025). These methods are less constrained by distributional assumptions and can flexibly adapt to heterogeneous datasets, making them attractive complements to geostatistical models. However, individual machine learning models are often prone to overfitting and may not provide reliable uncertainty quantification in highly heterogeneous mineralized zones (Maniteja et al. 2025; Mahboob, Celik, and Genc 2022).

Ensemble learning has emerged as a promising strategy to address these issues by integrating multiple base learners to exploit their complementary strengths (Dutta et al. 2006; Atalay 2025; Ganaie et al. 2022). Ensemble learning frameworks, including bagging, boosting, and more advanced ensemble strategies, reduce prediction variance, enhance predictive accuracy, and improve model robustness by combining the strengths of multiple predictors rather than relying on a single estimator (U. E. Kaplan, Dagasan, and Topal 2021). Recent studies in other geoscientific domains have shown that combining classical geostatistical estimators with machine learning models can yield substantial improvements in predictive performance (Maniteja et al. 2025; Singh, Ray, and Sarkar 2022). However, the systematic implementation of advanced ensemble methods in mineral grade estimation remains comparatively limited, and issues concerning the optimal combination of models and the adaptation of regional weights have yet to be fully addressed.

The present study seeks a novel framework by proposing data-driven ensemble approaches for ore grade estimation that combine the advantages of geostatistical methods and machine learning within an integrated framework. Specifically, five complementary base learners—Ordinary Kriging (OK), Inverse Distance Weighting (IDW), Artificial Neural Networks (ANN), Support Vector Regression (SVR), and K-Nearest Neighbors (KNN)—are employed to capture both the spatial dependence of ore grades and the complex nonlinear relationships within the data (Dumakor-Dupey and Arya 2021; Erdogan Erten et al. 2025). In this study, three ensemble schemes have been applied: the Basic Ensemble Method (BEM), which aggregates multiple resampled models to reduce variance; the Generalized Ensemble Method (GEM), which assigns weights to base learners according to their performance; and the Localized Ensemble Method (LEM), which assigns dynamic weights to base learners according to their local performance. To facilitate understanding of the proposed methodology, the overall workflow adopted in this study is illustrated in Fig. 1. The objectives of this study are to: (i) benchmark the predictive performance of individual base learners; (ii) assess the extent to which BEM and GEM enhance estimation accuracy; and (iii) provide a reproducible, data-driven workflow applicable to complex ore deposits with heterogeneous grade distributions. The proposed methodology integrates classical geostatistical approaches with modern machine learning techniques to generate more reliable ore grade predictions and support informed decision-making in mine planning and resource assessment.

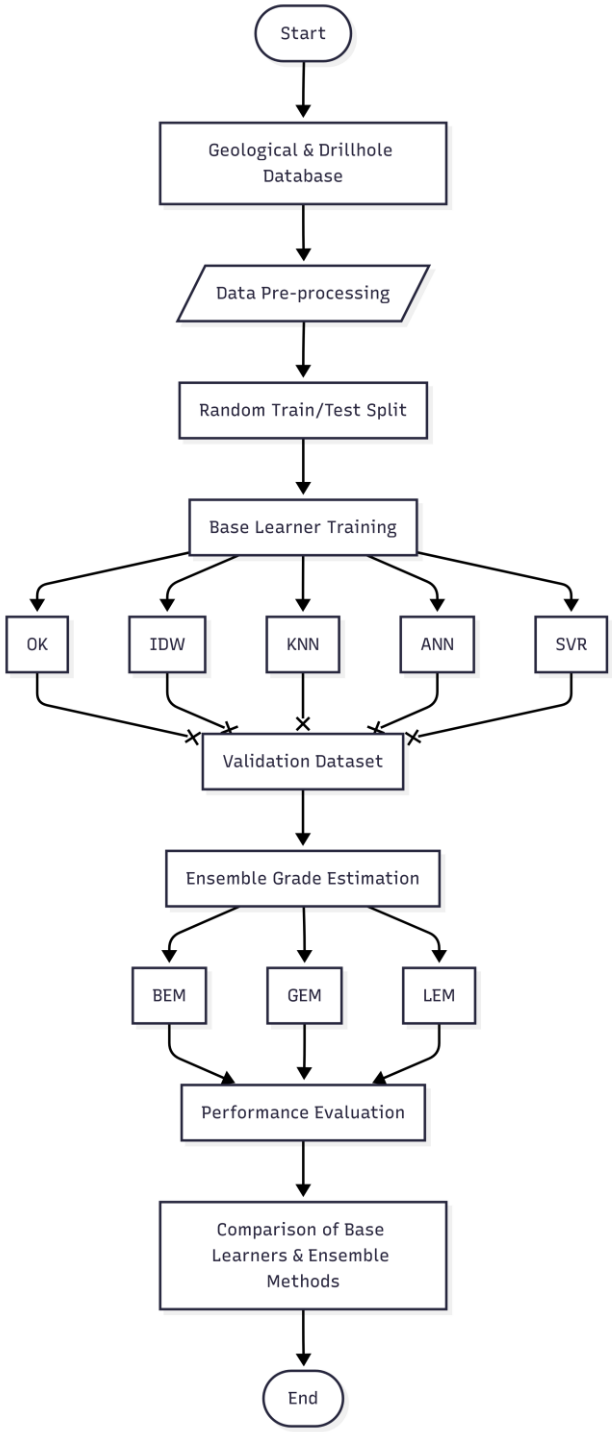

Fig. 1. Overall workflow of the proposed ore grade estimation framework

II. Materials and Methods

A. Study Area and Data

The Irankuh mineral district, located south of Isfahan, lies within the Malayer–Isfahan metallogenic belt of the Sanandaj–Sirjan Zone (Momenzadeh 1976; Rajabi, Rastad, and Canet 2012)(Fig. 2). The oldest rock units in the area are Lower Jurassic dark gray siltstone and sandstone. These are unconformably overlain by Cretaceous dolomitic limestone with minor shale and marl, with a total sedimentary sequence thickness exceeding 800 m (Sevieri et al. 2019)(Fig. 3). About 30 km southeast of the study area, the Kollah Qazi granodioritic intrusion has intruded Jurassic shales, although there is no evidence of its penetration into the overlying Cretaceous carbonate rocks (Momenzadeh 1976; Zarasvandi, Poursheikhi, and Saki 2021; Ayati et al. 2014). The region has been strongly affected by tectonic processes associated with multiple phases of the Alpine orogeny, which produced complex folding and faulting that facilitated hydrothermal fluid circulation (Zarasvandi, Poursheikhi, and Saki 2021). Lead and zinc ore deposits occur along both limbs of this structural zone, mainly within the Cretaceous dolostone host rocks (Ghazban, McNutt, and Schwarcz 1994; Rajabi, Rastad, and Canet 2012). Based on geological evidence, including alteration features, deposit morphology, mineralization textures, and characteristic mineral assemblages consisting of sphalerite, galena, barite, and dolomite, the Irankuh Pb–Zn mineralization is classified as a Mississippi Valley-Type (MVT) deposit (Rajabi, Rastad, and Canet 2012; Zarasvandi, Poursheikhi, and Saki 2021; Sevieri et al. 2019). Major deposits in this district include Gushfil, Tapeh-Sorkh, Kollah-Darvazeh, and Rou-Marmar.

In the Gushfil deposit, mineralization occurs as an epigenetic, structurally controlled body along a reverse fault trending N60°W with a dip of about 80°, at the contact between Jurassic shales and reddish-brown Cretaceous dolomites (Saboori and Malekzadeh Shafaroudi 2019). The host rocks of the lead–zinc mineralization are mainly dolomite and, to a lesser extent, shale (Saboori and Malekzadeh Shafaroudi 2019; Karimpour et al. 2017). In dolomitic host rocks, ore deposition occurs in two main forms: (1) replacement and (2) open-space filling within fault-related fractures, breccias, and cavities. In contrast, within the shale units, mineralization is confined to fault-related fractures filled with ore-bearing fluids, and the metal content is considerably lower than that observed in the dolomitic units (Saboori and Malekzadeh Shafaroudi 2019; Konari, Rastad, and Peter 2017; Hosseini-Dinani and Aftabi 2016). The ore mineralogy of the Gushfil deposit includes sphalerite, galena, and pyrite, associated with gangue minerals such as dolomite, quartz, organic matter, and minor barite. These minerals exhibit brecciated, veinlet-filling, open space filling, and disseminated textures. In the brecciated texture, the host rock is fractured (by faulting) and the fragments are cemented by hydrothermal dolomite, quartz, and ore minerals. In the disseminated texture, mineralizing fluids infiltrated cavities and pores within the host rock. The principal alteration styles in Gushfil are dolomitization and silicification — with silicification more strongly developed in shale units. Some studies also note sericitization as a subordinate alteration associated with the mineralizing system (Saboori and Malekzadeh Shafaroudi 2019; Konari, Rastad, and Peter 2017; Ayati et al. 2014).

In this study, a total of 518 composite samples with a length of 2 meters and a tolerance of 0.5 meters, obtained from 37 exploratory drill holes in the Gushfil Pb–Zn deposit, were used for ZnS grade modeling and estimation. The mean and standard deviation of ZnS grades in these samples were 2.53 and 1.94, respectively (Table 1). The histogram of ZnS grades (Fig. 4) indicates a positively skewed distribution.

From the total dataset of 518 samples, 426 samples were randomly selected for model training, while the remaining 92 samples were reserved as an independent test dataset. The random partitioning was performed without replacement to ensure that each sample was assigned to only one subset and to avoid selection bias. Following the data split, the statistical characteristics of the training and test datasets were examined to verify that they remained representative of the original dataset. As shown in Fig. 4 and Table 1, the two subsets exhibit comparable statistical properties, indicating that the random sampling procedure preserved the overall distribution of the data.

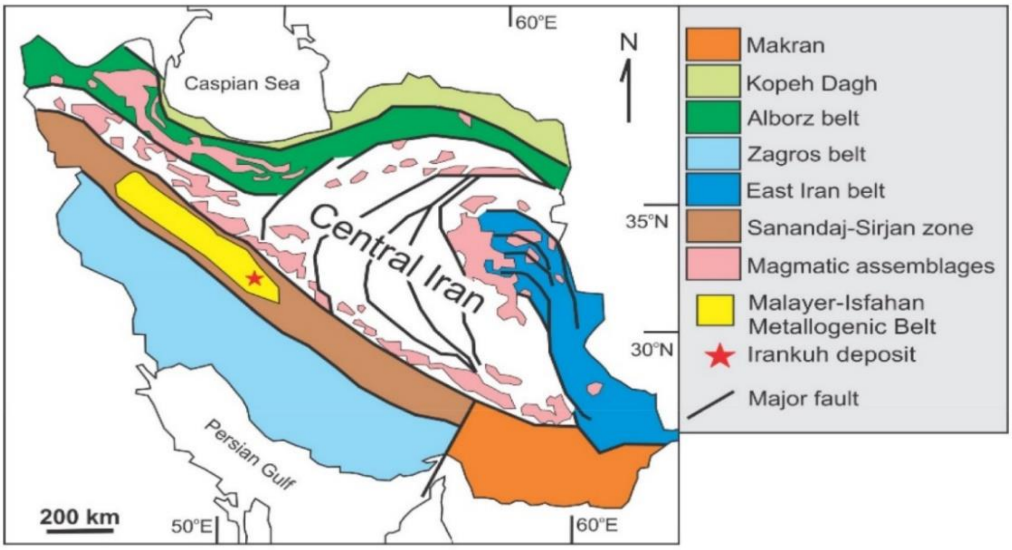

Fig. 2. Location of the Irankuh mining district within the Sanandaj–Sirjan zone and the Malayer–Isfahan metallogenic belt (Saboori and Malekzadeh Shafaroudi 2019).

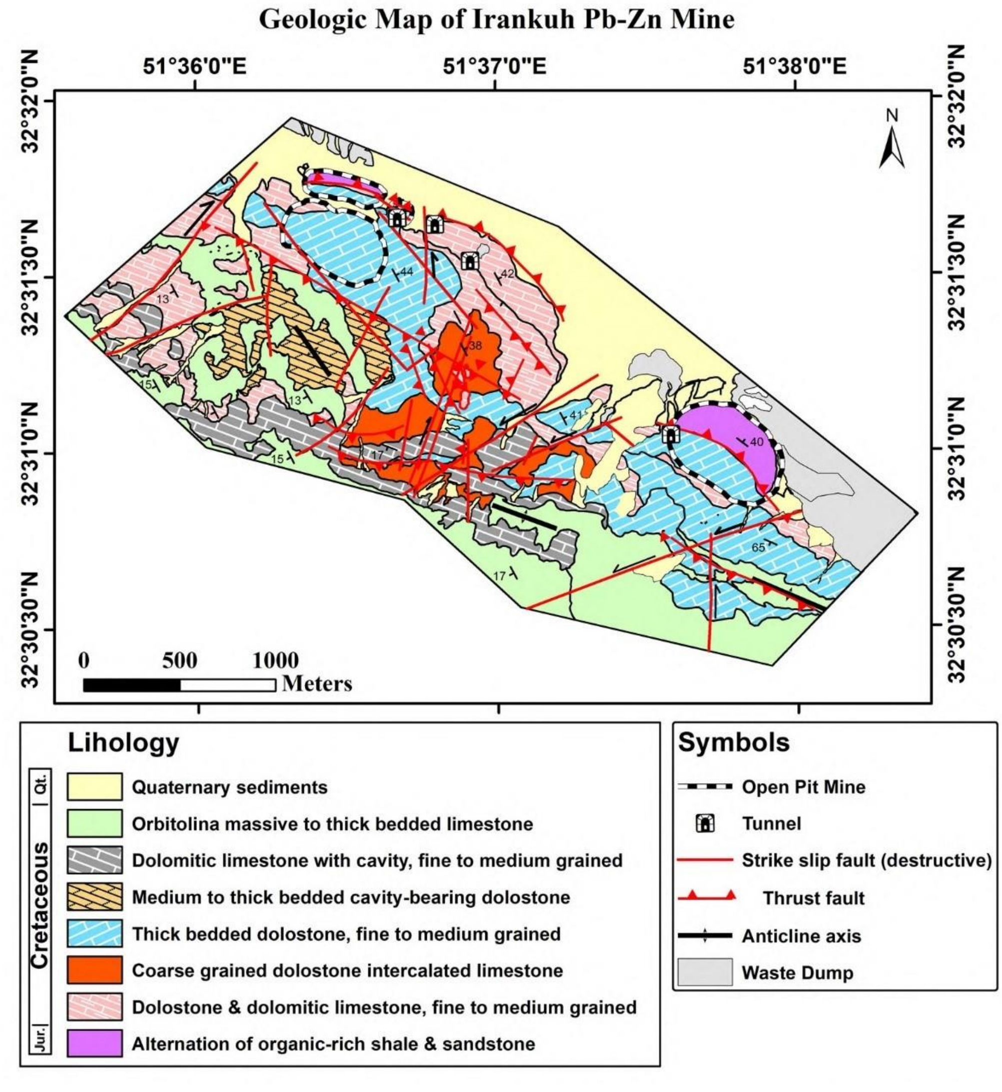

Fig. 3. Geological map of Irankuh mining district (Karimpour and Sadeghi 2018; Sevieri et al. 2019)

Table 1. Statistical characteristics of ZnS grade distribution in the Gushfil Pb–Zn mine.

	Dataset	Train Subset	Test Subset
Mean	2.53	2.79	2.78
Median	2.02	2	2.23
Mode	10	10	10
Standard Deviation	1.94	1.93	1.92
Range	9.81	9.1	9.6
Minimum	0.19	0.19	0.14
Maximum	10	10	10

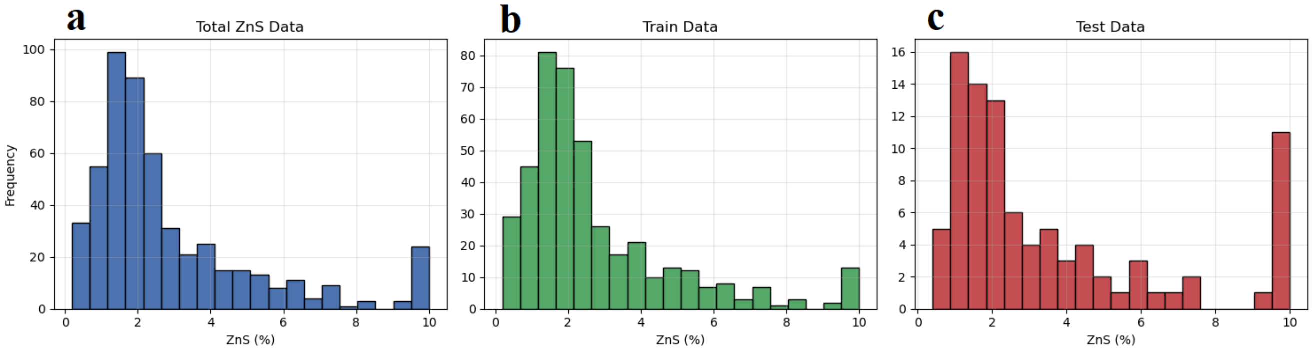

Fig. 4. Histogram of ZnS grade in a) Total dataset, and b) train, and c) test subsets

B. *Base Learners*

1) *Ordinary Kriging (OK)*

Ordinary Kriging (OK) is a widely used geostatistical interpolation method for mineral grade estimation because it provides the best linear unbiased estimator (BLUE) under the assumption of a constant but unknown local mean (Journel and Huijbregts 1978; Goovaerts 1997; Maniteja et al. 2025; Cressie 1991). The method relies on spatial autocorrelation, quantified using a semivariogram that describes how variance changes with distance (Lindi et al. 2024; Cressie 1991).

For a given location x_0, the grade estimate $z^*(x_0)$is expressed as:

$$z^*(x_0) = \sum_i w_i z(x_i) \tag{1}$$

where w_i are kriging weights obtained by solving linear equations derived from the semivariogram and the unbiasedness constraint $\sum w_i = 1$. These weights minimize estimation variance, providing a direct measure of prediction uncertainty (Wackernagel 2013; Goovaerts 1997; Maniteja et al. 2025).

OK's main advantage is its ability to incorporate both the spatial structure of the deposit and the geometry of sample locations, making it suitable for heterogeneous ore bodies. Its performance depends on accurate variogram modeling and second-order stationarity; violations or sparse sampling may bias (Journel and Huijbregts 1978; Goovaerts 1997).

2) *Inverse Distance Weighting (IDW)*

Inverse Distance Weighting (IDW) is a deterministic spatial interpolation technique that estimates unknown values at unsampled locations by calculating a weighted average of surrounding sample points, where the weights decrease as a function of distance (Shepard 1968; Li and Heap 2014). The core assumption of IDW is that observations closer to the prediction location exert greater influence on the estimated value than those farther away, thereby representing spatial continuity in a simple, non-geostatistical framework (Oliver and Webster 2014). The estimated grade $z^*(x_0)$at location $x_0$is expressed as:

$$z^*(x_0) = \frac{\sum_{i=1}^{n} \frac{z(x_i)}{d(x_i, x_0)^m}}{\sum_{i=1}^{n} \frac{1}{d(x_i, x_0)^m}} \tag{2}$$

where $z(x_i)$represents the known grade at sample i, $d(x_i, x_0)$is the Euclidean distance between the sample and prediction points, and m is a user-defined power parameter that controls the rate of distance decay. Larger m values give more weight to nearby samples, producing estimates that closely follow local measurements, while smaller m values yield smoother, more generalized surfaces (Li and Heap 2014).

IDW is conceptually simple, computationally efficient, and requires minimal statistical assumptions about data distribution, which makes it an attractive option when variogram modeling for kriging is impractical (Liu et al. 2021; Mahboob, Celik, and Genc 2022). However, it does not explicitly account for spatial autocorrelation or local geological variability, which can lead to biased or smoothed estimates in highly heterogeneous deposits (Oliver and Webster 2014). Despite these limitations, IDW remains a robust and widely applied interpolation method in mineral grade estimation, geochemical mapping, and other geoscientific applications (Liu et al. 2021; Mahboob, Celik, and Genc 2022).

3) *Artificial Neural Networks (ANNs)*

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of biological neural systems, widely applied in mineral resource and ore grade estimation due to their ability to capture complex, nonlinear relationships between geological variables and ore grades (Rumelhart, Hinton, and Williams 1986; Mahboob, Celik, and Genc 2022; Dumakor-Dupey and Arya 2021; Goswami, Mishra, and Patra 2017; Maniteja et al. 2025; U. Kaplan and Topal 2020). ANNs typically consist of interconnected layers of nodes (neurons), organized into input, hidden, and output layers. Each neuron computes a weighted sum of its inputs, followed by a nonlinear activation function, allowing the network to model intricate spatial and geochemical patterns (Goodfellow et al. 2016; Soltani-Mohammadi et al. 2022).

For ore grade prediction, geological and geochemical attributes, including spatial coordinates, serve as input features. The network is trained to minimize the difference between predicted and observed grades using a set of training samples, with the backpropagation algorithm commonly employed alongside optimizers such as Adam to reduce mean squared error (Adam 2014; Ismael et al. 2024; Soltani-Mohammadi et al. 2022). Hyperparameters—including the number of neurons, learning rate, and number of epochs—are optimized using techniques such as k-fold cross-validation, while strategies like early stopping and L2 regularization help prevent overfitting (Goswami, Mishra, and Patra 2017; Singh, Ray, and Sarkar 2022; Tsae, Adachi, and Kawamura 2023).

ANNs are particularly advantageous when ore grade distribution is heterogeneous and poorly described by traditional geostatistical models (Mahboob, Celik, and Genc 2022; Dumakor-Dupey and Arya 2021). Despite their predictive power, ANNs are sensitive to the quality and quantity of training data, network architecture, and hyperparameter choices, and they do not inherently provide measures of prediction uncertainty, limiting direct use in regulatory reporting (Mahboob, Celik, and Genc 2022). Nevertheless, ANNs have been successfully integrated with geostatistical methods and ensemble frameworks, where they often act as base learners, enhancing ore grade estimation and improving predictive reliability (U. Kaplan and Topal 2020; Tsae, Adachi, and Kawamura 2023; Ganaie et al. 2022).

4) *Support Vector Regression (SVR)*

Support Vector Regression (SVR) is a machine-learning technique derived from Support Vector Machines (SVM) that has been widely applied in mineral resource estimation due to its ability to model complex, nonlinear relationships while effectively controlling overfitting (Vapnik 1998; Drucker et al. 1996; Zuo and Carranza 2011; Mahboob, Celik, and Genc 2022; Dumakor-Dupey and Arya 2021). SVR operates by mapping input features—such as geological, geochemical, and spatial attributes—into a high-dimensional feature space using kernel functions, where it constructs a regression function that fits the training data within a specified tolerance margin (ϵ) while maintaining maximum generalization (Awad and Khanna 2015; Cortes and Vapnik 1995; Kaneko and Funatsu 2015).

In ore grade estimation, SVR learns the functional relationship between predictor variables and known grades to predict values at unsampled locations. The regression function is defined by a subset of training samples called support vectors, which lie close to the margin boundaries and determine the final model. A regularization parameter (C) balances the trade-off between model complexity and fitting error, while kernel parameters—such as the radial basis function (RBF) width (γ)—control the nonlinear mapping behavior (Vapnik 1998; Awad and Khanna 2015; Pedregosa et al. 2011).

SVR is particularly advantageous when ore grade distributions exhibit strong nonlinearity and spatial heterogeneity, capturing subtle geological patterns that traditional geostatistical approaches may overlook (Dumakor-Dupey and Arya 2021; Zuo and Carranza 2011; Mahboob, Celik, and Genc 2022). However, its performance depends heavily on careful hyperparameter tuning and kernel selection. Grid search and k-fold cross-validation are commonly employed to optimize parameters such as C, ϵ, and γ (Kaneko and Funatsu 2015; Pedregosa et al. 2011). Like ANNs, SVR does not inherently provide prediction uncertainty, which can limit its direct application in formal resource reporting (Mahboob, Celik, and Genc 2022).

Despite these challenges, SVR has been successfully used either independently or as part of ensemble modeling frameworks combined with Artificial Neural Networks (ANNs) and geostatistical methods, leading to improved ore grade estimation accuracy and predictive reliability (U. Kaplan and Topal 2020; Shamsi et al. 2021; Ismael et al. 2024).

5) *K-Nearest Neighbors (KNN)*

K-Nearest Neighbors (KNN) is a non-parametric, distance-based supervised learning algorithm that estimates the value of an unknown sample by exploiting the information from its closest observations in the training dataset. For each prediction, the algorithm identifies the k nearest neighbors in the feature space using a distance metric, such as the Euclidean distance. It computes the predicted value as the average of these neighboring samples. Since KNN relies directly on the local structure of the data rather than fitting an explicit mathematical model, it can capture nonlinear relationships between predictor variables and the target attribute. However, its prediction accuracy depends on the selection of an appropriate neighborhood size (k) and the distance metric. In this study, the KNN model was employed as one of the benchmark machine learning methods for ore grade estimation, and the optimal value of k was determined through cross-validation using the training dataset (Cover and Hart 1967; Hastie, Tibshirani, and Friedman 2009).

C. *Ensemble Strategies*

Ensemble learning techniques have emerged as a powerful framework for ore grade estimation. By integrating the predictive strengths of multiple models, they often achieve higher accuracy, better stability, and stronger generalization than individual learners. By aggregating the outputs of diverse base models, ensemble approaches can effectively reduce variance and bias, capture nonlinear and spatially complex relationships, and reduce the adverse effects of noisy or incomplete geological data (Dietterich 2000; Zhou 2012). These advantages are particularly relevant in mineral resource modeling, where ore grade variability and geological heterogeneity pose significant challenges to conventional geostatistical and deterministic methods.

In this study, three ensemble learning strategies—Basic Ensemble Model (BEM), Generalized Ensemble Model (GEM) and Localized Ensemble Method (LEM)—were applied to improve the robustness and reliability of ore grade estimation. The main difference between these two approaches lies in how they combine the outputs of individual base learners, enabling a comparative evaluation of simple versus adaptive ensemble integration methods.

The BEM approach employs a straightforward averaging (bagging-style) strategy, in which multiple base learners are independently trained on the same dataset, and their predictions are combined through arithmetic mean aggregation to produce final ore grade estimates, as follows:

$$\tilde{f}(x) = \left(\frac{1}{N}\right)\sum_{i=1}^{N} f_i(\mathrm{x}) \quad (3)$$

where N is the number of base learners, and f_i is the output of ith base learner. This technique is computationally efficient and provides stable performance, particularly under high spatial variability and complex geological conditions (Opitz and Maclin 1999). In contrast, the Generalized Ensemble Method (GEM) provides a statistically rigorous framework for combining multiple predictive models by explicitly incorporating the error covariance matrix among ensemble members. Unlike traditional ensemble averaging, which assumes independence of errors, GEM determines the optimal weight vector w by minimizing the total estimation variance using the covariance structure of model errors (Timmermann 2006). Given the error covariance matrix Σ, the optimal weights are derived by solving:

$$\min w^T \Sigma w, \quad subject\ to\ \ 1^T w = 1 \quad (4)$$

which yields a closed-form solution analogous to the Best Linear Unbiased Estimator (Gneiting and Raftery 2005). This formulation assigns smaller weights to models with highly correlated errors. Conversely, models with more independent error structures receive greater weights and therefore contribute more to the final prediction, as follows:

$$\tilde{f}(x) = \sum_{i=1}^{N} w_i\, f_i(\mathrm{x}) \quad (5)$$

By using the inverse covariance matrix Σ^{-1}, GEM effectively reduces the influence of redundant or strongly correlated errors, producing estimates with lower variance and improved robustness (Gneiting and Raftery 2005).

The LEM was developed to overcome key limitations of BEM and GEM, which do not account for spatial relationships among samples and assume uniform model performance across the study area. Given the inherently anisotropic and spatially heterogeneous nature of geological datasets, ignoring spatial context can lead to substantial estimation errors. LEM addresses this issue by assigning ensemble weights locally rather than globally.

After training the base learners, their estimation errors are computed using cross-validation and an error correlation matrix. For each target block, the N nearest training samples are identified, and the weight of each learner is determined based on its performance in estimating these local samples. Thus, the ensemble weights adapt dynamically to the local variability of the geological structure surrounding each estimation point(Erfan, Soltani Mohammad, and Abbaszadeh 2026).

III. Results

A. *Performance of Base Learners*

The predictive capabilities of the five base learners were assessed using mean squared error (MSE), root mean squared error (RMSE), and the correlation coefficient (R). Ordinary kriging (OK) demonstrated the best overall performance, with an MSE of 0.028, RMSE of 0.199, and R of 0.63 (Table 2). Among the conventional interpolation approaches, inverse distance weighting (IDW) achieved an MSE of 0.059, RMSE of 0.211, and R of 0.53, whereas k-nearest neighbors (KNN) yielded an MSE of 0.066, RMSE of 0.206, and R of 0.42. For the machine learning algorithms, the SVR exhibited the highest predictive accuracy (MSE = 0.032, RMSE = 0.197, R = 0.58), surpassing the artificial neural network (ANN), which recorded an MSE of 0.038, RMSE of 0.200, and R of 0.52 (Table 2). Fig. 5 presents scatter plots of the predicted versus observed test values, providing a visual representation of the model performance.

Table 2. Comparison of MSE, RMSE, and R2 between measured and predicted ZnS Grades based on the base learners for the Validation Dataset.

Base Learner	MSE	RMSE	R^2
KNN	0.066	2.41	0.33
IDW	0.059	2.148	0.47
OK	0.028	1.795	0.63
ANN	0.038	1.982	0.55
SVR	0.032	1.911	0.58

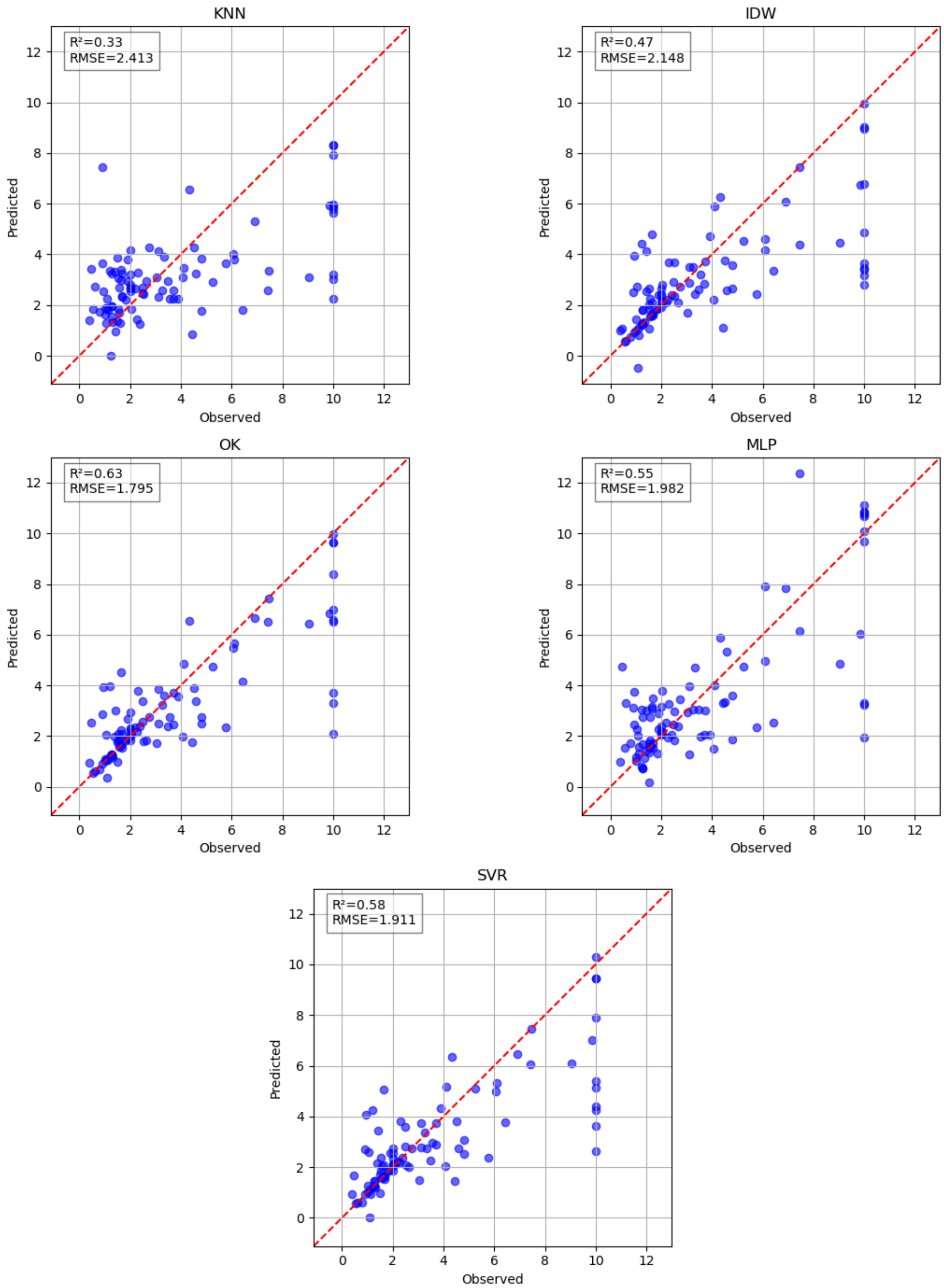

Fig. 5. Scatter plots illustrating the correlation between measured and predicted ZnS grades in the validation dataset for (a) IDW, (b) KNN, (c) OK, (d) ANN, and (e) SVR models

The ordinary kriging (OK) model shows data points most closely aligned with the 1:1 line, indicating minimal bias and strong agreement with the measured grades. The SVR also exhibits a compact clustering pattern, confirming its competitive predictive capability among the machine learning models. In contrast, the k-nearest neighbors (KNN) and inverse distance weighting (IDW) methods display broader scatter and greater deviation from the 1:1 line, reflecting their comparatively weaker predictive accuracy. These results demonstrate that OK remains the most reliable technique for grade estimation within this dataset, while SVR serves as the most effective alternative among the learning-based approaches. The visual evidence from Fig. 5 supports the quantitative results, suggesting that integrating geostatistical and machine learning methods could further enhance predictive accuracy in future applications.

A Taylor diagram was constructed to assess the performance of five grade estimation methods—KNN, IDW, OK, ANN, and SVR—in reproducing the observed data (Fig. 6). This diagram simultaneously illustrates the correlation coefficient (*R*), standard deviation (STD), and root mean square error (RMSE) of each model relative to the reference dataset. Among the evaluated methods, the ordinary kriging (OK) model exhibits the highest correlation (R = 0.63) and a standard deviation (STD ≈ 2.16) most closely matching that of the reference data (STD ≈ 2.96), indicating the best overall agreement with the observed values. The ANN and SVR models also display moderate performance. In contrast, the *k*-nearest neighbors (KNN) method shows the lowest correlation (*R* = 0.33) and the smallest standard deviation (STD ≈ 1.60), suggesting a limited ability to reproduce data variability. Overall, the Taylor diagram identifies OK as the most reliable technique for grade estimation, while KNN demonstrates the weakest performance.

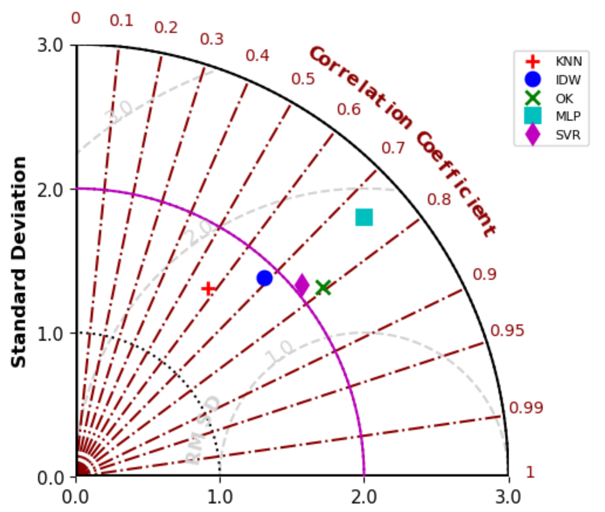

Fig. 6. Taylor diagram comparing the performance of the base learners (KNN, IDW, OK, ANN, and SVR)

B. *Ensemble Results*

To further enhance predictive performance, several ensemble strategies were applied. First, a simple bagging ensemble method (BEM), constructed by computing the arithmetic mean of the five base learners according to Equation (3), improved the correlation coefficient (R) from 0.63, obtained for the best individual base learner, to 0.64 (Fig. 8; Table 3). Subsequently, a weighted averaging approach was employed, in which the weights assigned to the base learners were determined using Equation (4), and the final ensemble prediction was computed based on Equation (5). Using the GEM method, the correlation coefficient between measured and predicted values decreased to −0.77 (Fig. 8; Table 3). The negative correlation obtained for the GEM model was verified by rechecking the implementation and evaluation procedure and therefore represents the actual behavior of this ensemble strategy for the present dataset rather than a computational error. Although ensemble methods are generally expected to improve predictive performance, their effectiveness depends on the suitability of the weighting scheme and the characteristics of the data. In the present case, GEM employs a single set of globally optimized weights derived from the covariance structure of model errors. Because the Gushfil orebody exhibits pronounced spatial heterogeneity, these global weights were unable to adequately represent local geological variability, resulting in the amplification of prediction errors for the validation dataset. This finding highlights that globally weighted ensemble methods do not necessarily outperform individual models and emphasizes the importance of incorporating local spatial information, as implemented in the proposed LEM approach. Finally, the LEM was implemented, in which the weights of the base learners were computed individually for each prediction location according to Equation (4). A critical parameter in this method is the number of neighboring samples used to estimate the local weights. To determine the optimal value, a grid search was performed in which the algorithm was executed for different neighborhood sizes, and the number of samples that minimized the root mean squared error (RMSE) was selected. The results of this search are presented in Fig. 7. For small neighborhood sizes, where only a few nearby samples are available, the LEM model exhibits higher RMSE than the GEM (RMSE = 0.019). This initial underperformance is mainly attributed to the limited spatial information available when only a few neighboring samples are considered. Consequently, the local weighting scheme cannot fully capture the spatial variability surrounding the target block. As the number of neighboring samples increases, the MSE of the LEM decreases steadily. This improvement stems from two factors. First, increasing the neighborhood size incorporates more spatially representative samples. Second, the adaptive weighting scheme assigns greater importance to the base learners that perform better in each local neighborhood. The MSE reaches a minimum when the number of neighboring samples is N = 40. Beyond this point, including additional samples leads to a gradual increase in MSE, as more distant samples are less representative of the local characteristics of the target block. Based on this analysis, the LEM algorithm was executed with 40 neighboring samples, achieving the best overall performance with a correlation coefficient (R) of 0.66 (Fig. 8; Table 3), representing the highest correlation obtained in this study. A Taylor diagram was constructed to evaluate the performance of three ensemble methods (BEM, GEM, and LEM) relative to the observed data (Fig. 9). The diagram simultaneously presents each model's correlation coefficient (R), standard deviation (STD), and root mean square error (RMSE) in comparison with the reference dataset (STD ≈ 2.96). Among the models, LEM exhibits the best overall agreement, with a high correlation (R = 0.66), a standard deviation (STD ≈ 2.48) close to the reference, and a low RMSE (1.779). BEM demonstrates moderate performance (R = 0.64, STD ≈ 1.93, RMSE = 1.867), whereas GEM shows a negative correlation (R = −0.77), a very low standard deviation (STD ≈ 0.47), and the highest RMSE (3.906), indicating poor predictive skill. Overall, the Taylor diagram clearly identifies LEM as the most reliable estimation method and GEM as the least accurate among the evaluated approaches.

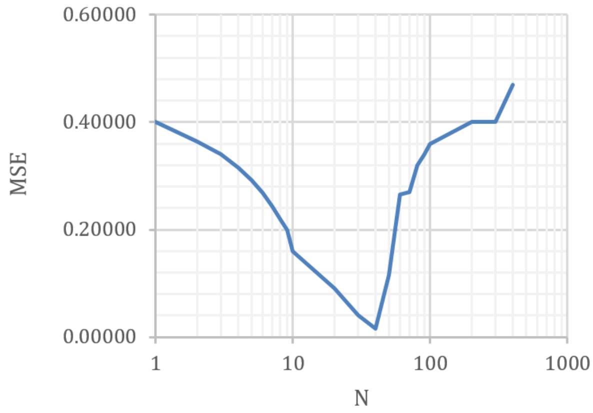

Fig. 7. Mean squared error (MSE) of the LEM ensemble versus the number of neighboring points for ZnS grade estimation

Table 3. Comparison of MSE, RMSE, and R^2 between measured and predicted ZnS grades for the validation dataset.

	MSE	*RMSE*	*R*
BEM	0.026	1.867	0.64
GEM	0.019	3.906	-0.77
LEM	0.015	1.779	0.66

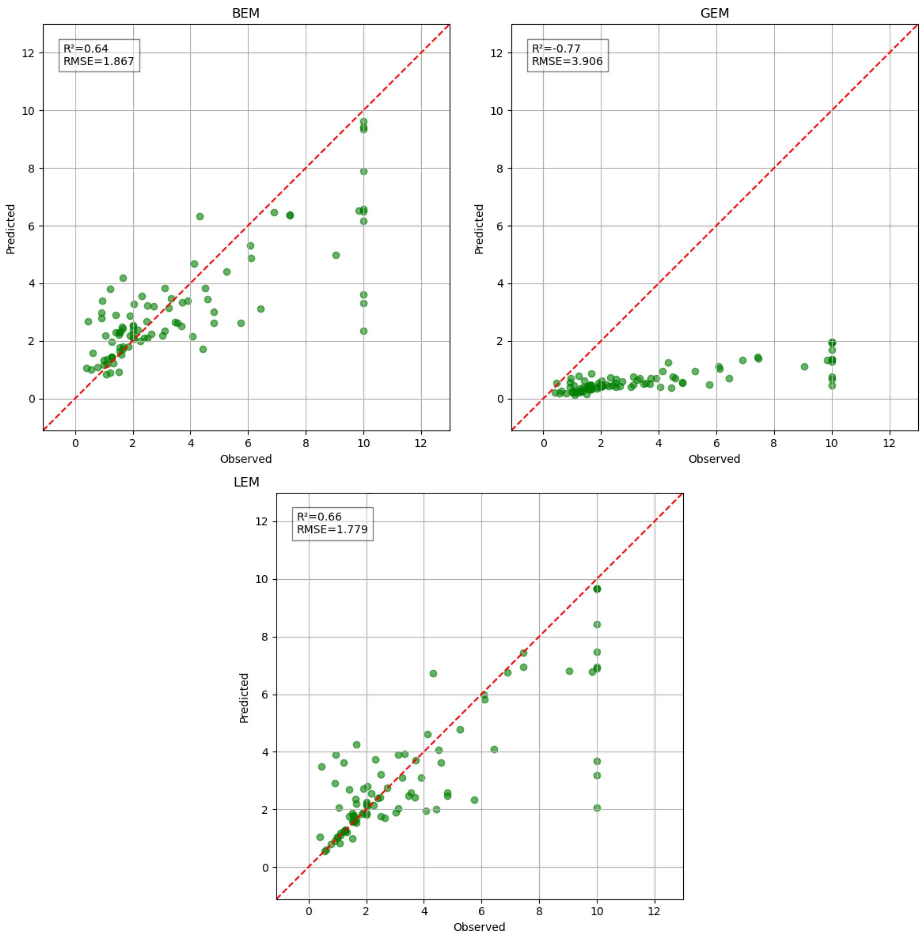

Fig. 8. Correlation plots between measured and predicted ZnS grades in the validation dataset for (a) BEM, (b) GEM, and (c) LEM

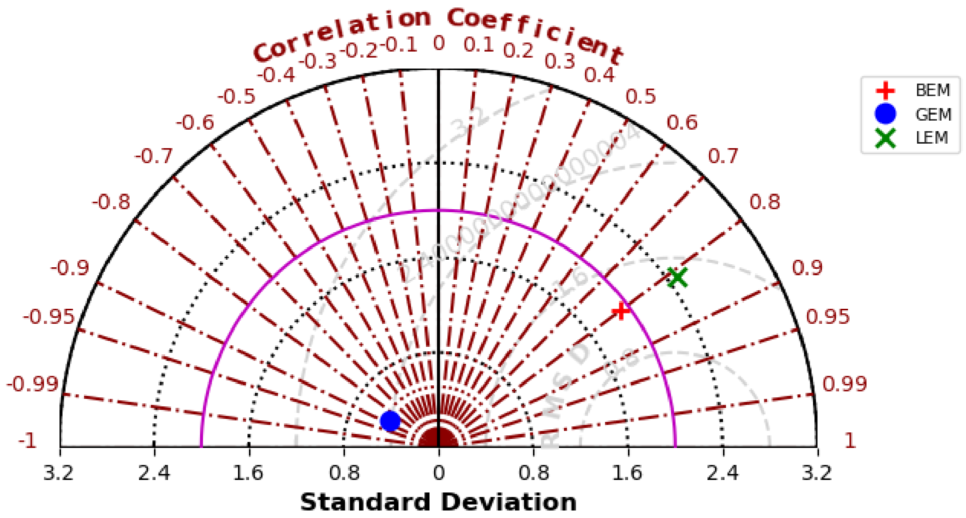

Fig. 9. Taylor diagram comparing the performance of different ensemble methods (BEM, GEM, and LEM) in ZnS grade estimation

IV. Conclusions

This study proposed a data-driven framework for ore grade estimation by integrating classical geostatistical techniques with machine learning models through ensemble learning. The proposed methodology was evaluated using an independent validation dataset, and all prediction models were assessed under identical training and testing conditions using MSE, RMSE, and the correlation coefficient (R). This validation framework enabled an objective comparison of the proposed Local Ensemble Method (LEM) with conventional interpolation methods (OK and IDW), machine learning models (KNN, ANN, and SVR), and two ensemble strategies (BEM and GEM).

Among the evaluated models, OK provided the best performance among the individual prediction methods, while SVR was the strongest machine learning model. The BEM produced a modest improvement over the best individual learner, whereas the GEM showed poor performance on the validation dataset because its globally optimized weighting scheme was unable to adequately represent the pronounced spatial heterogeneity of the Gushfil orebody. In contrast, the proposed LEM, which determines ensemble weights adaptively according to local prediction performance, achieved the lowest MSE and the highest correlation coefficient, demonstrating the effectiveness of incorporating local geological information into the ensemble process. These findings indicate that locally adaptive ensemble learning provides a promising strategy for improving ore grade estimation in geologically heterogeneous deposits. The superior performance of LEM is consistent with recent developments in hybrid geostatistical–machine learning frameworks(Erdogan Erten et al. 2025), which emphasize the importance of combining complementary prediction models while accounting for spatial variability. Beyond improving prediction accuracy, the proposed framework offers a flexible and reproducible workflow that can be readily adapted to other mineral deposits with complex geological characteristics.

Future research should investigate the performance of the proposed framework using larger datasets, different mineral deposit types, and additional machine learning algorithms. Furthermore, integrating uncertainty quantification and probabilistic prediction techniques into the locally adaptive ensemble framework may further improve its applicability to mineral resource estimation and support more reliable mine planning and decision-making.

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