GM-Geo: Graph-Enhanced Selective State Space Learning for Irregular Borehole Sequences

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Abstract. Lithology identification is essential for formation evaluation and reservoir characterization, serving as a crucial basis for assessing the presence of mineral deposits underground. However, due to the lateral spatial correlations and ordered vertical dependencies of subsurface lithology across boreholes, high-precision lithology prediction from irregular borehole observation data is extremely challenging. Existing methods typically focus on sequence modeling or graph-based neighborhood learning, but rarely integrate both into a unified framework. To address this issue, we propose GM-Geo, a graph-enhanced selective state space framework for lithology prediction from irregular borehole sequences. Specifically, the proposed method first transforms heterogeneous interval-based borehole records into standardized depth-wise samples through geology-aware resampling. It then constructs a sample-level spatial neighborhood graph to capture local geological relationships across boreholes. Finally, graph-aggregated spatial features are fused into a selective state space model to jointly encode lateral spatial continuity and vertical lithological evolution. This paper evaluates the framework in 218 boreholes in the Tangwuli fluorite mining area and compares it with baseline methods such as RF, XGBoost, Transformer, GNN, and ET4DD. GM-Geo achieved best precision, recall, macro F1 score, and micro F1 score of 0.845, 0.798, 0.812, and 0.821, respectively. Ablation experiments further demonstrated that both the graph module and the state-space module contributed to the final performance.

Keywords: Lithological prediction, irregular borehole sequences, selective state space model, graph-enhanced learning, geology-aware resampling.

1 Introduction

Lithology prediction using borehole data is an important task in intelligent geosciences, with wide applications in subsurface structural interpretation, mineral exploration, and digital geological modeling. However, in actual exploration scenarios, borehole data typically exhibits irregular spatial distribution and uneven depth ranges. Borehole layout often depends on topographic conditions, exploration objectives, and engineering

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constraints, leading to complex spatial relationships between boreholes. Furthermore, the lithological record within each borehole is usually presented in a layered form, with varying thicknesses and depth resolutions. These characteristics make borehole data a typical irregular spatiotemporal sequence, and how to fully explore the connections between boreholes has become an urgent problem to be solved.

In recent years, with the popularization of deep learning in temporal prediction and pattern recognition, lithology prediction has gradually entered the stage of automatic representation learning. Some scholars have combined recurrent structures with Transformers [1,2], a method that can better utilize the contextual information and multi-scale changes in borehole sequences, but often fails to adequately consider the lateral spatial connections between multiple boreholes. With the development of graph learning and structured modeling, some scholars have incorporated graph neural networks into lithology prediction. While graph neural network methods can encode the neighborhood structure between boreholes, they often fail to adequately represent the ordered lithological evolution along the depth direction [3]. Overall, existing methods typically focus on one side of "sequence modeling" or "spatial modeling," and have not yet effectively integrated intra-bore vertical dependencies and inter-bore lateral correlations within a unified framework.

Based on these issues, this paper proposes a graph-enhanced selective state-space model (GM-Geo) to address both problems. It considers both the impact of deep intra-bore sequences on lithology prediction and the neighborhood structure relationships between boreholes. This method constructs a spatial neighborhood graph between borehole samples to represent inter-well correlations and injects the spatial context features obtained from graph aggregation into a selective state-space model [4,5], thereby jointly modeling intra-bore depth-direction sequence dependencies and inter-bore spatial correlations. The contributions of this paper are as follows:

- We discovered the difficulty in utilizing feature information from irregular borehole data.
- We propose a graph-enhanced selective state space architecture that jointly models depth-wise sequential dependency and inter-borehole spatial correlation.
- We validate the framework on a real fluorite mining dataset and show superior classification and ablation performance against representative sequence, graph, and deep geological modeling baselines.

2 Related Work

2.1 Borehole-Based Lithology Prediction

Lithology prediction using borehole data is a crucial task in 3D geological modeling, mineral exploration [6], and digital earth science, as lithology labels provide direct evidence for understanding stratigraphic composition and subsurface structures. Early research relied primarily on manual interpretation, rules of thumb, or traditional machine learning methods [7] such as Support Vector Machines, Random Forests [8], and XGBoost. These methods can achieve good benchmark performance when the amount

of manually extracted features is sufficiently large, but they typically treat depth samples as independent observations, thus failing to explicitly model lithological continuity along the borehole.

In recent years, research has increasingly shifted towards data-driven lithology modeling based on deep learning [9]. This approach improves feature representation capabilities and reduces reliance on manual feature engineering. Sun et al. proposed a transformer-based lithology identification model that utilizes well logging data for lithology identification [10,11], demonstrating that a sequence-aware depth architecture better captures contextual changes, thereby improving prediction accuracy. Han et al. reformulated geological boundaries and topological relationships as a graph problem and used a Variational Graph Autoencoder (VGAE) to automatically predict unknown topological relationships, thereby enabling lithology prediction [12]. These studies indicate that lithology prediction has evolved from shallow classifiers to representation learning-based methods, but the structured characteristics of wellbore sequences are still not fully utilized.

2.2 Sequential Modeling for Irregular Borehole Records

Boreholes can be naturally viewed as depth-ordered sequences because adjacent lithological intervals typically follow stratigraphic continuity and transition patterns vertically. This has prompted the use of sequence models for lithology prediction. Early sequence learning methods primarily employed recurrent neural networks and their variants, particularly Long Short-Term Memory (LSTM) networks, to capture contextual dependencies in ordered observations. Later, Transformer-based models gained attention for their self-attention mechanism, which can more effectively model long-range interactions than traditional recurrent architectures. In geosciences and well logging applications, such sequence models have shown promising potential for lithology identification and stratigraphic prediction, especially where contextual depth information is crucial.

However, borehole records differ from standard regular sampling sequences: lithological observations are typically recorded as intervals of varying thickness, and the depth resolution may vary between different boreholes. This irregularity makes direct sequence learning more challenging. In recent years, structured state-space models such as S4 [4] and Mamba [5] have demonstrated powerful capabilities in long sequence modeling and improved computational efficiency, providing a promising alternative to attention-based encoders of ordered geological records. However, sequence-based methods primarily emphasize in-well dependencies and typically do not explicitly learn spatial information from adjacent wells.

2.3 Graph Learning for Spatial Relationships Among Boreholes

In addition to vertical sequence dependency, lithology prediction is also influenced by spatial relationships among boreholes. Nearby boreholes often share correlated geological characteristics because of lateral continuity in subsurface structures. Since

boreholes are distributed irregularly in space, graph learning provides a natural way to encode neighborhood relations and non-Euclidean spatial structure.

In recent years, graph neural networks have been increasingly introduced into geoscience problems. Hillier et al. presented a graph neural network approach for three-dimensional structural geological modeling, showing that graph-based learning can serve as an alternative to classical interpolation-based methods on irregular geological structures [3]. Related work has also used graph learning to identify topological relationships among geological boundaries, further demonstrating the value of graph representations for subsurface spatial reasoning [13]. These studies suggest that graph-based methods are well suited to modeling inter-borehole spatial interactions. However, most existing graph-learning approaches in geoscience focus mainly on spatial adjacency, topological relations, or structural interpolation, whereas the ordered lithological evolution along depth within each borehole is not explicitly modeled. As a result, graph-only models are often insufficient for lithology prediction tasks where both lateral spatial continuity and vertical stratigraphic dependency matter.

2.4 Current Challenges

Despite some progress in recent years, current lithology prediction methods still face several significant challenges. First, borehole observation data itself is irregular: lithological records are typically stored as depth intervals of varying thickness rather than uniformly sampled points, and the resolution of records from different boreholes may differ. This irregularity makes it difficult for standard sequence models to directly learn consistent depth orientation patterns. Second, lithology prediction requires effective modeling of the vertical correlations within each borehole. Adjacent lithological intervals are not independent but follow geological continuity and transition constraints. Third, lithology prediction is also influenced by spatial relationships between boreholes.

3 Methods

To address the aforementioned challenges, this paper proposes a graph-enhanced selective state-space learning framework called GM-Geo for processing irregular borehole sequences, as shown in Fig.1. This method combines sample-level spatial graph encoding with selective state-space sequence modeling, enabling it to simultaneously capture the spatial structure between boreholes and the depth dependence within boreholes, thus providing a new paradigm for lithological prediction based on irregular borehole records.

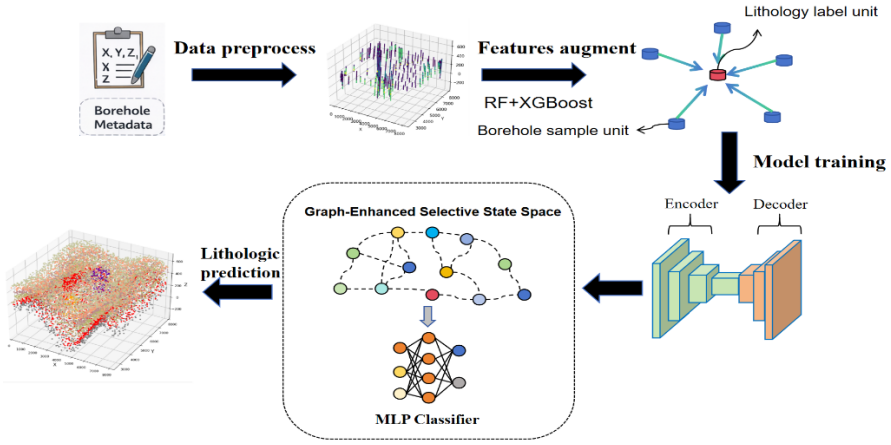

Fig. 1. GM-Geo: Overall framework of GM-Geo for lithology prediction.

3.1 Standardizing Resampled Borehole Points

Raw borehole data are usually recorded as lithological intervals with different thicknesses, making them unsuitable for direct sequence modeling. To obtain a consistent depth-wise representation, GM-Geo converts interval-based records into standardized samples through geology-aware adaptive resampling. This strategy preserves thin but important lithological units, such as fluorite ore bodies and fracture-related layers, while preventing very thick background layers from producing excessive redundant samples.

For the i-th lithological interval, let d_i^s and d_i^e denote its start and end depths, and its thickness is defined as

$$l_i = d_i^e - d_i^s. \tag{1}$$

Instead of using a fixed sampling step, an interval-specific step size is adopted:

$$\Delta d_i = \mathrm{clip}(\rho l_i, \Delta d_{\min}, \Delta d_{\max}),$$

where ρ is a proportional coefficient, and $\Delta d_{\min}$ and $\Delta d_{\max}$ are the lower and upper bounds of the sampling step. The number of resampled points in this interval is calculated as

$$n_i = \max\left(1, \left\lceil \frac{d_i^e - d_i^s}{\Delta d_i} \right\rceil\right). \tag{2}$$

The depth of the k-th resampled point is then given by

$$d_{i,k} = d_i^s + \left(k - \frac{1}{2}\right)\frac{d_i^e - d_i^s}{n_i}, k = 1,2,\ldots,n_i. \tag{3}$$

In this way, each interval contributes at least one sample, and the sampling density is adaptively controlled by interval thickness. Therefore, the relatively balanced label distribution after resampling should be regarded as a controlled training representation for alleviating class imbalance, rather than the raw lithological distribution of the study area.

After resampling, each standardized sample is mapped into a unified three-dimensional coordinate system according to the borehole collar location, azimuth, inclination,

and depth. Thus, each sample contains both depth-order information within a borehole and spatial-position information in the study area, providing the basis for subsequent graph construction and sequence modeling.

3.2 Sample-Level Spatial Graphs

To incorporate spatial information into lithology prediction, GM-Geo constructs maps at the sample level rather than the borehole level. This design is based on the fact that lithological continuity depends not only on the proximity of the entire borehole but also on the local spatial correspondences between samples at similar depths. For each sample, GM-Geo searches for candidate neighboring samples under spatial distance constraints and vertical consistency constraints. Only samples from different boreholes are retained, so that the map explicitly captures the relationships between boreholes, while leaving the ordered dependencies within boreholes to be handled by the sequence encoder. The process for constructing sample-level geological maps is shown in Algorithm 1.

To encode inter-borehole spatial interaction, we build a graph at the sample level rather than the borehole level. For a node v_i, candidate neighbors are searched under a spatial radius constraint

$$\left\|p_i - p_j\right\|_2 \leq r, \tag{4}$$

and a vertical-consistency constraint

$$\left|z_i - z_j\right| \leq \Delta z_{max}. \tag{5}$$

Only inter-borehole neighbors are retained, i.e., $b_i \neq b_j$. After sorting by Euclidean distance, the nearest k neighbors are preserved:

3.3 Graph-Enhanced Selective State Space Model

After spatial neighborhood information is encoded by the graph module, each borehole is treated as an ordered depth-wise sequence. GM-Geo then employs a graph-enhanced selective state space encoder to model the vertical evolution of lithology along depth (Fig.2). For the t-th sample, the input is formed by concatenating the local sample feature x_t and the graph-aggregated spatial feature $h_t^{(g)}$:

$$u_t = [\mathrm{x}_t; \mathrm{h}_t^{(g)}]. \tag{6}$$

Different from a conventional state space model with fixed parameters, GM-Geo adopts an input-dependent selective mechanism. Specifically, the state-space parameters are dynamically generated from the current input:

$$B_t = f_B(u_t), C_t = f_C(u_t), \Delta_t = \mathrm{softplus}(f_\Delta(u_t)), \tag{7}$$

where $f_B(\cdot)$, $f_C(\cdot)$, and $f_\Delta(\cdot)$ are learnable projection functions. The input-dependent step size Δ_t controls the information update at each depth position, enabling the model to adaptively respond to stable lithological intervals and abrupt geological boundaries.

The continuous transition matrix A is discretized using Δ_t:

$$\bar{A}_t = exp(\Delta_t A), \tag{8}$$

$$\bar{B}_t = (\Delta_t A)^{-1}(\exp(\Delta_t A) - I)\Delta_t B_t. \tag{9}$$

The hidden state and output are updated as follows:

$$h_t = \bar{A}_t h_{t-1} + \bar{B}_t u_t, \tag{10}$$

$$y_t = C_t h_t + D u_t. \tag{11}$$

Here, $s_t$denotes the hidden state, $y_t$is the encoded sequence representation, and Dis a learnable skip-connection parameter. Since B_t, C_t, and $\Delta_t$are conditioned on the current input, the model can selectively control the information flow along the depth direction. This makes it more suitable for irregular borehole sequences than standard SSMs with fixed parameters.

Finally, the encoded representation is fed into a classifier to predict the lithology label:

$$\hat{p}_t = \mathrm{Softmax}(W_c z_t + b_c). \tag{12}$$

This design allows GM-Geo to jointly exploit inter-borehole spatial continuity and intra-borehole vertical lithological evolution.

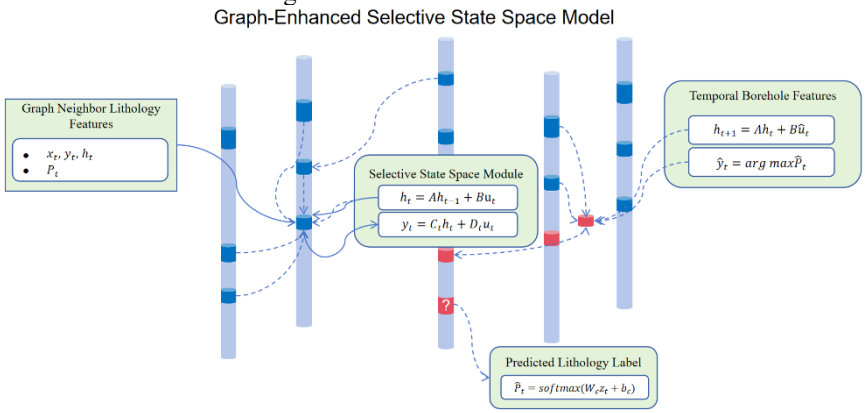

Fig. 2. Graph-enhanced selective state space model.

4 Experiments

4.1 Dataset

The study area is the Tangwuli fluorite mining area in Zhejiang Province, China. The dataset contains 218 boreholes with collar coordinates, azimuth, inclination, depth intervals, lithology labels, geological descriptions, and CaF_2 content. After preprocessing, each borehole is converted into a standardized sequence of depth-wise samples in a shared 3D coordinate system. After standardized resampling operations, the number of samples in the dataset increased to 86,104. As shown in Table 1, We conducted a statistical analysis of the label counts for various lithologies; taking into account the geological age and lithology of the study area, we identified 18 lithological categories, with an average count of 4,784 and a median of 4,775.

Table 1. Count of Each Lithological Label.

Label	Lithology	Total number
0	Aphanitic Porphyry	5689
1	Vitrified Tuff	4982
2	Granite Porphyry	5012
3	Rhyolite	4786
4	Fluorite mineralization fracture	5078
5	Sandstone	4687
6	Mudstone	4486
7	Crystalline Tuff	4625
8	Residual Slope Deposits	4875
9	Fracture Zone	4357
10	Fluorite Ore Body	4224
11	Fracturing Zone	4629
12	Diorite	4764
13	Rhyolite Porphyry	4567
14	Shale	5001
15	Brecciated Tuff	4867
16	Fluorite Mineralization	4761
17	Breccia	4954

It should be noted that the counts in Table 1 refer to standardized depth-wise samples after geology-aware resampling, rather than the raw lithological intervals in the original borehole logs. The original data are naturally imbalanced due to differences in lithological occurrence frequency and interval thickness. The adaptive resampling strategy increases the representation of thin but exploration-critical units, such as fluorite ore bodies, fluorite mineralization, and fracture-related lithologies, while limiting redundant samples from very thick background layers. Therefore, the relatively balanced distribution in Table 1 should be regarded as a controlled training representation for alleviating class imbalance, rather than the natural lithological distribution of the study area.

4.2 Implementation Details

The GM-Geo model is implemented using PyTorch. Its input dimension is determined by the feature dimension of the training data, while its output dimension corresponds to the number of lithological classes. The hidden layer dimension is set to 128, and the dropout rate is set to 0.15. The model is optimized using the Adam optimizer, with a learning rate of 1e-3 and a weight decay coefficient of 1e-4. The cross-entropy loss function is employed during the training process. The number of training epochs is set to 100. All models are trained on 2 RTX 4090 GPUs.

For sample-level graph construction, the neighborhood radius is set to r=8, the maximum number of neighbors is set to k=12, and the vertical consistency threshold is set to $\Delta z_{max} = 3$. The spatial and vertical decay parameters in the edge-weight function are set to $\sigma_d = 4$ and $\sigma_z = 1.5$, respectively.

To avoid sample leakage caused by depth-wise resampling, this study adopts a borehole-level data splitting protocol. The splitting operation is performed before resampling-based model training and evaluation. Specifically, the 218 boreholes are

divided into training, validation, and test sets at the borehole level with a ratio of 7:1:2. All standardized samples generated from the same borehole are assigned exclusively to one subset. Therefore, samples from a test borehole never appear in the training or validation set.

4.3 Baselines and Metrics

To evaluate the effectiveness of GM-Geo, we compare it with five representative baselines, including Random Forest, XGBoost, Transformer, GNN, and ET4DD. For a fair comparison, all methods are trained and evaluated under the same borehole-level train/validation/test split. The same standardized depth-wise samples are used as input, unless a specific model requires a different structural form.

Random Forest [8] and XGBoost are adopted as classical machine learning baselines and use sample-level features directly. Transformer [10] is used as a sequence-based baseline, where samples from each borehole are ordered by depth. GNN is adopted as a spatial graph baseline and uses the same sample-level graph construction strategy as GM-Geo, but without the selective state space module. ET4DD [14] is included as a representative deep geological modeling baseline and is trained using the same data split and resampled input representation.

For all deep learning baselines, hyperparameters such as hidden dimension, optimizer, learning rate, dropout, and training epochs are kept as consistent as possible with GM-Geo, and the final settings are selected according to validation performance. The training objective is multiclass cross-entropy:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log\,\hat{p}_{ic}. \tag{13}$$

where $N$is the number of samples, $C$is the number of lithological classes, $y_{ic}$is the ground-truth label, and $\hat{p}_{ic}$is the predicted probability.

The performance of lithological precision is evaluated using precision, recall, macro-F1 score, micro-F1 [15], and confusion matrix [7].

4.4 Main Results

Table 2 shows the classification performance of different models on the same dataset. In the lithology prediction task, sequence-based methods outperform graph-based methods. The prediction accuracy of using sequence prediction or graph-based prediction methods alone is not particularly high, possibly because sequence prediction methods ignore information from neighboring boreholes, while graph-based prediction methods ignore contextual information and multi-scale variations in the borehole sequence. Our proposed method achieves the best performance in the lithology prediction task, with a precision of 84.5, recall of 79.8% macroscopic F1 scores of 81.2%, and microscopic F1 scores of 82.1%, indicating that our proposed graph-enhanced selective state-space model achieves a good balance between local spatial continuity and in-well lithology evolution.

Table 2. Performance comparison of different models.

Model	Precision(%)	Recall(%)	Macro-F1(%)	Micro-F1(%)
Random Forest	75.7	73.7	71.2	73.4
XGBoost	77.1	73.2	72.5	69.2
Transfomer	79.4	78.7	75.4	76.1
GNN	78.4	70.6	72.4	71.5
ET4DD	82.1	78.3	79.5	74.3
GM-Geo	**84.5**	**79.8**	**81.2**	**82.1**

Fig.3 shows the normalized confusion matrices of Transformer, GNN, ET4DD, and GM-Geo. Overall, GM-Geo exhibits the strongest diagonal concentration, indicating more accurate recognition of the major lithological classes. Transformer performs relatively well in lithological intervals with strong vertical continuity, but its misclassification increases in areas where lateral spatial correlation is important. GNN improves recognition in some spatially correlated lithologies, yet shows weaker discrimination for stratigraphic sequences with strong depth-wise dependency. ET4DD achieves moderate performance, but its overall diagonal clustering remains lower than that of GM-Geo.

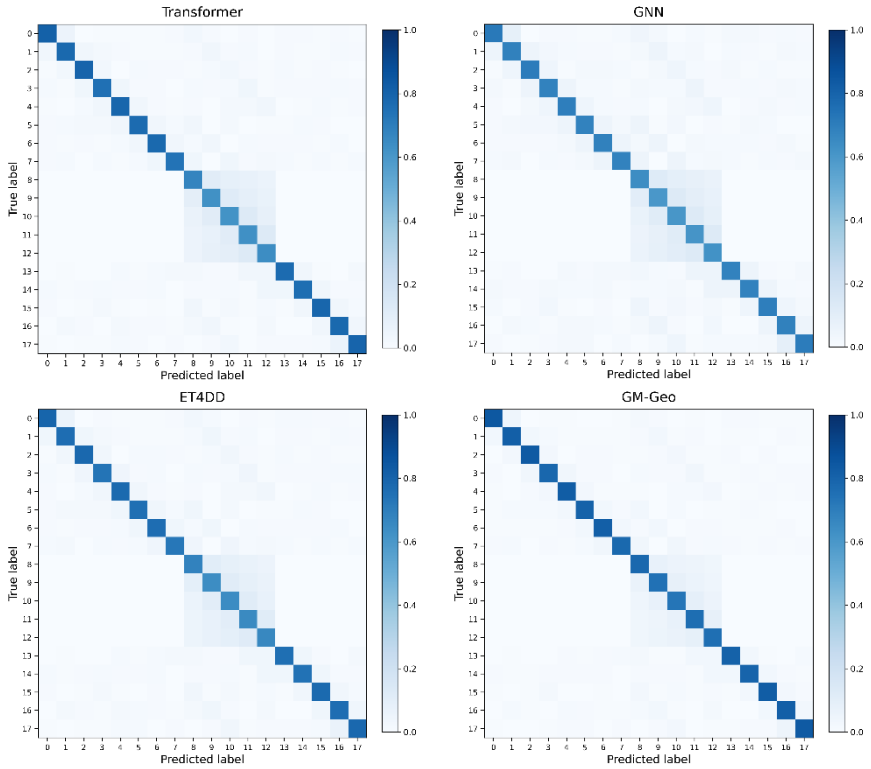

Fig. 3. Normalized confusion matrix for each classifier.

To further evaluate the practical value of the proposed model in mineral exploration, we conducted a class-wise analysis focusing on ore-related and fracture-related lithologies, including Fluorite Ore Body, Fluorite Mineralization, and fracture-zone classes. As shown in Fig.4, GM-Geo achieves the highest recall across all five critical classes, consistently outperforming ET4DD, Transformer, and GNN. In particular, GM-Geo shows more pronounced improvements on Fluorite Mineralization and Fracture Zone, indicating that the joint modeling of inter-borehole spatial continuity and intra-borehole depth dependency is beneficial for identifying ore-related and structurally complex lithologies. These results suggest that GM-Geo is more effective in reducing missed predictions for exploration-critical targets.

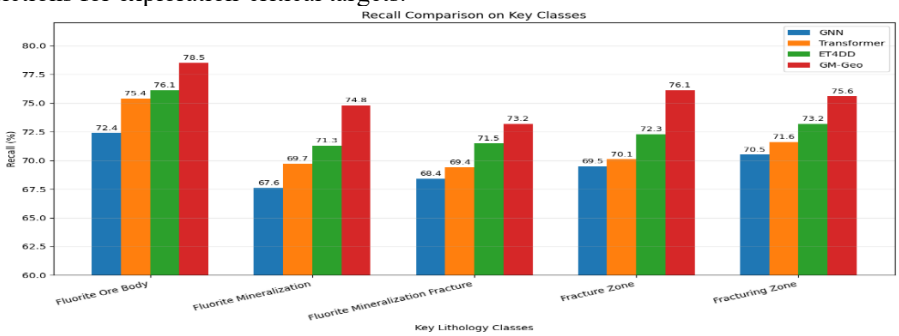

Fig. 4. Recall comparison on key classes.

4.5 Ablation Experiment

To further verify the contribution of each key component, we compare GM-Geo (w/o Graph), GM-Geo (w/o SSM), and GM-Geo (Full). As shown in Table 3, removing either the graph module or the selective state space module causes a clear decline in performance. This confirms that lateral spatial encoding and depth-wise sequence modeling play complementary roles in lithology prediction.

Table 3. Ablation study of GM-Geo components.

Model	Precision(%)	Recall(%)	Macro-F1(%)	Micro-F1(%)
w/o Graph	80.7	74.4	76.9	76.4
w/o SSM	82.4	77.4	78.4	79.1
GM-Geo (Full)	**84.5**	**79.8**	**81.2**	**82.1**

To validate the contributions of each key module to the model optimization process, this paper further presents the training loss curves under various ablation settings. As shown in Fig.5, GM-Geo (Full) consistently exhibits a superior downward trend throughout the entire training process; it not only demonstrates a faster convergence rate during the initial stages but also achieves a lower and more stable loss level in the later stages, thereby demonstrating superior training stability and optimization capabilities.

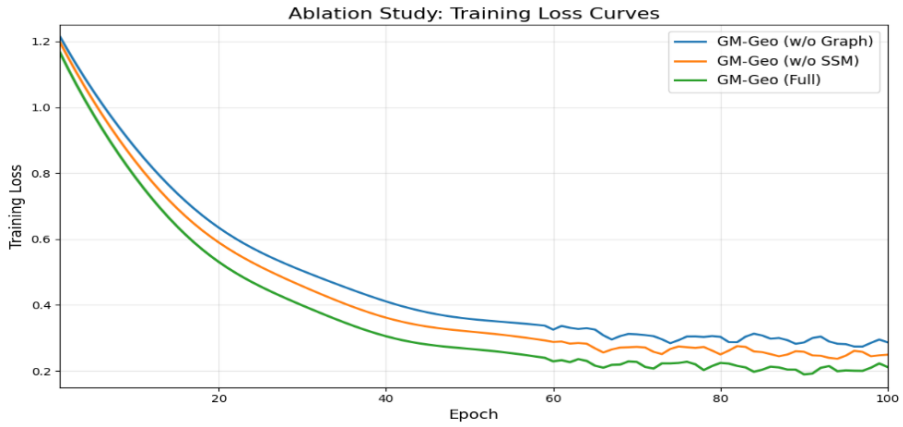

Fig. 5. Training loss curves of different ablation variants.

The results demonstrate that removing either component leads to a clear decline in performance. When the graph module was removed, the model lost its ability to explicitly exploit inter-borehole spatial neighborhood relationships, resulting in reduced classification accuracy. When the selective state space module was removed, the model could no longer adequately characterize the sequential evolution of lithological units along the depth direction, which also led to inferior performance. In contrast, the full GM-Geo model achieved the best results in Precision, Recall, Macro-F1 score, and Micro-F1 score confirming that the spatial graph module and the selective state space module play complementary roles in lithology prediction under sparse borehole conditions.

4.6 Sensitivity Analysis of Neighborhood Radius r

To evaluate the effect of the neighborhood radius r, we performed a parameter sensitivity analysis and report the results in Fig.6. It can be observed that both Macro-F1 and Micro-F1 first improve and then decline as r increases, and the optimal performance is achieved at around r=8. This suggests that an appropriate radius is necessary to capture useful inter-borehole spatial dependencies while avoiding the introduction of irrelevant neighbors. Therefore, r=8 is selected in our experiments.

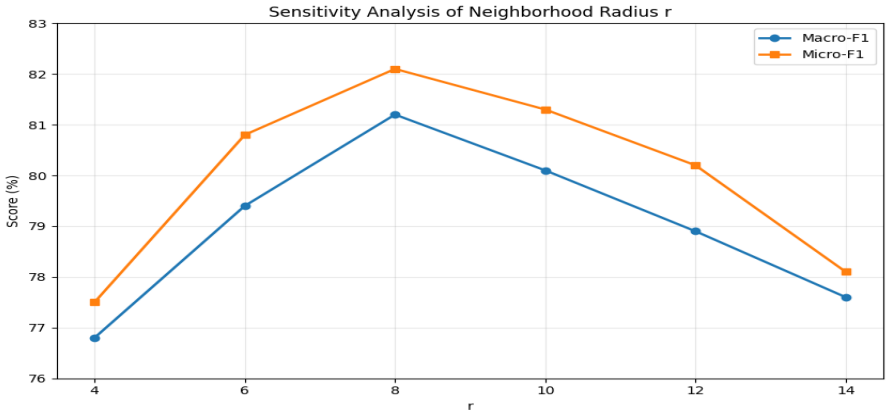

Fig. 6. Sensitivity analysis of neighborhood radius r.

5 Conclusion

This paper proposes a graph-enhanced selective state space framework, GM-Geo, for lithology prediction under irregular drilling conditions. GM-Geo integrates sample-level spatial graphs with a deep selective state space model, simultaneously capturing lateral continuity between boreholes and vertical correlation within boreholes. Experimental results validate the complementary roles of these two components. Compared to representative baseline methods, GM-Geo achieves more significant improvements in lithology categories related to ore bodies and mineralization, while also demonstrating higher recall rates for key exploration targets. This indicates its effectiveness in reducing missed detections of ore-bearing lithologies and structurally complex lithologies. These results demonstrate that GM-Geo provides an efficient and practical solution for lithology prediction and mineral exploration under irregular drilling conditions.

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