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Application of XGBoost Extreme Gradient Boosting Model in the Evaluation of Shallow Gas Hazards in Urban Strata—A Case Study of a Typical Area in LG City

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Abstract: Current research on susceptibility assessment of shallow gas disasters predominantly relies on knowledge-driven models. To address this limitation, this study investigates the feasibility of applying data-driven models for the assessment of urban shallow gas hazards. The typical shallow gas disaster area in Longgang was selected as the study region. Through the Analytic Hierarchy Process (AHP) involving expert scoring, combined with literature review, eight evaluation factors were identified for assessing shallow gas susceptibility: pressure coefficient, fluid factor, burial depth, organic carbon content, number of gas-bearing layers, gas saturation, porosity, and formation pressure. The XGBoost (Extreme Gradient Boosting) model was optimized using a Bayesian hyperparameter tuning algorithm, which significantly improved its predictive performance. The results demonstrate that the data-driven model has promising application potential in urban shallow gas disaster susceptibility evaluation.

1. Introduction

Shallow gas typically refers to various types of natural gas resources located within burial depths of 1500 meters, characterized by relatively small reserves. Due to its shallow burial and limited accumulation, shallow gas often exhibits high pressure. Tao Jiaqi^[1] further suggested that rapid sediment deposition commonly contributes to the formation of shallow gas zones. During exploration and drilling operations, such gas-bearing formations can lead to serious incidents including blowouts and borehole collapse, potentially triggering additional geological hazards. These events pose significant risks to human safety—affecting both site personnel and nearby residents—as well as substantial economic losses^[2]. Therefore, accurate assessment and prediction

of shallow gas hazards are essential to reduce the likelihood of such disasters, ensure drilling safety, and protect both urban environments and public security.

Current research on shallow gas hazards primarily focuses on hazard identification, genesis analysis, and site-specific investigations within particular engineering contexts, with an emphasis on prevention and control measures^[3–5].

Susceptibility assessment constitutes a critical component in the evaluation and prediction of shallow gas disasters. It refers to the likelihood of such hazards occurring in a given area based on local geological conditions, combined with predisposing and triggering factors. Currently, neural network analysis is widely employed in academia for evaluating shallow gas susceptibility. For instance, Bai Zhenhua et al.^[6] applied cross-plot techniques and statistical methods to establish criteria for natural gas zone identification. Guo Jinrong^[7] analyzed factors contributing to gas blowouts based on the distribution patterns of shallow gas in the Putaohua Oilfield. Zhao Liangxiao et al.^[8] developed a volumetric model using shale content and reservoir shale parameters to calculate formation porosity and saturation for gas layer discrimination. He Xing et al.^[9] discussed shallow gas hazards from perspectives of geological structure, lithology, and faults. Meanwhile, Guo Xingjie et al.^[10] integrated coastal erosion, shallow gas activity, and offshore submarine landslides in a coastal zone context.

Data-driven models are now widely used in disasters such as landslides and rockfalls^[11–12]; however, their application in ground collapse susceptibility assessment—particularly in urban settings—remains limited. For instance, Cao et al.^[13] employed neural networks, including Backpropagation (BP), Particle Swarm Optimization-enhanced BP (PSO-BP), Probabilistic Neural Network (PNN), and Fully Connected Deep Neural Network (DNN), to identify shallow gas in deepwater drilling. Ma Yuanhong^[14] compared three machine learning methods for predicting Estimated Ultimate Recovery (EUR) of shallow shale gas and found that BP neural networks and Long Short-Term Memory (LSTM) models performed effectively in forecasting decline curves and cumulative production, respectively, enabling rapid and accurate EUR prediction. Zhang Zhenxiang^[15] integrated seismic attributes as input features and applied a BP neural network to identify shallow gas hazards during deepwater drilling operations.

This study focuses on the susceptibility assessment of shallow gas disasters, especially in urban areas. Through precise delineation of the study area and collapse locations, sample points were selected including historical ground collapse sites and underground cavities—identified via radar detection—with high collapse potential.

highly mineralized, brackish, and weakly alkaline formation water. The ambient temperature falls within the optimal range of 35 – 42° C for methanogenic bacteria to decompose organic matter and generate biogas (methane). Methane is continuously produced within muddy clay layers of river floodplains, then migrates and accumulates dynamically into lenticular sand bodies (“ mud-wrapped sand ”) within the floodplain, where it forms accumulations or escapes. Further migration also occurs into underlying channel sands and overlying littoral-shallow marine sands, resulting in dynamic accumulation and leakage. Consequently, the investigation and risk management of shallow gas geological hazards in Longgang—particularly those integrating both prevention and utilization—pose significant challenges. Nonetheless, the findings are expected to provide valuable insights and serve as a reference for geological risk management in coastal urban clusters across ZJ Province and even nationwide. Key geological factors facilitating shallow gas generation include: Burial within Quaternary sedimentary strata; Abundant supply of sapropelic/humic organic matter; A suitable temperature window (35 – 42° C in eastern coastal Quaternary sequences); Presence of methanogens capable of decomposing sedimentary organic matter; High salinity of formation water; Brackish and weakly alkaline formation conditions; Depositional environments with low hydrodynamic energy, such as fine-grained floodplain muddy clays; Sediments in early diagenesis stages, weakly consolidated or unconsolidated, with localized differential compaction.

It is important to emphasize that biogas formation is not strictly confined to specific depths, temperatures, or pressures. As evidenced by the typical Qaidam Basin Sanhu Quaternary biogas system (Zheng Hongjun, 2008 – 2010), previous scientific understanding has been continually revised. For instance, biogenic gas was once thought to be absent in structural lows, yet industrial quantities have been drilled in synclines and saddle structures. Similarly, although microbial activity was believed to cease beyond 1700 meters depth and 75° C, subsequent drilling has confirmed the presence of economically viable biogas beyond these limits, demonstrating the broader than previously expected conditions conducive to biogenic gas accumulation.

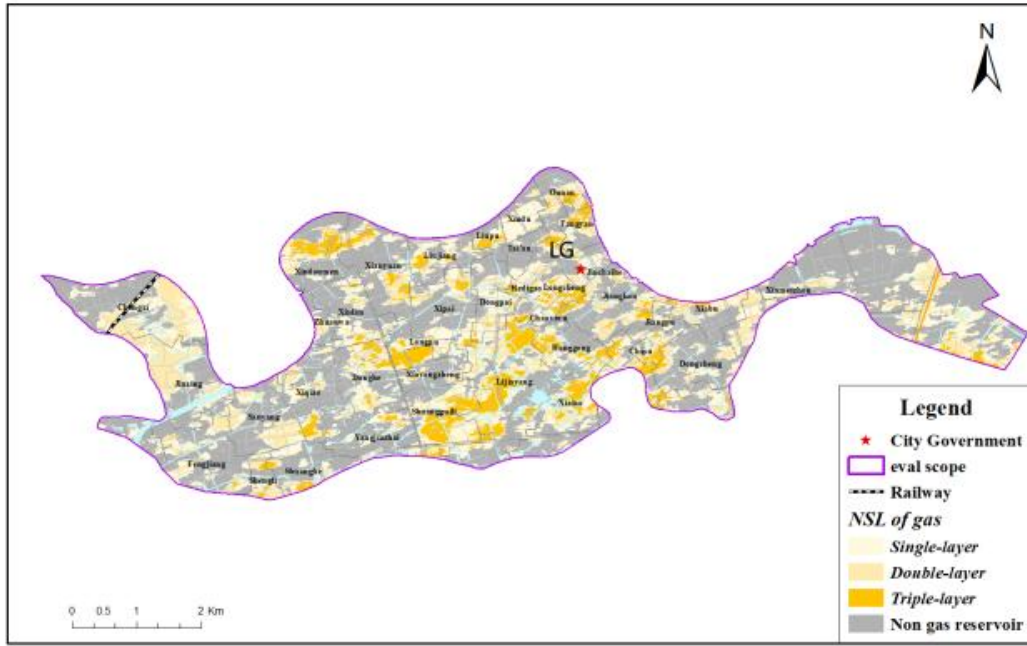


Figure 2. Distribution Map of Shallow Gas in Longgang City

3. Methodology and Model Algorithms

3.1 Research Workflow

This study employs machine learning algorithms to assess shallow gas hazards in the Longgang area. The research framework is structured as follows: First, basic geographic data and the distribution of recorded shallow gas disaster incidents in Longgang are collected to construct a geospatial database. Through literature review and the Analytic Hierarchy Process (AHP) involving expert scoring, potential influencing factors related to shallow gas hazards were identified, and the final set of evaluation factors was selected based on local conditions. According to the actual situation, incident points within communities are enclosed within 200-meter buffer zones designated as hazard areas, while the remaining regions are classified as non-hazard areas. The entire study area is rasterized into grid cells. The dataset is then split into training and testing sets at a ratio of 7:3. A Bayesian hyperparameter optimization approach is applied to tune the selected machine learning model and achieve optimal performance. An XGBoost model is constructed for hazard susceptibility prediction. Furthermore, the SHAP (SHapley Additive exPlanations) interpretability framework is introduced to identify and analyze key driving factors. Finally, a spatial susceptibility

prediction map for shallow gas hazards is generated. The detailed workflow is illustrated in Figure 3.

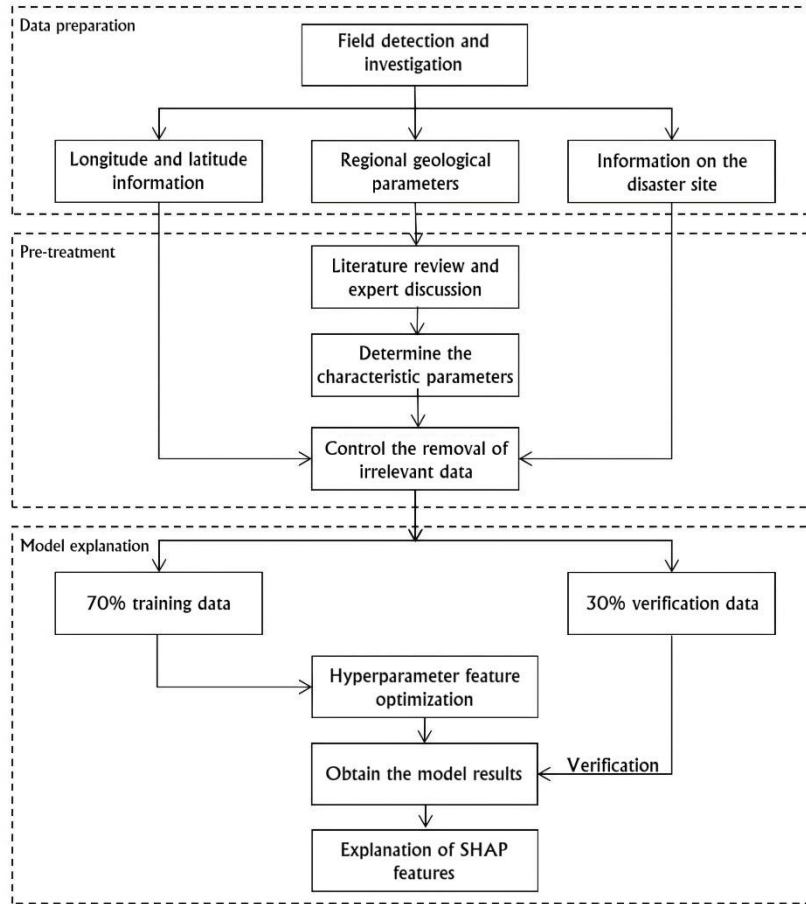


Figure 3. Flowchart of Experimental Operation

3.2 Bayesian Hyperparameter Optimization

As an efficient and flexible ensemble machine learning algorithm, eXtreme Gradient Boosting (XGBoost) is highly sensitive to its parameter configuration. However, the hyperparameter space of XGBoost is often high-dimensional, non-linear, and characterized by complex interactions among parameters. To address this challenge, a Bayesian optimization strategy is introduced, providing an advanced and efficient solution for hyperparameter tuning of XGBoost.

The Bayesian hyperparameter search process involves the following steps: first, selecting a set of hyperparameters; then, incorporating them into the model and evaluating its performance; and subsequently updating the probabilistic model to guide

the search toward optimal parameter combinations. The specific workflow is illustrated in Figure 4.

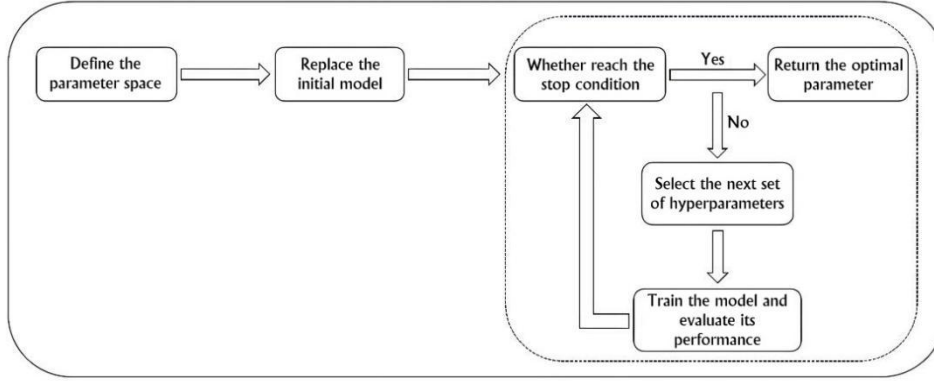


Figure 4. Flowchart of Bayesian Hyperparameter Search

3.3 SHAP-based Feature Interpretation

XGBoost makes predictions by iteratively building an ensemble of decision trees, which involves high-order interactions and complex nonlinear weighted combinations among features. Conventional feature importance metrics can only provide a global ranking of contributions and fail to quantify the direction and magnitude of each feature's effect on individual predictions. In practice, along with overall predictive performance, it is often essential to interpret how individual features influence specific predictions.

To address this need, this study employs the SHAP (SHapley Additive exPlanations) framework to quantify feature contributions. SHAP values are rooted in cooperative game theory, specifically the Shapley value, which fairly allocates the predictive contribution among all features. For each feature i , the SHAP value represents its marginal contribution to the prediction across all possible feature subsets.

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!} (v(S \cup \{i\}) - v(S)) \quad (3-1)$$

where N denotes the set of all features, S represents a subset of features excluding feature j , $f(S)$ is the model prediction using subset S , and $f(S \cup \{j\})$ is the prediction when feature j is included. This formulation quantifies the average marginal contribution of feature j across all possible feature combinations, thereby

highlighting its unique effect on the prediction outcome.

3.4 XGBoost Model

The eXtreme Gradient Boosting (XGBoost) model, proposed by Chen Tianqi et al. in 2016, is an ensemble learning algorithm based on an optimized version of Gradient Boosted Decision Trees (GBDT). It aims to enhance predictive performance through the integration of multiple classification and regression trees and is widely used in both regression and classification tasks. The core idea of XGBoost is to iteratively train multiple decision trees using an additive modeling strategy, gradually minimizing prediction errors. The final output is a weighted integration of predictions from all individual trees, as illustrated in Figure 5. This model is particularly suitable for detecting shallow gas layers, which are typically less than 5 meters thick. XGBoost can effectively identify and respond to subtle subsurface anomalies. Moreover, in cases where recorded disaster incidents are scarce, the model can adjust through built-in category weighting and handle challenging samples via boosting iterations.

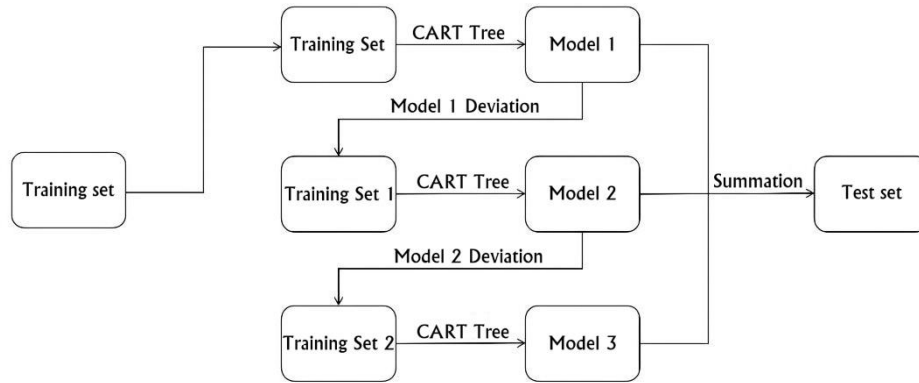


Figure 5. Schematic Diagram of XGBoost Model Principle

The objective function of the XGBoost model follows a risk minimization principle, which consists of a loss function and a regularization term. It is defined as follows:

$$\mathcal{L}(\phi) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (3-2)$$

Here, $l(y_i, \hat{y}_i)$ denotes the loss function (e.g., mean squared error,

logarithmic loss, etc.) for the i sample. The predicted value $\hat{y}_i$ obtained by integrating outputs from all K trees: $\hat{y}_i = \sum_{k=1}^K f_k(x_i)$. The regularization term , $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|\omega\|^2$ penalizes the complexity of the k -th tree, where T represents the number of leaf nodes, ω denotes the leaf weights, and λ and γ are regularization parameters.

4. Data Sources and Evaluation Factors

4.1 Data Sources

The foundational data for this study were obtained from project investigations, existing research, and socio-economic and demographic statistics of LG City. Specifically, the data include: ① Geological, hydrological, and human activity data within the study area, primarily used for selecting evaluation factors and subsequent susceptibility assessment; ② Parameters related to shallow gas reservoirs, such as number of gas-bearing layers, burial depth, pressure coefficient, fluid factor intensity, and pressure gradient; ③ Field survey data, including borehole records and in-situ measurements of shallow gas seepage points. Using ArcGIS software, the study area in LG City was rasterized into a grid with a cell size of $6 \text{ m} \times 6 \text{ m}$. This process resulted in the identification of 4,434 hazard-prone units and 37,508 non-hazard units.

4.2 Selection of Evaluation Factors

The occurrence of shallow gas disasters is often influenced by multiple factors during underground excavation activities. Hazard-forming environmental factors include natural conditions such as shallow gas pressure, fluid properties, burial depth, and number of gas-bearing layers, while triggering factors are more closely related to human activities such as excavation and other specific conditions.

Given the complexity of urban shallow gas environments and the unique mechanisms behind shallow gas disasters, the selection of evaluation factors must comprehensively consider both the geological context and anthropogenic characteristics of the study area. Based on a thorough review of existing research and field data, this study identifies the following key factors contributing to

shallow gas disasters in the study area: pressure coefficient, fluid factor, burial depth, organic carbon content (TOC), number of gas-bearing layers, gas saturation, porosity, and formation pressure.

With support from geological and hydrogeological surveys conducted by the Zhejiang Geological Bureau and the Nanjing Center of Geological Survey, the following eight factors were selected as preliminary evaluation indicators for urban ground collapse susceptibility:

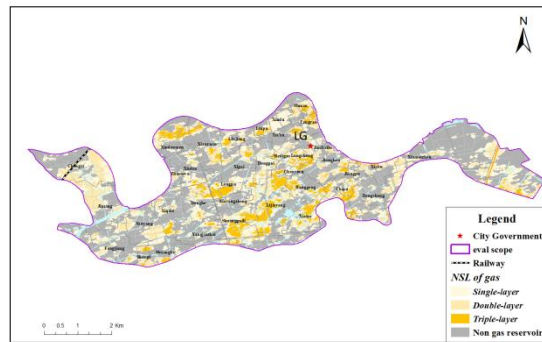
- (1) **Number of gas-bearing layers:** Classified into low, medium, and high levels based on abundance (see Fig. 6a).
- (2) **Burial depth:** Refers to the vertical distance from the ground surface to the shallow gas layer. Shallower depths generally correlate with higher disaster susceptibility. Classified into three tiers (Fig. 6b).
- (3) **Pressure coefficient:** Categorized into three grades (Fig. 6c).
- (4) **Fluid factor:** The presence and activity of fluids can intensify shallow gas movements and increase hazard potential. Divided into three levels (Fig. 6d).
- (5) **Formation pressure:** Represents the pressure exerted by shallow gas on surrounding soil and structures. Higher pressure may exceed soil bearing capacity and trigger disasters. Classified into three tiers (Fig. 6e).
- (6) **Porosity:** The proportion of pore space in the soil. Lower porosity reduces available space for gas storage and increases disaster likelihood. Classified into three categories based on local conditions (Fig. 6f).
- (7) **Total Organic Carbon (TOC):** Higher organic carbon content reduces the probability of shallow gas disasters. Classified into three levels from low to high (Fig. 6g).
- (8) **Gas saturation:** Lower saturation levels indicate higher potential for gas accumulation and eventual eruption. Divided into three tiers (Fig. 6h).

Table 4.2-1 Grading Table of Each Index Factor

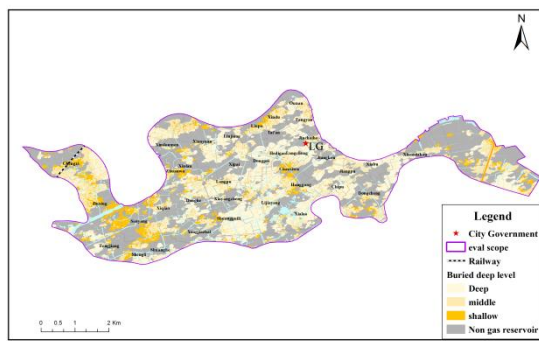
Indicator	Parameter grade		
	High	Medium	Low

Number of gas storage layers	3	2	1
Burial depth (m)	2.78-64.49	64.49-83.66	83.66-145.37
Pressure coefficient	0.4883-0.9879	0.9879-0.9984	0.9984-0.9986
Fluid factor	251022-256280	256280-258846	258846-264114
Pressure	<200.2	200.2-601.8	>601.8
Porosity	25.06%-31.76%	31.76%-32.78%	32.78%-39.48%
TOC	0.66-1.15	1.15-1.29	1.29-1.77
Gas saturation	38.68%-44.52%	44.52%-51.51%	51.51%-59.87%

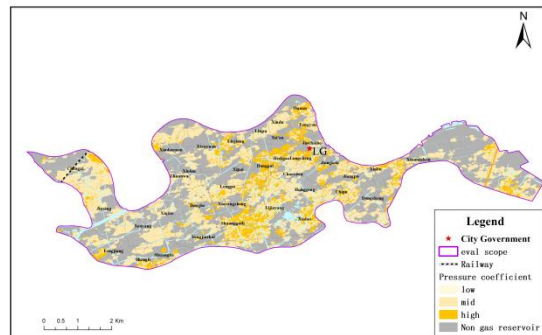
According to the above parameter division range, compile the grade zoning map of each parameter factor (Figures 6 (a) - Figure 6 (h)).



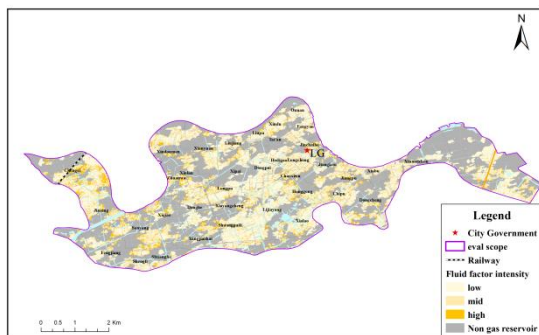
(a) Number of gas storage layers



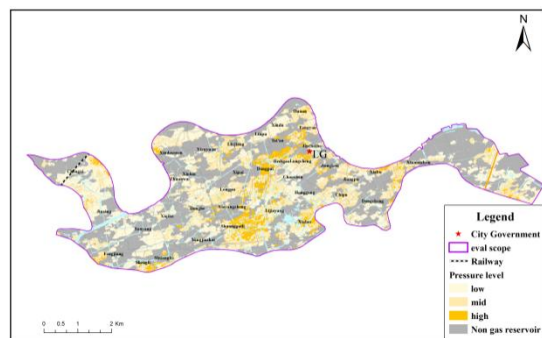
(b) Burial depth



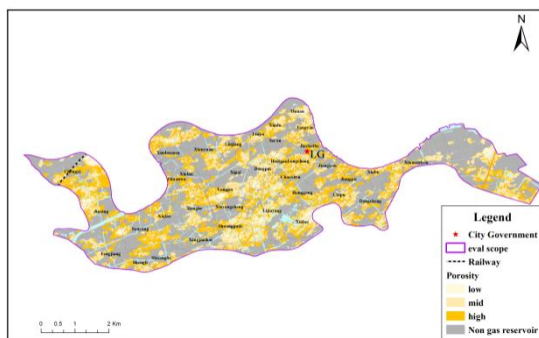
(c) Pressure coefficient



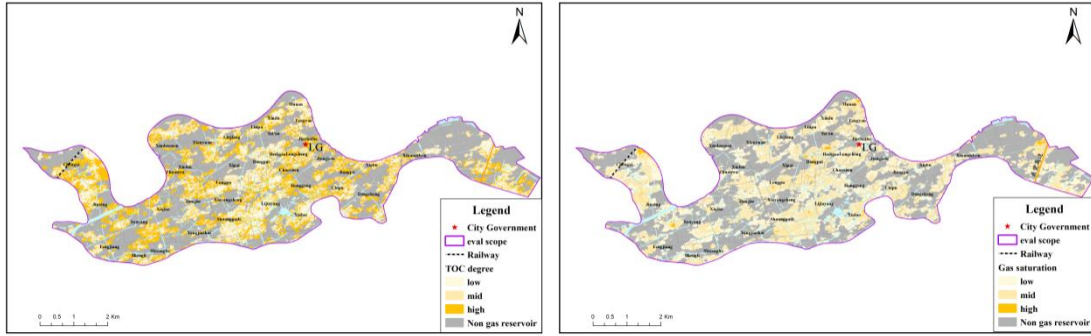
(d) Fluid factor



(e) Pressure rating



(f) Porosity



(g) TOC grade

(h) Gas saturation

Figure 6. Graded Chart of Evaluation Factors for Shallow Gas Disasters in the Study Area

5. Susceptibility Assessment and Analysis of Shallow Gas Disasters in the Study Area

5.1 Experimental Environment

The software environment for this study included ArcGIS Pro 3.0 and Python 3.9. The primary data were derived from project investigations, existing research findings, and economic and demographic data of LG City. Specifically, the data consist of:

- ① Geological, hydrological, and human activity data within the study area, used mainly for selecting evaluation factors and conducting the susceptibility assessment;
- ② Parameters related to shallow gas reservoirs, including the number of gas-bearing layers, burial depth, pressure coefficient, fluid factor intensity, and pressure level;
- ③ Field survey data, such as borehole records and on-site measurements of shallow gas seepage points.

5.2 Accuracy Evaluation

After completing the prediction, the Area Under the Receiver Operating Characteristic Curve (ROC-AUC) was employed to evaluate model accuracy. This metric is widely used to assess the predictive performance of models in geological hazard analysis (Pham et al., 2020; Wang et al., 2020). The AUC value, which ranges between 0 and 1, provides a scalar measure of the model's ability to distinguish between positive and negative instances without relying on a specific classification threshold. An AUC value closer to 1 indicates higher predictive accuracy, while a value of 0.5 suggests performance no better than random guessing.

As shown in Figure 7, the ROC-AUC curve derived for the specific hazard zones in the Longgang area demonstrates that the model exhibits strong performance in predicting shallow gas-related hazards.

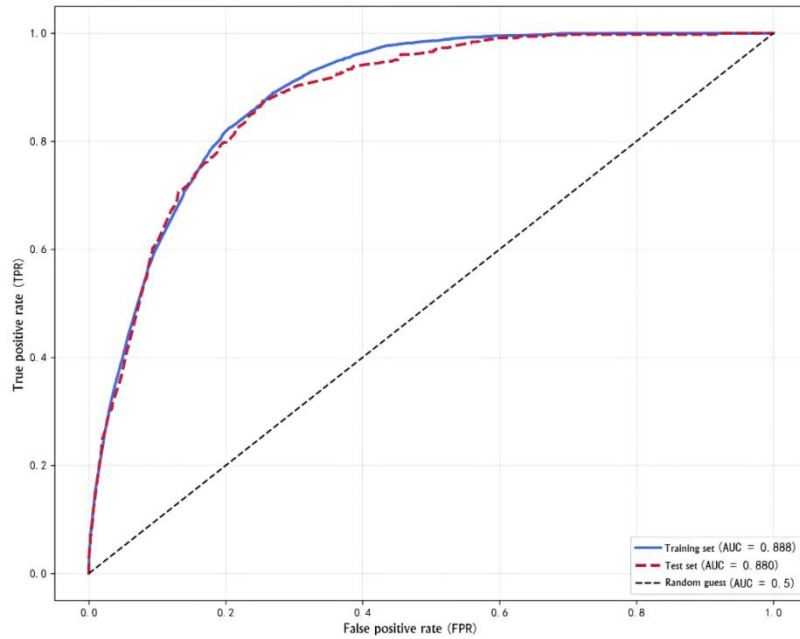


Figure 7. ROC-AUC Curve of the Specific Study Area in Longgang District

5.3 Susceptibility Mapping

After completing model predictions in typical study areas, the training and testing datasets were combined and subsequently extended to cover the entire Longgang community. All data points were then integrated into ArcGIS Pro 3.0 to generate a risk assessment map for the entire survey area. The susceptibility values of shallow gas disaster-prone zones, which range from 0 to 1, were reclassified using manual classification intervals. This process categorized the study area into four distinct susceptibility classes: low (0 – 0.3), moderate (0.3 – 0.6), and high (0.6 – 1.0).

On the shallow gas risk prediction map, the Dongpai and Xipai communities were identified as the most susceptible areas. Additional susceptible zones were also observed in the Donghe, Fengjiang, and Xialao communities. The final shallow gas disaster susceptibility map is presented in Figure 8, which illustrates the detailed spatial distribution and classification of susceptibility levels across the region.

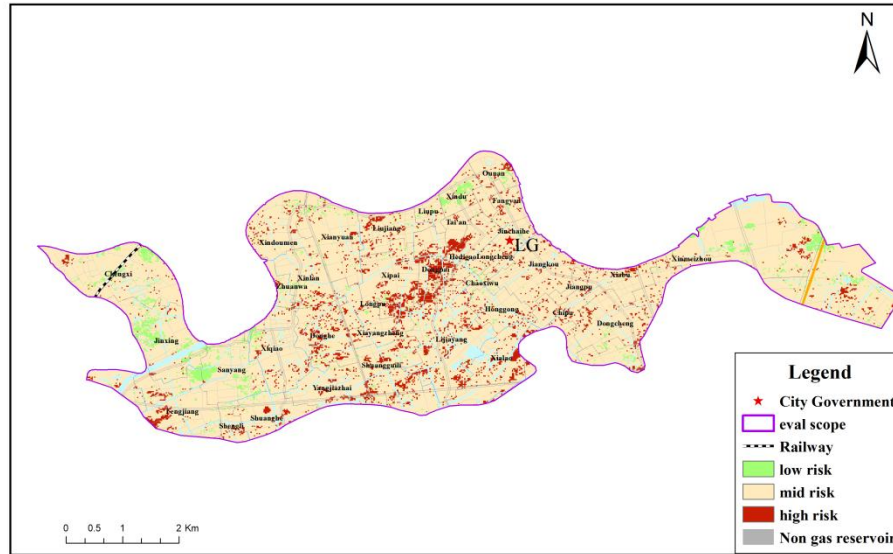


Figure 8. Prediction Map of Shallow Gas Risk Levels in Longgang Area

5.4 Model Interpretability

SHAP plots serve as an effective tool for illustrating model interpretability. Through experiments conducted in the specific study area, three types of plots were generated: global feature importance plots, analysis of feature impact direction, and high-risk feature interpretation plots. Each provides a distinct way to visualize and understand the behavior of both the data and the model without requiring in-depth technical expertise (Yang et al., 2022). As shown in Figure 9, the global feature importance plot displays all geological features along the vertical axis, while the horizontal axis represents the mean $|\text{SHAP value}|$. A larger absolute SHAP value indicates a more critical influence of the corresponding feature on the model's prediction of formation characteristics. Among these features, the number of gas-bearing layers (Gas Layers) has the highest $|\text{SHAP value}|$, indicating it is the dominant factor contributing to disaster susceptibility in the Longgang area. Gas saturation (GasSat) ranks second, suggesting that, in addition to the number of gas-bearing layers, the degree of gas saturation within the reservoirs is also a significant contributor to hazard occurrence.

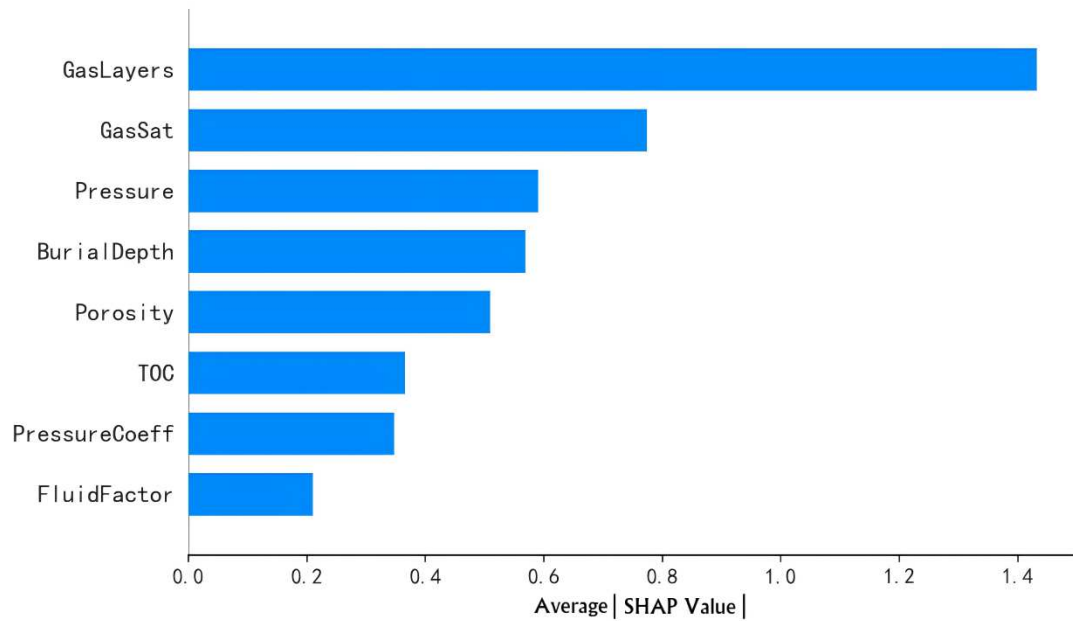


Figure 9. Global Importance Map of Geological Features

5.4 Model Interpretability (Continued)

As shown in Figure 10, the high-risk case interpretation plot illustrates how different features contribute to model predictions. The baseline value represents the model's average prediction. Features indicated by red arrows increase risk, while those in blue decrease risk. This visualization helps decompose the cumulative contribution—expressed in SHAP values—of each geological feature to the final prediction of shallow gas disaster susceptibility.

From the plot, it can be observed that *Pressure* and *Porosity* are associated with blue arrows, indicating that they inhibit the occurrence of shallow gas disasters. In contrast, although *GasSat* (gas saturation) and *FluidFactor* (fluid factor) are displayed in red, their negative SHAP values likewise suggest a mitigating effect on disaster risk. On the other hand, *TOC* (total organic carbon), *GasLayers* (number of gas-bearing layers), and *BurialDepth* exhibit both red arrows and positive SHAP values, confirming that they act as positive contributing factors to shallow gas disaster occurrence.

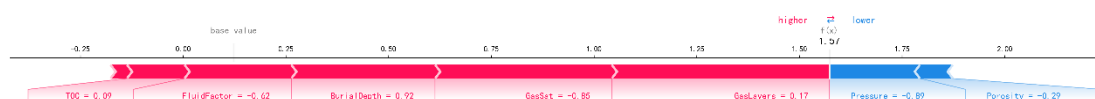


Figure 10. Explanatory Diagram of High-risk Characteristics

In addition to determining the directional influence of each feature, the summary

plot in Figure 11 illustrates the distribution and average impact of each feature across all observations. The horizontal axis represents the SHAP value, indicating both the direction and magnitude of a feature's influence on the model output—positive values promote risk, while negative values suppress it. The vertical axis lists the regional geological features, and the color reflects the feature value (red for high, blue for low). The distribution of points helps visualize the relationship between feature values and their impact on model predictions.

For example, in the ground subsidence analysis, the number of gas-bearing layers (GasLayers) exhibits the greatest contribution to the model's predictions. Variations in this feature significantly alter risk outcomes. In contrast, the fluid factor (FluidFactor) shows the smallest influence, with its impact on risk prediction being closest to zero.

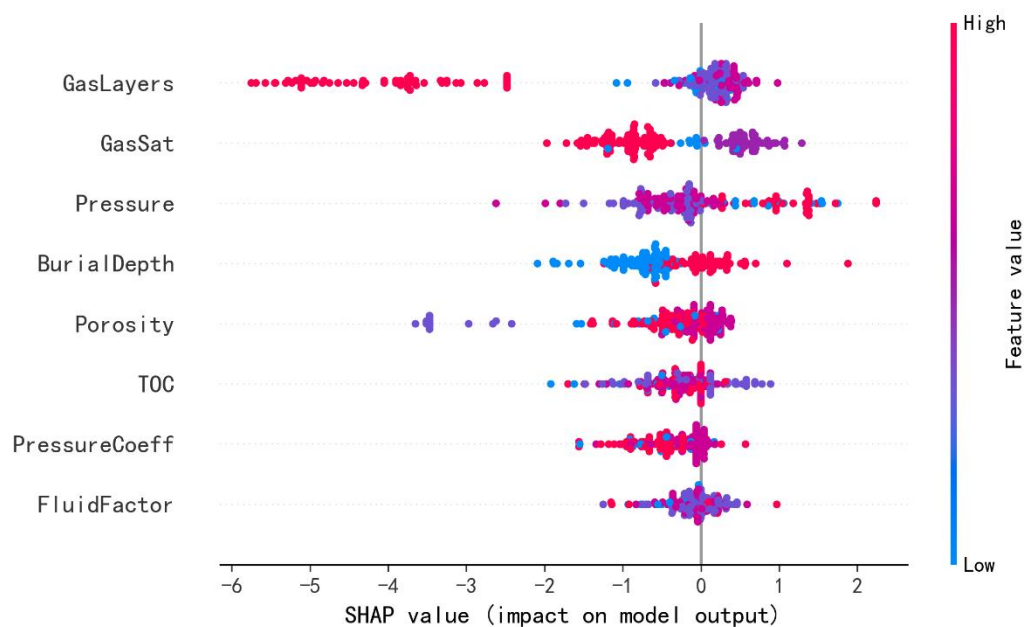


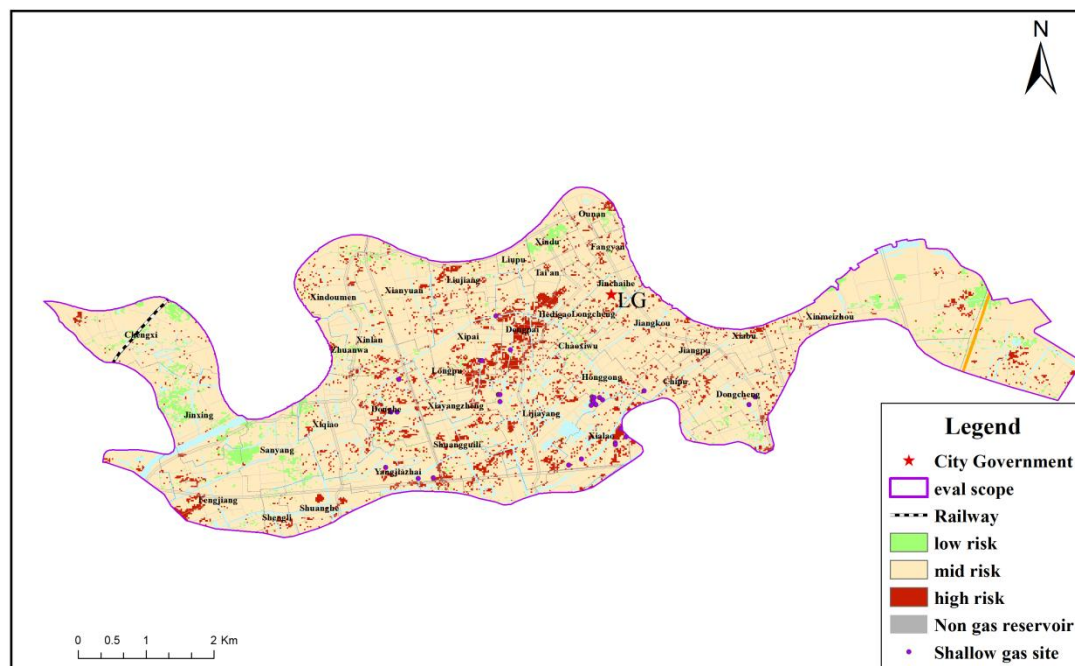
Figure 11. Additive Feature Map of Geological Characteristics

6. Conclusions and Outlook

To address the challenges in assessing and predicting shallow gas hazards, this study selected LG City as a case study and considered the combined effects of hazard-forming and triggering factors. Eight evaluation factors were ultimately chosen: pressure coefficient, fluid factor, burial depth, organic carbon content, number of gas-bearing layers, gas saturation, porosity, and formation pressure. A Bayesian hyperparameter optimization approach was applied to tune the machine learning model, and an XGBoost model was constructed to predict regional disaster susceptibility. The SHAP interpretability framework was introduced to identify key driving factors, enabling

spatial prediction of shallow gas disaster occurrence within the study area.

Based on the XGBoost susceptibility zonation, the study area was classified into three risk levels (Figure 12): low-risk (4.1%), moderate-risk (88.3%), and high-risk zones (7.5%). Notably, 95% of recorded ground collapse incidents occurred within high and very high susceptibility areas, confirming the accuracy of the assessment.



the Study Area

Author Contributions: Conceptualization: J.H. (Jian Hua) and W.Y.G. (Weiya Ge); Methodology: J.H., S.M.C. (Siming Chen), and Y.F.L. (Yunfeng Li); Software: S.M.C. and J.Y.L. (Jiayi Liu); Validation: W.Y. (Wu Ye) and M.Y.Z. (Mingyang Zhang); Formal analysis: J.H., S.M.C., and D.X.L. (Daoxiu Lin); Investigation: H.J.Z. (Hongjun Zheng) and R.J.S. (Rujia Shen); Data curation: Y.F.L., W.Y., and D.X.L.; Writing – original draft: J.H., S.M.C., and J.Y.L.; Writing – review & editing: W.Y.G., H.J.Z., and R.J.S.; Visualization: M.Y.Z. and D.X.L.; Supervision: W.Y.G. and J.H.; Project administration: W.Y.G. and H.J.Z.; Funding acquisition: W.Y.G. All authors have read and approved the final manuscript.

Data and Code Availability: The datasets generated and/or analysed during the current study are not publicly available due to project data management restrictions, but are available from the corresponding author on reasonable request. The model code and processing workflow are available from the corresponding author upon reasonable request, provided that no sensitive spatial location information is involved. Informed consent was obtained from all the experts involved in the study.

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