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Intelligent formation pore-pressure prediction via feature optimization and cascaded transfer learning

Xiao-Xiao Xu^{1,2}, Bing Zhang^{1*}, Jia-Liang Xu¹, Bo Yu³, and Fu-Ying Xu^{1,2}¹Sanya Offshore Oil & Gas Research Institute, Northeast Petroleum University, Sanya, Hainan, China²State Key Laboratory of Continental Shale Oil, Northeast Petroleum University, Daqing, Heilongjiang, China³Department of Seismic Data Processing, School of Earth Sciences, Northeast Petroleum University, Daqing, Heilongjiang, China

Abstract

Traditional pore-pressure prediction relies heavily on empirical formulas and subjective judgment, whereas existing machine learning models exhibit limited generalization across regions and overpressure mechanisms. This study proposes an intelligent prediction method integrating feature optimization with cascaded domain-adaptive transfer learning to improve the generalizability of pore-pressure prediction. A regional dataset was first constructed from well-logging data of 14 exploratory wells in an offshore area. The continuous pore-pressure profiles used as regression targets were derived using conventional pore-pressure evaluation methods and independently assessed against available formation-pressure measurements, rather than being treated as direct pressure measurements at every depth. Hydrostatic pressure was introduced as a vertical physical constraint, and a deviation feature based on an independently constructed, target-well-excluded regional reference velocity curve was developed to reduce reliance on manually defined normal compaction trends, thereby improving inter-well feature comparability and physical interpretability. To mitigate physical inconsistencies and data distribution shifts caused by differences in overpressure mechanisms, including hydrocarbon-generation-related unloading and undercompaction, a cascaded domain-adaptation model combining canonical correlation analysis and transfer component analysis was established. This model adopts a strategy of semantic alignment followed by distribution adaptation, thereby reducing the maximum mean discrepancy between the source and target domains. Validation was conducted using blocked-depth validation, same-mechanism whole-well validation, and multiple cross-mechanism source–target transfer experiments, together with repeated perturbation-based uncertainty analysis. Results show that the proposed features and transfer-learning model improved prediction performance and physical interpretability under the tested conditions. The proposed method demonstrates potential for cross-well pore-pressure prediction under the tested multi-mechanism conditions within the study area.

***Corresponding author:**Bing Zhang
(aaayin0909@126.com)

Citation: Xu X-X, Zhang B, Xu J-L, Yu B, Xu F-Y. Intelligent formation pore-pressure prediction via feature optimization and cascaded transfer learning. *J Seismic Explor.* doi: 10.36922/JSE026300145

Received: July 20, 2026**Revised:** August 27, 2026**Accepted:** September 1, 2026**Published online:** September 14, 2026

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Keywords: Pore-pressure prediction; Transfer learning; Well logging; XGBoost; Domain adaptation

1. Introduction

Accurate prediction of formation pore pressure is essential for drilling safety, drilling-fluid density optimization, wellbore stability assessment, and reservoir evaluation, because reliable pressure estimation can help reduce drilling risks such as kicks, lost circulation, and blowouts, especially in offshore and structurally complex exploration areas.^{1,2} Formation pore pressure is closely related to sediment compaction, porosity reduction, effective stress, and fluid-pressure evolution in sedimentary basins.^{3,4} Early log-based pore-pressure prediction methods were developed using shale compaction properties and electrical survey responses.^{5,6} Eaton⁷ proposed a classical normal-compaction-trend-based method for estimating geopressure from well logs, while Bowers⁸ introduced a velocity-effective stress model that accounts for overpressure mechanisms besides undercompaction. These studies laid the foundation for modern pore-pressure prediction based on well logs, velocity information, and effective-stress theory.

However, accurate pore-pressure prediction remains challenging in basins where multiple overpressure mechanisms coexist. Overpressure may be generated by undercompaction, hydrocarbon generation, unloading, fluid expansion, and lateral pressure transfer, and different mechanisms can produce distinct velocity, density, and effective-stress responses.^{9–11} Comprehensive studies have shown that conventional pore-pressure prediction methods heavily depend on the identification of normal compaction trends, empirical parameters, and overpressure-mechanism assumptions.¹² In undercompaction-dominated intervals, abnormally high pressure is usually associated with delayed compaction and relatively low velocity, whereas unloading-related overpressure may cause velocity reduction without equivalent density reduction. As a result, the same pore-pressure magnitude may correspond to different logging responses under different geological mechanisms. This mechanism-dependent inconsistency limits the transferability of models calibrated in one well, pressure system, or structural block when they are directly applied to another target well.

Seismic velocity and rock-physics constraints provide important support for extending pore-pressure prediction from well control to seismic-scale interpretation. The elastic properties of heterogeneous and porous rocks, velocity–density relationships, and the effects of lithology, porosity, and clay content on wave velocity provide the physical basis for using velocity and density responses in pressure and reservoir prediction.^{13–17} Seismic inversion and rock-physics-based reservoir characterization further connect well-log responses with seismic-scale elastic

attributes, making it possible to infer reservoir properties and pressure-related information beyond well locations.^{18–20} Recent studies have also used abnormal formation velocities and rock-physics-guided seismic inversion to improve pore-pressure prediction.^{21,22} In addition, data-driven prediction from geophysical logs has shown that machine learning models can capture nonlinear relationships between logging parameters and pore pressure.²³ These studies indicate that velocity, density, and rock-physics features are key carriers of pressure-related information. Nevertheless, direct use of raw logging variables may still be affected by burial-depth trends, lithological variations, and mechanism-dependent velocity–pressure responses. Therefore, physically meaningful feature construction is necessary for improving the robustness and interpretability of intelligent pore-pressure prediction.

Transfer learning provides a promising way to improve pore-pressure prediction under limited labeled data and cross-well distribution discrepancies. Recent machine learning studies have also demonstrated applications in reservoir-property prediction, electrical-resistivity estimation from conventional well logs, bottom-hole temperature prediction, well-log anomaly detection, and basin-agnostic log imputation using pre-trained time-series models.^{24–28} Xu *et al.*²⁹ developed a transfer-learning-based formation pore-pressure prediction method using well-logging data and showed that transfer learning can improve prediction accuracy and model generalization across different well-log data and block conditions. In the field of seismic exploration, transfer learning has also been used to improve seismic impedance inversion under limited-sample conditions.³⁰ Physics-guided or deep learning-based methods have been further applied to seismic inversion, multiple attenuation, gas-bearing prediction, porosity prediction, and pre-stack elastic-parameter inversion.^{31–35} These studies demonstrate the potential of intelligent methods for subsurface-property prediction, seismic interpretation, and cross-domain geophysical analysis. However, most existing intelligent pore-pressure prediction studies mainly focus on improving prediction accuracy or reducing statistical distribution differences between wells or blocks. The physical semantic inconsistency caused by different overpressure mechanisms, especially the inconsistent velocity-density responses between undercompaction-related and unloading-related pressure systems, remains insufficiently addressed. Consequently, statistical distribution alignment alone may not fully account for the mechanism-dependent physical relationship between logging responses and pore pressure during cross-well transfer.

To address these problems, this study proposes an intelligent formation pore-pressure prediction method integrating physically guided feature optimization with cascaded domain-adaptive transfer learning. First, hydrostatic pressure (P_h) is introduced as a physically defined pressure-background feature that provides a common hydrostatic reference for comparing pore-pressure evolution across wells. Second, a regional velocity-deviation feature (R_v) is constructed from an independently derived, target-well-excluded regional reference velocity curve to quantify the relative departure of measured velocity from the regional velocity-depth background. This feature reduces the dependence on manually selected normal compaction trends and enhances the comparability of pressure-sensitive velocity responses across wells. Third, a cascaded canonical correlation analysis (CCA)–transfer component analysis (TCA) transfer strategy is used to address cross-well mismatch at two complementary levels. CCA first reorganizes the mechanism-sensitive velocity–density responses to improve their cross-well comparability,³⁶ while TCA subsequently reduces the remaining statistical distribution discrepancy between the source and target domains.^{37–39} Finally, extreme gradient boosting (XGBoost) is employed for nonlinear pore-pressure regression,⁴⁰ and SHapley Additive exPlanations (SHAP) analysis is used to interpret the contributions of the physically guided and transfer-adapted features.⁴¹

2. Methodology

2.1. Dataset and study area

This study was conducted in the Bozhong Sag and adjacent structural zones of the Bohai Bay Basin, eastern China. The region experienced rapid Cenozoic subsidence and strong tectonic deformation, which led to widespread abnormal pressure development. Both undercompaction and hydrocarbon-generation-related unloading occur in the study area, making pore-pressure prediction more challenging than in areas controlled by a single mechanism. Because different pressure-generation processes may produce different logging responses, the relationship between petrophysical parameters and formation pressure can vary considerably across structural blocks.

To establish a regional dataset, logging and pressure data from 14 exploratory wells were compiled. The available data include P-wave velocity (v_p), bulk density (Rho), natural gamma ray (GR), caliper (CAL), compensated neutron log (CN), resistivity logs (RS), and formation-pressure records. Prior to analysis, all logs were subjected to depth matching, environmental correction, and quality control to improve inter-well consistency. After preliminary screening, pressure-sensitive variables were retained for

subsequent modeling. The wells were assigned different roles according to the experimental design. Wells A–C were used for primary model development and validation, Wells D–M were used exclusively to construct the regional reference velocity background, and Well N was retained as an additional independent target well for cross-mechanism validation.

From the regional database, three representative wells (Wells A, B, and C) were selected for detailed modeling and validation based on data completeness and dominant overpressure mechanisms. Wells A and B are located in the central sag, where overpressure is mainly related to hydrocarbon-generation unloading. Well A was used as the source well for model development and blocked-depth validation, whereas Well B was retained for same-mechanism whole-well external validation and was also used as an alternative source well in the supplementary transfer experiments. Well C is located in the marginal structural zone and is primarily influenced by undercompaction. It was used as the primary unlabeled target well for cross-structural and cross-mechanism transfer. Target-well logging features were available for unsupervised domain adaptation, whereas the derived reference pore-pressure values of the target well were withheld from feature alignment, parameter selection, and model training and were used only for final evaluation. The geological setting, effective depth ranges, sample sizes, dominant overpressure mechanisms, and modeling roles of the principal wells are summarized in [Table 1](#). The velocity–density responses of Wells A–C are shown in [Figure 1](#). The 10 auxiliary wells (Wells D–M) were used exclusively to construct the regional reference velocity curve and were not used for supervised model training or prediction-performance evaluation. Wells A–C and Well N were excluded from the construction of this regional reference. Well N, which is also dominated by undercompaction, was retained as an additional independent target well for the supplementary cross-mechanism transfer experiments. This separation of well roles prevents target-well information from entering the engineered velocity-deviation feature through the regional reference curve.

The continuous pore-pressure profiles used as regression targets were not direct formation-pressure measurements at every depth. Instead, they were derived using conventional pore-pressure evaluation methods selected according to the interpreted dominant overpressure mechanism. The Eaton method was applied primarily to undercompaction-dominated intervals, whereas the Bowers method was used for intervals characterized by hydrocarbon-generation-related unloading. The resulting estimates were combined according to the interpreted

Table 1. Geological characteristics and modeling roles of the primary wells

Well	Structural setting	Dominant overpressure mechanism	Effective depth range (m)	No. of valid samples	Modeling role
Well A	Central sag	Hydrocarbon-generation-related unloading	785.8–3,848.7	30,460	Source well; model development
Well B	Central sag	Hydrocarbon-generation-related unloading	1,095.3–3,749.6	26,544	Same-mechanism external validation; alternative source well
Well C	Marginal structural zone	Undercompaction	1,848.0–3,632.9	17,830	Primary cross-structural and cross-mechanism target well

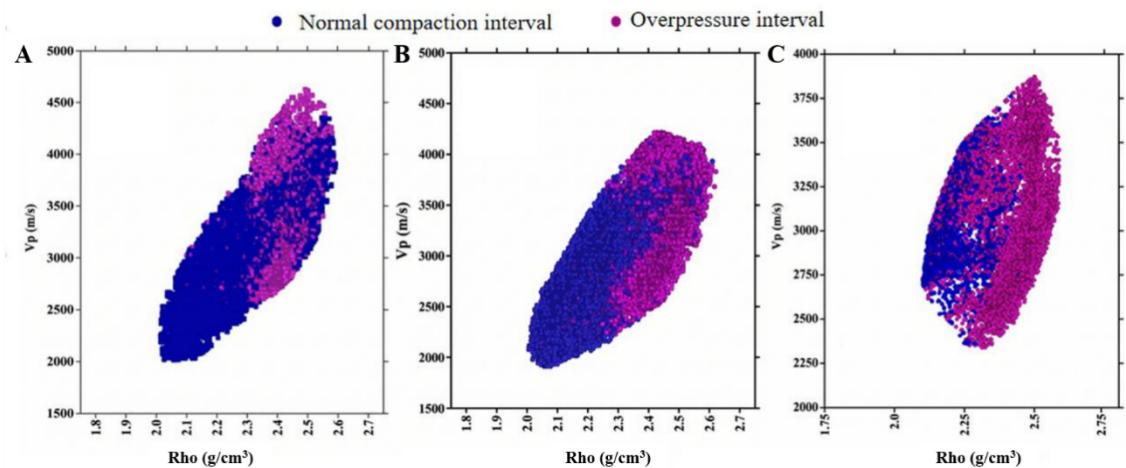


Figure 1. Velocity–density (Rho) cross-plots of the representative wells: (A) Well A, (B) Well B, and (C) Well C

pressure mechanism to construct continuous derived reference pore-pressure profiles. Accordingly, these profiles are referred to throughout this study as derived reference pore-pressure profiles rather than direct formation-pressure measurements. Independent formation-pressure measurements were available at selected depths in Wells A–C. These discrete measurements were not used to construct or calibrate the continuous derived reference pore-pressure profiles and were excluded from feature construction, domain adaptation, parameter selection, and model training. Instead, they were retained exclusively for independent assessment of the reliability of the derived reference pore-pressure profiles. Figure 2 presents the hydrostatic pressure (P_h), overburden pressure (P_{ob}), and derived reference pore-pressure (P_p) profiles of Wells A–C, together with the available independent measured-pressure points at their corresponding depths. This comparison was used to independently assess the consistency of the derived reference profiles with the available formation-pressure measurements.

2.2. Data preprocessing

Raw well-log data are commonly affected by acquisition noise and operational uncertainties, and appropriate preprocessing is therefore essential for improving the reliability of data-driven modeling. Borehole enlargement, mud invasion, tool instability, depth mismatch, and sensor drift may introduce missing values, random fluctuations, and abnormal spikes into logging curves. Such contamination can weaken the physical relationship between logging responses and pore pressure, thereby reducing the reliability of machine learning models.

To improve data quality, several preprocessing procedures were implemented before feature extraction and model training. All logging channels were first depth-matched and resampled onto a unified depth grid using linear interpolation, ensuring consistency among different curves. Short missing intervals were then filled using neighboring-depth interpolation to preserve vertical continuity. Noise reduction was subsequently applied to v_p and GR , which are sensitive to compaction state and

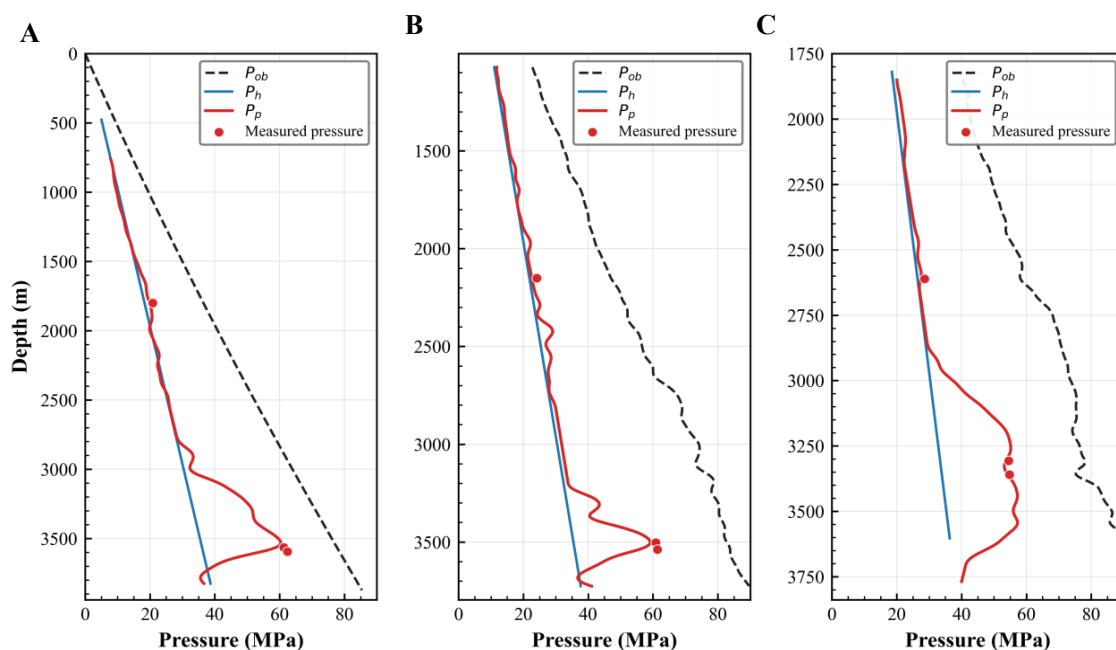


Figure 2. Comparison of the derived reference pore-pressure profiles with independent measured formation-pressure data for the three primary wells. Hydrostatic pressure and overburden pressure are also shown for reference: (A) Well A, (B) Well B, and (C) Well C.

lithological variation. Noise reduction was carried out in the RokDoc environment (Version 2023.1.0.231, Ikon Science, United Kingdom) using a seven-point median moving-window filter. Compared with conventional averaging methods, median filtering is less sensitive to isolated outliers and better preserves abrupt lithological boundaries and pressure-transition intervals. The processed v_p and GR curves before and after filtering are shown in Figure 3.

After preprocessing, the representative logs exhibited improved continuity and reduced random noise, providing a more reliable basis for subsequent feature optimization and pore-pressure prediction.

2.3. Feature engineering

Effective feature engineering is essential for pore-pressure prediction because conventional logging variables often contain redundant information, noise, and inconsistent sensitivities under different geological conditions. Direct use of all logging parameters may increase model complexity and reduce prediction stability, especially in cross-well applications. Therefore, physically meaningful feature construction is required to improve robustness and generalization performance, especially when pore-pressure prediction relies on compaction-related velocity and effective-stress responses. In this study, two engineered variables were introduced. The first engineered variable is

P_h which is introduced as a physically defined pressure-background feature associated with vertical burial rather than as an independent indicator of overpressure. Although depth is widely used as an input parameter in data-driven models, pressure conditions at the same burial depth may differ substantially between structural settings. To reduce this limitation, hydrostatic pressure was calculated using Equation 1:

$$P_h = \rho_w \times g \times z \quad (1)$$

where ρ_w is the formation-water density (1.02 g/cm³), g is the gravitational acceleration (9.8 m/s²), and z is the true vertical depth. Thus, P_h should be regarded as a pressure-domain representation of the large-scale burial background rather than as a direct indicator of abnormal pressure.

The second engineered variable is the objective R_v , which was designed to quantify the relative departure of the measured V_p from the regional compaction-related velocity background. Acoustic velocity generally increases with burial depth under normal compaction conditions; therefore, the normal compaction trend is commonly used as a reference baseline in conventional pore-pressure prediction methods. However, manually picking the normal compaction trend from a single well is subjective and may not be applicable across different wells or pressure systems.

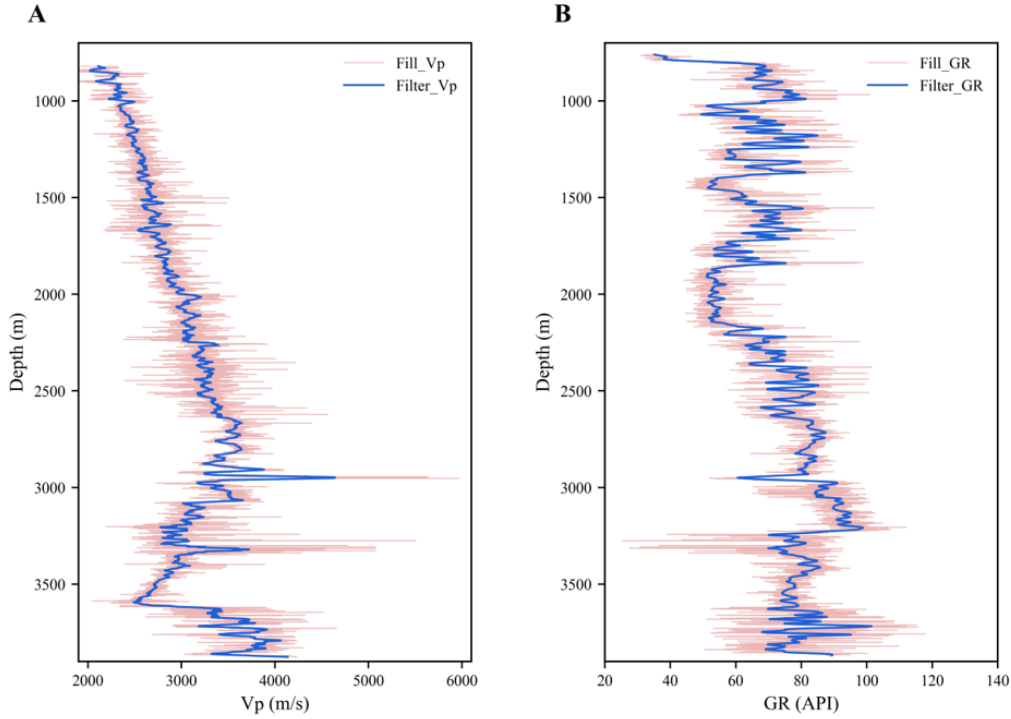


Figure 3. Well-log filling and filtering results: (A) P-wave velocity (V_p) and (b) gamma ray (GR)

To provide a consistent regional reference while avoiding information leakage from the model-development and validation wells, the regional reference velocity curve (v_{enct}) was constructed exclusively from the 10 auxiliary wells (Wells D–M). Wells A–C and Well N were completely excluded from the reference-curve construction. v_{enct} is therefore used here as a regional first-order velocity-depth background rather than as a strict normal compaction trend for any individual well. After quality control, valid v_p -depth samples from each auxiliary well were summarized using the median v_p values within 10 m depth bins to reduce the effects of local fluctuations and unequal logging-sample densities. A well-balanced Huber robust regression was then applied to the depth-binned data. The regional reference relationship was expressed as:

$$v_{enct} = kz + v_{water} \quad (2)$$

where v_{water} is the shallow reference velocity, fixed at 1,500 m/s; z is burial depth; and k is the regional velocity-depth gradient estimated from the 10 auxiliary wells. For the present dataset, the fitted k was 0.59627.

As shown in Figure 4A, the depth-binned velocity samples from the 10 auxiliary wells scatter around the fitted regional reference curve. The scatter of individual samples around v_{enct} is expected because the curve represents a

regional first-order background rather than the detailed velocity profile of any single well.

To examine the stability of the regional reference, a leave-one-well-out sensitivity analysis was additionally performed. Each auxiliary well was excluded in turn, and the reference curve was reconstructed from the remaining nine wells using the same fitting procedure. As shown in Figure 4B, the reconstructed curves remain close to the full 10-well reference, with a maximum variation of 4.21% in the fitted velocity-depth gradient, indicating that the regional first-order trend is not dominated by any single auxiliary well.

Based on this reference trend, the velocity-deviation feature was defined as follows:

$$R_v = v_p / v_{enct} \quad (3)$$

where v_p is the measured P-wave velocity. When the measured velocity is close to the regional background trend, R_v approaches 1. A value lower than 1 indicates that the measured velocity is lower than the regional reference velocity, suggesting a relative low-velocity anomaly that may be associated with abnormal pressure development. In contrast, a value greater than 1 indicates a velocity higher than the regional background.

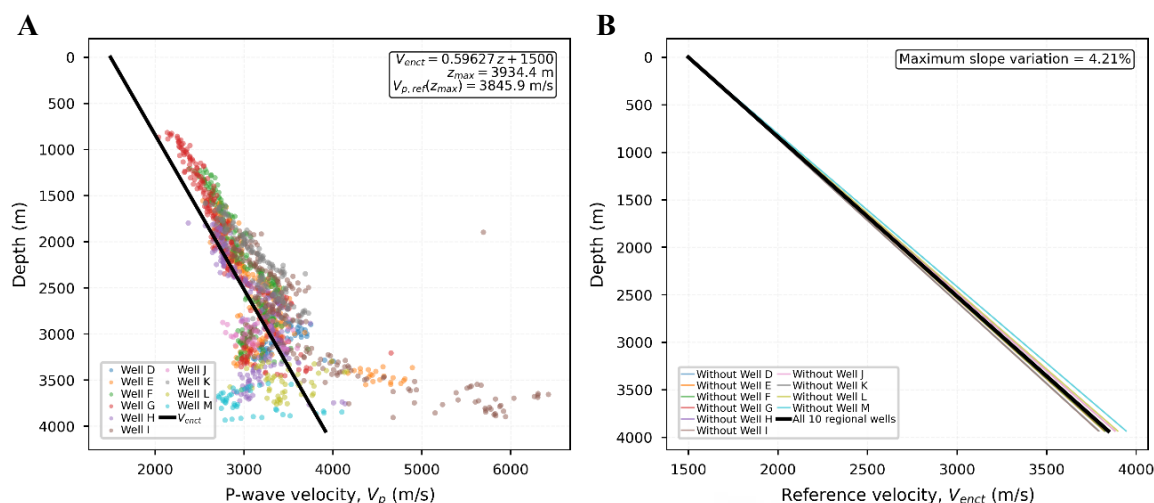


Figure 4. Construction and sensitivity of the regional reference velocity curve. (A) Reference curve fitted using the 10 auxiliary wells. (B) Leave-one-well-out sensitivity analysis.

By transforming raw velocity into a dimensionless velocity-deviation indicator, R_v , reduces the influence of absolute velocity differences among wells and improves the comparability of pressure-sensitive velocity responses across different structural blocks and overpressure mechanisms. Because v_{enct} was constructed exclusively from Wells D–M, the calculation of R_v for Wells A–C and Well N does not introduce information from the model-development or target-validation wells into the regional reference background. Beyond avoiding information leakage, the sensitivity of the final prediction to reasonable variations in the regional reference curve was also examined. The 10 leave-one-well-out reference curves were used to recalculate R_v for the source and target wells, and the resulting prediction profiles were compared with their pointwise ensemble means. The mean inter-realization absolute deviation was 0.193 MPa, and the mean pointwise min–max spread was 0.699 MPa. Although the maximum local spread reached 2.426 MPa, the overall prediction variability remained limited, indicating that the influence of the regional reference-curve variation is generally small but not spatially uniform along the well. Detailed results are provided in Figure A1.

After feature construction, Pearson correlation analysis and preliminary model tests were used to evaluate candidate variables and remove redundant inputs. The correlation analysis was performed using only source-well data, so that target-well-derived reference pore-pressure information was not introduced into the feature assessment. Because P_h is explicitly depth-dependent, its strong correlation with the derived reference pore pressure should be interpreted

primarily as a representation of the large-scale burial trend rather than as independent evidence of pressure sensitivity. In contrast, R_v represents the relative departure of measured velocity from the regional reference. The correlation matrix is presented in Figure 5.

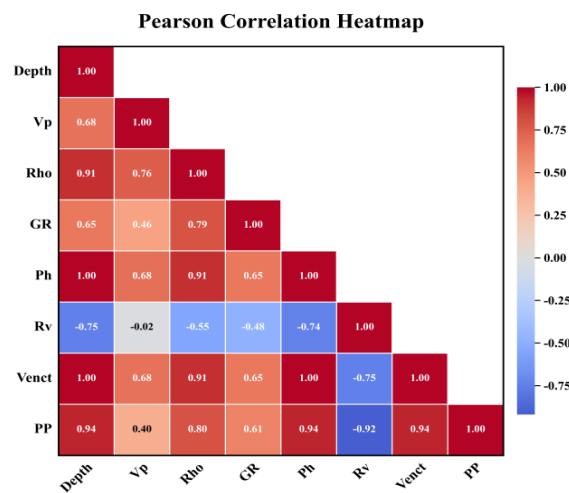


Figure 5. Pearson correlation matrix of candidate features and the derived reference pore pressure

For subsequent comparative experiments, three feature combinations were defined: $F1 = [v_p, Rho, GR]$, $F2 = [v_p, Rho, GR, P_h]$, and $F3 = [v_p, Rho, GR, P_h, R_v]$. These feature sets were used to quantify the contributions of the physically guided variables, P_h and R_v , to pore-pressure prediction and transferability.

2.4. Cascaded transfer-learning framework

Based on the optimized F3 feature set constructed in **Section 2.3**, a cascaded CCA–TCA–XGBoost framework was developed for cross-well pore-pressure prediction under different overpressure mechanisms. In this framework, only source-well-derived reference pore-pressure labels are used for model training, while target-well logging features are used for unsupervised feature alignment and domain adaptation. Target-well-derived reference pore-pressure labels are withheld during feature alignment, transfer-parameter selection, regression training, and model selection, and used only for independent evaluation.

The framework follows a sequential strategy: CCA is first used to align mechanism-sensitive velocity–density responses between source and target wells, TCA is then applied to reduce the remaining distribution discrepancy, and XGBoost is finally trained on the transfer-adapted source features to predict target-well pore pressure. The physically guided variables P_h and R_v are retained outside the TCA transformation to preserve their original physical meaning. The overall workflow is summarized in **Figure 6**.

2.4.1. Mechanism-aware canonical correlation analysis semantic alignment

To reduce mechanism-induced inconsistencies between wells, CCA is applied to the velocity–density responses. CCA is a multivariate feature-representation method that

identifies maximally correlated projections between two sets of variables and has been widely used for learning shared representations.³⁶ In this study, the original feature space was divided into two groups. The mechanism-sensitive feature group is defined as:

$$X_{sens} = [v_p, Rho] \quad (4)$$

where X_{sens} denotes the mechanism-sensitive feature subset composed of v_p and Rho , both of which directly reflect compaction and effective-stress variation. The physically constrained feature group is defined as:

$$X_{phy} = [GR, P_h, R_v] \quad (5)$$

where X_{phy} denotes the physically constrained feature subset composed of GR , P_h and R_v . These features are retained outside CCA to preserve lithological information, hydrostatic-pressure background, and regional velocity-deviation constraints.

Only v_p and Rho are used as inputs to CCA, since they are directly controlled by compaction state and effective stress. After depth matching and normalization, the source and target matrices are defined as $X_{s,sens}$ and $X_{t,sens}$. CCA constructs a shared latent representation by maximizing cross-domain correlation:

$$\rho = \max_{a,b} \text{corr}(a^T X_{s,sens}, b^T X_{t,sens}) \quad (6)$$

where ρ denotes the canonical correlation coefficient, a

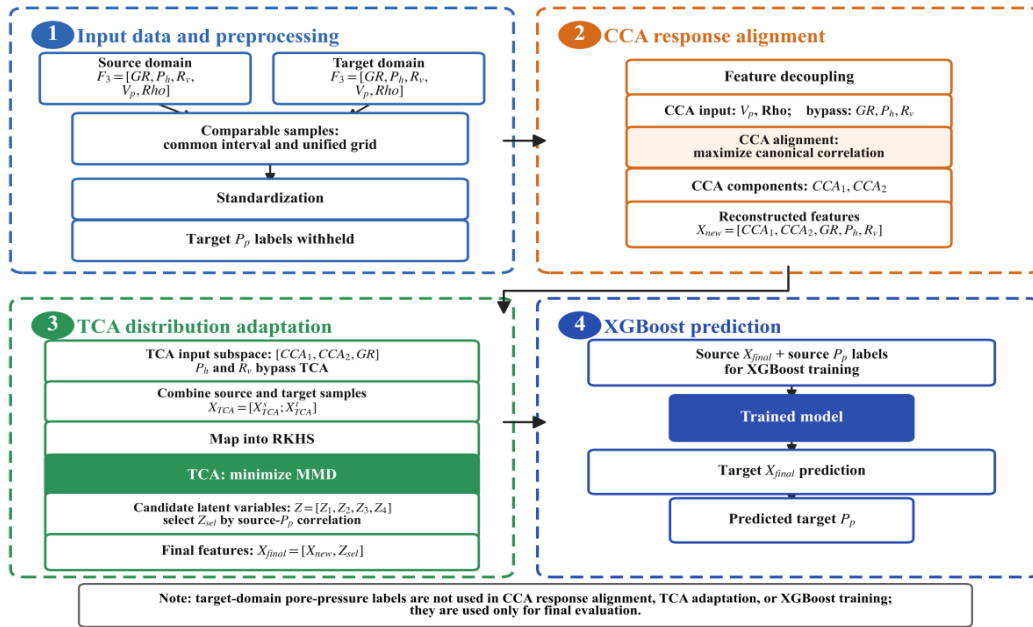


Figure 6. Overall workflow of the proposed cascaded CCA–TCA–XGBoost framework for cross-mechanism pore-pressure prediction. Abbreviations: CCA: Canonical correlation analysis; MMD: Maximum mean discrepancy; RKHS: Reproducing kernel Hilbert space; TCA: Transfer component analysis; XGBoost: Extreme gradient boosting.

and b are the projection vectors for the source and target domains, respectively, and $X_{s,sens}$ and $X_{t,sens}$ are the velocity-density matrices constructed from v_p and Rho in the source and target domains. Two canonical components are retained:

$$X_{CCA} = [CCA1, CCA2] \quad (7)$$

where $CCA1$ and $CCA2$ are the first two canonical variables extracted from the velocity-density response. The reconstructed feature space is:

$$X_{new} = [CCA1, CCA2, GR, P_h, R_v] \quad (8)$$

In this reconstructed feature space, the original mechanism-sensitive variable v_p and Rho are replaced by the CCA-aligned components, while GR , P_h and R_v are retained as stable physical constraints.

2.4.2. Distribution alignment via transfer component analysis

Although CCA reduces mechanism-dependent inconsistencies, residual statistical differences between wells still exist. Therefore, TCA is introduced to further reduce domain shift. To preserve the physical meaning of P_h and R_v , TCA is applied only to the statistical subspace composed of the two CCA-derived components and GR :

$$X_s^T = [CCA1_s, CCA2_s, GR_s] \quad (9)$$

$$X_t^T = [CCA1_t, CCA2_t, GR_t] \quad (10)$$

The source and target samples were combined as:

$$X_{joint} = [X_s^T; X_t^T] \quad (11)$$

where X_{joint} is the concatenated joint matrix used for unsupervised TCA adaptation. TCA maps the data into a reproducing kernel Hilbert space, where domain discrepancy is measured using maximum mean discrepancy (MMD):

$$MMD^2(D_s, D_t) = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(x_{s,i}) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(x_{t,j}) \right\|_H^2 \quad (12)$$

where $\phi(\cdot)$ is a nonlinear mapping function, D_s and D_t denote the source and target domains, respectively, n_s and n_t are the corresponding numbers of samples, and H denotes the reproducing kernel Hilbert space. A projection matrix A is learned by solving:

$$\min_A \text{tr}(A^T K L K A) + \mu \text{tr}(A^T A), \text{ s.t. } A^T K C K A = I \quad (13)$$

where A is the projection matrix, K is the kernel matrix, L is the MMD matrix, C is the centering matrix, μ is the regularization parameter, and I is the identity matrix. The resulting latent representation is:

$$Z = A^T K \quad (14)$$

where Z denotes the d -dimensional transfer representation, and its source and target portions are denoted as Z_s and Z_t , respectively.

After TCA transformation, four candidate latent components $Z = [Z_1, Z_2, Z_3, Z_4]$ are obtained from the statistical transfer subspace. Rather than replacing the CCA-based representation, the TCA-derived components are used as supplementary domain-adaptive features. To retain pressure-relevant transfer information without using target-domain-derived reference pore-pressure labels, the TCA components are ranked according to the absolute correlation between each component and the source-domain-derived reference pore pressure, and the top- k component(s) are retained. The selected TCA representation is denoted as Z^* .

The final regression feature spaces are constructed by augmenting the CCA-based representation with the selected TCA-derived component(s):

$$X_{s,final} = [CCA1_s, CCA2_s, GR_s, P_{h,s}, R_{v,s}, Z_s^*] \quad (15)$$

$$X_{t,final} = [CCA1_t, CCA2_t, GR_t, P_{h,t}, R_{v,t}, Z_t^*] \quad (16)$$

where $X_{s,final}$ and $X_{t,final}$ are the final transfer-adapted source and target feature matrices, respectively. Z_s^* and Z_t^* denote the selected TCA-derived latent component(s) for the source and target domains, respectively. The source-domain final features and source-domain-derived reference pore-pressure labels are used for XGBoost training, whereas the corresponding target-domain features are used for prediction. Target-domain-derived reference pore-pressure labels are not used during TCA fitting, TCA component selection, or XGBoost training, and are accessed only after prediction for final evaluation.

2.4.3. Parameter configuration and leakage control

Two canonical components were retained in the CCA stage. TCA was implemented using a radial basis function (RBF) kernel with kernel parameter $\gamma = 0.20$, regularization coefficient $\mu = 0.01$, and latent dimension $d = 4$. The P_h and R_v features were excluded from TCA and were directly concatenated with the transfer representation before regression.

The transfer parameters were determined without using target-domain-derived reference pore-pressure values. Target-well logging features were used only to quantify unsupervised source-target distribution discrepancy, whereas predictive information used for model or component selection was derived exclusively from the source-domain training data. The same parameter settings were subsequently applied to the reported cross-well transfer experiments.

2.5. XGBoost regression and model implementation

Extreme gradient boosting, a representative gradient-boosting tree model, was employed as the final regression model because it is suitable for capturing nonlinear relationships and complex feature interactions in structured well-log datasets.³⁹ The workflow of XGBoost regression is shown in Figure 7.

For an input sample x_p , the predicted pore pressure after K regression trees is expressed as an additive ensemble:

$$\hat{P}_{p,i}^{(K)} = \hat{P}_{p,i}^{(0)} + \eta \sum_{k=1}^K f_k(x_i), \quad f_k \in F \quad (17)$$

where $\hat{P}_{p,i}^{(0)}$ is the initial prediction, η is the learning rate, $f_k(x_i)$ denotes the output of the k -th CART regression tree, and F is the space of regression trees. Each subsequent tree is fitted along the negative-gradient direction of the loss function to progressively correct the residual error from the previous ensemble.

Model training was performed by minimizing an objective function composed of prediction loss and model complexity regularization as follows:

$$Obj = \sum_{i=1}^n l(P_{p,i}, \hat{P}_{p,i}^{(K)}) + \sum_{k=1}^K \Omega(f_k) \quad (18)$$

where $P_{p,i}$ is the derived reference pore pressure, $\hat{P}_{p,i}^{(K)}$ is the predicted pore pressure after K boosting iterations, $l(\cdot)$ is the regression loss function, and $\Omega(f_k)$ is the regularization term used to control model complexity. The regularization term for each regression tree is defined as:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 + \alpha \sum_{j=1}^T |w_j| \quad (19)$$

where T represents the number of leaf nodes, and w_j denotes the weight of the j -th leaf. The parameter γ penalizes excessive tree complexity, while λ and α control the L_2 and L_1 regularization of the leaf weights, respectively.

In this study, XGBoost was applied to both the original feature combinations and the transfer-adapted feature representations. For the feature-optimization experiments, Well A was evaluated using five-fold continuous blocked-depth cross-validation rather than random sample splitting. The samples of Well A were first sorted by depth and divided into five contiguous depth blocks of approximately equal sample size. In each fold, one complete depth block was withheld for validation, while the remaining four blocks were used for model training. Each block served once as the validation interval, and the resulting out-of-fold predictions were combined to evaluate performance over the complete modeling interval. This blocked-depth design was adopted to reduce optimistic bias caused by the

strong vertical correlation between neighboring logging samples. Wells B and C were retained as whole-well external validation datasets under same-mechanism and cross-mechanism conditions, respectively. A single set of XGBoost hyperparameters was used for the F1, F2, and F3 feature combinations to ensure a consistent comparison. The parameter settings are listed in Table 2.

Table 2. Tuned hyperparameters of the extreme gradient boosting regressor

Parameter	Value
n_estimators	300
max_depth	3
learning_rate	0.05
subsample	0.8
colsample_bytree	0.8
reg_lambda	5
reg_alpha	0.1

Model performance was quantitatively evaluated using the coefficient of determination R^2 , root mean square error (RMSE), and mean absolute error (MAE), defined as follows:

$$R^2 = 1 - \frac{\sum (P_{p,i} - \hat{P}_{p,i})^2}{\sum (P_{p,i} - \bar{P}_p)^2} \quad (20)$$

$$RMSE = \sqrt{\frac{1}{n} \sum (P_{p,i} - \hat{P}_{p,i})^2} \quad (21)$$

$$MAE = \frac{1}{n} \sum |P_{p,i} - \hat{P}_{p,i}| \quad (22)$$

where $P_{p,i}$ is the derived reference pore pressure, $\hat{P}_{p,i}$ is the predicted value, $\bar{P}_p$ is the mean reference pore pressure, and n is the number of samples. Overall, XGBoost serves as the final nonlinear predictor in the proposed framework, enabling the physically optimized and transfer-adapted features to be effectively translated into accurate pore-pressure estimates.

3. Results

To evaluate the proposed prediction framework, experiments were carried out using the representative wells described in Section 2.1. Wells A and B are located in an area mainly controlled by hydrocarbon-generation-related unloading, whereas Well C belongs to a block dominated by undercompaction. Well A was used for

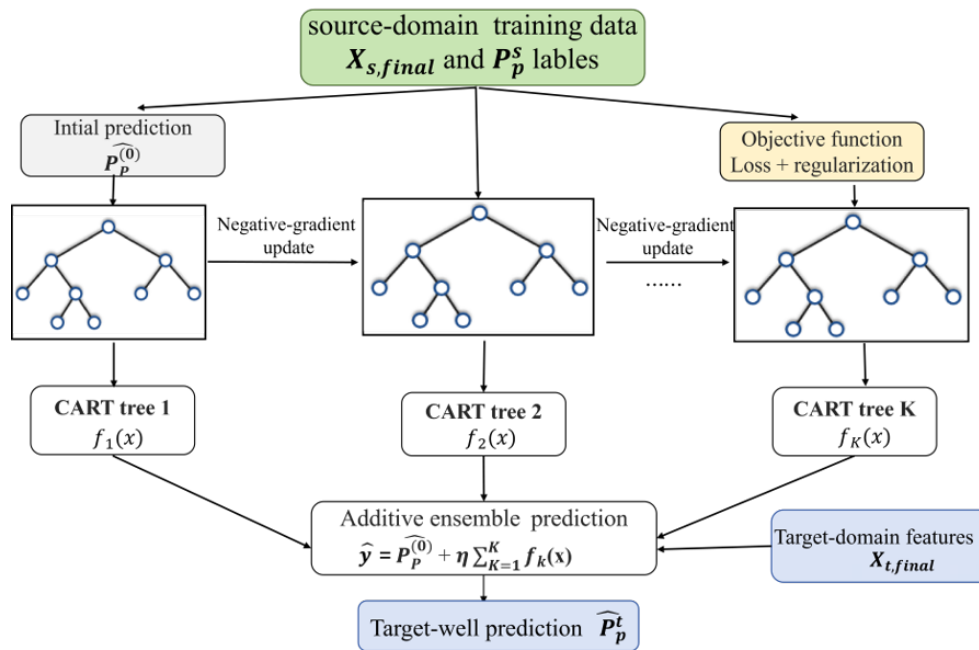


Figure 7. Extreme gradient boosting regression workflow for pore-pressure prediction

model development and internal blocked-depth validation, while Wells B and C were reserved as whole-well external validation wells for same-mechanism and cross-mechanism prediction, respectively. In addition, Well N was retained as an independent target well for supplementary cross-mechanism transfer experiments involving alternative source–target combinations. Throughout this section, all reported performance metrics were calculated against the derived reference pore-pressure profiles described in **Section 2.1** rather than against direct formation-pressure measurements.

3.1. Effectiveness of feature optimization and baseline modeling

To evaluate the effectiveness of the proposed feature optimization strategy, three groups of input features were designed and tested using XGBoost as the baseline regression model. The first feature set, F1, consisted of the conventional logging variables, including GR , v_p , and Rho . The second feature set, F2, further introduced P_h to provide a physically constrained vertical pressure background. The third feature set, F3, incorporated R_v in addition to the F2 variables, forming the final optimized feature combination: $F1 = [GR, v_p, Rho]$, $F2 = [GR, P_h, v_p, Rho]$, and $F3 = [GR, P_h, R_v, v_p, Rho]$. In this experiment, Well A was used for model development. Instead of randomly splitting neighboring depth samples into training and test sets, five-fold continuous blocked-depth cross-validation

was adopted for Well A to reduce optimistic bias arising from the strong vertical correlation of adjacent logging samples. In each fold, one contiguous depth block was withheld for validation, and the remaining four blocks were used for model training, with all five blocks serving once as the held-out interval. Wells B and C were then used as whole-well external validation datasets to evaluate the generalization capability of different feature combinations. Well B represents same-mechanism external validation, while Well C provides a more challenging cross-structural and cross-mechanism validation case.

The quantitative comparison of F1, F2, and F3 is presented in **Table 3** and **Figure 8**. Across all validation settings, the prediction performance improved progressively from F1 to F3. Under the blocked-depth cross-validation of Well A, F3 achieved an R^2 of 0.918 and an RMSE of 4.099 MPa, compared with 0.545 and 9.658 MPa for F1, respectively. The sustained improvement under this more stringent validation scheme indicates that the physically guided features provide additional predictive information beyond that captured by the conventional logging variables.

Similar trends were observed in the two external validation wells. F3 achieved R^2 values of 0.984 and 0.959 for Wells B and C, with corresponding RMSE values of 1.401 and 2.715 MPa, respectively. The improvement from F2 to F3 in both external wells suggests that the independently constructed regional R_v provides complementary predictive

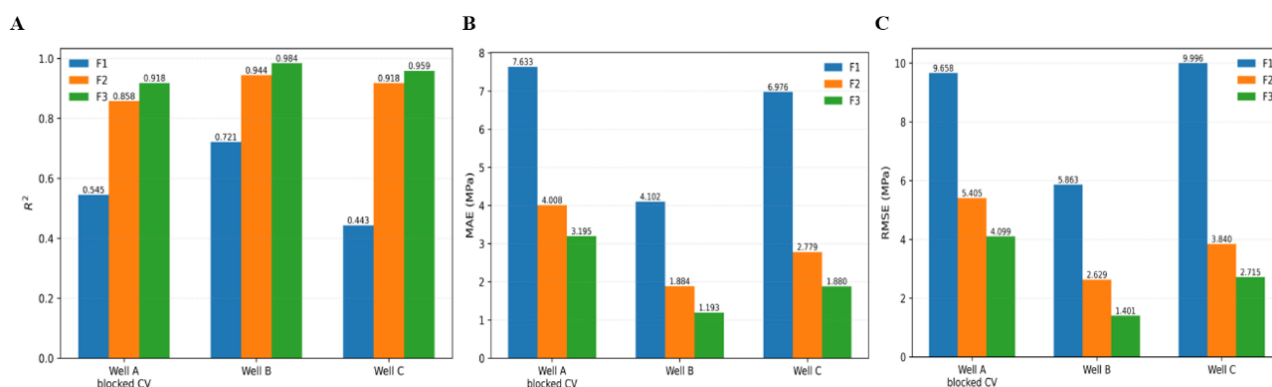


Figure 8. Prediction performance of different feature combinations. (A) R^2 . (B) Mean absolute error (MAE). (C) Root mean square error (RMSE).

Table 3. Prediction performance of different feature combinations

Dataset	R^2			RMSE (MPa)			MAE (MPa)		
	F1	F2	F3	F1	F2	F3	F1	F2	F3
Well A	0.545	0.858	0.918	9.658	5.405	4.099	7.633	4.008	3.195
Well B	0.721	0.944	0.984	5.863	2.629	1.401	4.102	1.884	1.193
Well C	0.443	0.918	0.959	9.996	3.840	2.715	6.976	2.779	1.880

Note: For Well A, the reported metrics were calculated from the pooled out-of-fold predictions obtained from the five blocked-depth folds.

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error.

information beyond the hydrostatic-pressure background represented by P_h . In particular, the improvement observed in Well C supports the effectiveness of the physically guided feature representation under the tested cross-mechanism condition, although residual cross-well discrepancies remain.

The prediction profiles of the three feature combinations are shown in Figure 9. Consistent with the quantitative results, the deviations from the derived reference pore-pressure profiles generally decreased from F1 to F3. For Well A, the relatively large local discrepancies produced by F1 were reduced after incorporating the physically guided features. A similar improvement was observed in Well B, where F3 followed the derived reference pore-pressure profile more closely over most of the evaluated depth interval. For Well C, F3 reproduced the overall pressure evolution and the main overpressured interval more accurately than F1 and F2, although local discrepancies remained in several depth intervals. These profile comparisons are consistent with the quantitative results in Table 3.

3.2. Effectiveness of cascaded transfer learning

To further address the remaining prediction errors in cross-

mechanism validation, the proposed cascaded domain-adaptive transfer learning framework was evaluated using Well A as the source well and Well C as the target well. Well A is mainly associated with hydrocarbon-generation-related unloading, whereas Well C is primarily controlled by undercompaction. This experiment was designed to examine whether semantic alignment and distribution adaptation can improve pore-pressure prediction across different overpressure mechanisms. To ensure comparability, all modeling schemes were implemented using the F3 feature combination and XGBoost as the regression model, while only the domain adaptation strategy was varied. Throughout this transfer experiment, the target-well-derived reference pore-pressure labels were withheld from CCA, TCA, transfer-parameter selection, XGBoost training, and model selection, and were used only after prediction to calculate the evaluation metrics.

The four modeling schemes are summarized in Table 4. The first was the F3–XGBoost baseline model without domain adaptation (M1), in which the source-domain samples were directly used for XGBoost training. The second was a CCA-based transfer model (M2), in which CCA was used to align mechanism-sensitive velocity-density responses between the source and target domains

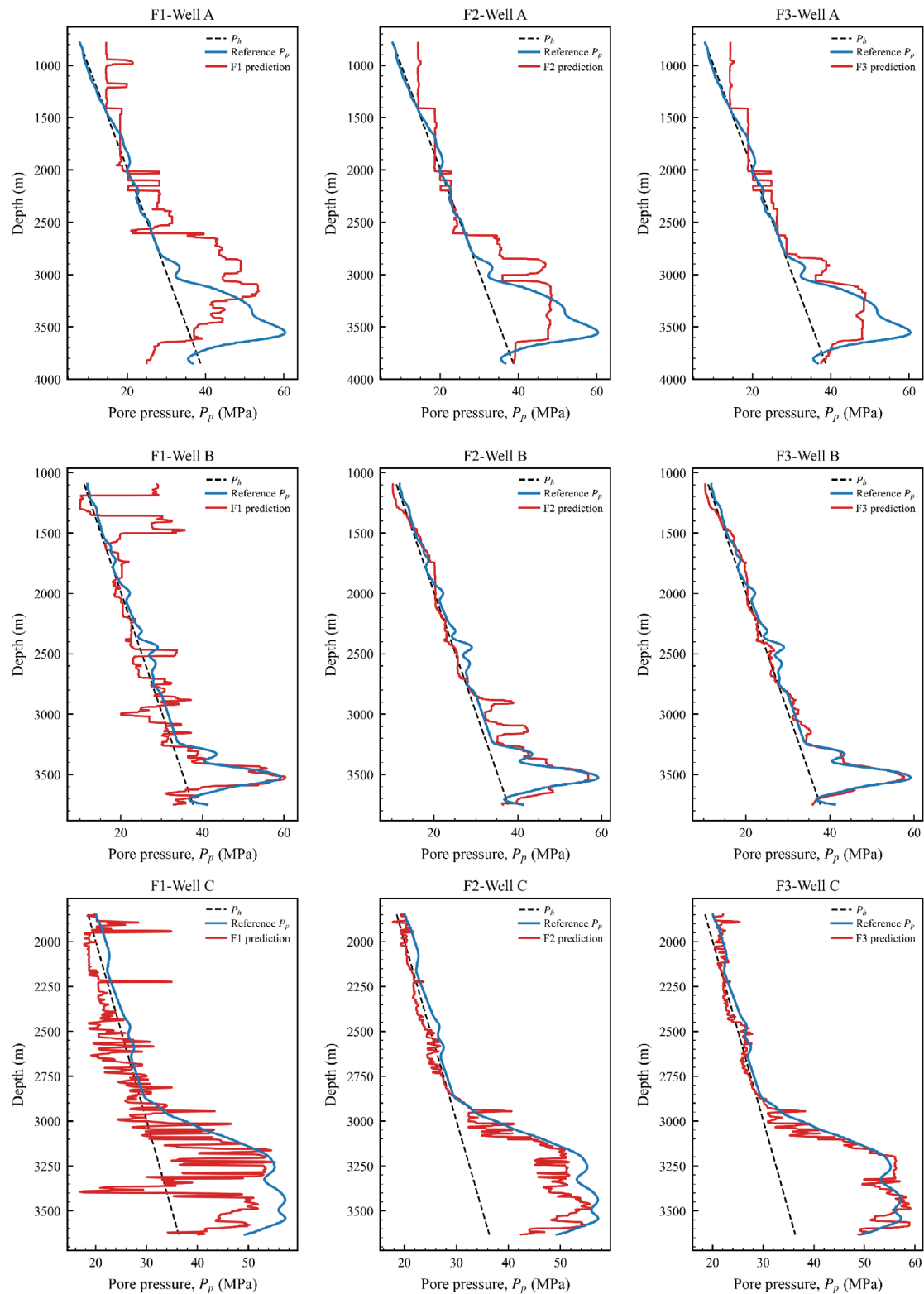


Figure 9. Prediction profiles of different feature combinations compared with the derived reference pore-pressure profiles: (A) F1, (B) F2, and (C) F3 for Well A; (D) F1, (E) F2, and (F) F3 for Well B; and (G) F1, (H) F2, and (I) F3 for Well C

before regression. The third was a TCA-based transfer model (M3), in which TCA was applied to reduce the statistical distribution discrepancy between the source and target domains. In the TCA-based model, P_h and R_v were retained outside the transfer transformation, consistent with the procedure described in **Section 2.4**. The fourth was the proposed cascaded model (M4), in which CCA was first used for semantic alignment, followed by TCA for domain adaptation, and finally coupled with XGBoost for pore-pressure prediction. This experimental design enables independent assessment of semantic correction and distribution alignment, while also allowing quantitative verification of the effectiveness of their sequential integration.

Table 4. Transfer-learning schemes for cross-mechanism prediction

Model	Strategy	Purpose
M1	XGBoost	Baseline
M2	CCA–XGBoost	Semantic alignment
M3	TCA–XGBoost	Distribution adaptation
M4	CCA–TCA–XGBoost	Cascaded transfer

Abbreviations: CCA: Canonical correlation analysis; TCA: Transfer component analysis; XGBoost: Extreme gradient boosting.

The predictive performance of the different transfer-learning schemes is summarized in **Table 5**. Compared with M1, both M3 and M4 substantially improved the cross-mechanism prediction of Well C, whereas M2 provided only a modest improvement. M4 achieved the best overall performance, reducing the RMSE by 27.0% relative to M1 and by 2.4% relative to M3. These results indicate that TCA provides the major gain in source–target adaptation, while the preceding CCA transformation offers a smaller but complementary contribution.

Table 5. Prediction performance of different transfer-learning schemes

Model	R^2	RMSE (MPa)	MAE (MPa)
M1	0.959	2.715	1.880
M2	0.962	2.607	1.711
M3	0.977	2.031	1.400
M4	0.978	1.983	1.381

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error.

The prediction profiles in **Figure 10** further support the quantitative results. M1 generally captured the increasing pressure trend but still showed deviations in the main overpressure interval. After CCA or TCA was introduced, the predicted curves became closer to the derived reference pore-pressure profile. M4 provided the most consistent prediction curve, especially in the middle and deep overpressure intervals, indicating that semantic alignment and distribution adaptation have complementary effects.

The feature-space evolution shown in **Figure 11** provides further evidence for the effectiveness of the cascaded transfer process. Before CCA, the source and target wells exhibited different velocity–density response patterns. After CCA, the retained canonical components showed a more comparable cross-well response, with source–target correlations of 0.648 and 0.445 for CCA1 and CCA2, respectively. The first canonical component therefore captured the stronger common component of the velocity–density response, whereas the second retained additional variation between the two wells.

In the subsequent TCA stage, the source and target feature distributions became more overlapped in the latent space. The RBF-kernel MMD² decreased from 0.067 to 0.008, while the domain-classification area under the curve (AUC) decreased from 0.680 to 0.505. Because an AUC of 0.5 corresponds to nearly random domain discrimination, the post-adaptation value indicates that the source and target feature distributions became substantially less distinguishable after TCA. These results support the complementary roles of the two stages: CCA improves the comparability of the mechanism-sensitive velocity–density response, whereas TCA further reduces the residual statistical distribution discrepancy.

Taken together, the prediction and feature-space results indicate that CCA and TCA serve different but complementary roles in the proposed model. CCA improves the comparability of the mechanism-sensitive velocity–density response, whereas TCA provides the main reduction in the remaining statistical-domain discrepancy. Because the analysis above was based on the primary Well A → Well C transfer pair, additional source–target combinations were examined, as discussed in **Section 3.3**.

3.3. Cross-mechanism and cross-well validation

The Well A → Well C experiment in **Section 3.2** represents the primary cross-mechanism transfer setting. To examine whether the observed improvement depends on a particular source–target pair, three additional transfer experiments were conducted using different combinations of source and target wells. Wells A and B are mainly characterized by hydrocarbon-generation-related unloading, whereas

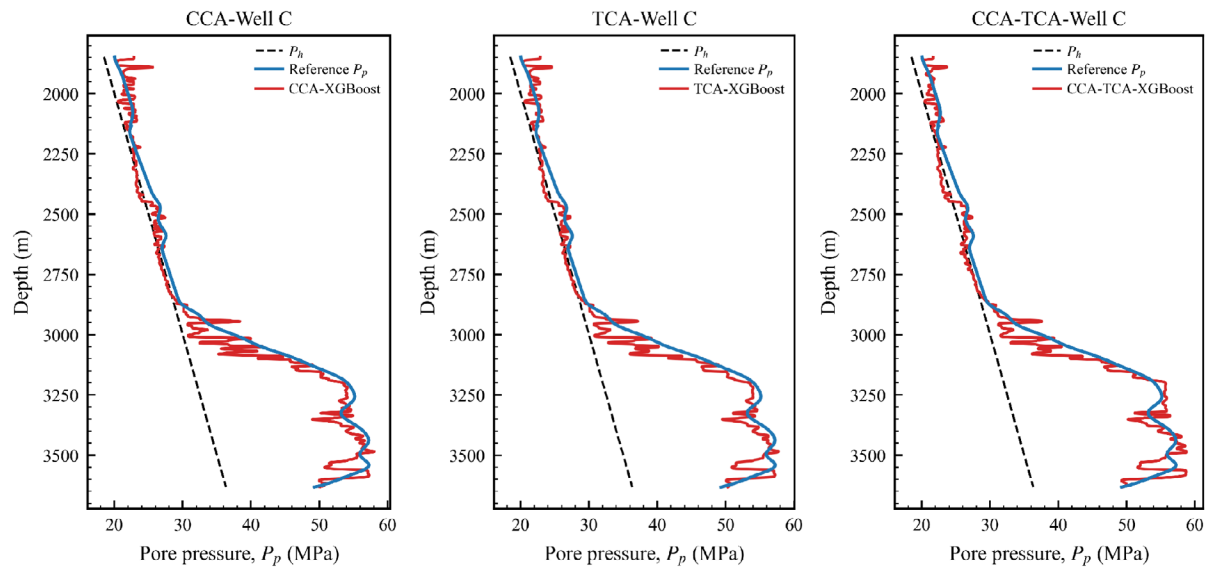


Figure 10. Prediction profiles of different transfer-learning schemes compared with the derived reference pore-pressure profile of Well C (M1). (A) CCA-XGBoost (M2). (B) TCA-XGBoost (M3). (C) CCA-TCA-XGBoost (M4).

Abbreviations: CCA: Canonical correlation analysis; TCA: Transfer component analysis; XGBoost: Extreme gradient boosting.

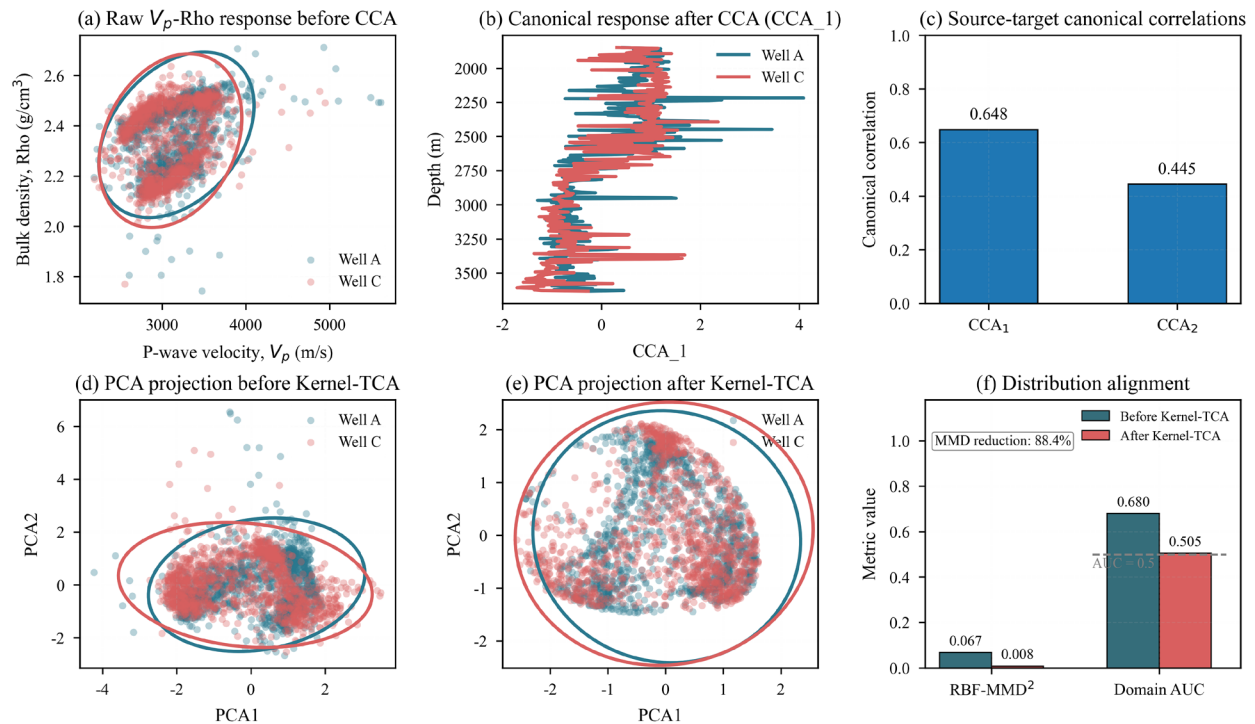


Figure 11. Feature-space alignment achieved by the cascaded CCA-TCA strategy. (a) Raw velocity-density response before CCA. (b) Canonical response after CCA. (c) Source-target correlations of the retained canonical components. (d) PCA projection of the $[CCA1, CCA2, GR]$ feature space before TCA. (e) PCA projection of the latent feature space after TCA. (f) Distribution-alignment metrics before and after TCA. PCA is used only for two-dimensional visualization and is not involved in model training.

Abbreviations: CCA: Canonical correlation analysis; MMD: Maximum mean discrepancy; PCA: Principal component analysis; RBF: Radial basis function; TCA: Transfer component analysis; XGBoost: Extreme gradient boosting.

Wells C and N are dominated by undercompaction. The additional experiments therefore included Well B → Well C, Well B → Well N, and Well A → Well N, all representing transfer from hydrocarbon-generation-related source wells to undercompaction-dominated target wells. Well N was retained as an additional independent target well and was not involved in constructing the regional reference velocity curve v_{encr} . For each transfer experiment, the target well was treated as an unlabeled domain during adaptation. Its logging features were available for unsupervised CCA-TCA adaptation, whereas its derived reference pore-pressure labels were withheld from domain adaptation, parameter selection, and XGBoost training, and were used only for final performance evaluation.

The quantitative results are summarized in Table 6. Compared with M1, M4 improved the prediction performance across all three additional source–target

pairs. The RMSE was reduced by 14.2% for Well B → Well C and 13.3% for Well B → Well N, while a smaller improvement was observed for Well A → Well N. These results indicate that the cascaded adaptation remains beneficial across different source–target combinations, although the magnitude of improvement depends on the specific transfer setting.

The corresponding depth-dependent prediction profiles are shown in Figure 12. For Well B → Well C, both models reproduced the overall pressure increase with depth, while M4 showed closer agreement with the derived reference profile over parts of the principal overpressured interval. When Well N was used as the target well, the degree of improvement depended on the source well. For Well B → Well N, the adapted prediction generally followed the derived reference profile more closely than M1, particularly in the deeper interval. For Well A → Well N, the difference

Table 6. Prediction performance for additional cross-mechanism source–target pairs

Source–target pair	Model	R^2	RMSE (MPa)	MAE (MPa)
Well B → Well C	M1	0.951	2.968	1.901
	M4	0.963	2.547	1.595
Well B → Well N	M1	0.703	4.763	4.048
	M4	0.776	4.131	3.658
Well A → Well N	M1	0.763	4.251	3.515
	M4	0.789	4.009	3.513

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error.

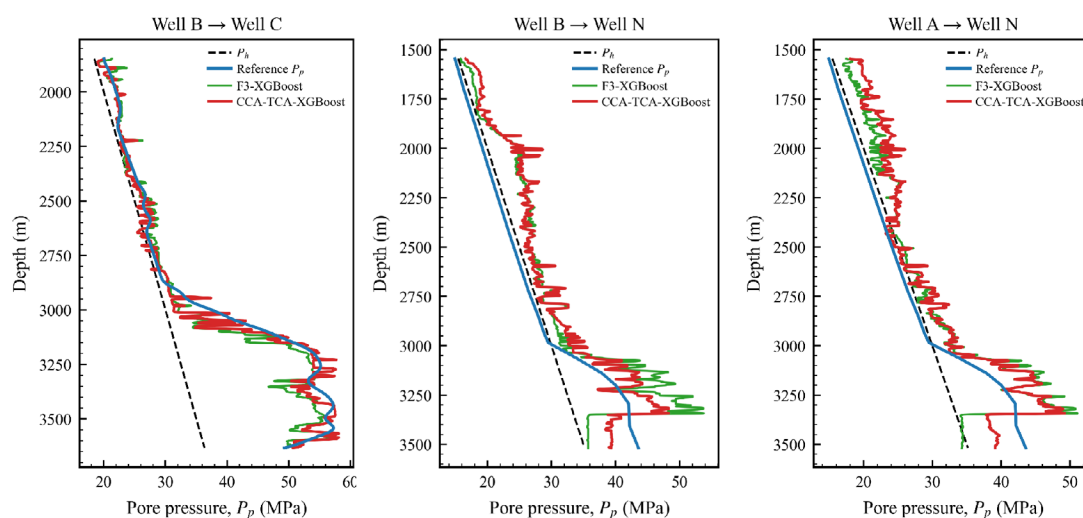


Figure 12. Cross-mechanism pore-pressure predictions for additional source–target pairs compared with the derived reference pore-pressure profiles: (A) Well B → Well C, (B) Well B → Well N, and (C) Well A → Well N

Abbreviations: CCA: Canonical correlation analysis; TCA: Transfer component analysis; XGBoost: Extreme gradient boosting.

between the two models was more modest, consistent with the smaller improvement in the quantitative metrics reported in Table 6. Local discrepancies remained around several rapid pressure transitions, indicating that cascaded adaptation reduces cross-well prediction error but does not completely eliminate source–target differences.

3.4. Uncertainty and robustness analysis

Because the continuous reference pore-pressure profiles were derived from conventional pore-pressure evaluation methods rather than direct formation-pressure measurements at every depth, the robustness of the cross-mechanism predictions was further examined through repeated perturbation experiments. Two representative transfer cases, Well A → Well C and Well B → Well C, were selected with the undercompaction-dominated Well C as the common target well. For each transfer case, 30 realizations were generated by perturbing the source-side training conditions, including contiguous-depth block resampling, source-label perturbation, and variation of the model random seed. The derived reference pore-pressure labels of Well C were not used during domain adaptation, model training, or uncertainty construction and were accessed only for final evaluation. For each target depth, the mean prediction and the empirical P5–P95 uncertainty envelope were calculated from the 30 realizations.

The perturbation-based analysis indicates that both cross-mechanism transfer cases retained relatively stable predictive performance under repeated perturbations. For Well A → Well C, the mean R^2 , RMSE, and MAE were 0.957 ± 0.010 , 2.755 ± 0.291 MPa, and 1.863 ± 0.227 MPa, respectively. Similar stability was observed for Well B → Well C, with $R^2 = 0.954 \pm 0.008$, $\text{RMSE} = 2.848 \pm 0.232$ MPa, and $\text{MAE} = 1.744 \pm 0.171$ MPa. The mean P5–P95 widths were 2.145 and 2.073 MPa, respectively. Although the perturbed performance is moderately lower than the nominal results reported in Tables 5 and 6, both cases retained R^2 values above 0.95, indicating reasonable robustness to the considered perturbations.

Figure 13 further illustrates the depth-dependent variability of the predictions. In both transfer cases, the mean prediction generally followed the overall trend of

the derived reference pore-pressure profile, while the empirical P5–P95 envelope varied with depth. Relatively narrow envelopes occurred over intervals with gradual pressure variation, whereas greater prediction spread appeared around the main pressure-transition zone and in parts of the deeper overpressured interval. This indicates that the perturbation-induced prediction variability is not uniformly distributed along the well and tends to increase around intervals characterized by rapid pressure changes. Although the present analysis does not encompass the full range of geological, measurement, and model uncertainties, the results support reasonable robustness of the proposed model under the tested perturbations and cross-mechanism transfer conditions.

4. Discussion

To further understand the prediction mechanism of the proposed model, SHAP analysis was conducted for the baseline XGBoost model, M2, and M4. The SHAP summary plots and mean SHAP importance results are shown in Figures 14 and 15. Overall, P_h exhibited the largest contribution in all models, indicating that the hydrostatic-pressure background is the dominant factor controlling the large-scale increasing trend of pore pressure with depth. This result is consistent with the physical understanding that pore pressure generally evolves under the constraint of burial depth and hydrostatic pressure.

The R_v also showed a high contribution, ranking only behind P_h in most cases. In the SHAP summary plots, low R_v values tend to make positive contributions to pore-pressure prediction, whereas high R_v values tend to reduce the predicted pressure. This is physically reasonable because a lower measured velocity relative to the regional reference velocity usually indicates abnormal compaction or overpressure development. Therefore, R_v provides more direct pressure-sensitive information than the original v_p , Rho , and GR variables.

After introducing CCA and TCA, the importance of P_h and R_v remains dominant, while the CCA-derived variables and the selected TCA latent component provide additional contributions. In the final model (M4), the TCA-derived feature is appended to, rather than substituted for, the

Table 7. Perturbation-based uncertainty statistics for representative cross-mechanism transfer cases

Source–target pair	R^2	RMSE (MPa)	MAE (MPa)	Mean P5–P95 width (MPa)
Well A → Well C	0.957 ± 0.010	2.755 ± 0.291	1.863 ± 0.227	2.145
Well B → Well C	0.954 ± 0.008	2.848 ± 0.232	1.744 ± 0.171	2.073

Abbreviations: MAE: Mean absolute error; RMSE: Root mean square error.

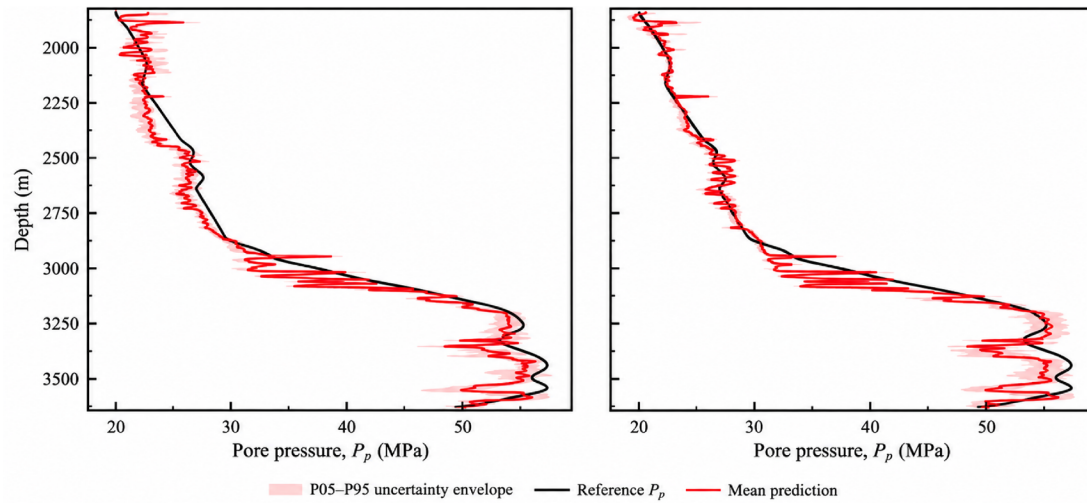


Figure 13. Perturbation-based prediction uncertainty for representative cross-mechanism transfer cases: (A) Well A → Well C and (B) Well B → Well C. The red curve denotes the pointwise mean prediction across repeated perturbation realizations, and the shaded region represents the empirical P5–P95 prediction envelope. The black curve denotes the derived reference pore-pressure profile used only for final evaluation.

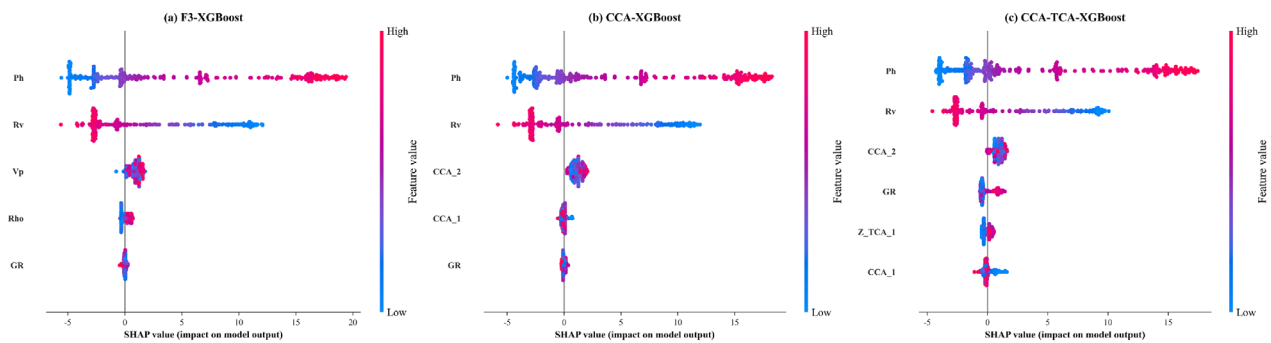


Figure 14. SHapley Additive exPlanations (SHAP) summary plots of different models: (A) M1, (B) M2, and (C) M4

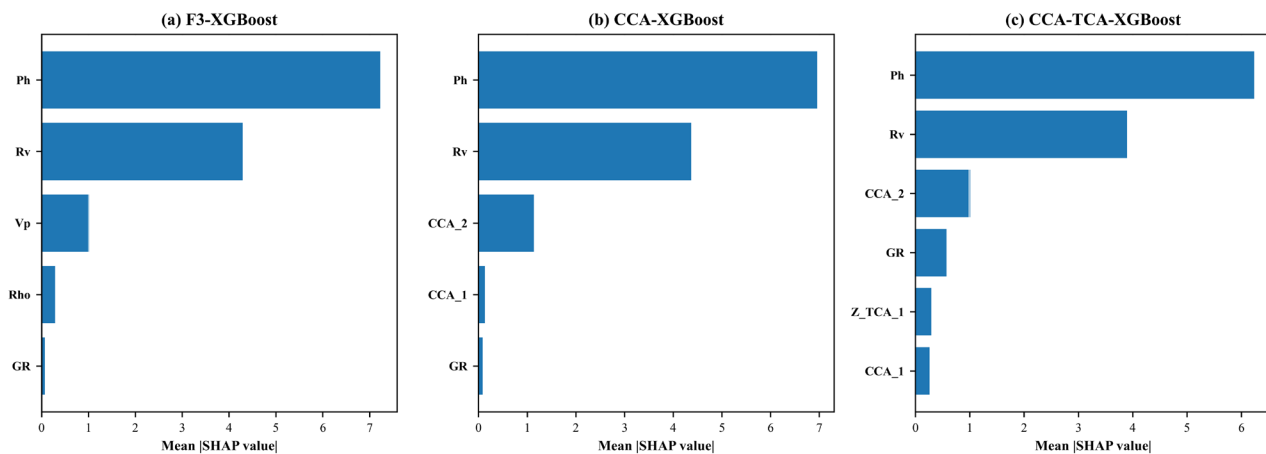


Figure 15. Mean SHapley Additive exPlanations (SHAP) feature importance of different models: (A) M1, (B) M2, and (C) M4

CCA-based representation. Therefore, CCA1, CCA2, and GR remain available to the XGBoost regressor together with P_h , R_p , and the selected TCA component. As shown by the mean absolute SHAP comparison in Figure 15, the physically guided features remained dominant, whereas the selected TCA component provided supplementary domain-adaptive information. This result indicates that the cascaded transfer procedure improves source–target adaptation without removing the physically interpretable and CCA-aligned information retained in the preceding stage.

The additional cross-well experiments showed that the benefit of CCA–TCA adaptation varied among different source–target combinations, indicating that transfer performance depends on the geological and statistical similarities between wells. The perturbation experiments further showed that both Well A → Well C and Well B → Well C retained relatively stable performance under the considered perturbations, with only modest differences in variability between the two source–target settings. These results suggest that the proposed transfer strategy can improve cross-mechanism prediction, although its performance and robustness may still vary among different well combinations.

Several limitations should also be noted. The present validation is restricted to a single offshore study area, and the continuous pore-pressure targets are derived from reference profiles rather than direct measurements at every depth, so uncertainty in these profiles may propagate into model evaluation. In addition, the leave-one-well-out prediction-sensitivity analysis showed that variations in the independently constructed regional reference velocity curve had a limited overall influence on the final prediction profile, although localized sensitivity remained at some depth intervals. Nevertheless, this analysis considers only the variability associated with the available auxiliary wells and does not encompass the full range of geological and measurement uncertainties.

5. Conclusion

This study proposed an intelligent formation pore-pressure prediction model integrating physically guided feature optimization with cascaded CCA–TCA transfer learning. By introducing P_h and R_p , the input feature space was enhanced with pressure-background and relative velocity-deviation information. The optimized F3 feature set achieved the best prediction performance, confirming the effectiveness of the proposed physical feature construction, while the cascaded transfer strategy further improved cross-well prediction under different overpressure mechanisms.

Overall, the proposed framework improves both

prediction accuracy and interpretability, providing a useful approach for cross-well pore-pressure prediction under limited well-control conditions and multiple overpressure mechanisms within the tested study area, although further validation is required for broader application.

Acknowledgments

None.

Funding

This research was supported by the Science and Technology Program of Sanya Yazhou Bay Science and Technology City (Grant Nos. SKJC-JYRC-2025-03 and SKJC-JYRC-2024-05), the National Natural Science Foundation of China (Grant Nos. 42274169 and 42274170), the Hainan Provincial Natural Science Foundation of China (Grant No. 426QN0662), and the Scientific Research Project of Higher Education Institutions of Hainan Province (Grant Nos. Hnky2025-102 and Hnkg2026-310).

Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Xiao-Xiao Xu, Bing Zhang, Jia-Liang Xu

Data curation: Xiao-Xiao Xu, Jia-Liang Xu, Bo-Yu, Fu-Ying Xu

Formal analysis: Xiao-Xiao Xu, Fu-Ying Xu

Investigation: Xiao-Xiao Xu, Jia-Liang Xu, Bo-Yu, Fu-Ying Xu

Methodology: Xiao-Xiao Xu, Jia-Liang Xu

Supervision: Bing Zhang

Visualization: Xiao-Xiao Xu, Fu-Ying Xu

Writing–original draft: Xiao-Xiao Xu

Writing–review & editing: Bing Zhang, Jia-Liang Xu, Bo-Yu, Fu-Ying Xu

All authors have read and approved the final manuscript.

Availability of data

The well-log and pore-pressure data used in this study are not publicly available due to confidentiality restrictions related to exploration data. Processed data supporting the main findings may be made available from the corresponding author upon reasonable request and with permission from the data owner.

References

1. Zhang J. Pore pressure prediction from well logs: methods, modifications, and new approaches. *Earth Sci Rev.* 2011;108(1-2):50-63.

- doi: 10.1016/j.earscirev.2011.06.001
2. Dutta NC. Geopressure prediction using seismic data: current status and the road ahead. *Geophysics*. 2002;67(6):2012-2041.
doi: 10.1190/1.1527101
 3. Athy LF. Density, porosity, and compaction of sedimentary rocks. *AAPG Bull.* 1930;14(1):1-24.
doi: 10.1306/3D93289E-16B1-11D7-8645000102C1865D
 4. Hubbert MK, Rubey WW. Role of fluid pressure in mechanics of overthrust faulting: I. Mechanics of fluid-filled porous solids and its application to overthrust faulting. *Geol Soc Am Bull.* 1959;70(2):115-166.
doi: 10.1130/0016-7606(1959)70[115:ROFPIM]2.0.CO;2
 5. Hottmann CE, Johnson RK. Estimation of formation pressures from log-derived shale properties. *J Pet Technol.* 1965;17(6):717-722.
doi: 10.2118/1110-PA
 6. Foster JB, Whalen HE. Estimation of formation pressures from electrical surveys—offshore Louisiana. *J Pet Technol.* 1966;18(2):165-171.
doi: 10.2118/1200-PA
 7. Eaton BA. The effect of overburden stress on geopressure prediction from well logs. *J Pet Technol.* 1972;24(8):929-934.
doi: 10.2118/3719-PA
 8. Bowers GL. Pore pressure estimation from velocity data: accounting for overpressure mechanisms besides undercompaction. *SPE Drill Complet.* 1995;10(2):89-95.
doi: 10.2118/27488-PA
 9. Osborne MJ, Swarbrick RE. Mechanisms for generating overpressure in sedimentary basins: a reevaluation. *AAPG Bull.* 1997;81(6):1023-1041.
doi: 10.1306/522B49C9-1727-11D7-8645000102C1865D
 10. Yardley GS, Swarbrick RE. Lateral transfer: a source of additional overpressure? *Mar Pet Geol.* 2000;17(4):523-537.
doi: 10.1016/S0264-8172(00)00007-6
 11. Tingay MRP, Hillis RR, Swarbrick RE, Morley CK, Damit AR. Origin of overpressure and pore-pressure prediction in the Baram province, Brunei. *AAPG Bull.* 2009;93(1):51-74.
doi: 10.1306/08080808016
 12. Zhang J. Effective stress, porosity, velocity and abnormal pore pressure prediction accounting for compaction disequilibrium and unloading. *Mar Pet Geol.* 2013;45:2-11.
doi: 10.1016/j.marpetgeo.2013.04.007
 13. Wyllie MRJ, Gregory AR, Gardner LW. Elastic wave velocities in heterogeneous and porous media. *Geophysics*. 1956;21(1):41-70.
doi: 10.1190/1.1438217
 14. Gardner GHF, Gardner LW, Gregory AR. Formation velocity and density—the diagnostic basics for stratigraphic traps. *Geophysics*. 1974;39(6):770-780.
doi: 10.1190/1.1440465
 15. Castagna JP, Batzle ML, Eastwood RL. Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks. *Geophysics*. 1985;50(4):571-581.
doi: 10.1190/1.1441933
 16. Han DH, Nur A, Morgan D. Effects of porosity and clay content on wave velocities in sandstones. *Geophysics*. 1986;51(11):2093-2107.
doi: 10.1190/1.1442062
 17. Xu S, White RE. A new velocity model for clay-sand mixtures. *Geophys Prospect.* 1995;43(1):91-118.
doi: 10.1111/j.1365-2478.1995.tb00126.x
 18. Bosch M, Mukerji T, Gonzalez EF. Seismic inversion for reservoir properties combining statistical rock physics and geostatistics: a review. *Geophysics*. 2010;75(5):75A165-75A176.
doi: 10.1190/1.3478209
 19. Grana D, Azevedo L, de Figueiredo L, Connolly P, Mukerji T. Probabilistic inversion of seismic data for reservoir petrophysical characterization: review and examples. *Geophysics*. 2022;87(5):M199-M216.
doi: 10.1190/geo2021-0776.1
 20. Yu B, Shi Y, Tian Y, et al. Anisotropic Bayesian linearized stochastic seismic inversion with multi-parameter decoupling. *J Geophys Eng.* 2024;21(3):961-980.
doi: 10.1093/jge/gxae049
 21. Liu L, Shen G, Wang Z, Yang H, Han H, Cheng Y. Abnormal formation velocities and applications to pore pressure prediction. *J Appl Geophys.* 2018;153:1-6.
doi: 10.1016/j.jappgeo.2018.02.013
 22. Wang H, Ma J, Li L. Pore pressure prediction based on rock physics theory and its application in seismic inversion. *J Appl Geophys.* 2024;229:105494.
doi: 10.1016/j.jappgeo.2024.105494
 23. Radwan AE, Wood DA, Radwan AA. Machine learning and data-driven prediction of pore pressure from geophysical logs: a case study for the Mangahewa gas field, New Zealand. *J Rock Mech Geotech Eng.* 2022;14(6):1799-1809.
doi: 10.1016/j.jrmge.2022.01.012
 24. Al-Fakih A, Kaka SI, Koeshidayatullah AI. Reservoir property prediction in the North Sea using machine learning. *IEEE Access.* 2023;11:140148-140160.
doi: 10.1109/ACCESS.2023.3336623

25. Al-Fakih A, Ibrahim AF, Elkatatny S, Abdulraheem A. Estimating electrical resistivity from logging data for oil wells using machine learning. *J Pet Explor Prod Technol.* 2023;13(6):1453-1461.
doi: 10.1007/s13202-023-01617-2
26. Al-Fakih A, Li K. Estimation of bottom-hole temperature based on machine/deep learning. In: *Proceedings of the 2021 International Petroleum and Petrochemical Technology Conference*. Singapore: Springer; 2022:340-353.
doi: 10.1007/978-981-16-9427-1_33
27. Al-Fakih A, Koeshidayatullah A, Mukerji T, Kaka SI. Enhanced anomaly detection in well log data through the application of ensemble GANs. *Appl Comput Geosci.* 2026;29:100316.
doi: 10.1016/j.acags.2025.100316
28. Koeshidayatullah A, Al-Fakih A, Kaka SI. Toward basin-agnostic well log imputation and anomaly detection via a pre-trained time-series foundation model. *Energy Geosci.* 2026;7(2):100536.
doi: 10.1016/j.engeos.2026.100536
29. Xu Y, Yang L, Xu J, *et al.* Prediction method for formation pore pressure based on transfer learning. *Geoenergy Sci Eng.* 2024;236:212747.
doi: 10.1016/j.geoen.2024.212747
30. Wang ZF, Cao H, Yang ZF, Xu HQ, Yang MQ, Zhao YS. Transfer learning seismic impedance inversion method based on temporal convolutional networks. *J Seism Explor.* 2022;31(4):391-405.
31. Zhang Y, Singh S, Thanoon D, Devarakota P, Jin L, Tsvankin I. Physics-guided unsupervised deep-learning seismic inversion with uncertainty quantification. *J Seism Explor.* 2023;32(3):257-270.
32. Li ZX, Ma JH, Qi Z, Zhang LW, Xie F, Yang JL. Accelerating the U-Net-based adaptive subtraction with transfer learning for removing seismic multiples in field data. *J Seism Explor.* 2023;32(4):373-384.
33. Tian L, Sun S, Li Q, Shi J. Data-driven high-resolution gas-bearing prediction in tight sandstones: a case study from block L, eastern Ordos Basin. *J Seism Explor.* 2025;34(3):13-24.
doi: 10.36922/JSE025320053
34. Guo Q, Zhao X, Ba J, Luo C. Porosity prediction with Bi-LSTM network for deep methane reservoirs. *J Seism Explor.* 2025;34(6):29-44.
doi: 10.36922/JSE025410087
35. Li F, Zhang M, Liang Q, *et al.* A two-branch convolutional neural network for pre-stack elastic parameter inversion of coal-bearing gas reservoirs. *J Seism Explor.* 2026;35(2):271-289.
doi: 10.36922/JSE025390076
36. Hardoon DR, Szedmak S, Shawe-Taylor J. Canonical correlation analysis: an overview with application to learning methods. *Neural Comput.* 2004;16(12):2639-2664.
doi: 10.1162/0899766042321814
37. Pan SJ, Yang Q. A survey on transfer learning. *IEEE Trans Knowl Data Eng.* 2010;22(10):1345-1359.
doi: 10.1109/TKDE.2009.191
38. Zhuang F, Qi Z, Duan K, *et al.* A comprehensive survey on transfer learning. *Proc IEEE.* 2021;109(1):43-76.
doi: 10.1109/JPROC.2020.3004555
39. Pan SJ, Tsang IW, Kwok JT, Yang Q. Domain adaptation via transfer component analysis. *IEEE Trans Neural Netw.* 2011;22(2):199-210.
doi: 10.1109/TNN.2010.2091281
40. Bentéjac C, Csörgő A, Martínez-Muñoz G. A comparative analysis of gradient boosting algorithms. *Artif Intell Rev.* 2021;54(3):1937-1967.
doi: 10.1007/s10462-020-09896-5
41. Lundberg SM, Erion G, Chen H, *et al.* From local explanations to global understanding with explainable AI for trees. *Nat Mach Intell.* 2020;2(1):56-67.
doi: 10.1038/s42256-019-0138-9

Appendix

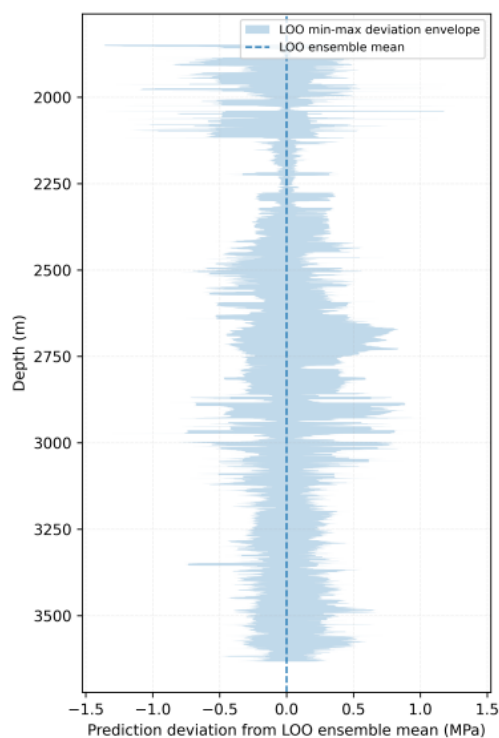


Figure A1. Sensitivity of pore-pressure predictions to leave-one-well-out variations in the regional reference velocity curve. The shaded region denotes the pointwise min–max deviation envelope across the 10 leave-one-well-out realizations relative to their pointwise ensemble mean, and the dashed line represents the ensemble mean ($\Delta P_p = 0$). A 10 m centered moving-median filter was applied for visualization only, whereas all quantitative sensitivity statistics were calculated from the unsmoothed predictions.