

Rock-physics-guided machine learning estimation of anisotropy parameters

Introduction

Shale formations are ubiquitous and often exhibit strong vertical transverse isotropy (VTI) anisotropy due to their internal structure, which has a substantial impact on seismic amplitude-variation-with-offset (AVO) responses. Therefore, VTI anisotropy parameters are required for accurate interpretation of seismic AVO data. However, measuring VTI anisotropy in the field is challenging because of the high costs associated with coring and laboratory testing. As a result, interpreters must estimate anisotropy parameters using available information.

Several methods have been proposed to estimate or constrain the anisotropy parameters of shale formations, including the use of upper and lower bounds (e.g., Chichinina and Vernik, 2018), comparisons of sonic logs from vertical and deviated wells (e.g., Sams et al., 2025), and rock-physics-based approaches (e.g., Asaka et al., 2021; Asaka, 2024). Rock-physics-based approaches have been successfully applied in several fields (e.g., Asaka, 2024). However, these methods require detailed knowledge of the underlying rock-physics models and a significant amount of time to optimize model parameters. To overcome these challenges, a rock-physics-guided machine learning approach for anisotropy-parameter estimation has been developed and validated against core-testing results.

Method

Asaka et al. (2021) proposed a rock-physics-based approach for estimating Thomsen's VTI anisotropy parameters δ and ϵ (Thomsen, 1986), in which model parameters are optimized to match modeled elastic constants (C_{33} , C_{44} , and C_{66}) with those derived from well logs using a brute-force grid search. Note that C_{66} can be estimated from Stoneley-wave velocity logs (e.g., White and Tongtaow, 1981). They demonstrated that the method is applicable to shales from various fields; however, interpreters must possess detailed rock-physics knowledge, including an understanding of the physical meaning of the model parameters and their typical ranges, and must also spend significant time performing the grid search to optimize the parameters.

These limitations can be overcome by machine learning models that directly relate available logs to anisotropy parameters and provide rapid predictions. Supervised learning methods suitable for regression tasks are appropriate for this purpose. In this study, Random Forest (RF; Breiman, 2001) is adopted because it is simple to implement and provides useful diagnostic information, such as variable-importance measures and out-of-bag (OOB) residuals. RF has been shown to provide comparable, and in some cases superior, performance to other supervised learning methods, such as support vector regression and extreme gradient boosting, in predicting missing log data (e.g., Cao et al., 2025).

The RF training process consists of the following steps:

1. **Training data generation**, in which C_{33} , C_{44} , C_{66} , δ , and ϵ are calculated over a range of model-parameter values based on the rock-physics model of Asaka et al. (2021).
2. **RF model training** to predict δ and ϵ using input parameters selected based on their variable importance.

The ranges of model parameters used in step 1 are as follows:

- Initial porosity (PHI0): 0.7–0.9
- Current porosity (PHIT): 0.02–0.52
- Clay mineral volume fraction within the solid phase (V_{clay}): 0.2–1.0
- Quartz volume fraction within the solid phase: 0–0.8
- Volume fraction of interparticle material other than porosity (e.g., kerogen) within the clay matrix (V_{im}): 0–0.3

- Interparticle medium bulk modulus: 0.1–8.5 GPa
- Interparticle medium shear modulus: 0.01–4 GPa
- Clay particle aspect ratio: 0.001–0.99

These parameter ranges include some unrealistic combinations that result in unusually large anisotropy-parameter values. Therefore, generated samples with either δ or ϵ greater than 0.9 were removed from the training dataset. Approximately 6 million samples were used for training. The RF model was configured with 400 bootstrap trees, a maximum tree depth of 10, $\sqrt{p}$ predictors considered at each split, and a subset size of 200,000 samples.

Results

As described in the previous section, the variables used to predict δ and ϵ were optimized based on their importance, as shown in Figure 1. The ratios C_{66}/C_{44} and C_{66}/C_{33} , which contain important information related to anisotropy, exhibit high importance scores. The difference $\text{PHI0} - \text{PHIT}$ was included because it forms the basis for calculating the compaction factor in the rock-physics model. PHIT and Vim were excluded from the prediction because they show very low variable importance and have a negligible impact on prediction accuracy.

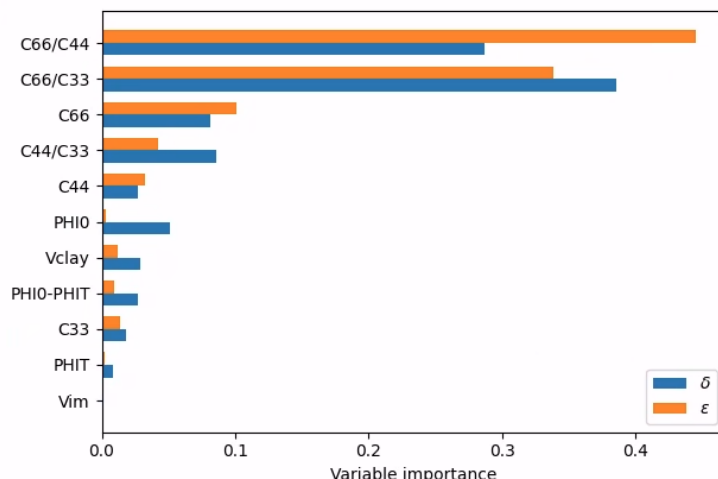


Figure 1 Variable importance plot for predicting δ and ϵ .

The trained RF model was applied to experimental data examined by Asaka et al. (2021). The experimental dataset was compiled from the Mr. Anisotropy database (Horne, 2013) and published studies from the SINTEF Industry AS research group (Lozovyi and Bauer, 2019; Szewczyk et al., 2018; Bakk et al., 2023). The dataset includes measurements acquired using conventional pulse transmission (PT), forced oscillation (FO), and static testing techniques. Vclay ranges from 0.33 to 0.76, and porosity ranges from 0.025 to 0.285, representing a variety of shale types from different geological settings. The samples encompass a range of water saturations. Data points with extremely low V_P/V_S ratios (< 1.37) were excluded from the analysis. An initial porosity PHI0 of 0.8 was assumed for all samples, as values near 0.8 have been shown to yield reasonable predictions (Asaka et al., 2021; Asaka, 2024).

Figure 2 compares measured and predicted anisotropy parameters. Predictions of ϵ show high accuracy ($R^2 = 0.82$, $\text{RMSE} = 0.06$), whereas δ exhibits lower correlation ($R^2 = 0.35$) but remains effectively unbiased, with an RMSE comparable to that of ϵ . Samples with large prediction errors include FO measurements at very low frequencies with unusually low V_P/V_S ratios. Given the experimental uncertainty associated with δ —particularly the difficulty of accurately measuring P-wave velocities propagating at oblique angles to the symmetry axis using the PT technique (e.g., Dellinger and Vernik, 1994)—the achieved predictive performance for δ is considered reasonable.

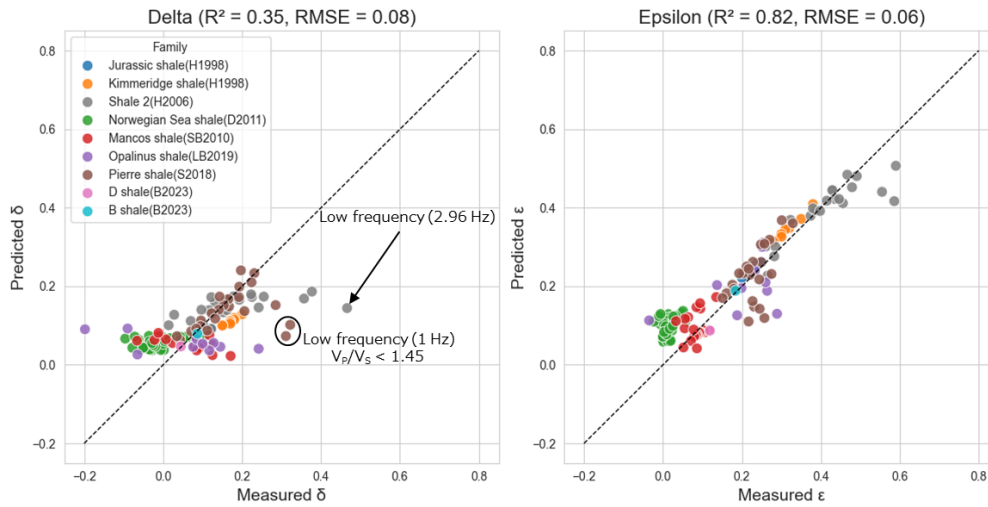


Figure 2 Measured versus predicted anisotropy parameters for shales from various fields.

The trained RF model was also applied to the log data used in Asaka et al. (2026), and results were compared with those from the full rock-physics-based approach adopted in that study. The results, shown in Figure 3 (d) and (e), indicate that the trained RF model produces predictions consistent with the full rock-physics-based approach. Therefore, the model can be reliably used for seismic forward modelling and subsequent seismic reservoir characterization.

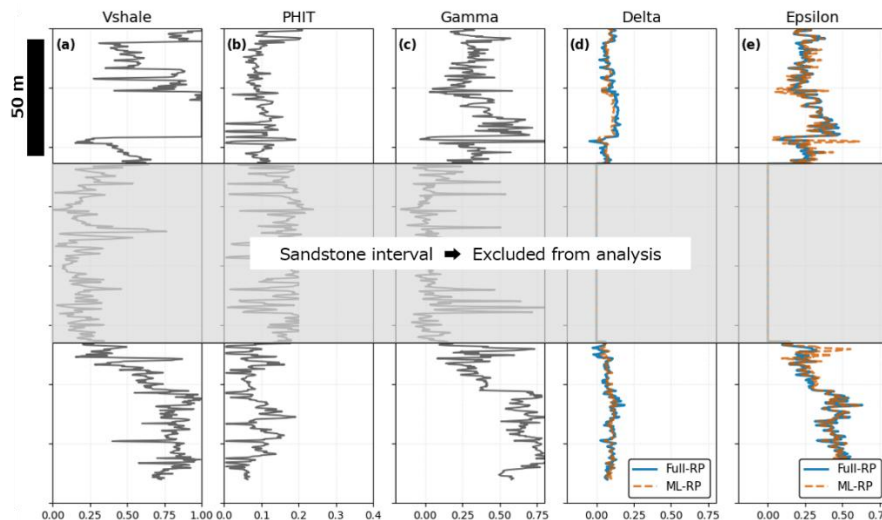


Figure 3 Application results for the log data used in Asaka et al. (2026). Panels (d) and (e) compare these results with the full rock-physics-based approach adopted in that study.

Conclusions

Neglecting VTI anisotropy parameters in shale formations can introduce critical errors in subsurface evaluation based on seismic AVO responses. However, direct measurement of VTI anisotropy in the field is challenging, and rock-physics approaches validated in the literature require substantial expertise and computational effort. To address these limitations, a rock-physics-guided machine learning approach for estimating anisotropy parameters has been developed. A Random Forest model was successfully trained and applied, and its application to experimental datasets confirms good predictive performance.

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References

- Asaka, M. [2024] Rock physics-based anisotropy parameters estimation of Marcellus Shale using log data acquired in a vertical well. *The Leading Edge*, **43**, 272-277.
- Asaka, M., Holt, R. M., and Bakk, A. [2021] Rock physics model of shale: Predictive aspect. *Journal of Geophysical Research: Solid Earth*, **126**, no.9, e2021JB021993.
- Asaka, M., Yamatani, T., and Dotare, T. [2026] Optimized AVO interpretation in the Northern North Sea: Incorporating shale anisotropy. 87th EAGE Annual Conference & Exhibition.
- Bakk, A., Duda, M., Xie, X., Stenebraten, J. F., Yan, H., MacBeth, C., and Holt, R. M. [2023] Third-order elasticity of transversely isotropic field shales. *Geophysical Prospecting*, **72**, 1049-1073.
- Breiman, L. [2001] Random forests. *Machine Learning*, **45**, 5-32.
- Cao, M., Yuan, S., Yu, Y., Yuan, J., and Liu, H. [2025] Inverse distance weighted Random Forest for S-wave velocity prediction. *Journal of Applied Geophysics*, **242**, 105908.
- Chichinina, T., and Vernik, L. [2018] Physical bounds on C_{13} and δ for organic mudrocks. *Geophysics*, **83**, A75-A79.
- Dellinger, J., and Vernik, L. [1994] Do traveltimes in pulse-transmission experiments yields anisotropic group or phase velocities?. *Geophysics*, **59**, no.11, 1774-1779.
- Horne, S. A. [2013] A statistical review of mudrock elastic anisotropy. *Geophysical Prospecting*, **61**, 817-826.
- Lozovyi, S., and Bauer, A. [2019] Static and dynamic stiffness measurements with Opalinus Clay. *Geophysical Prospecting*, **67**, 997-1019.
- Sams, M., Nasser, J., and Turm, S. T. H. [2025] Anisotropy estimation from deviated wells: uncertainties and their implications – A case study. *Interpretation*, **13**, T247-T262.
- Szewczyk, D., Bauer, A., and Holt, R. M. [2018] Stress-dependent elastic properties of shales-laboratory experiments at seismic and ultrasonic frequencies. *Geophysical Journal International*, **212**, 189-210.
- Thomsen, L. [1986] Weak elastic anisotropy. *Geophysics*, **51**, no.10, 1954-1966.
- White, J. E., and Tongtaow, C. [1981] Cylindrical waves in transversely isotropic media. *The Journal of Acoustical Society of America*, **70**, 1147-1155.