Seismic Attributes - from Interactive Interpretation to Machine Learning

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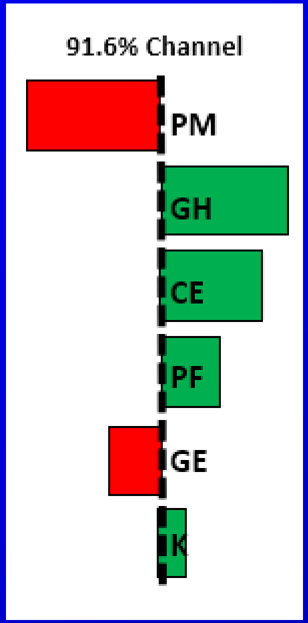
Explainable Artificial Intelligence (AI) techniques (SHAP and LIME)

Explainable AI

Local Interpretable Model-Agnostic Explanations (LIME)

Ribeiro et al. (2016)

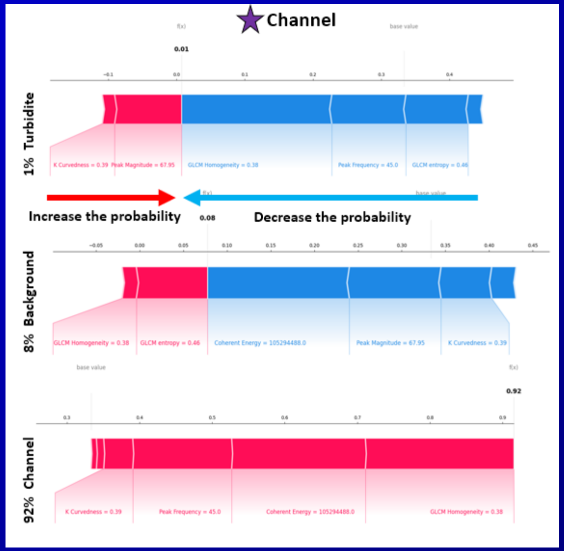
- Works for any ML method.
- Approximates a model by maximizing interpretability and local fidelity to make explanations.
- Provide only local explanations.

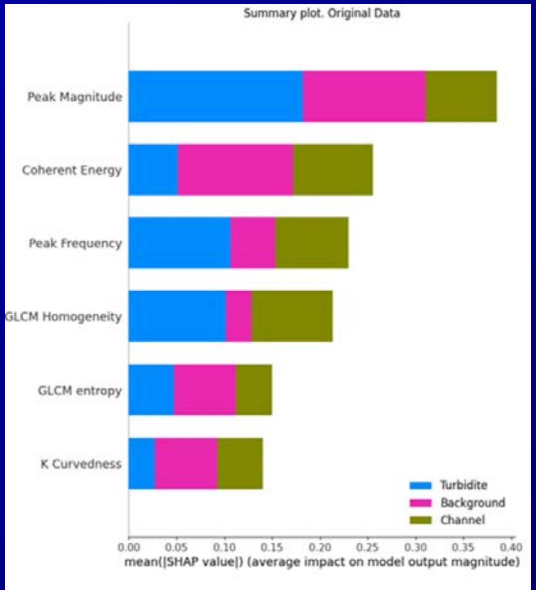


Shapley additive explanations (SHAP)

Lundberg and Lee (2017), Lundberg et al. (2018)
Seismic detailed example – Lubo-Robles et al. (2022)

- Works for any ML method.
  - Faster for tree ensemble architectures (e.g., random forest, XGBoost, etc.)
- Computes Shapley values to measure contribution of individual features.
  - Linear model combining SHAP values and input features matches the final model prediction

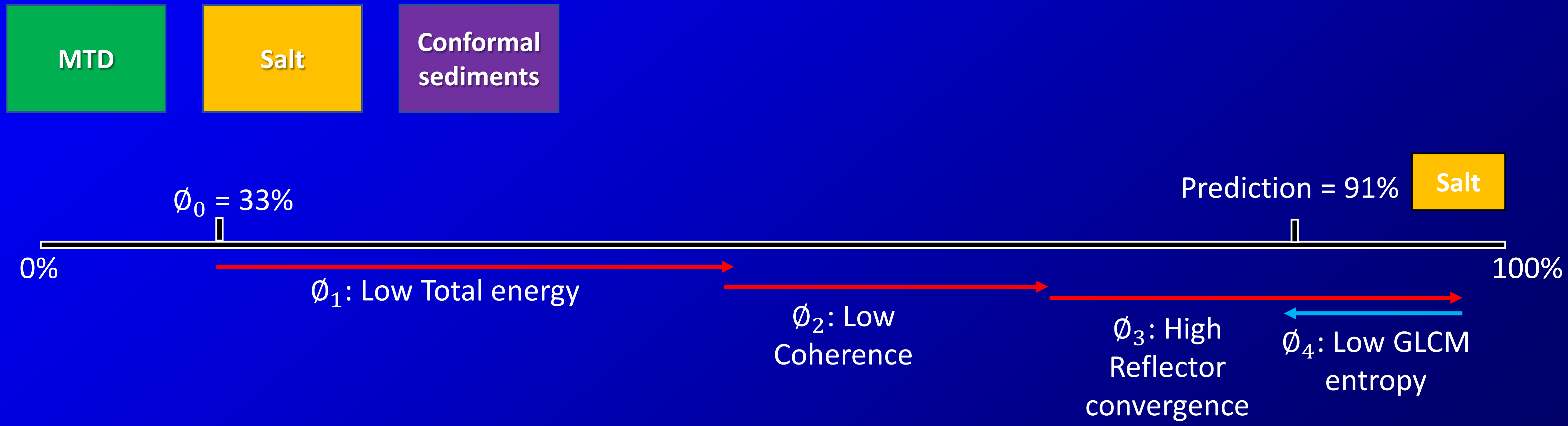




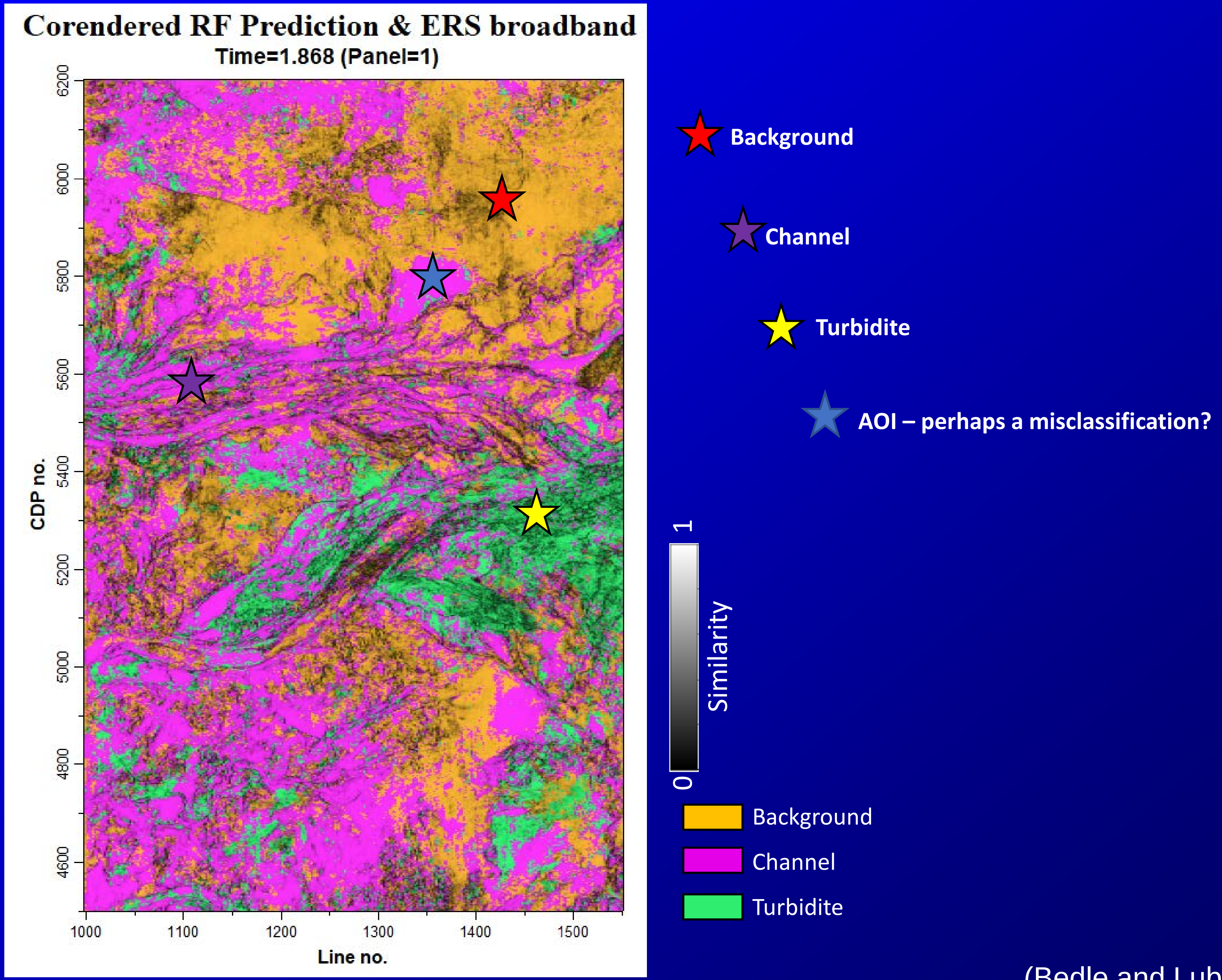
(Bedle and Lubo-Robles, 2024)

Shapley additive explanations (SHAP)

- Following Lundberg and Lee (2017), Lundberg et al. (2018):
  - SHAP are a recent development that enable quantitative estimation of model interpretability.



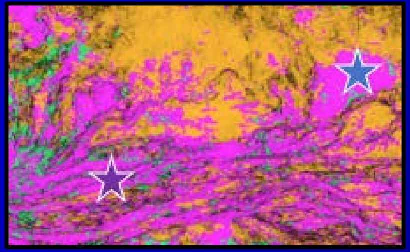
Case 1: Random Forest results in the Canterbury Basin, NZ



(Bedle and Lubo-Robles, 2024)

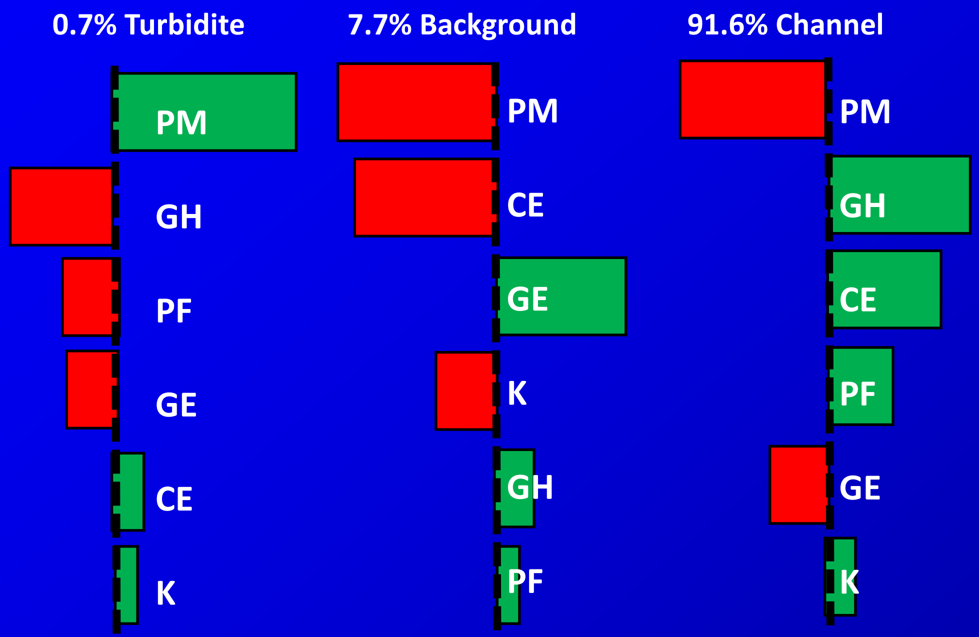
LIME (local interpretability)

Channel



- Reveals relative importance of attribute for each class in the ML classification
- Also allows insight into the ML's cutoff ranges for each class

Channel



Green: Attribute value is lending toward that class.
Red: Attribute value not in the class cutoffs

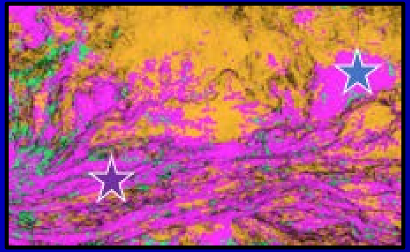
Channel

Attribute	Cutoff
CE = Coherent Energy	> 0.07
K = Curvedness	> 0.21
GE = GLCM entropy	<= 0.70
GH = GLCM homogeneity	> 0.40
PF = Peak Freq. CWT	0.24 <PF <= 0.47
PM = Peak Mag. CWT	>0.29

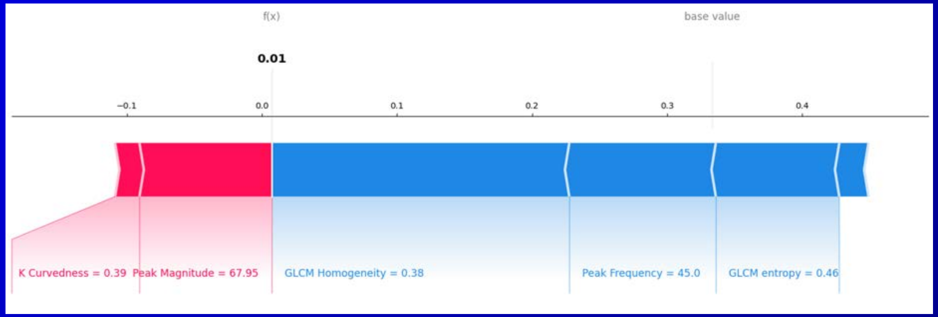
(Bedle and Lubo-Robles, 2024)

SHAP Force Plots (local interpretability)

Channel



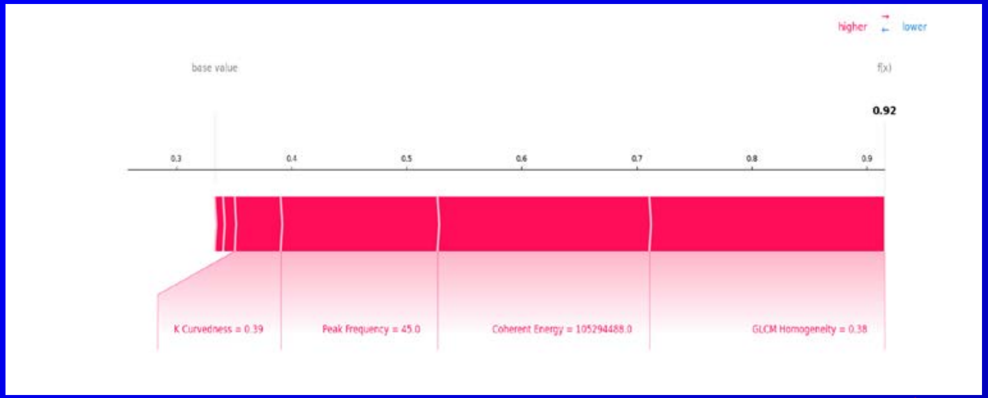
1% Turbidite



Increase the probability

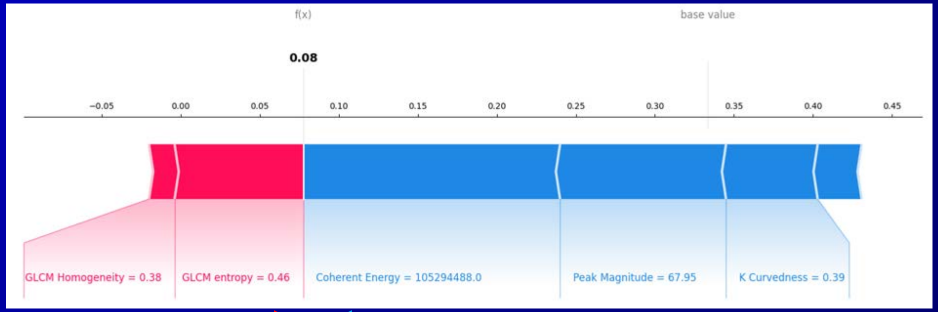
Decrease the probability

92% Channel



Value of all 6 attributes at this voxel increase the probability

7% Background

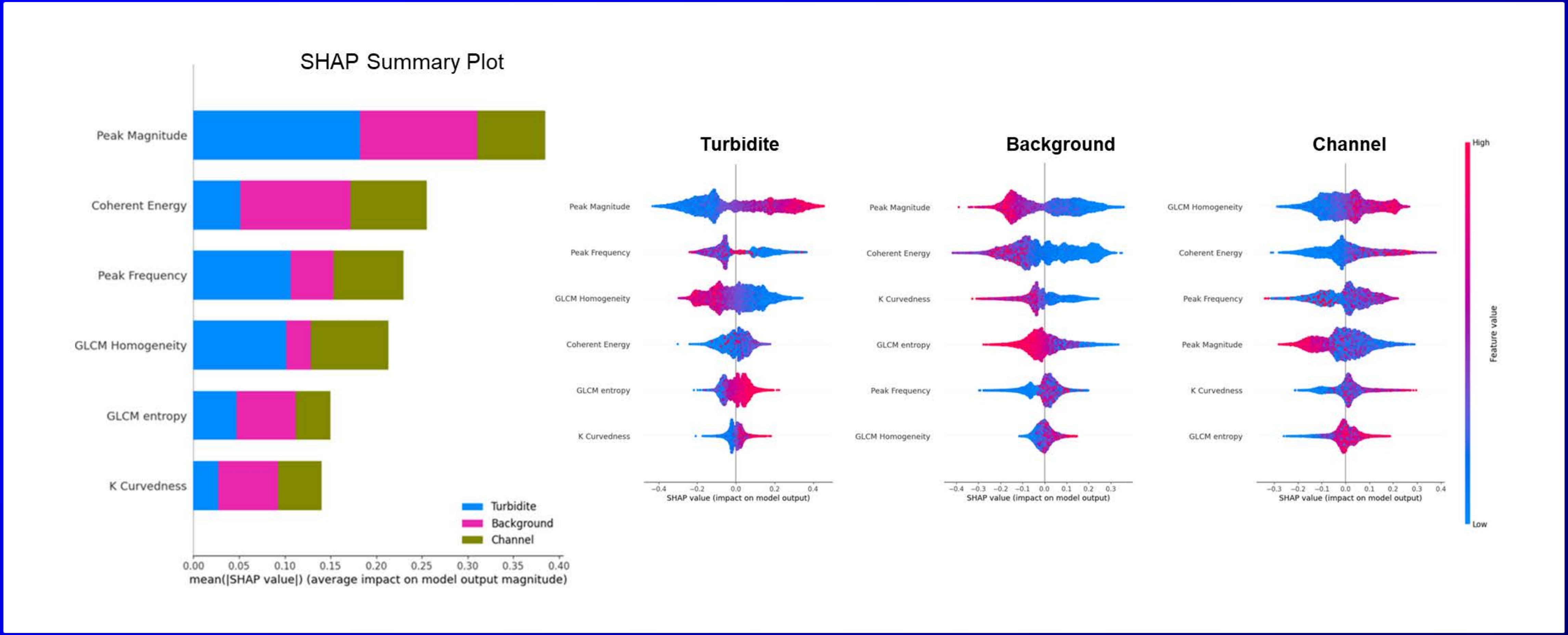


Increase the probability

Decrease the probability

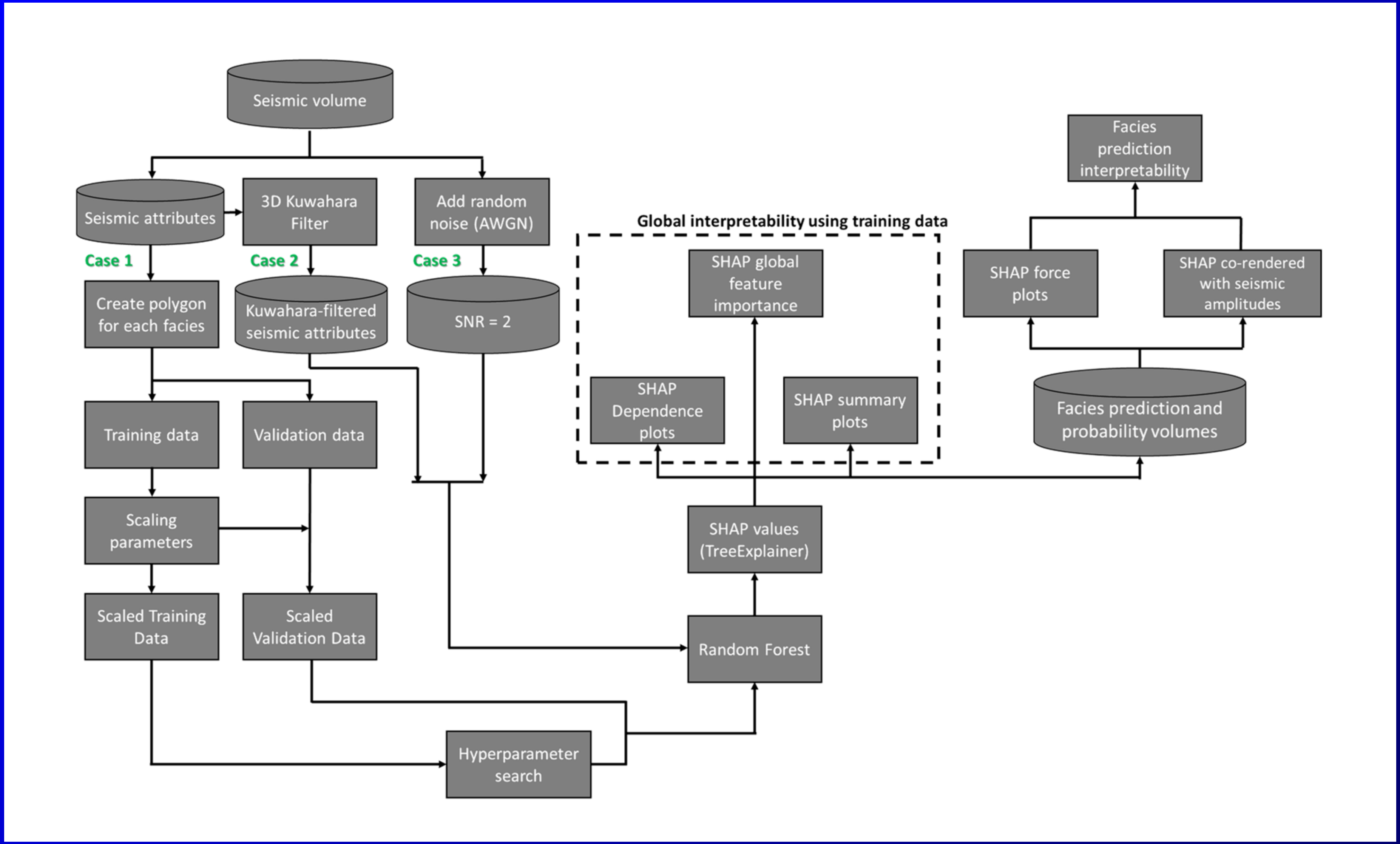
(Bedle and Lubo-Robles, 2024)

SHAP Summary Plots (global interpretability)



(Bedle and Lubo-Robles, 2024)

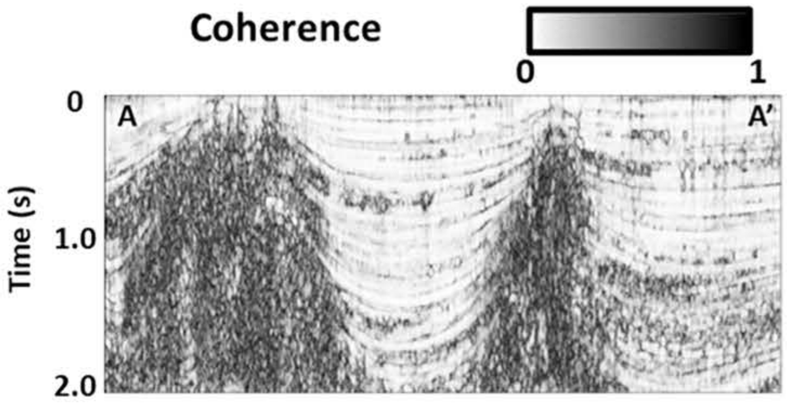
Case 2: SHAP for ML interpretability in the Gulf of Mexico



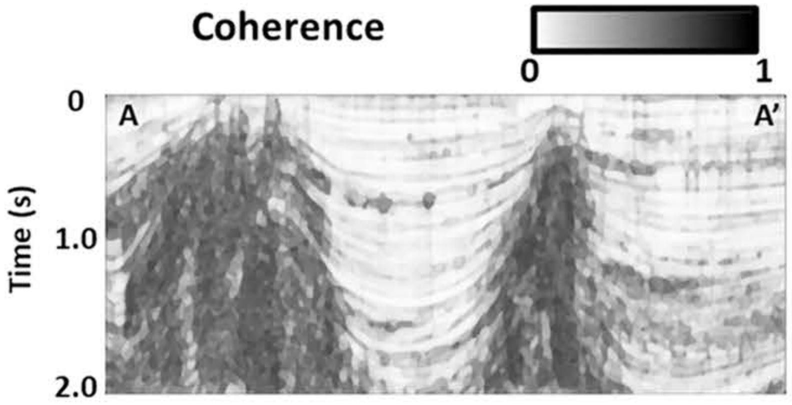
(Lubo-Robles et al., 2022)

Kuwahara blocks and smooths the response. Bandlimited AWGN decreases facies separation

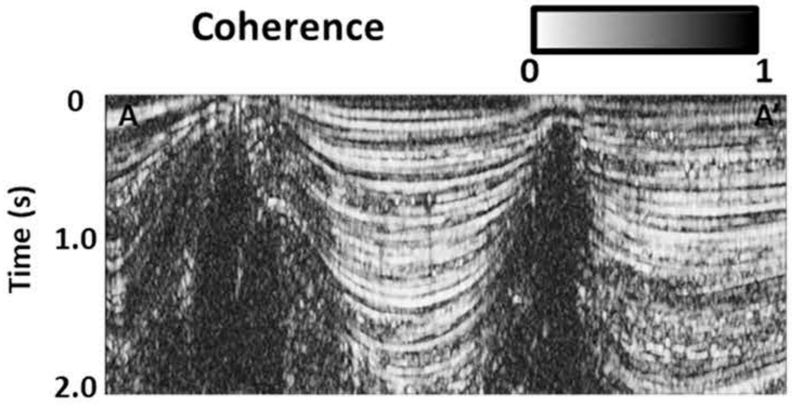
Case 1: Original



Case 2: Kuwahara



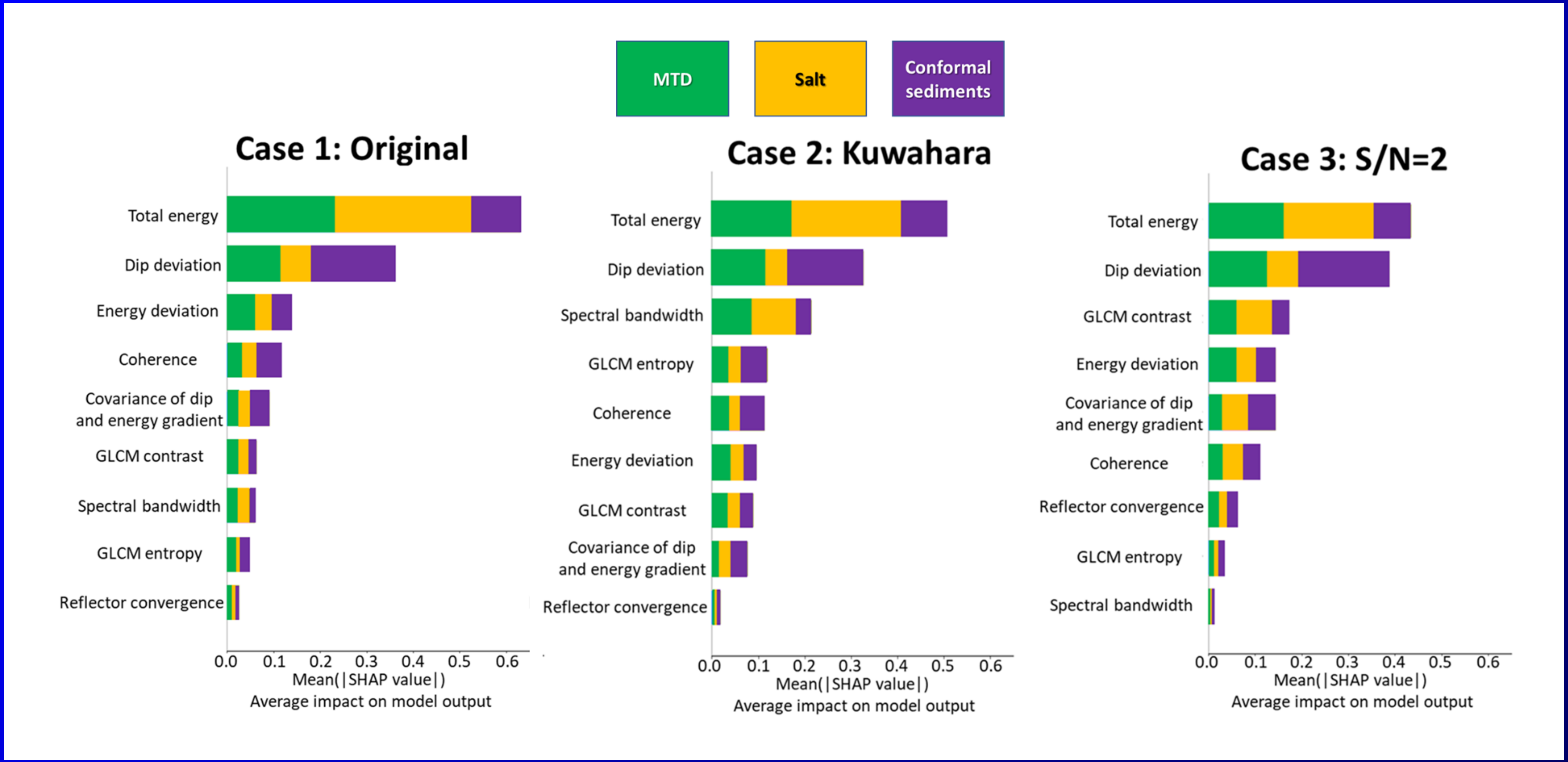
Case 3: S/N=2



- Additive white Gaussian noise (AWGN)
- 9 candidate seismic attributes:
  1. Coherence
  2. Total energy
  3. GLCM entropy
  4. Reflector convergence
  5. Spectral bandwidth
  6. GLCM contrast
  7. Dip deviation
  8. Energy deviation
  9. Covariance of dip and energy gradient

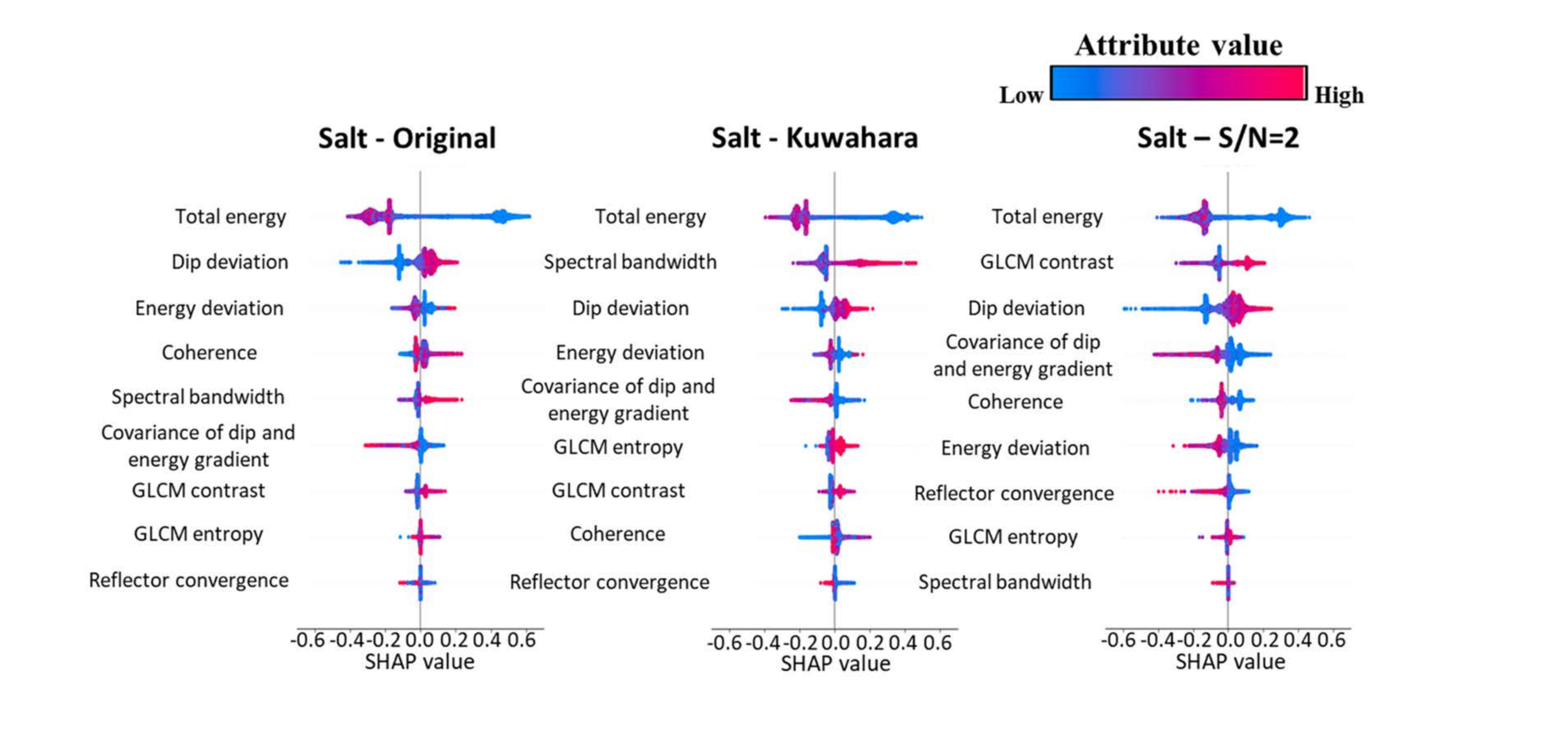
(Lubo-Robles et al., 2022)

Total energy and dip deviation show the largest impact for all cases



(Lubo-Robles et al., 2022)

SHAP summary plots



(Lubo-Robles et al., 2022)

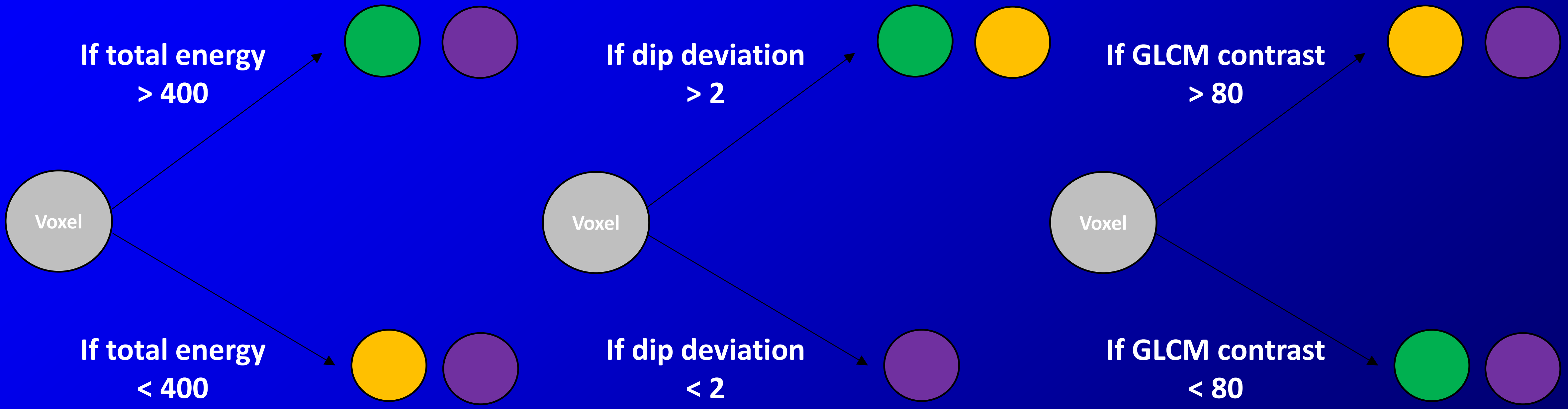
Rules "learned" by the ML model

Attribute	MTD trend 1	MTD trend 2	Salt	Conformal sediments trend 1	Conformal sediments trend 2
Total energy	> 400	> 400	< 400	< 400-500	> 400-500
Dip deviation	> 2	> 2	> 2.5	2.5-4	< 2.5
Energy deviation	> 2.5	> 2.5	< 2.5 < 4.0 (S/N=2)	> 2.5	< 2.5
Coherence	<0.9 0.4 – 0.9 (Kuwahara) 0.35-0.9 (S/N=2)	<0.9 0.4 – 0.9 (Kuwahara) 0.35-0.8 (S/N=2)	< 0.85 (original and Kuwahara) < 0.3 (SNR=2)	< 0.85 <0.45 (Kuwahara) <0.4 (S/N=2)	> 0.85 > 0.85 (Kuwahara) > 0.4 (S/N=2)
Covariance of dip and energy gradient	< 0.15	> 0.15	< 0.15-0.2	> 0.1-0.2	< 0.1-0.2
GLCM contrast	< 90 <140 (S/N=2)	< 90 <140 (S/N=2)	> 75-80 > 140 (S/N=2)	> 75-80 > 100-110 (S/N=2)	< 75-80 < 100-110 (S/N=2)
Spectral bandwidth	<60-65 Hz.	<60-65 Hz.	> 65-70 Hz.	60-70 Hz	< 60-65 Hz.
GLCM entropy	> 0.5	> 0.5	> 0.5	> 0.5	< 0.5
Reflector convergence	< 0.25-0.3	> 0.25-0.3	< 0.3	> 0.2	< 0.2

(Lubo-Robles et al., 2022)

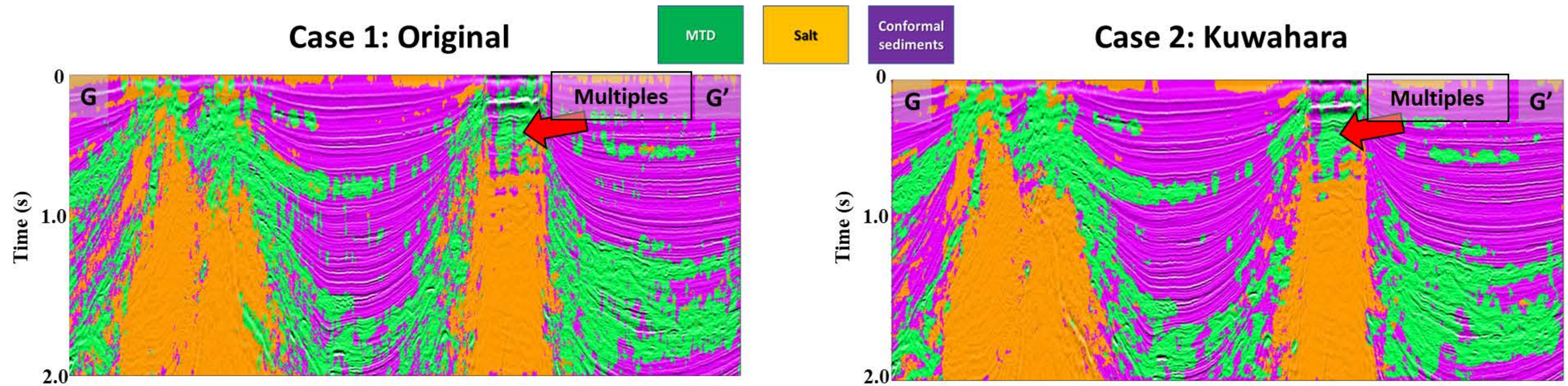
The ML model “learns” a set of rules in multi-attribute space

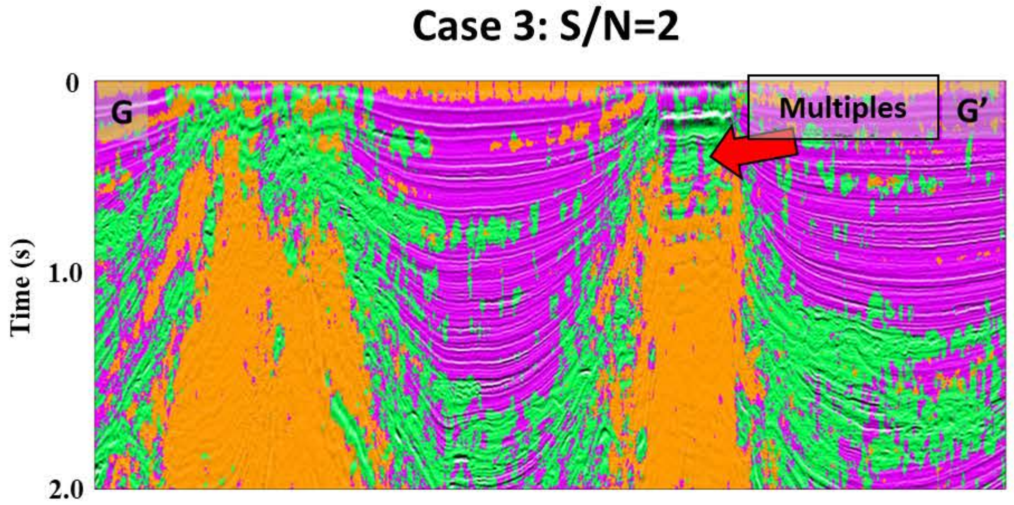
- 81 SHAP dependence plots are interpreted in this study
  - 9 attributes, 3 facies, and 3 cases in my sensitivity analysis



- Using multiple attributes as input represents a good approach for seismic facies classification
  - It allows to discriminate among seismic facies that might have similar seismic responses in some attributes but better differentiation when considering other attributes.

Kuwahara filtering offers better classification than other cases

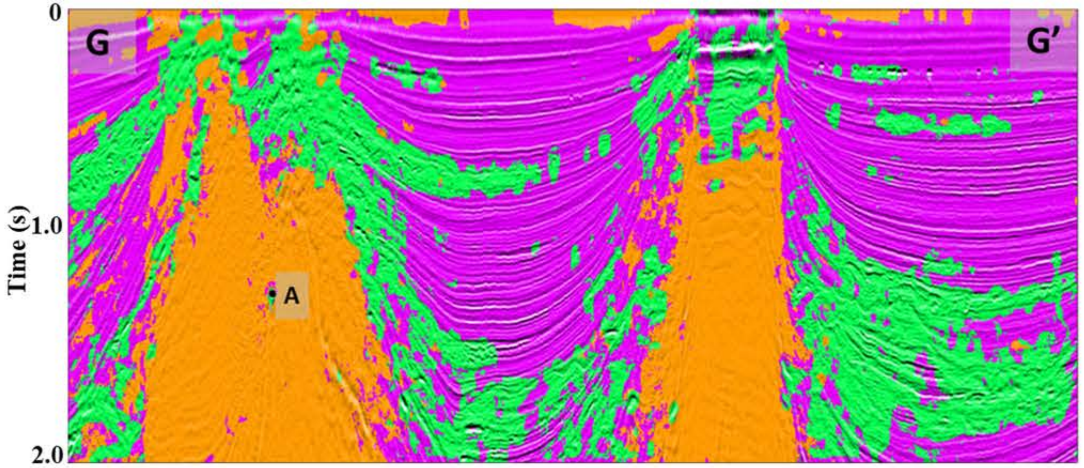




- Kuwahara filtering shows a smoother facies response, sharper edges, and better classification of previously unseen/unlabeled data than other cases.
- High amplitude, parallel conformal reflectors tend to be well classified in all cases.
  - MTDs and conformal sediments show more overlap when adding band-limited AWGN or using the original attributes.

(Lubo-Robles et al., 2022)

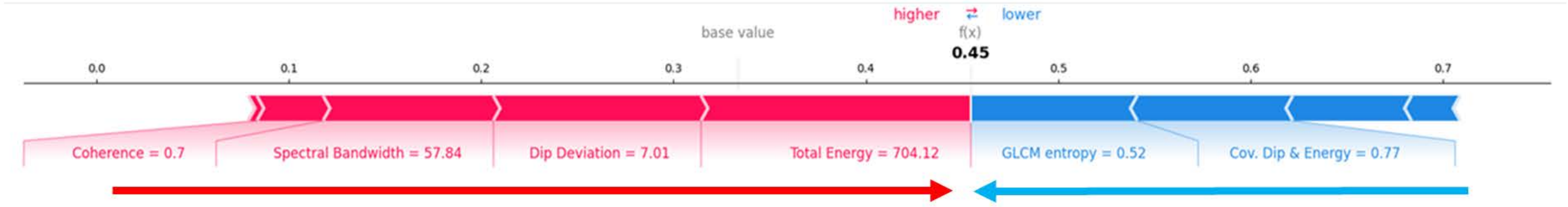
Voxel A matches MTD response with 45% probability



MTD | **Salt** | **Conformal sediments**

Voxel	Predicted class	Probabilities (%)		
		MTD	Salt	Conf. Seds.
A	MTD	45	13	42

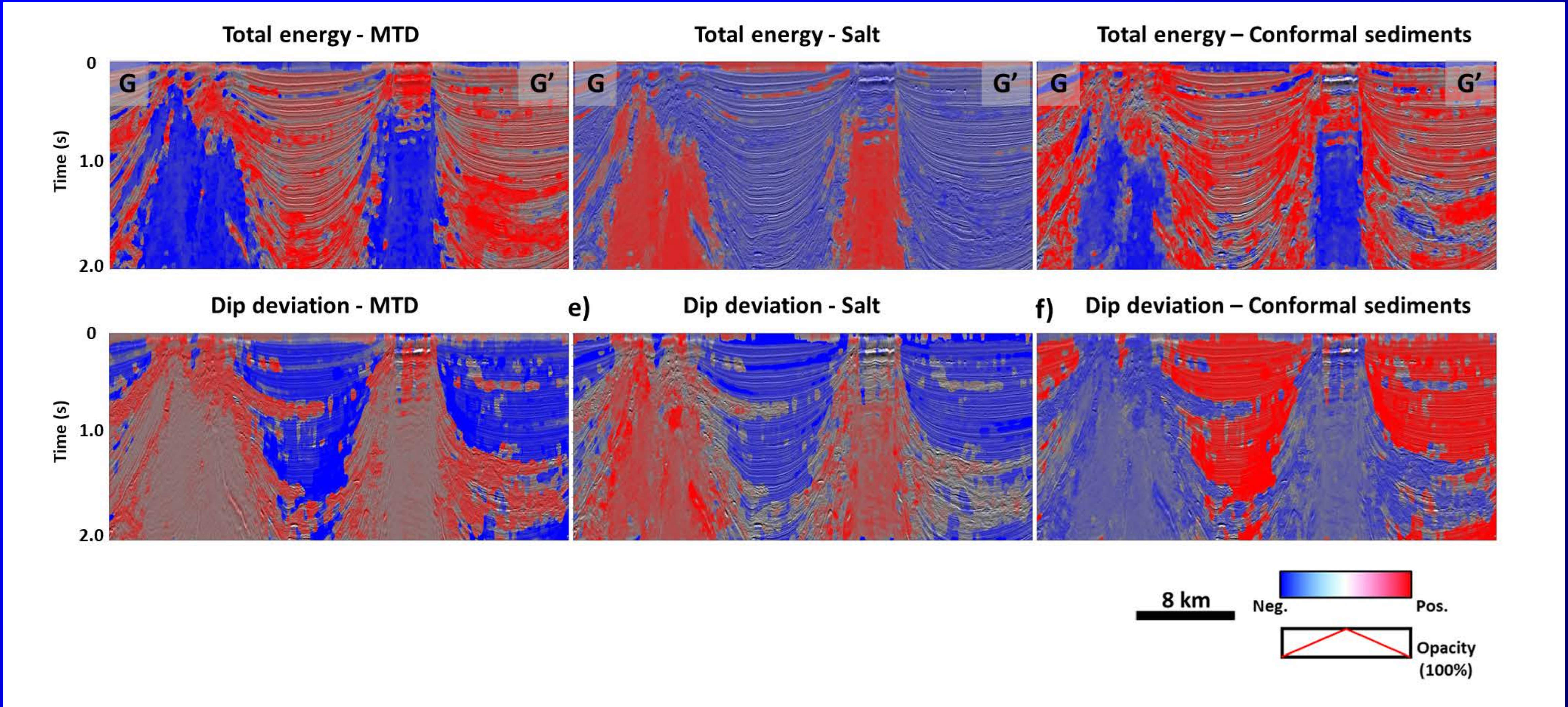
MTD:



Increase the probability | **Decrease the probability**

(Lubo-Robles et al., 2022)

ML model correctly classifies between facies. Some overlap might exist



(Lubo-Robles et al., 2022)