Supplementary Material

1. Hyperparameter Tuning Details

The hyperparameter tuning for all models (Extra Trees, Feed-forward Neural Network, and XGBoost) was conducted using Optuna with the Tree-structured Parzen Estimator (TPE) Sampler. Each tuning process involved 100 trials, and the optimal hyperparameters were determined based on minimizing the Root Mean Squared Error (RMSE) on the tuning (validation) set.

Table S1: Hyperparameter Tuning Configuration for Extra Trees

Hyperparameter	**Range Explored**	**Optimal Value**
Number of Trees	100-1200	150
Maximum Depth	5-20, None	None
Minimum Samples Split	2-10	2
Minimum Samples Leaf	1-10	1
Criterion	• Squared Error • Absolute Error • Friedman MSE	Squared Error

Table S2: Hyperparameter Tuning Configuration for XGBoost

Hyperparameter	**Range Explored**	**Optimal Value**
Number of Trees	100-1200	1000
Maximum Depth	5-20, 0	0
Learning Rate	0.01-0.5	0.05
Subsample	0.5-1.0	1.0
Objective	• Squared Error • Squared Log Error • Absolute Error	Squared Error
Maximum Bin	1000 – 6000	5096
Tree Method	• Exact • Approximate • Histogram	Histogram

Table S3: Hyperparameter Tuning Configuration for FNN

Hyperparameter	**Range Explored**	**Optimal Value**
Hidden Layers	1-5	3
Neurons per Layer	128-5000	2048, 1500, 1000
Learning Rate	1e-5 - 1e-2	1e-4
Batch Size	16-256	128
Activation Functions	• ReLU • Tanh • Sigmoid	ReLU

2. Feature Importance Plots Open and Vegetated Areas

Since the XGBosst has the best performance overall, the following feature importance plots are based on the XGBoost model.

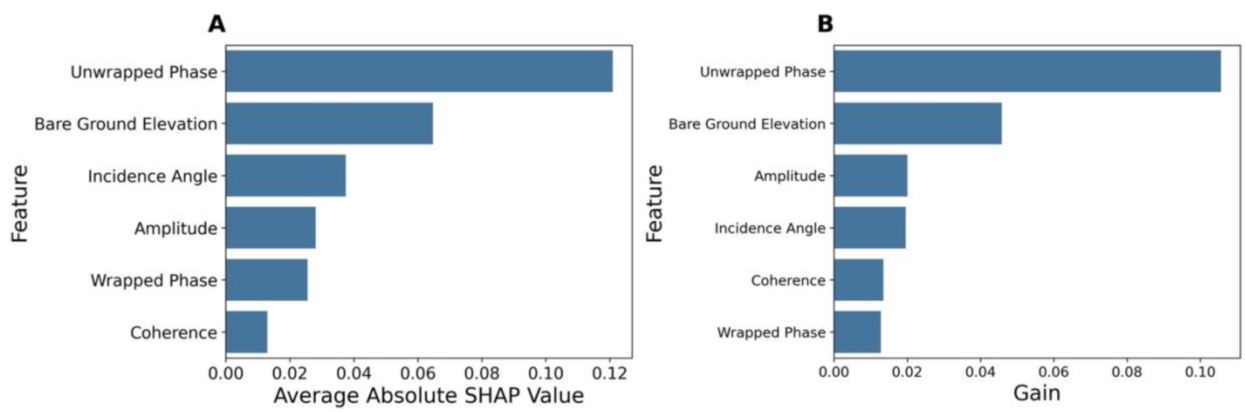

Figure S1: Feature Importance in Open Areas: (**A**) SHAP Importance (**B**) Impurity-based importance

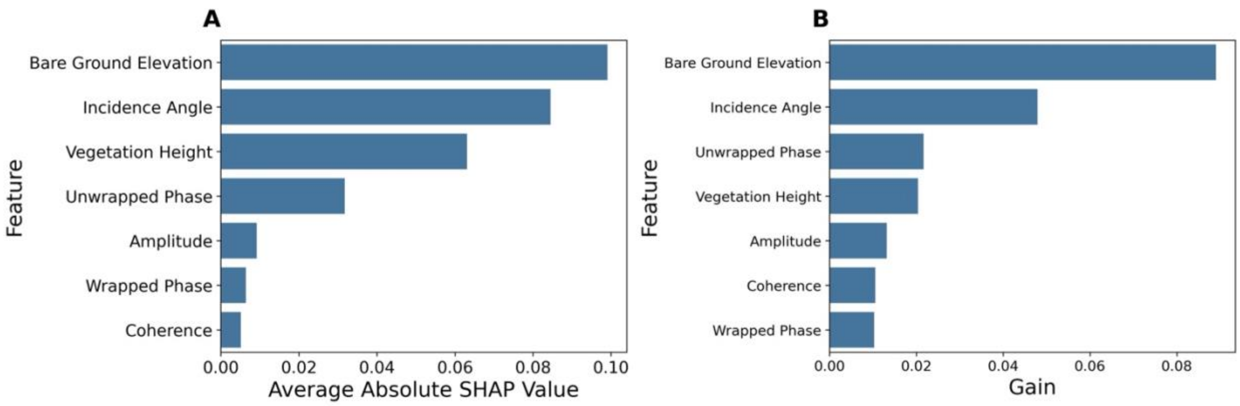

Figure S2: Feature Importance in Vegetated Areas: (**A**) SHAP Importance (**B**) Impurity-based importance