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Role of machine learning in optimising prediction of blast fragmentation in mines using site-specific geological data

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Role of machine learning in optimising prediction of blast fragmentation in mines using site-specific geological data

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Research Context

- **Accurate fragmentation is critical for mine-to-mill efficiency**
- **Predictive Models used to manage fragmentation in blast designs**
- **Traditional and ML models**

Why Models Fail

Category	*Kuz-Ram Inputs*	*Typical ML Model Inputs*
Blast Geometry	Burden (B), Spacing (S), Bench Height (H)	Burden, Spacing, Bench Height, Hole Depth, Diameter
Drilling Parameters	Hole Diameter, Hole Depth	Hole Diameter, Hole Depth, Hole Accuracy
Charging Parameters	Charge per Hole (Q), Stemming Length (SL)	Charge, Stemming, Powder Factor
Explosive Properties	Relative Weight Strength (RWS)	Explosive Type, RWS, Energy per Delay
Rock Properties	Rock Factor (A) (subjective)	Sometimes RMR, UCS, GSI (generalised)

Research Context

Geological Factors

Uneven Explosive Energy Distribution

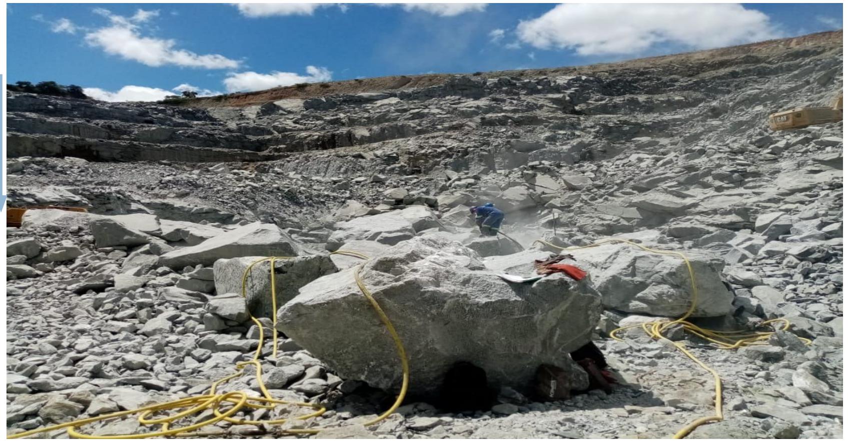
Cracks absorb or redirect blast energy

Escaping of explosives and energy through cracks

Fragmentation

fines

Oversized



Research Gap

- ML models rarely include detailed geological discontinuity data.

AIM

- Integrate site-specific geological data into ML models to improve prediction accuracy.

Study Area


Waste Zone: Sheared Greenstone
Bench Level 1180
Lithological Contact
Ore Zone: Granodiorite + Quartz/Pegmatite
Bench Level 1120

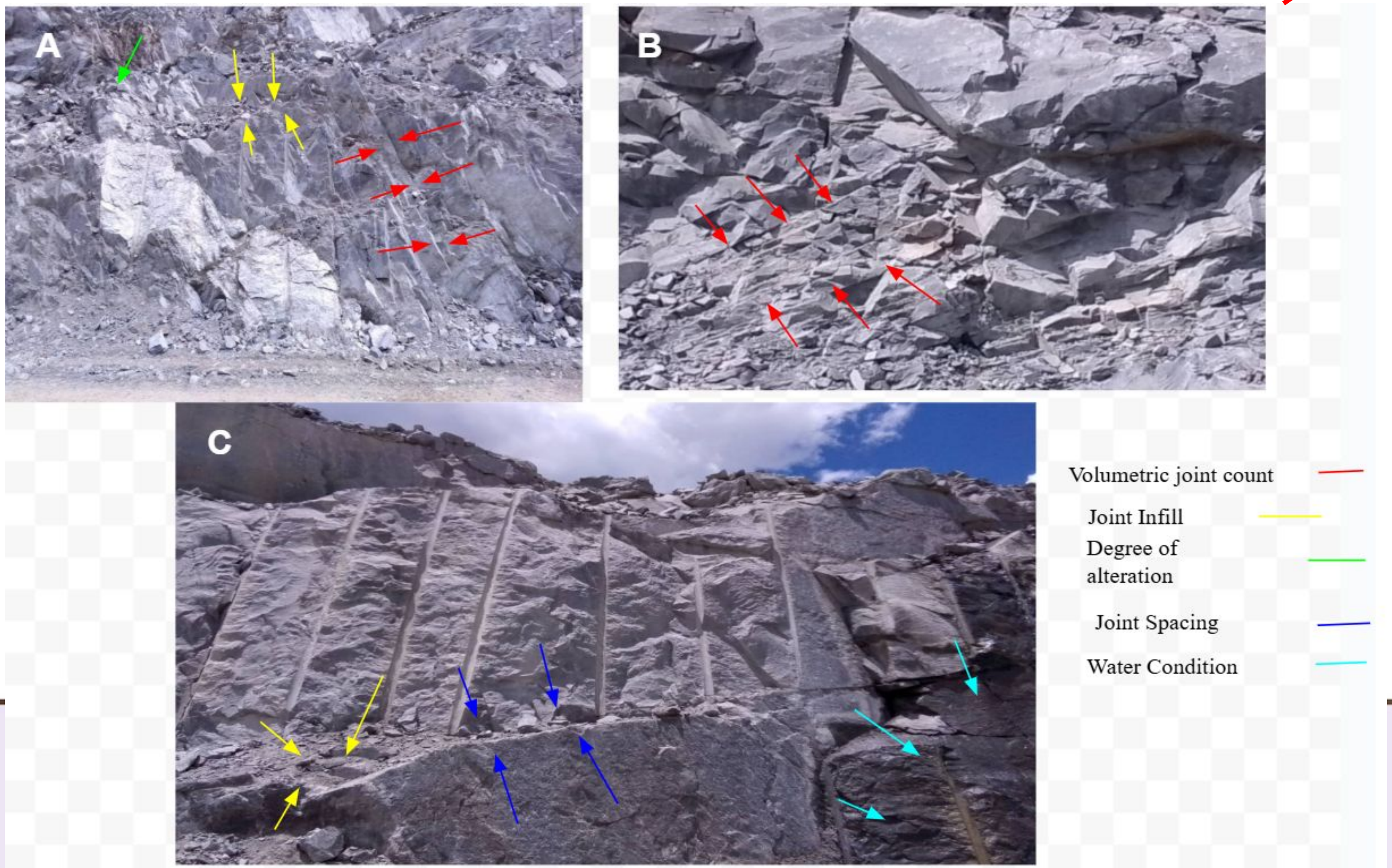
Methodology

1. Data Collection
2. Development and Validation of ssDI
3. EDA and Preprocessing
4. Numerical Modelling

1. GEOLOGICAL AND

ssDI formulation

Geological window mapping /core logging data



Drill Core Tray showing Intersecting Joints, Variation in Fracture Persistence and Visible Alteration Zones

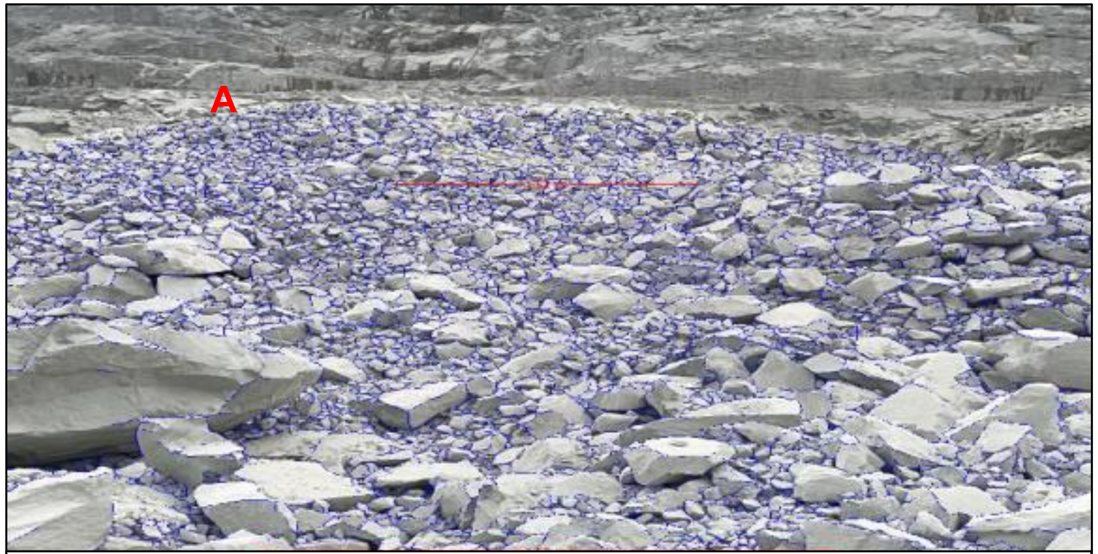
Summary statistics for geological parameters

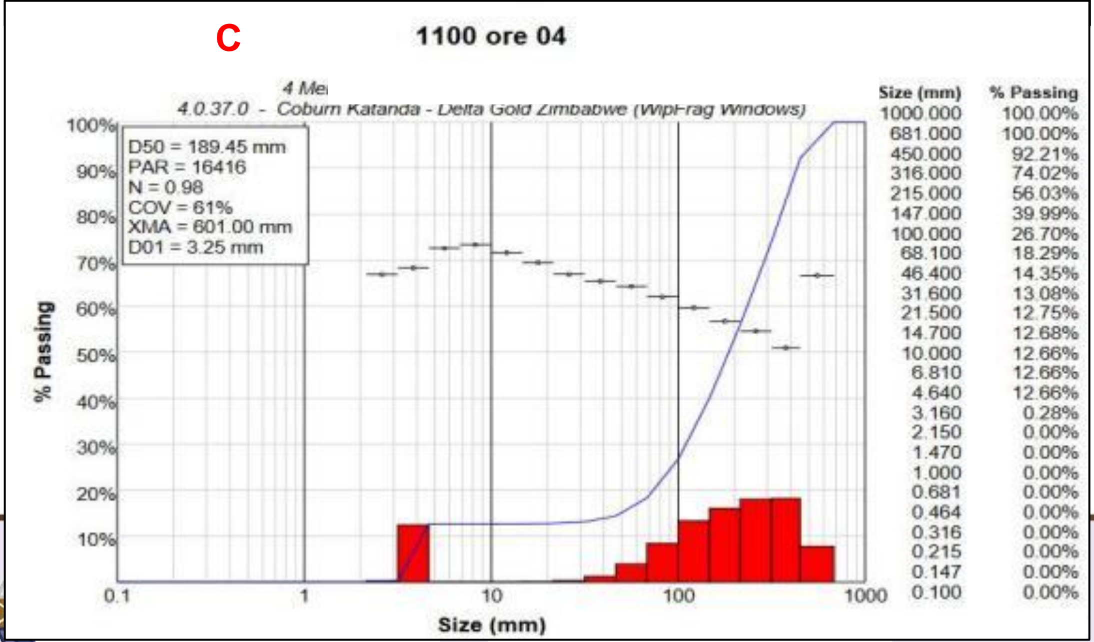
Parameter	Count	Mean	Std	Min	Lower quartile	Median	Upper quartile	Max
Joint Volume (Jv)	270	246.74	419.50	60	60	60	200	2000
Joint Orientation (O)	270	114.74	54.74	-71	82.25	100	142	277
Joint Persistence (Jp)	270	3.30	3.20	1	1	3	3	10
Joint Alteration (A)	270	1.49	0.55	1	1	1	2	3
Joint Infilling (I)	270	8.69	1.18	3	9	9	9	9
Water content (W)	270	1.58	0.94	1	1	1	2	5
Microstructures (Mi)	270	4.70	1.14	1	5	5	5	8
Macrostructures (Ma)	270	1.16	0.45	1	1	1	1	3

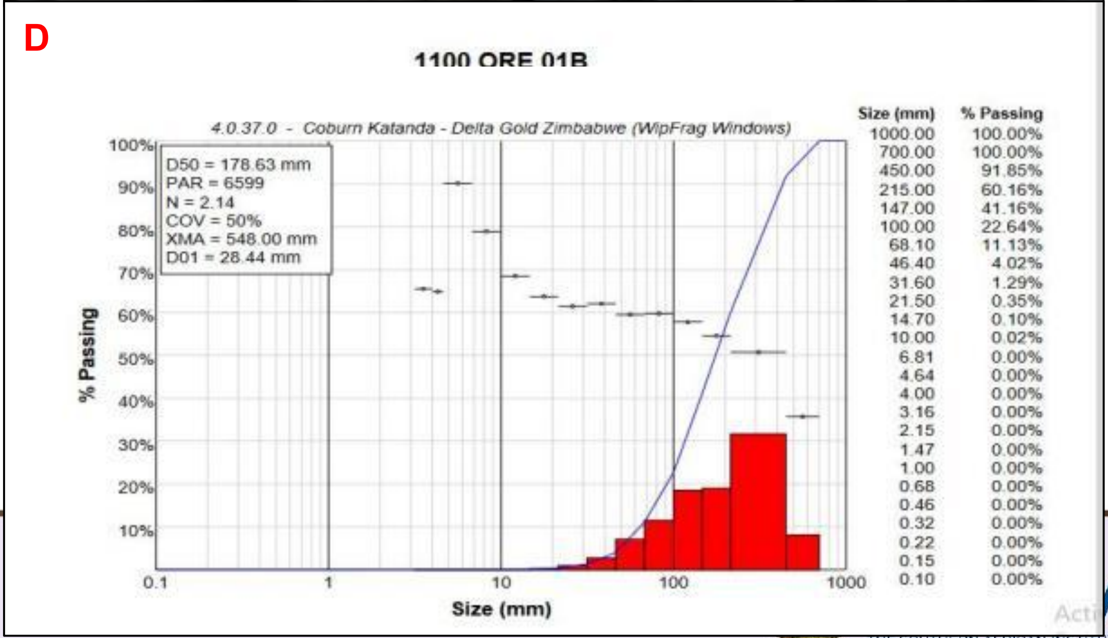
2. Drilling and Charging data

Parameter	Ore zones	Waste zones
Hole diameter (mm)	115	127
Burden (m)	2.7	3.1
Spacing (m)	3.1	3.6
Average hole depth (m)	9.9	8.5
Hole Inclination	90	90
Average Hole accuracy (%)	88	92
Average Collapsed holes (%)	9	11
Average redrills per blast (%)	11	16.8
Powder Factor	1.4	1.2

3. Fragmentation Data







Development and Validation of ssDI

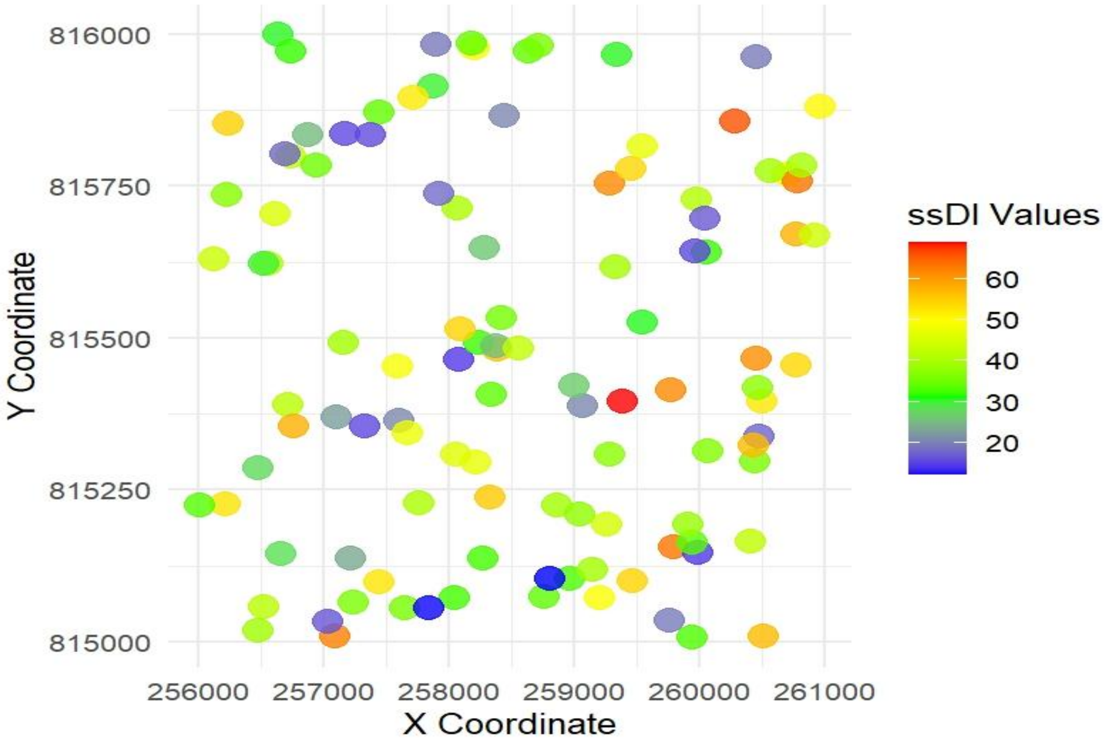
- **Draws from RMR , the Q-system and blastability index**
- **Jv is the core multiplier**
- **Weights and scaling tuned for site-specificity**
- **Joint orientation and Joint volume retained in raw form**
- **Scaling factor *k for* normalising the ssDI to make it comparable across sites.**

STRUCTURE of ssDI

- $$\mathbf{ssDI} = \boldsymbol{Jv}\left[\mathbf{1} + \frac{\mathbf{1}}{\boldsymbol{P}} + \frac{\mathbf{2}}{\boldsymbol{O}} + \frac{\mathbf{1}}{\boldsymbol{W}} + \frac{\mathbf{0.5}}{(\boldsymbol{Mi}+\boldsymbol{Ma})} + \frac{\mathbf{1}}{\boldsymbol{A}} + \frac{\mathbf{1}}{\boldsymbol{I}}\right] \times \mathbf{k}$$

Computation of ssDI

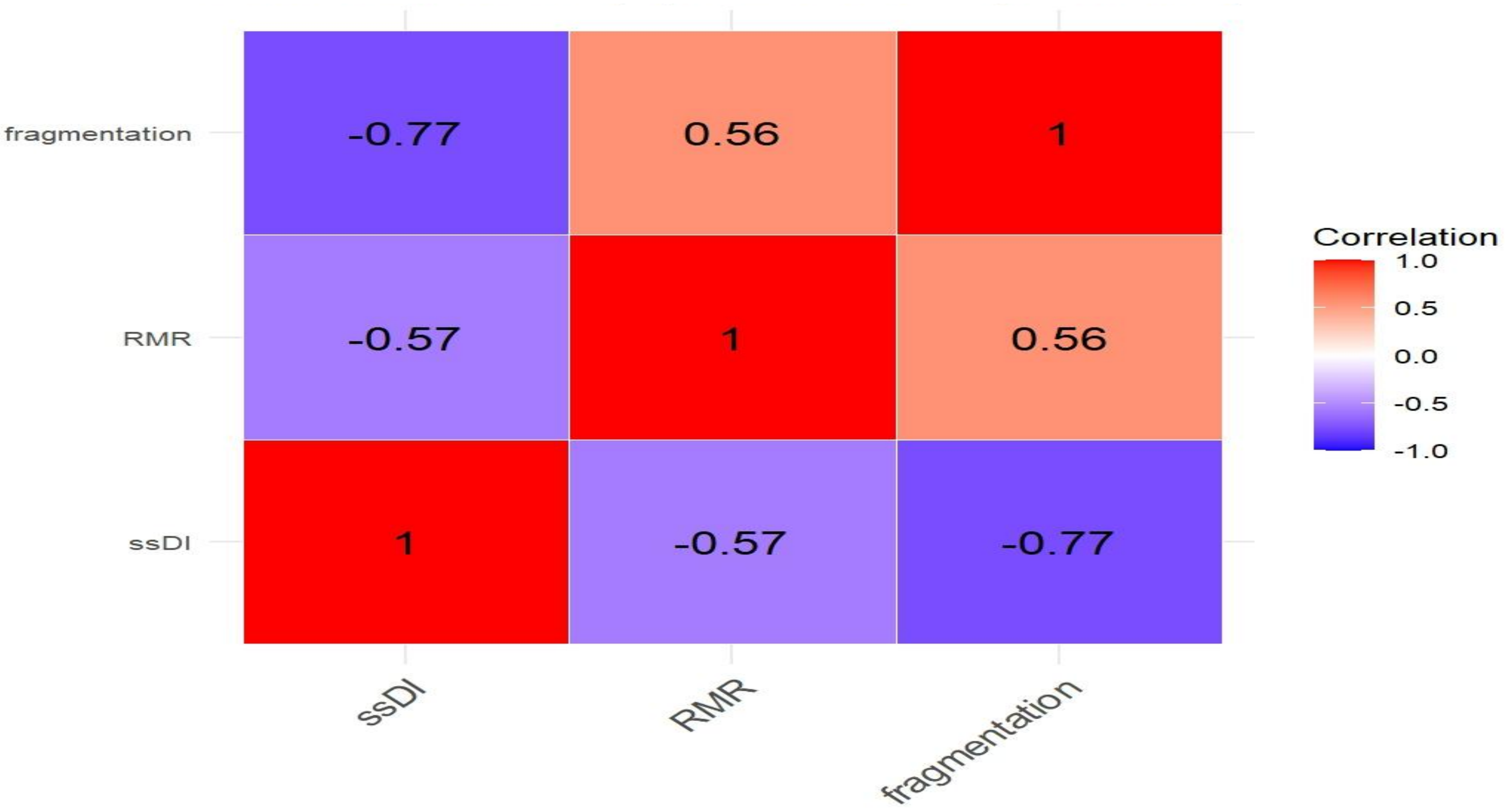
Metric	Count	mean	Std	Min	Lower quartile	Median	Upper quartile	Max
ssDI	110	12.96	12.12	12.12	32	37.4	49.4	69



Spatial Distribution of ssDI at different Geological Points within the Mine Pit Areas (110 blasts)

Testing and validation of ssDI

- **Pearson correlation test between ssDI, existing RMR values and corresponding fragmentation results**

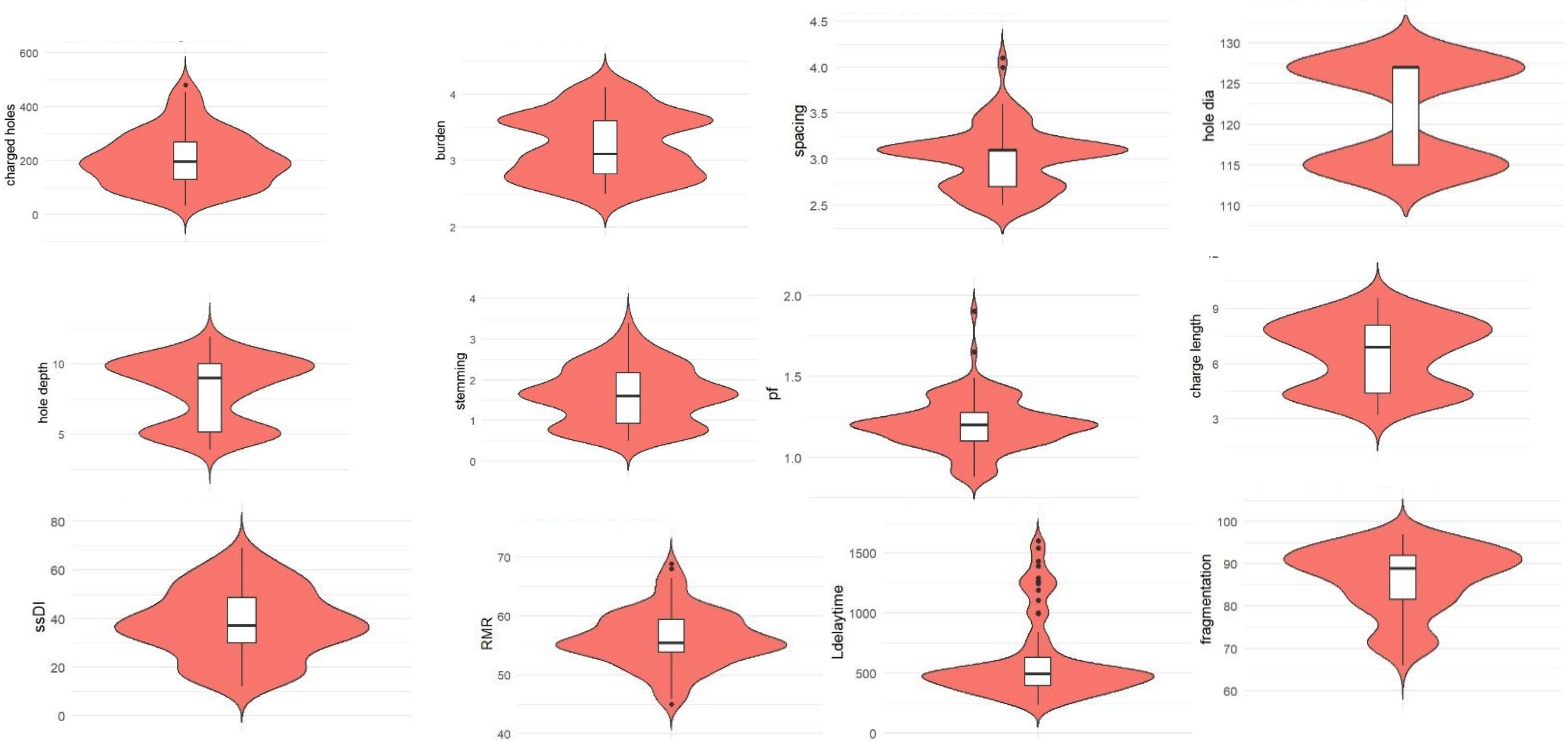


Pearson Correlation matrix

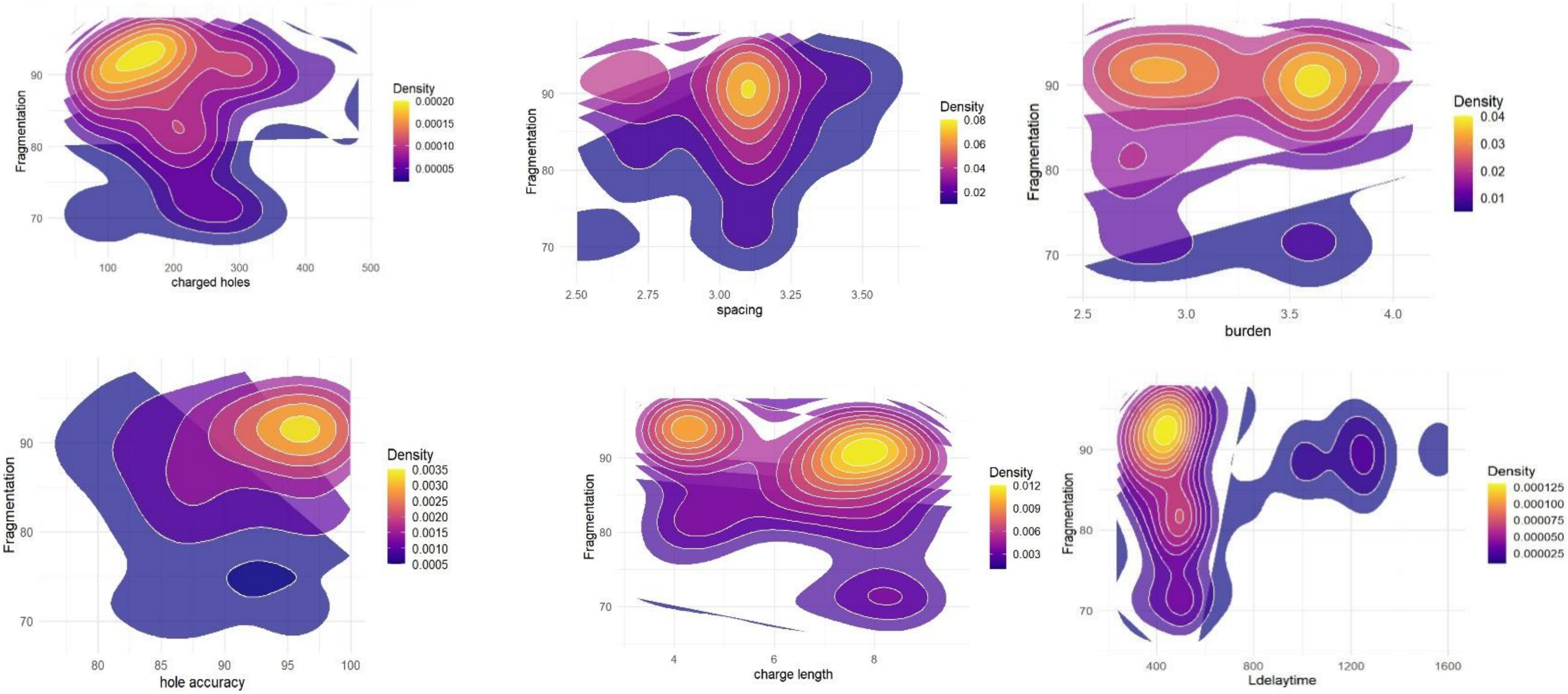
Exploratory data analysis and preprocessing

- Violin plots
- 2D Kernel density
- Pearson correlation analysis
- Feature Importance

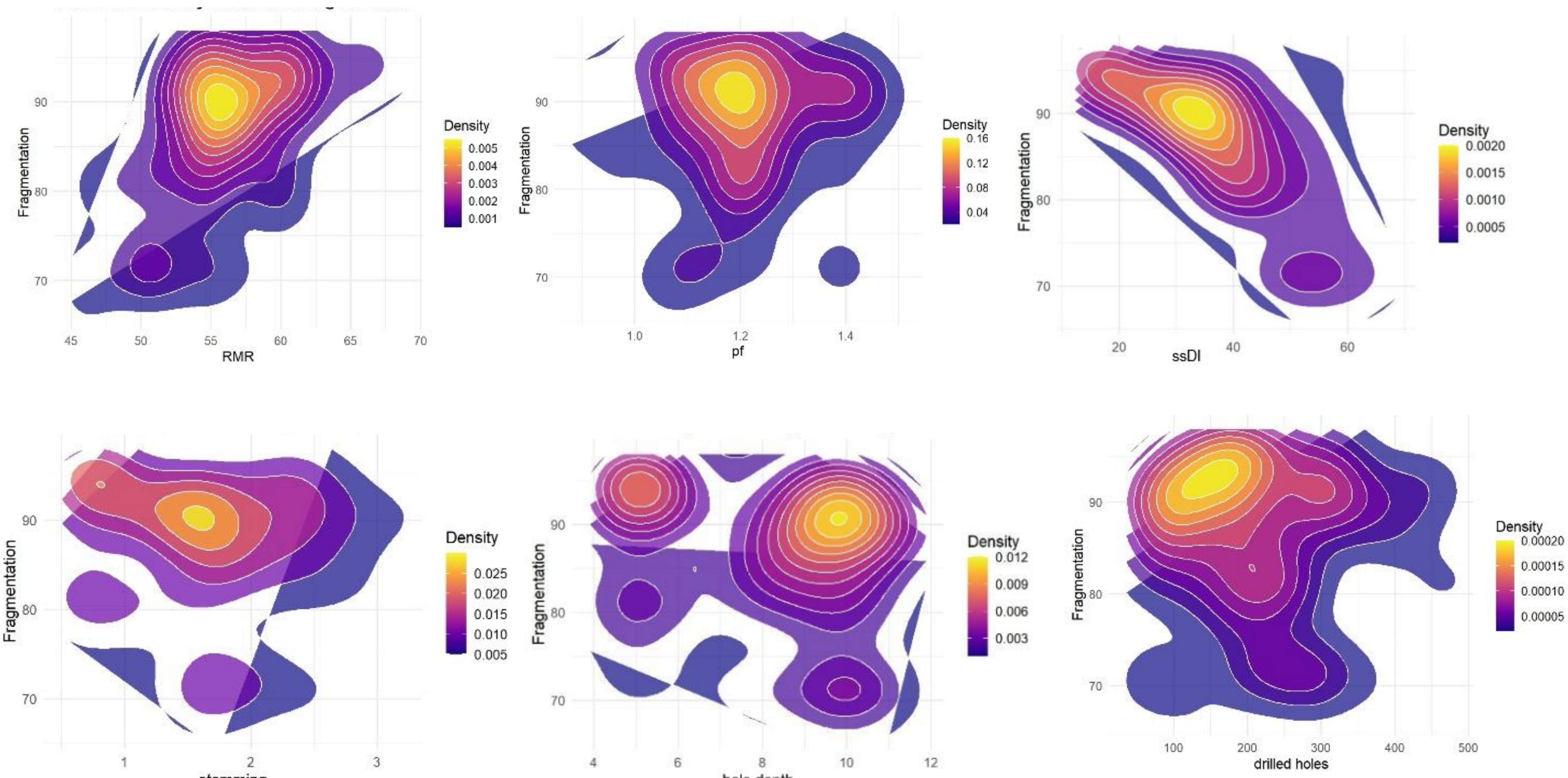
Violin Plots

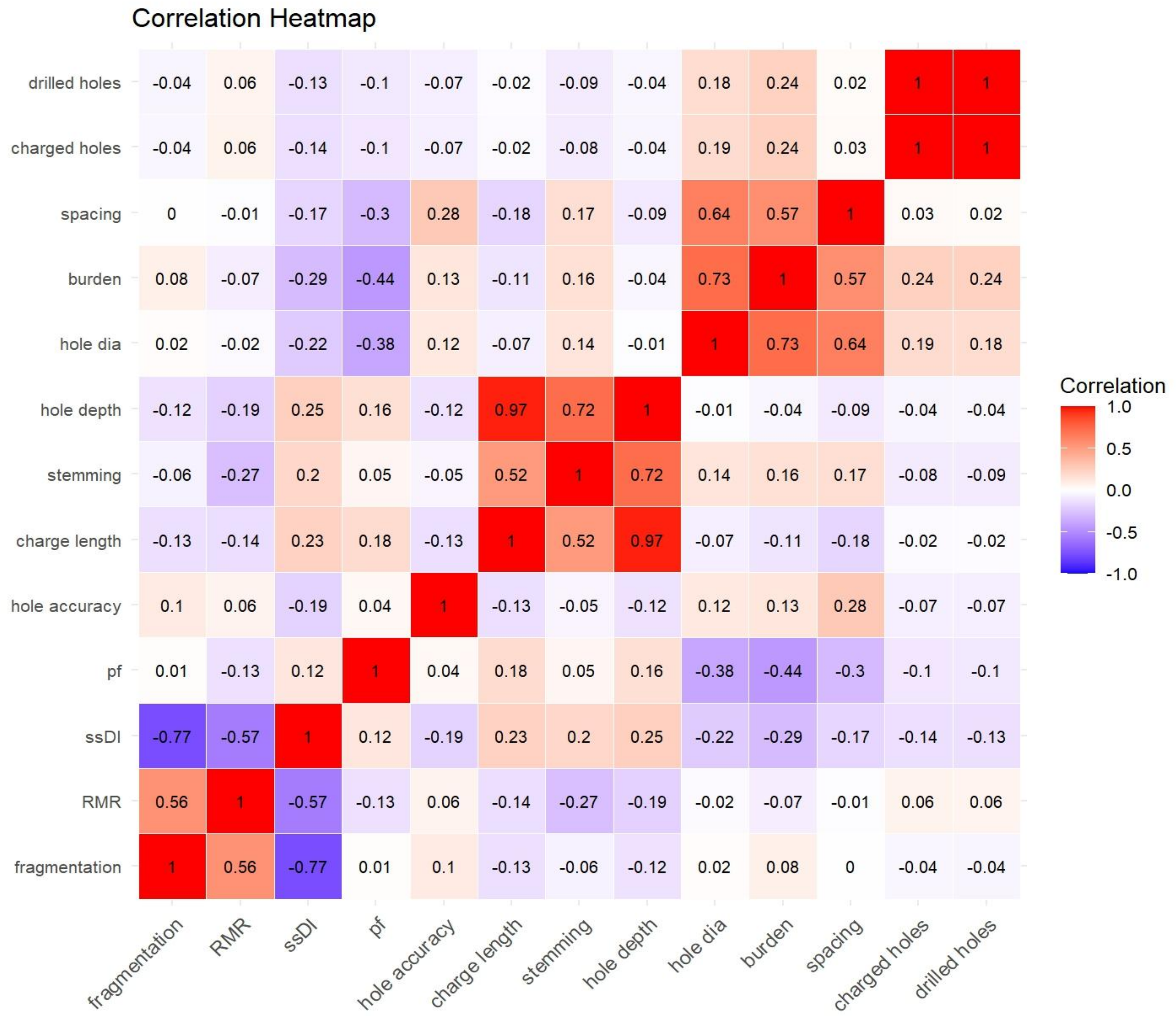


2d Kernel Density Plots



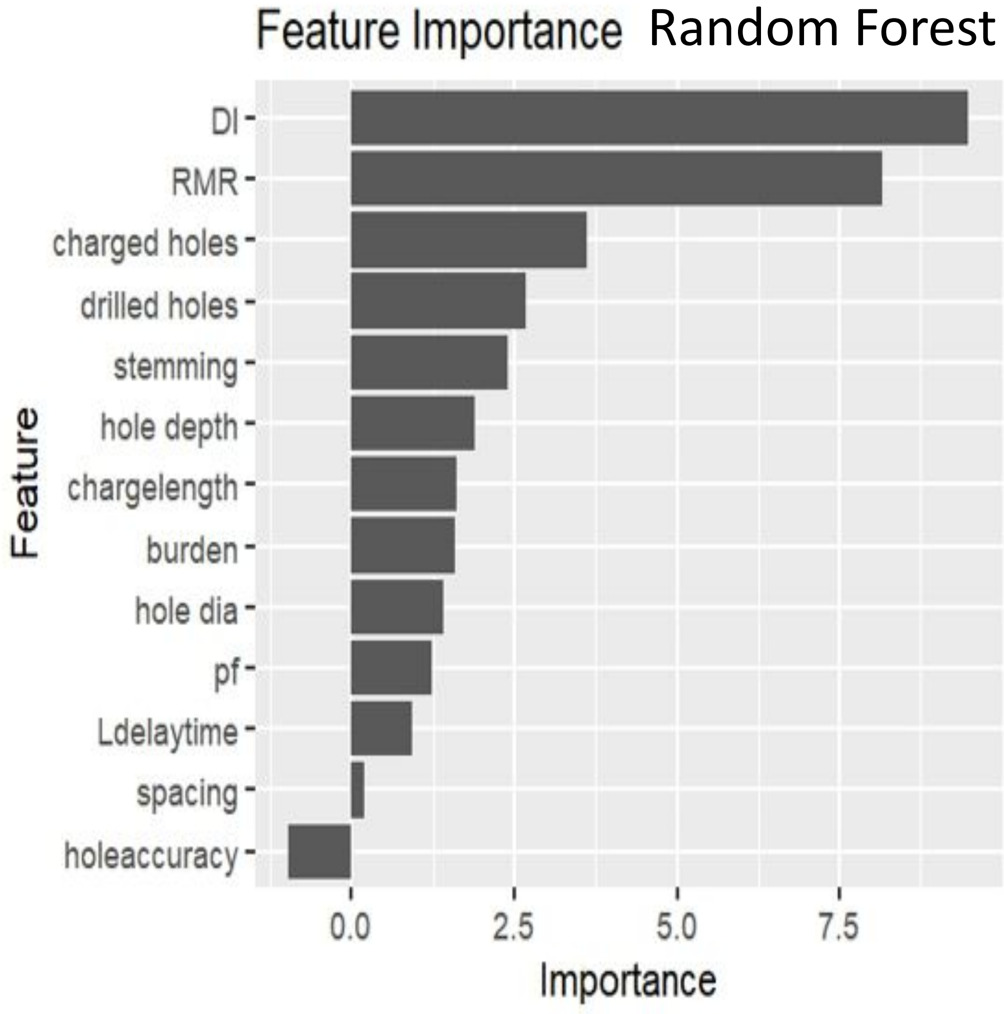
Comparative analysis (2D kernel density plots)

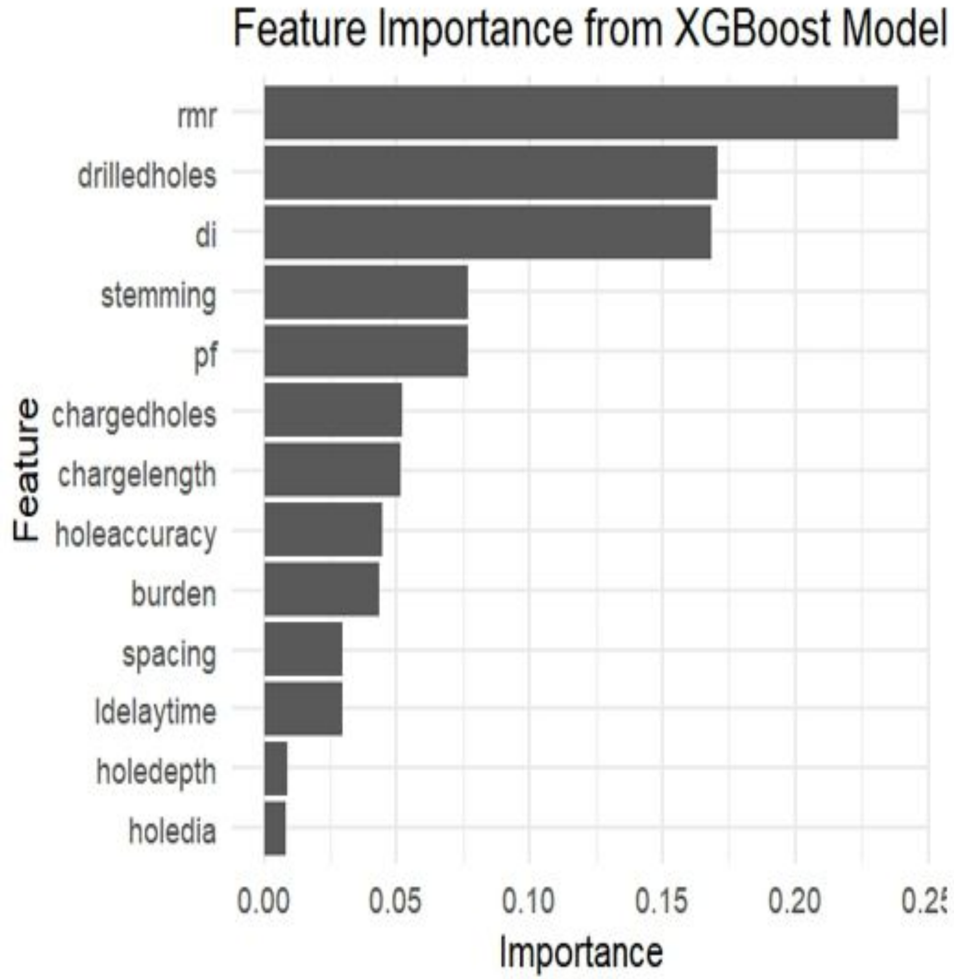

Fragmentation
RMR
45
50
55
60
65
70
90
80
70
Density
0.005
0.004
0.003
0.002
0.001
Fragmentation
pf
1.0
1.2
1.4
90
80
70
Density
0.16
0.12
0.08
0.04
Fragmentation
ssDI
20
40
60
90
80
70
Density
0.0020
0.0015
0.0010
0.0005
Fragmentation
stemming
1
2
3
90
80
70
Density
0.025
0.020
0.015
0.010
0.005
Fragmentation
hole depth
4
6
8
10
12
90
80
70
Density
0.012
0.009
0.006
0.003
Fragmentation
drilled holes
100
200
300
400
500
90
80
70
Density
0.00020
0.00015
0.00010
0.00005



Correlation Matrix

Feature Importance





Results from parameter selection

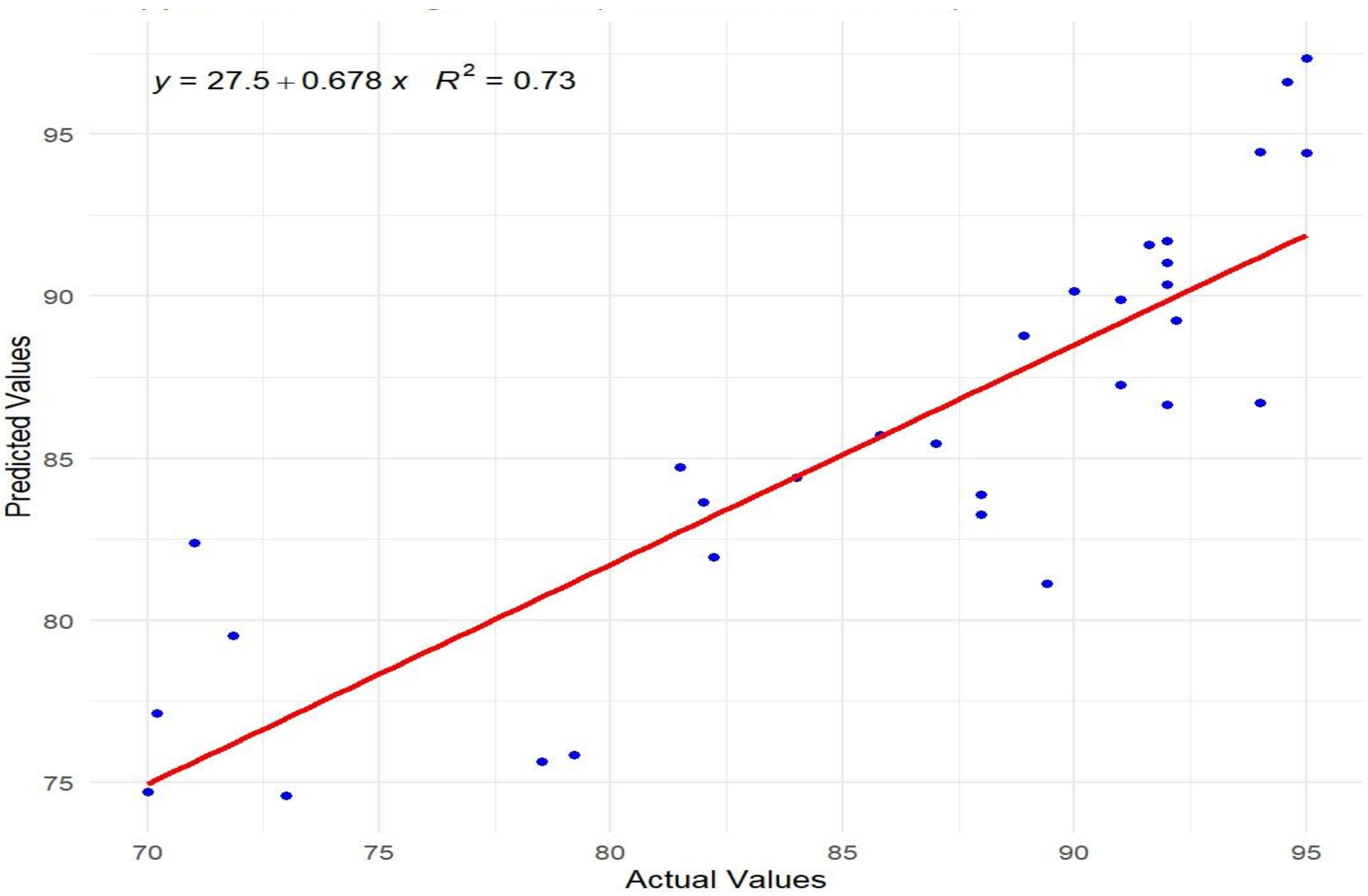
Method	Selected Parameters
2D Kernel density plots	RMR, ssDI, burden , hole diameter, hole accuracy , powder factor
Pearson Correlation Matrix	ssDI, RMR, burden , hole depth, spacing, stemming , charge length
Feature Importance (XG BOOST and Random Forest)	ssDI, RMR drilled holes, hole depth , hole accuracy, stemming

Final Model Input Parameters

- **Stemming, burden, spacing, hole diameter, hole depth, ssDI, RMR, hole accuracy, & powder factor.**
- **Stemming to hole depth ratio ; Burden to spacing ratio.**

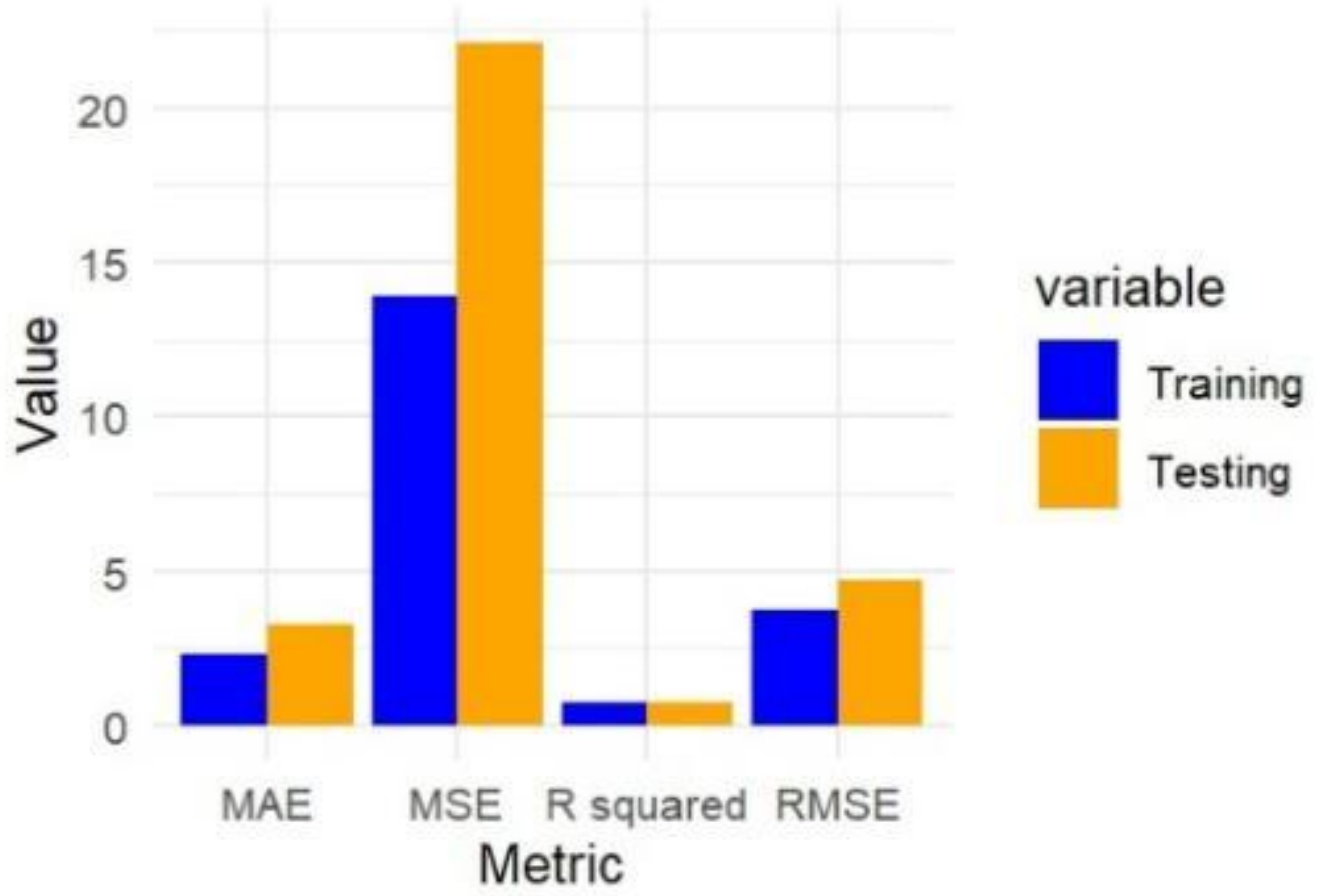
Model Selection

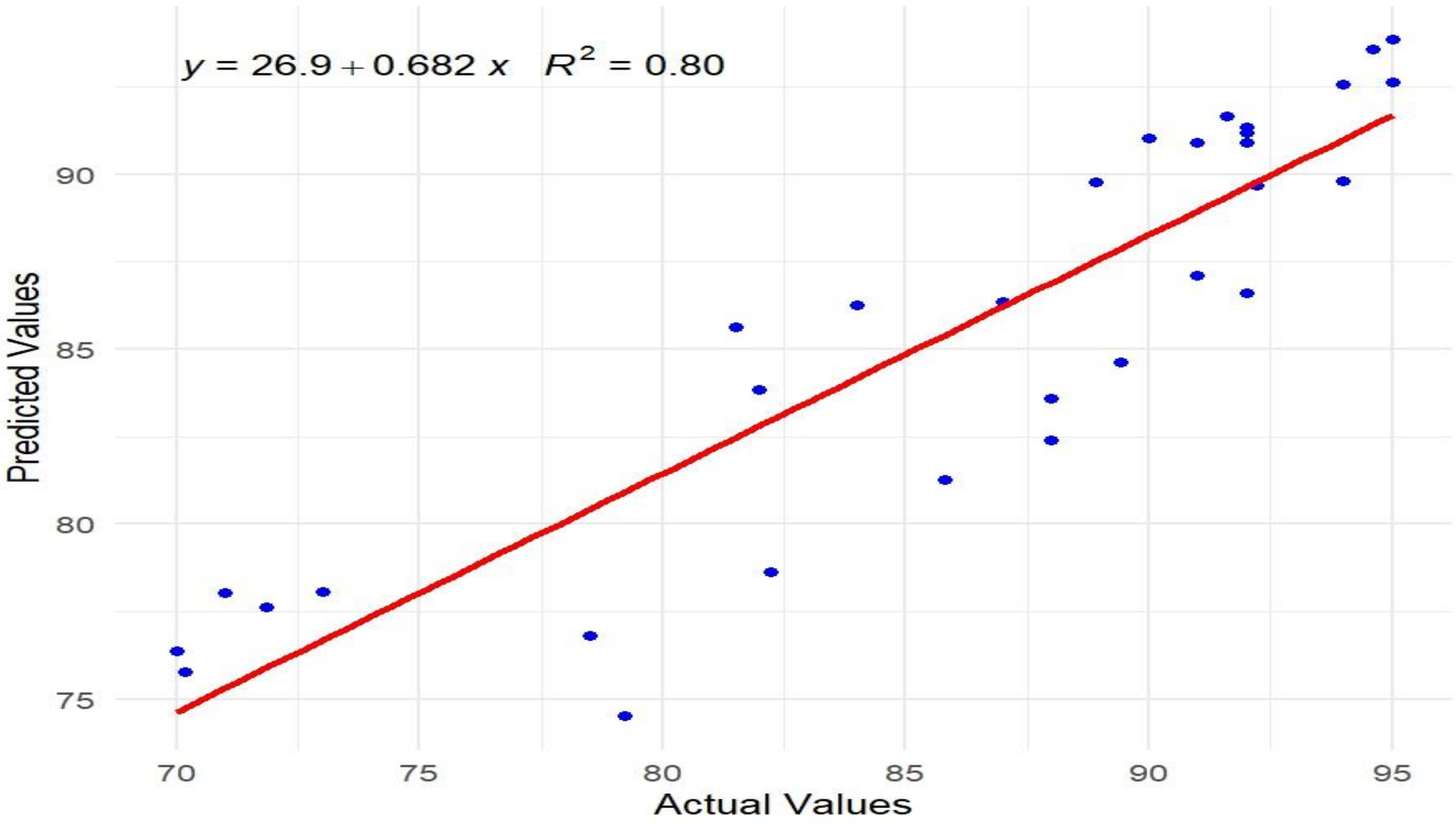
Model	Key Features	Algorithm	Hyperparameters
Random Forest	Handles complex, nonlinear relationships and large datasets	$Y = \frac{1}{T}\sum_{t=0}^{T} \hat{y}it = \hat{Y}\, t$	(n tree = 1000); interaction terms, Polynomial features + Recursive feature importance
Support Vector Regression (SVR)	Captures nonlinear interactions using kernel methods	Min $\frac{1}{2}\|\|W\|\|^2$ subject to $\|- (w.xi + b)\| \leq \epsilon$	epsilon = 0, c = 8, gamma = 0.5. Linear kernel + polynomial features.
XG BOOST	Iteratively optimizes weak learners with regularization	Obj = L(yi, $\widehat{yi}$) + $\sum_{i=1}^{k} \Omega(fk)$	cross validation (best of rounds), polynomial features + interaction terms + logarithmic transformation



Support Vector Regression Model

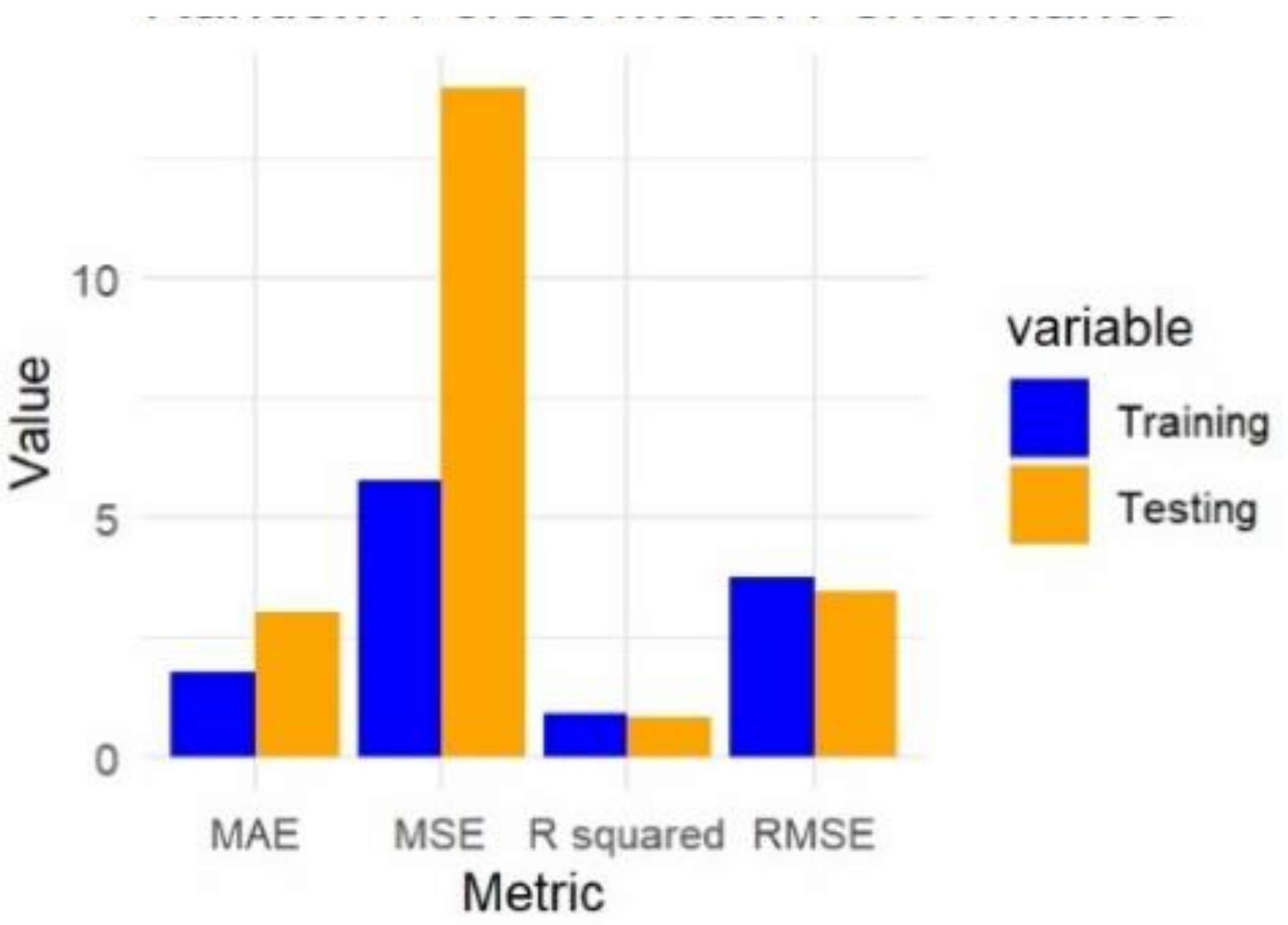
SVR Model Performance Summary

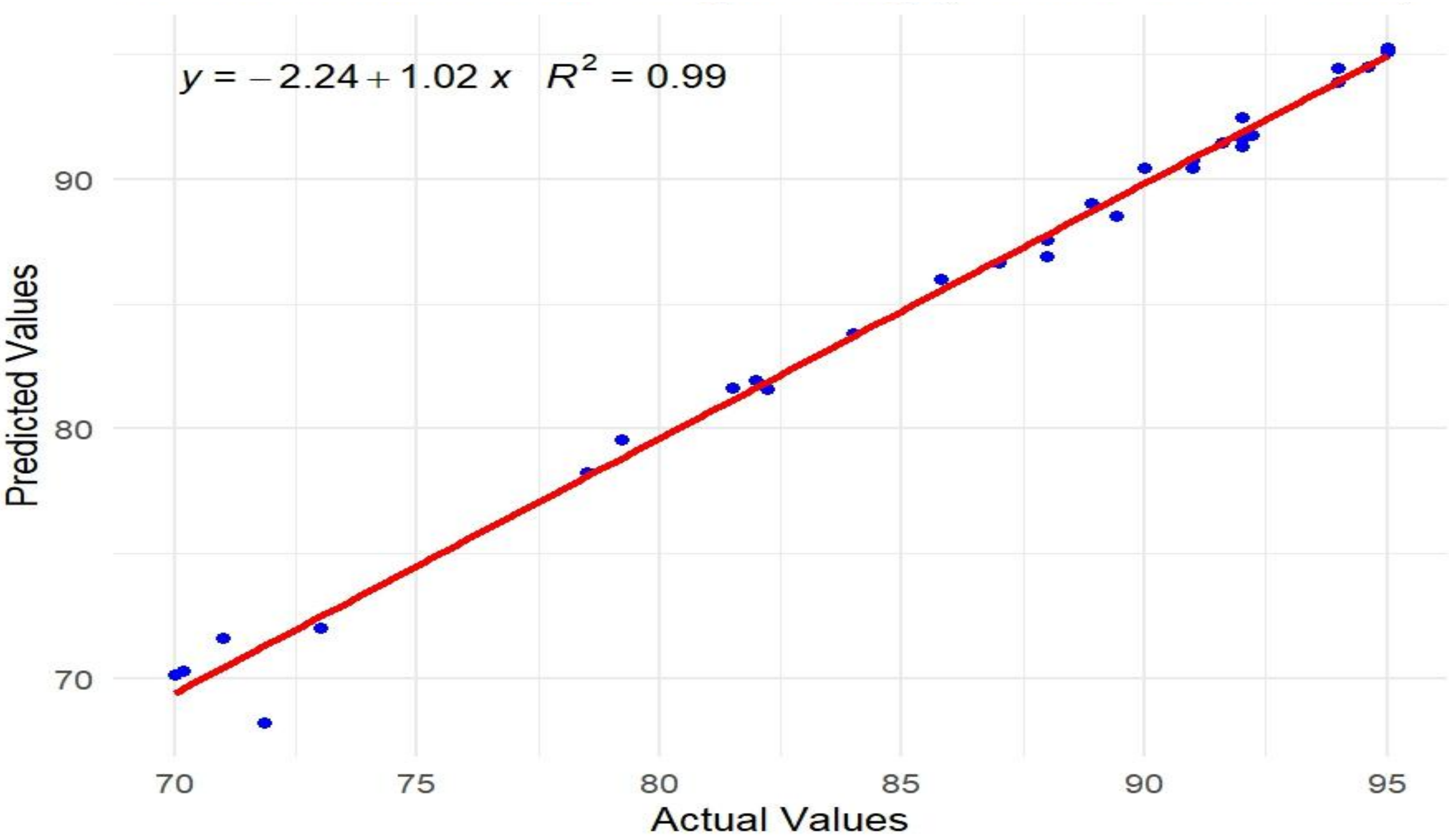




Random Forest Model

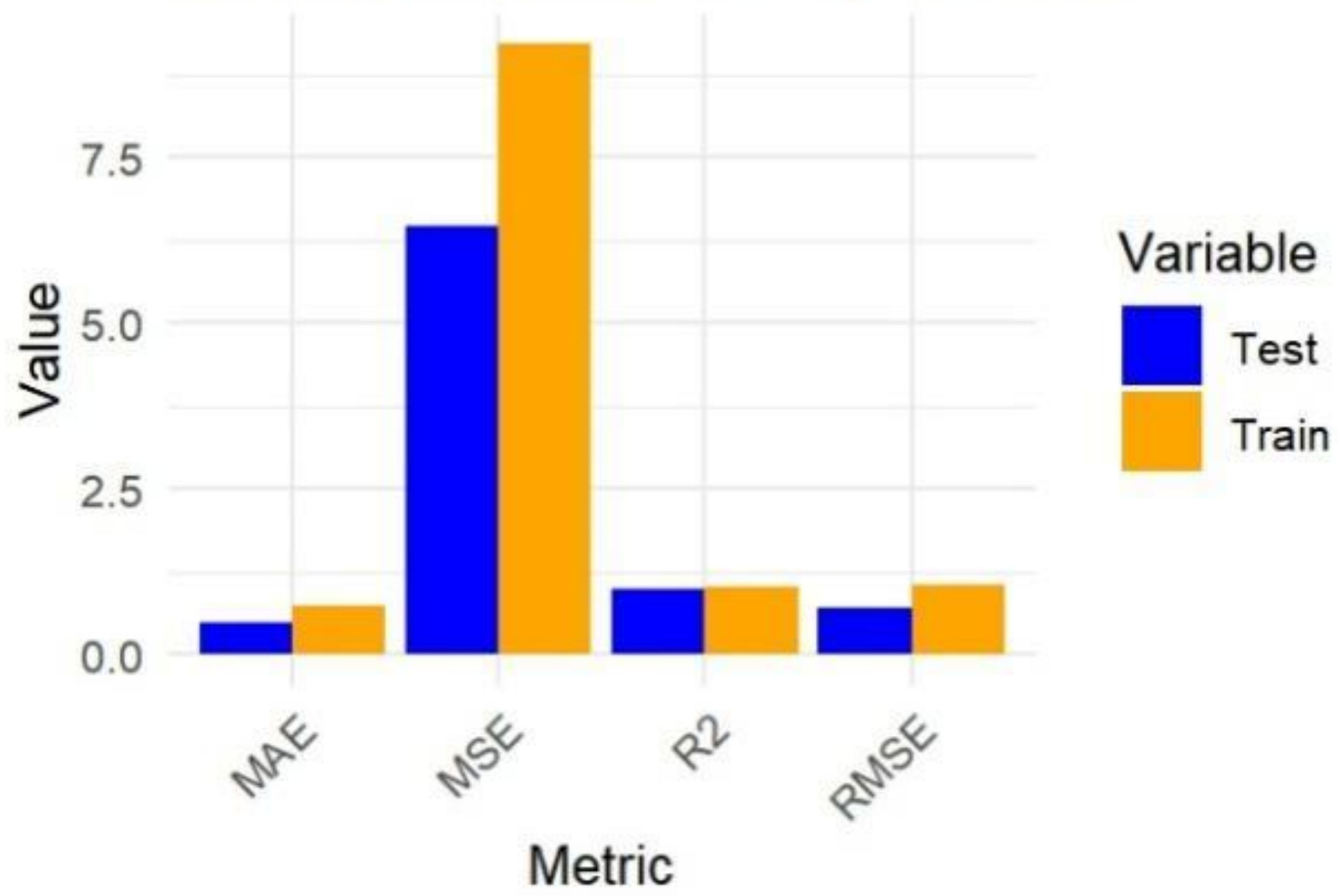
Random Forest Perfomance Summary





XG Boost Model

XG BOOST Model Perfomance Summary



Key Findings

- Geological discontinuities significantly influence blast fragmentation behavior.
- Crucial need for site specific geological indices (ssDI).
- ssDI strongly correlates negatively with fragmentation outcomes.

Key Findings

- XGBoost achieved near-perfect fragmentation prediction accuracy
- Integration of geological data in ML models enables accurate fragmentation prediction
- Adaptive blast design strategies to align with site specific geological constraints

THANK YOU

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