TROBOLOGIE - DLC COATINGS

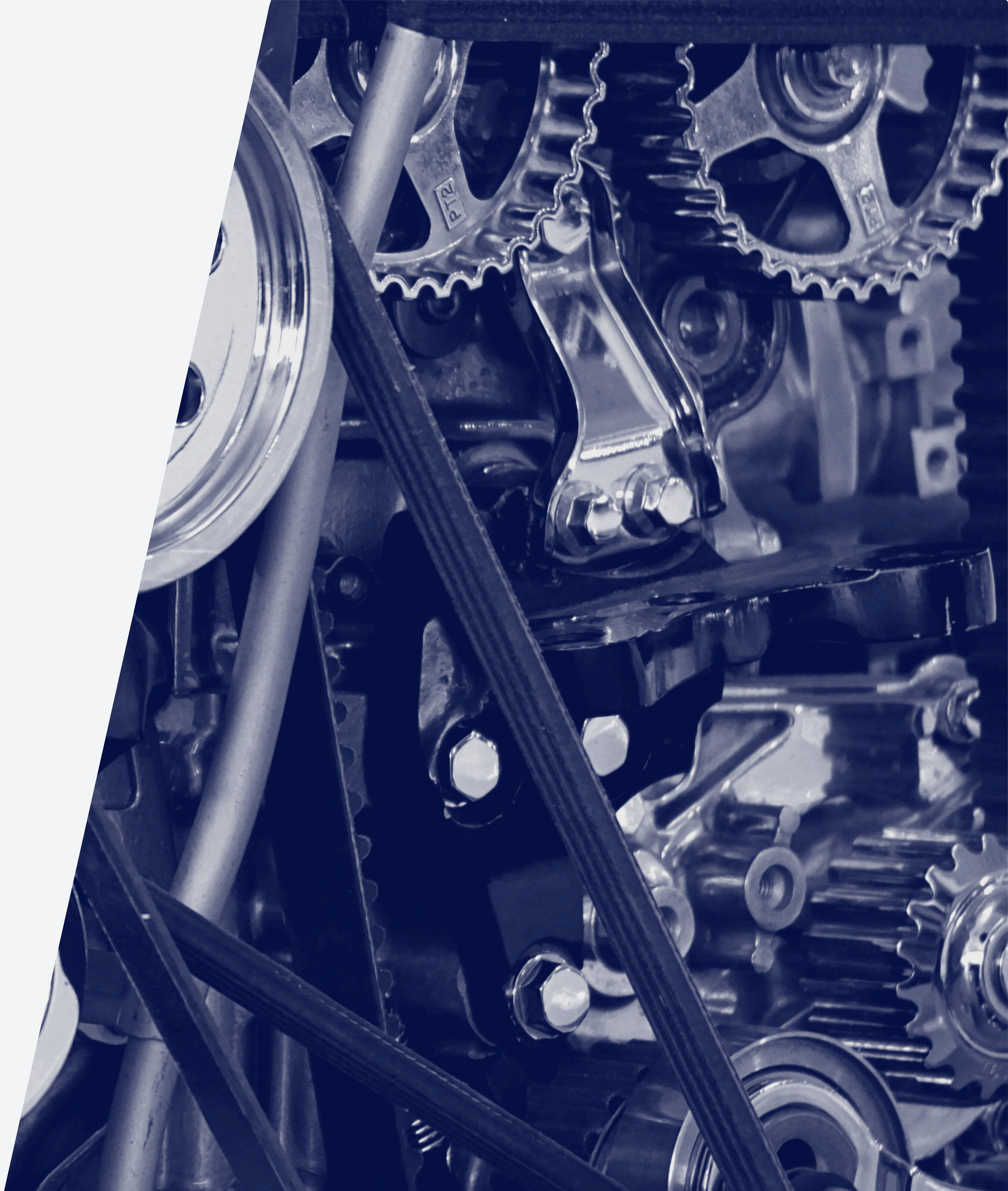
Prédiction du Coeffiction de Frottement et de l'Usure

SOPHIE CALLENS

MINES PARIS | PSL | Cemef

SOMMAIRE

1. analyse des données
2. selection de la méthode
3. selection du scenario
4. prédiction CoF et Usure
5. améliorations possibles



1. ANALYSE DES DONNÉES

a. Colonnes simplifiées

DLC type

plus de 50 DLC types différents mais qui peuvent représenter les mêmes éléments

→

DLC groupe

on garde seulement les 4 groupes :
a-C, ta-C, a-C:H, ta-C:H

Éléments (H, Si, ...)

environ 10 éléments différents avec des présences complexes

→

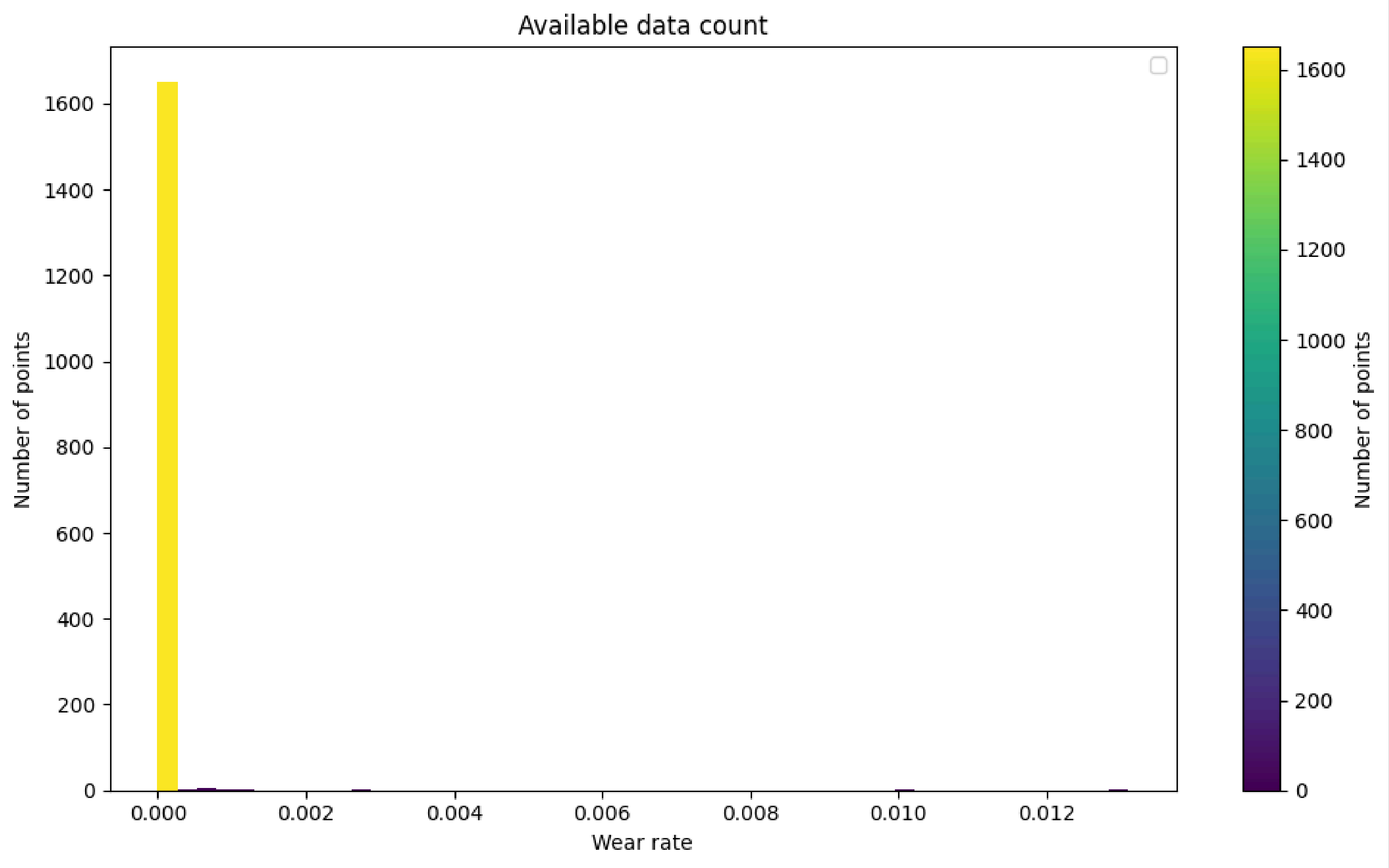
Doped

1 pour présence d'un dopant, 0 sinon
on garde présence ou non des éléments

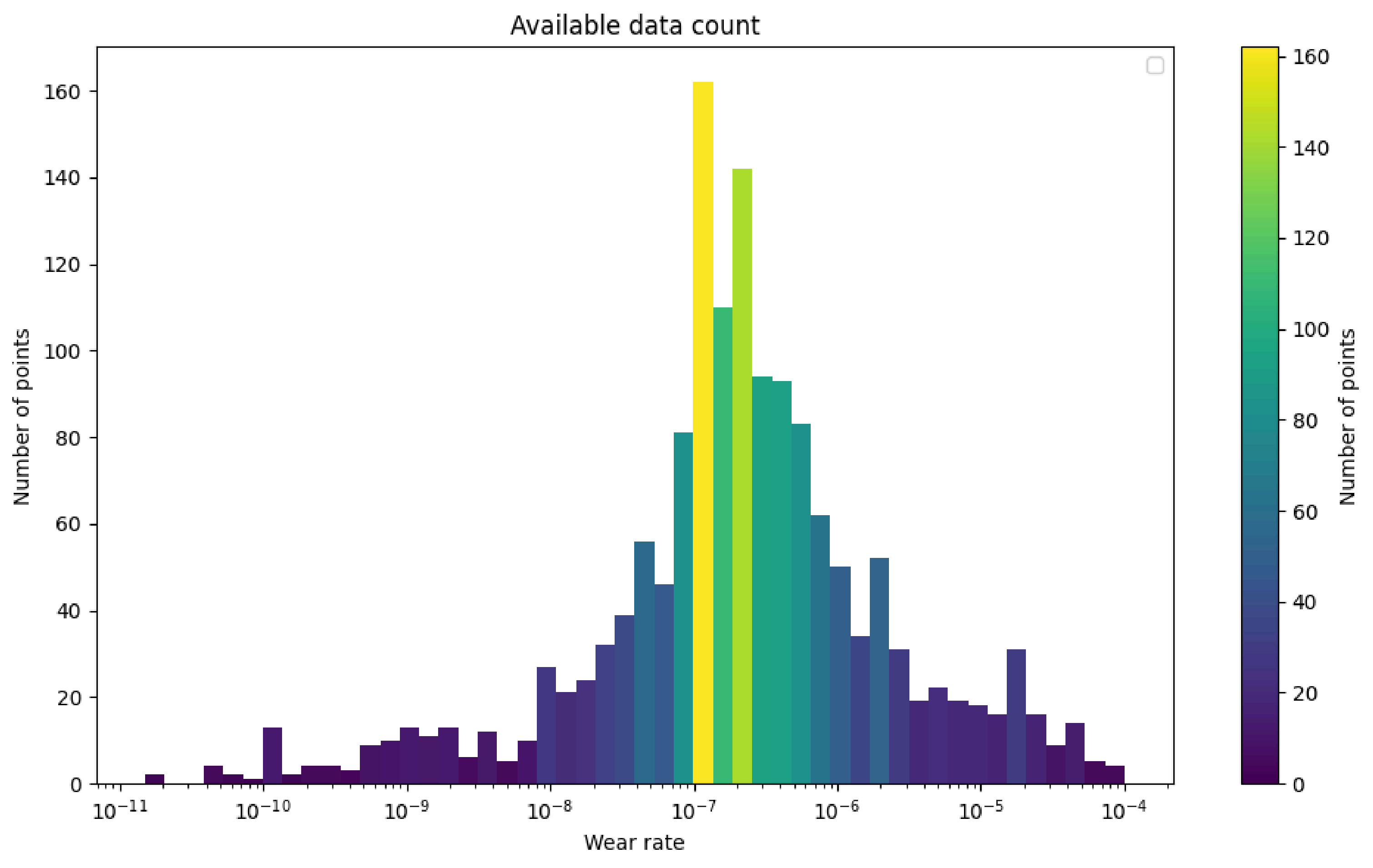
1. ANALYSE DES DONNÉES

b. passage à l’échelle log

Wear rate :



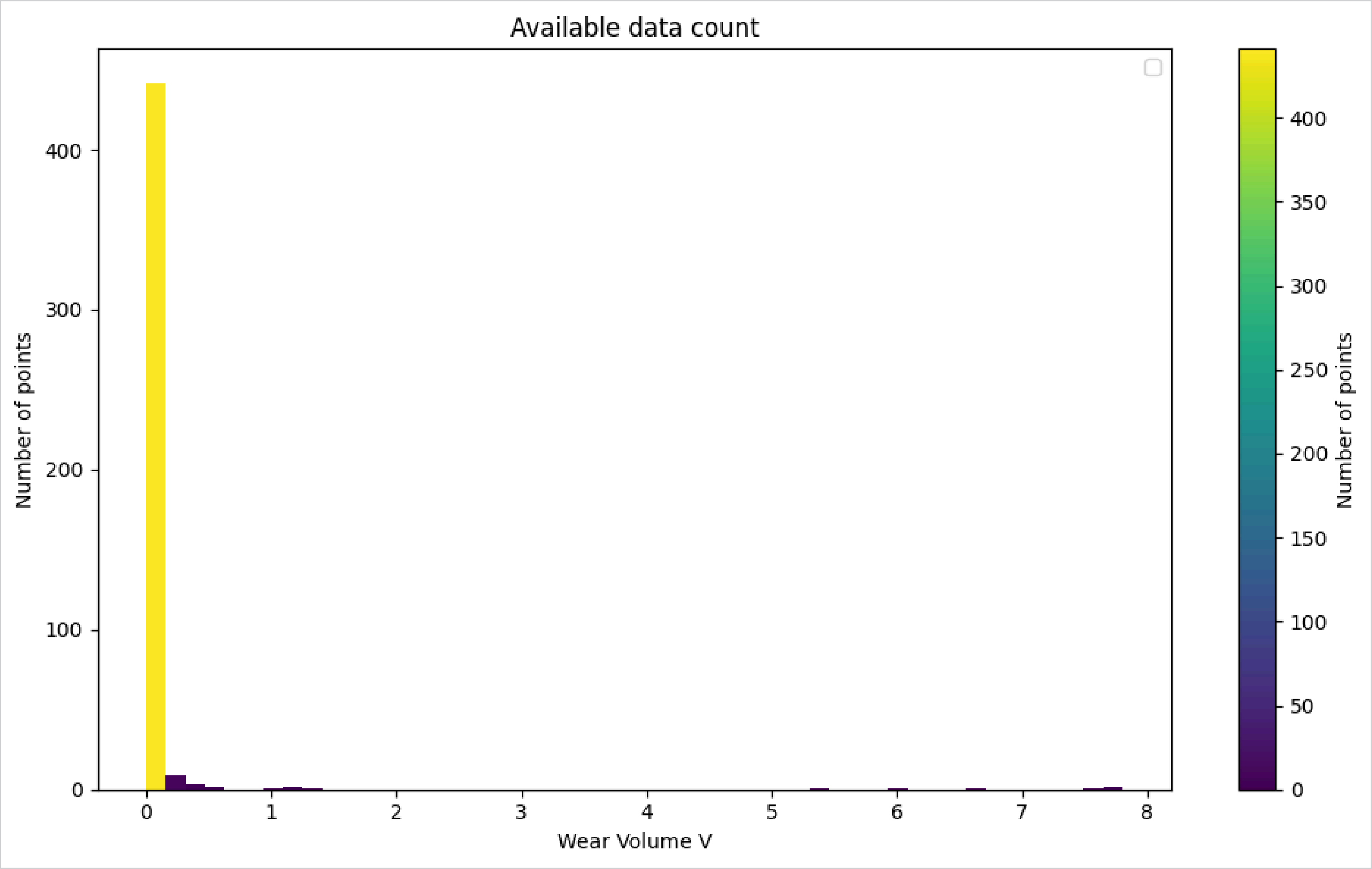
log10(Wear rate) :



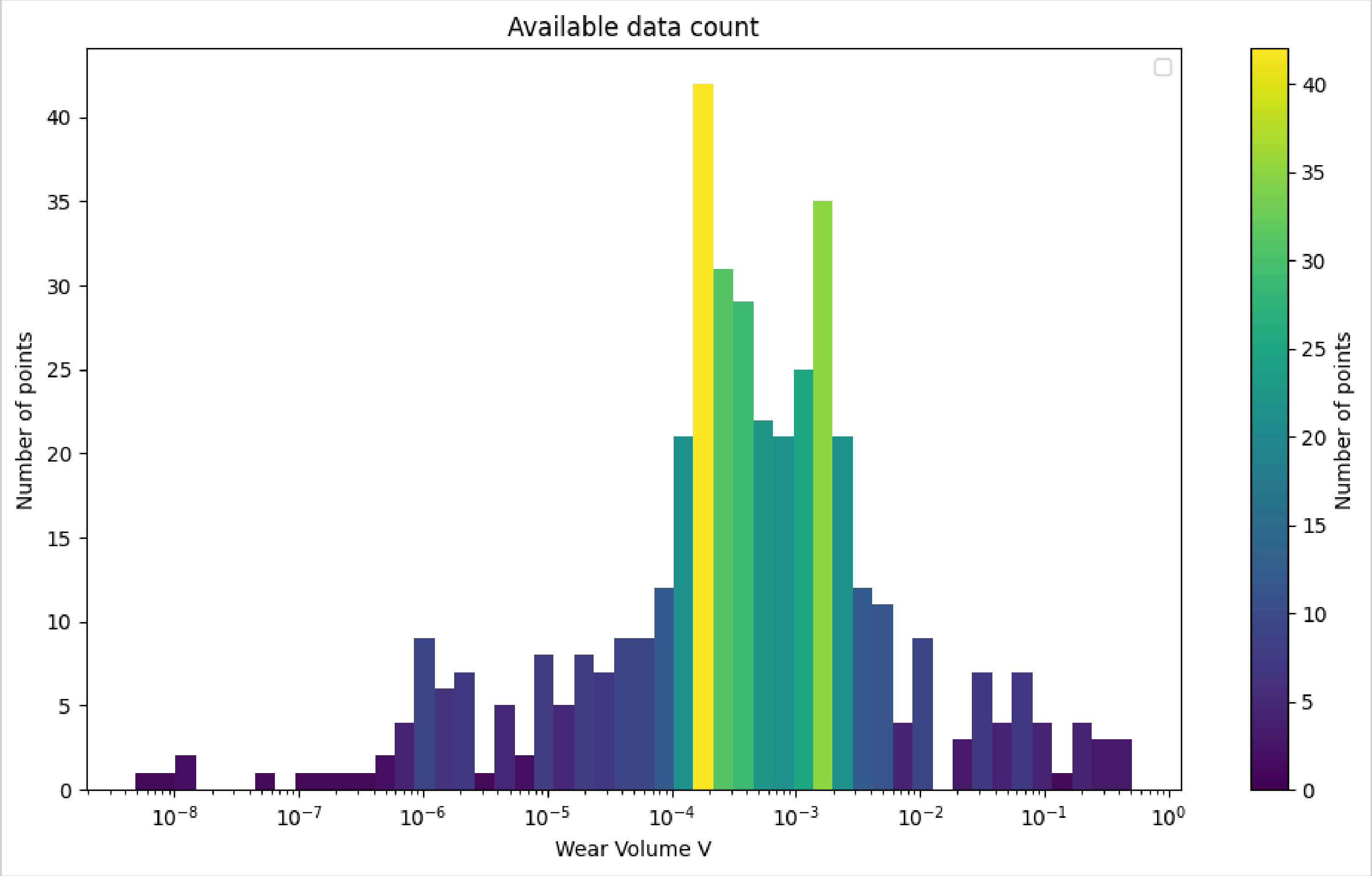
1. ANALYSE DES DONNÉES

b. passage à l’échelle log

Wear Volume :



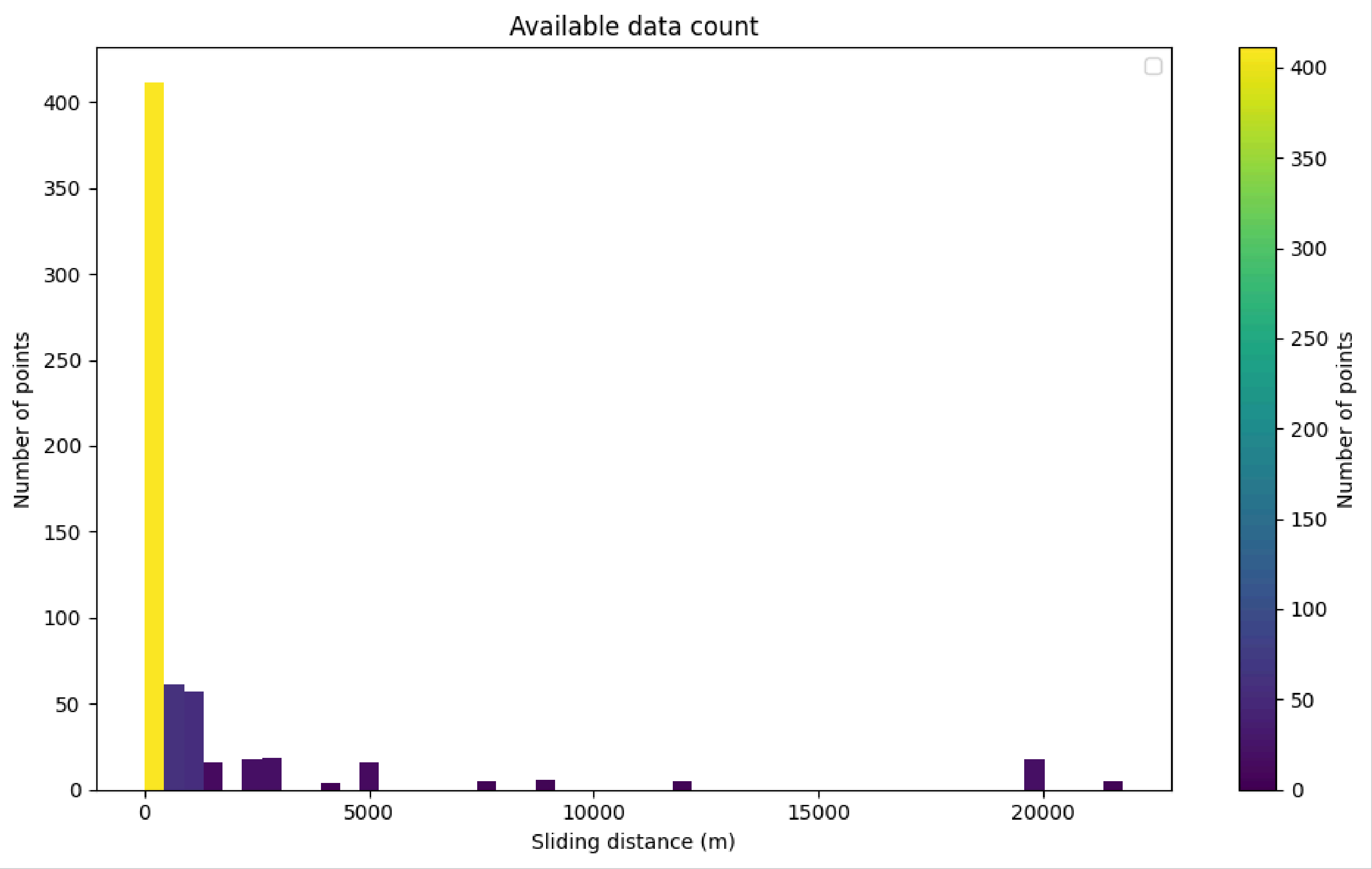
log10(Wear Volume) :



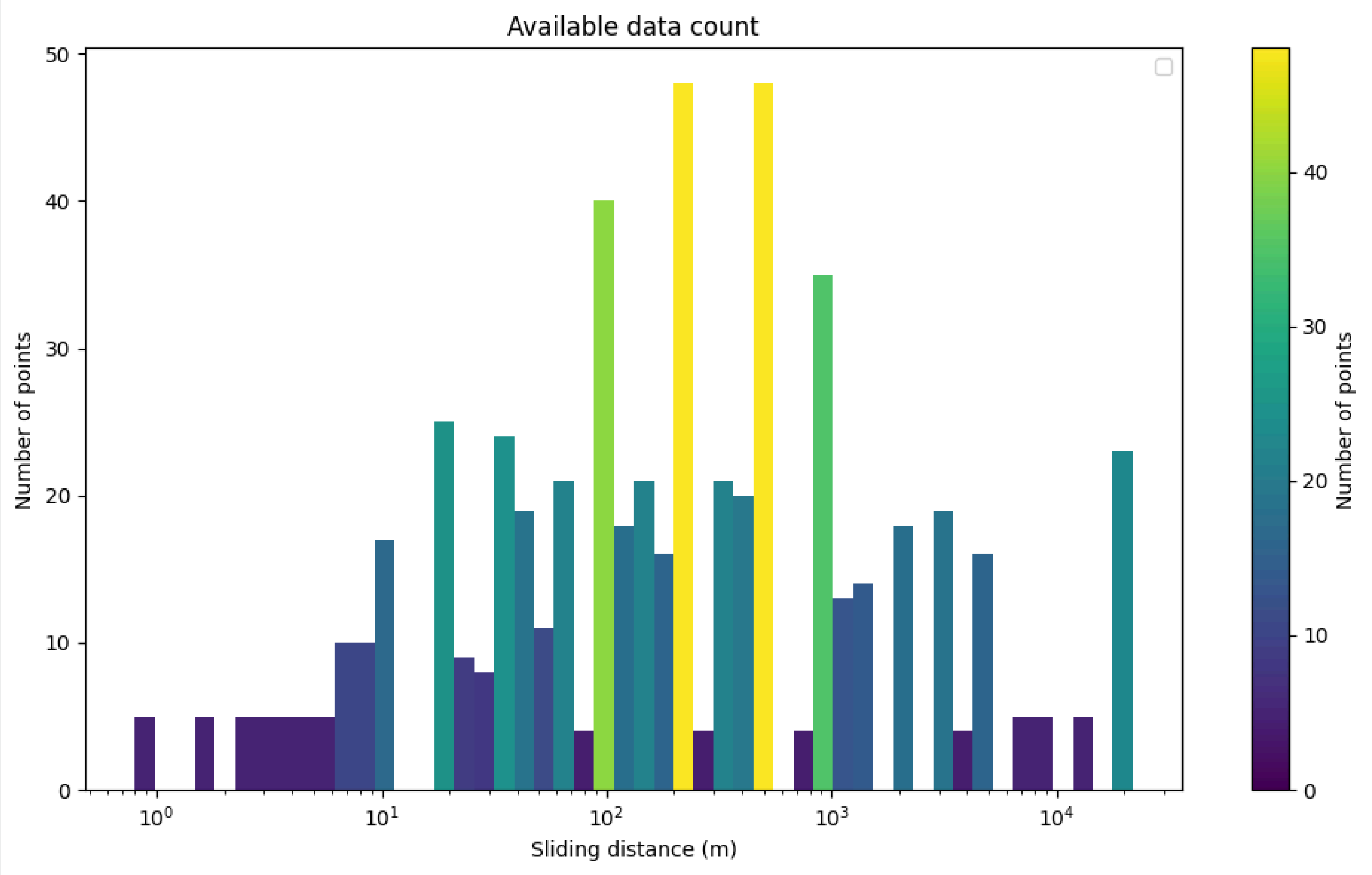
1. ANALYSE DES DONNÉES

b. passage à l'échelle log

Sliding distance :



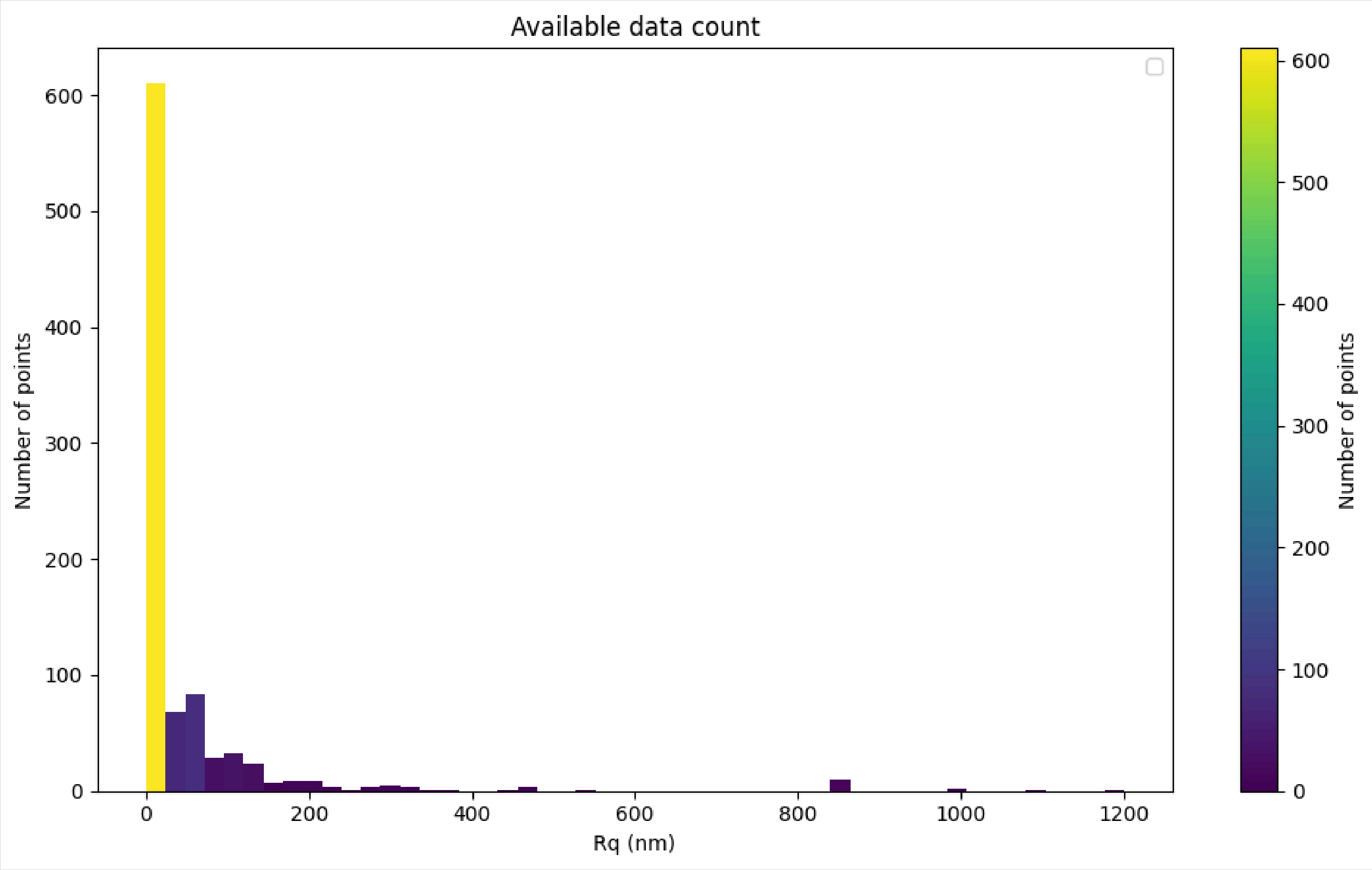
log10(Sliding distance) :



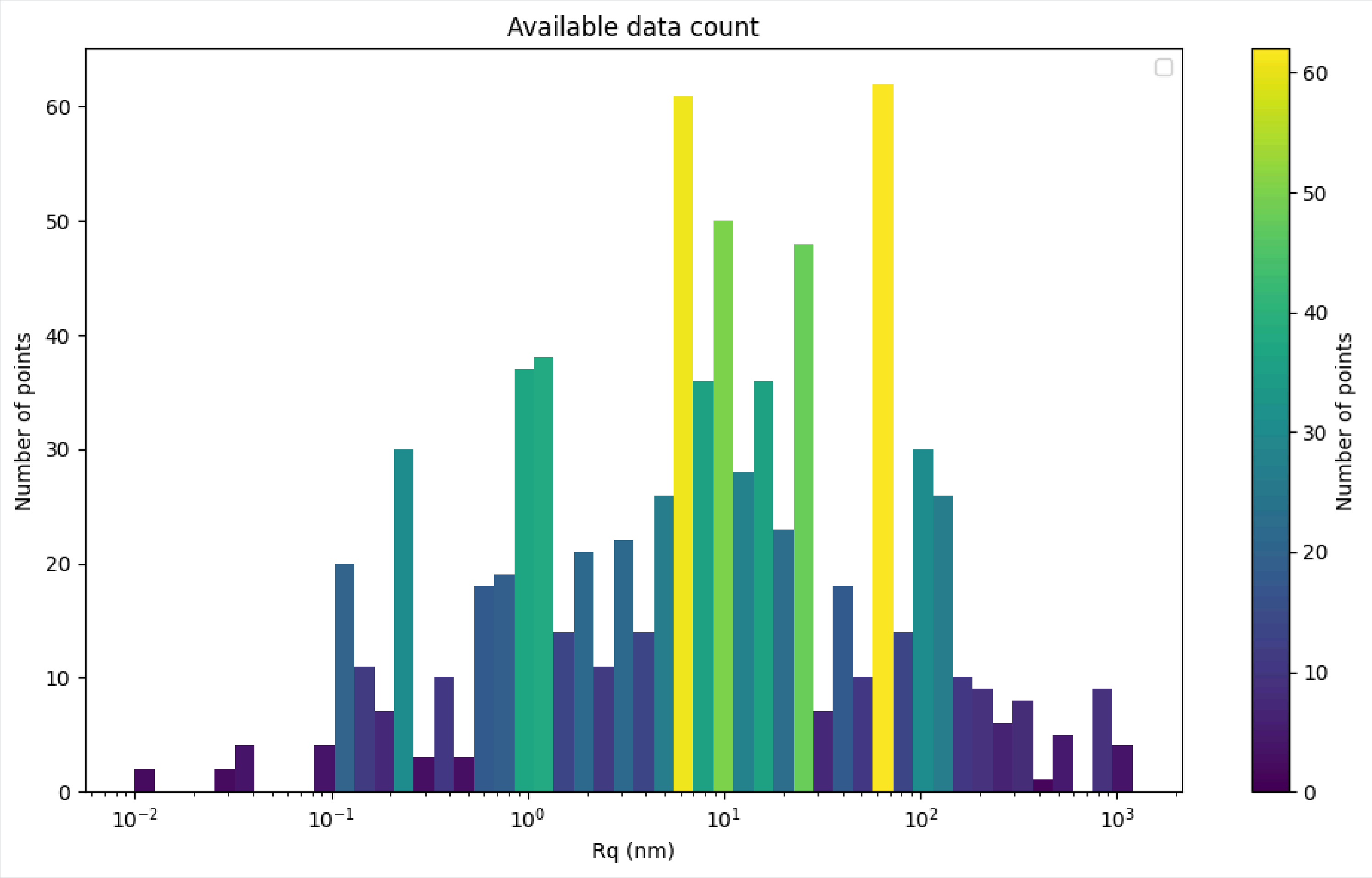
1. ANALYSE DES DONNÉES

b. passage à l'échelle log

Rq (nm) :



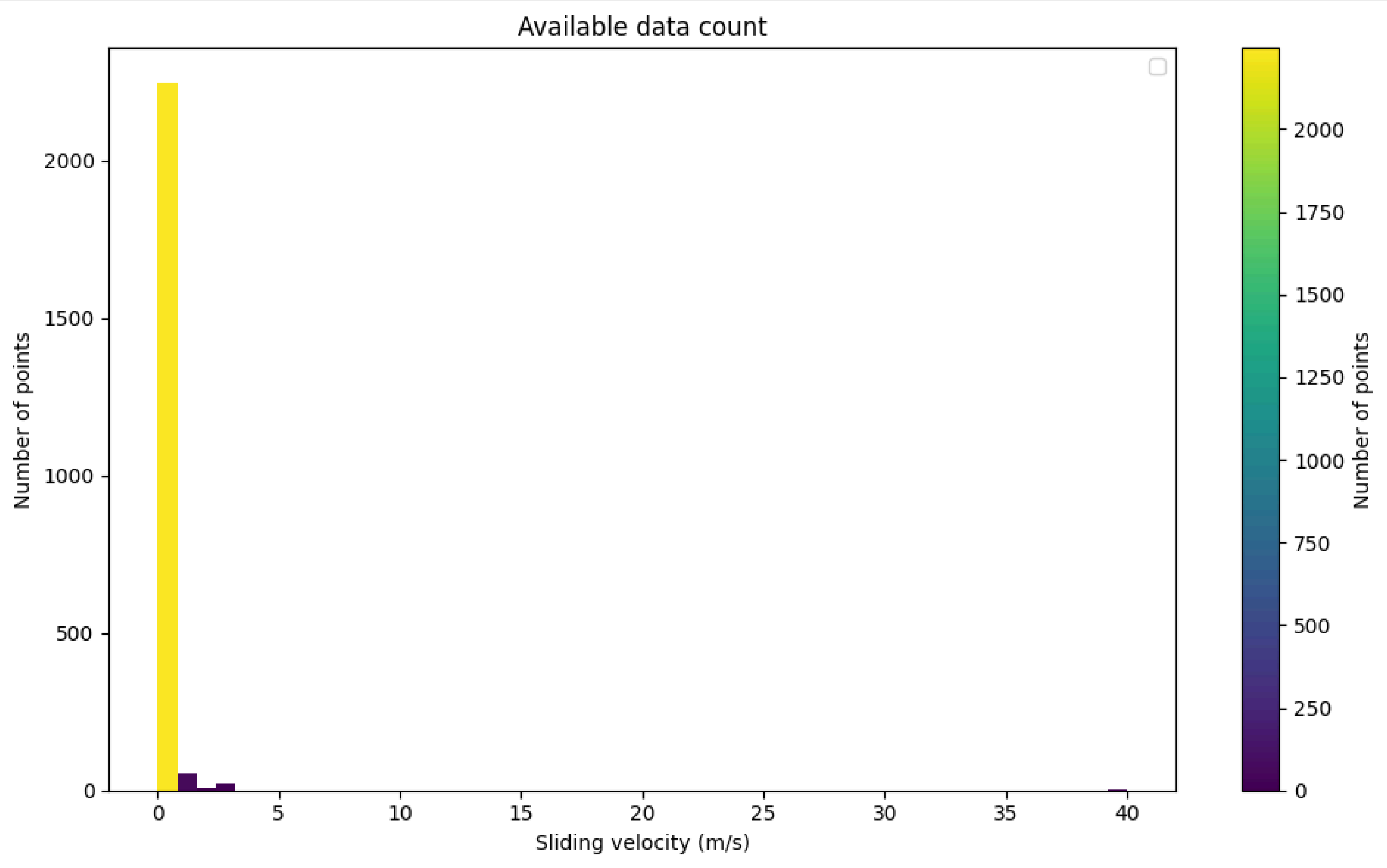
log10(Rq (nm)) :



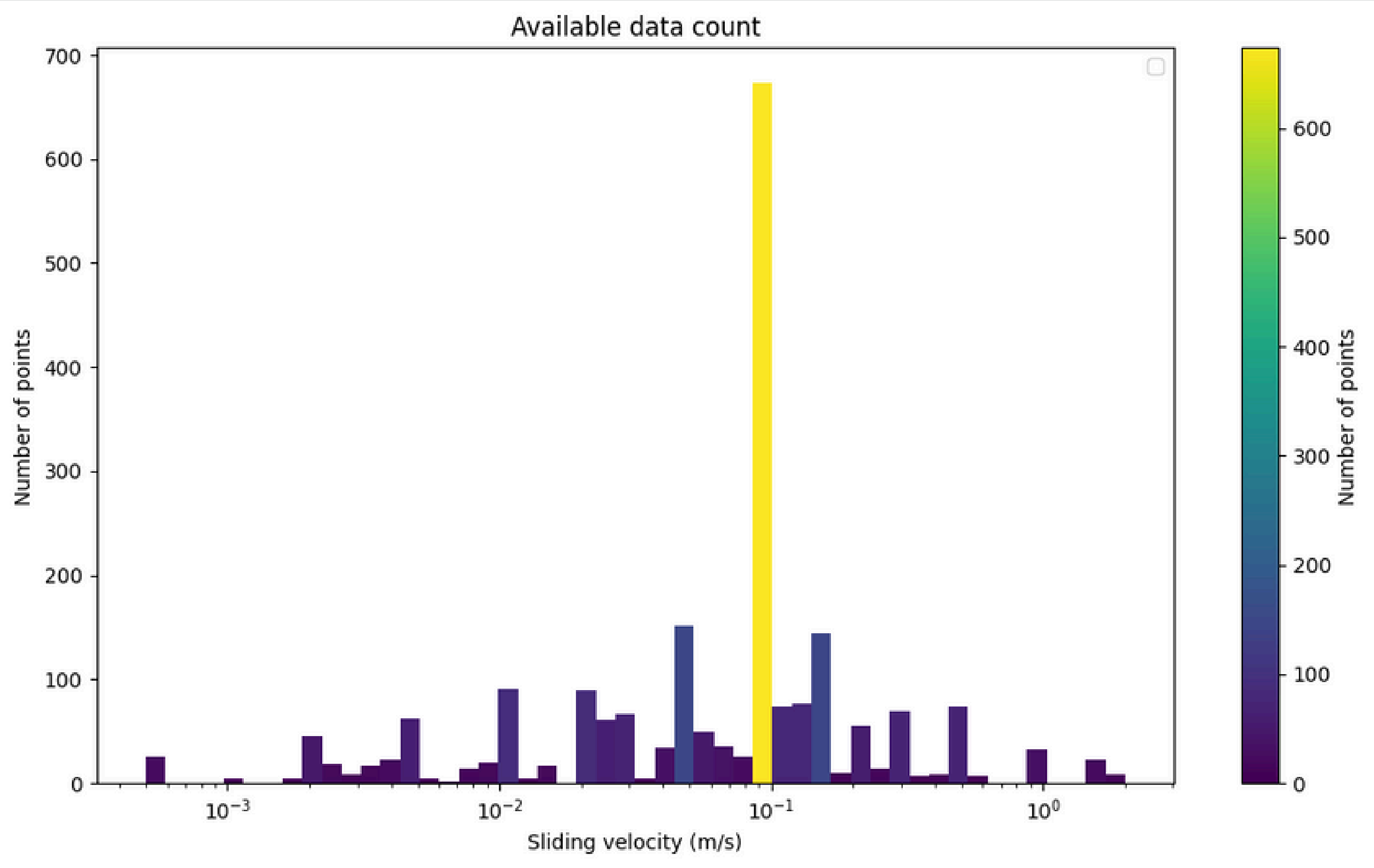
1. ANALYSE DES DONNÉES

b. passage à l'échelle log

sliding velocity :

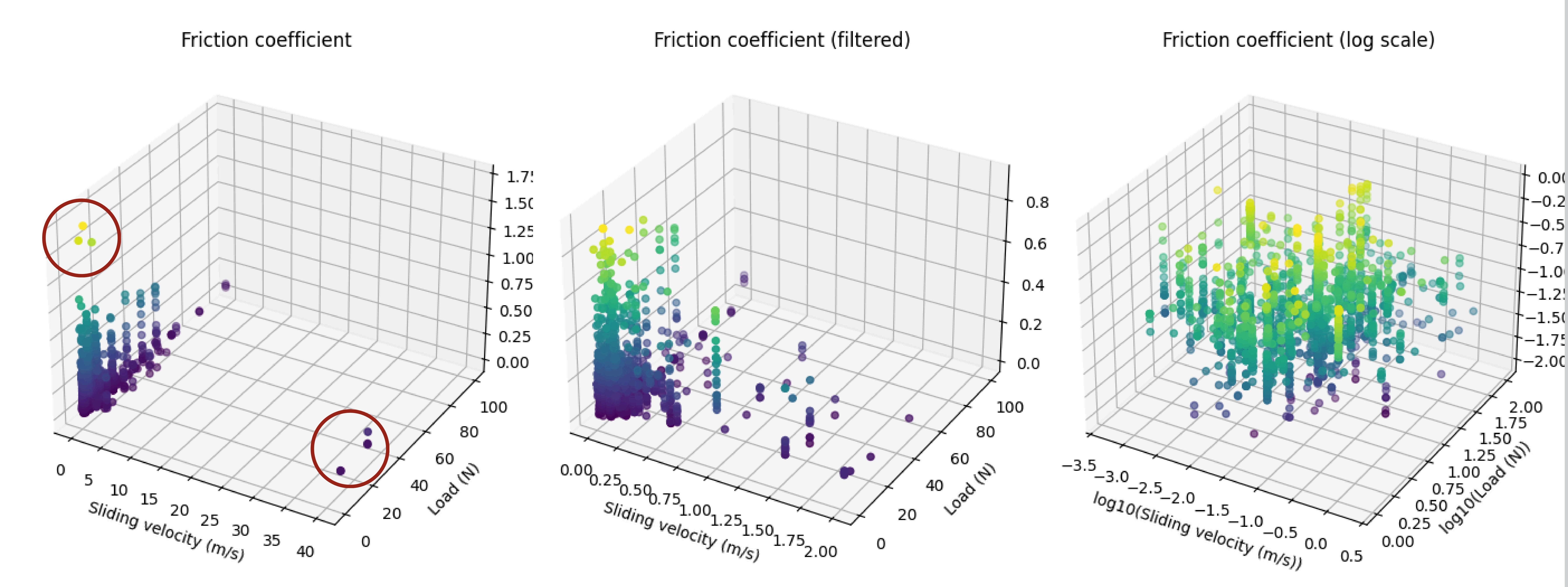


log10(sliding velocity) :



1. ANALYSE DES DONNÉES

c. suppression des valeurs extrêmes



2. SELECTION DE LA MÉTHODE

a. définition méthodes d’implémentation

passthrough (none)

mean

median

knn

Humidity	Load (N)	...	Film Hardness
40	2	...	8,5
NaN	1	...	14
60	5	...	12,5
50	**NaN**	...	8,8
40	5	...	11,4
60	1	...	**NaN**

2. SELECTION DE LA MÉTHODE

a. définition méthodes d’implémentation

passthrough (none)

mean

median

knn

Humidity	Load (N)	...	Film Hardness
40	2	...	8,5
50	1	...	14
60	5	...	12,5
50	**2,8**	...	8,8
40	5	...	11,4
60	1	...	**11,04**

2. SELECTION DE LA MÉTHODE

a. définition méthodes d'implémentation

passthrough (none)

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Humidity	Load (N)	...	Film Hardness
40	2	...	8,5
50	1	...	14
60	5	...	12,5
50	**2**	...	8,8
40	5	...	11,4
60	1	...	**8,8**

2. SELECTION DE LA MÉTHODE

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Humidity	Load (N)	...	Film Hardness
40	2	...	8,5
60	1	...	14
60	5	...	12,5
50	**2**	...	8,8
40	5	...	11,4
60	1	...	**14**

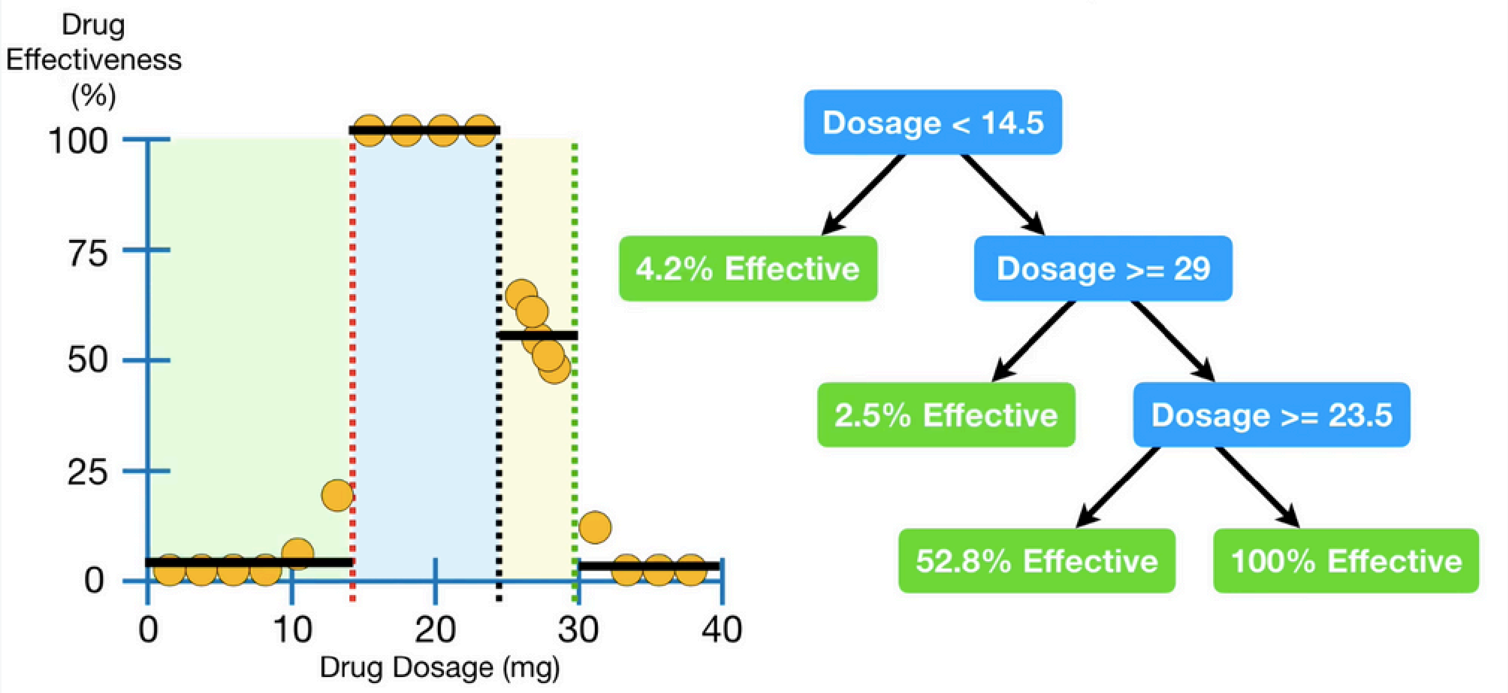
2. SELECTION DE LA MÉTHODE

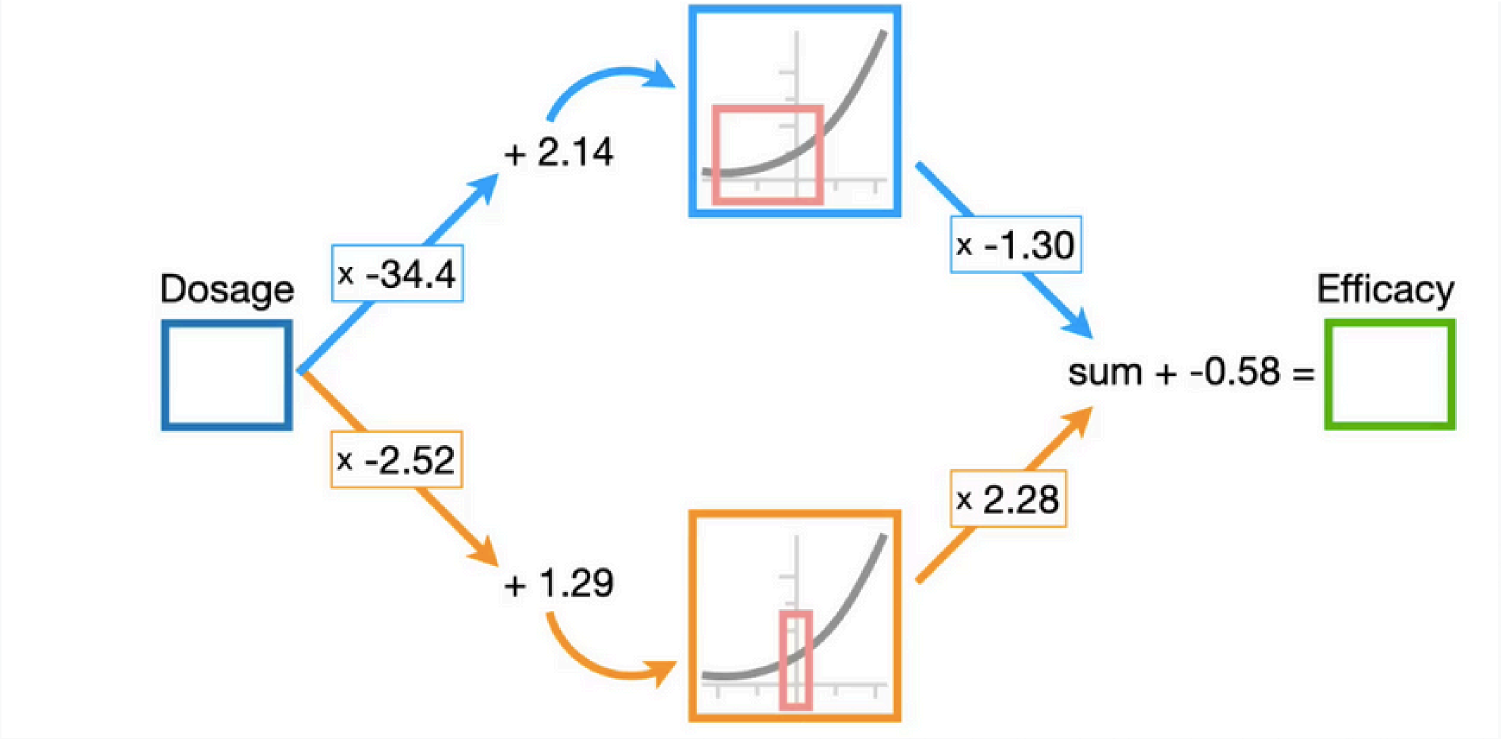
a. définition méthodes de prédiction

Extra trees
random forest
xgboost

→ **arbres de regression**

elastic net → **réseau de neurones**





source des graphiques :
StatQuest with Josh Starmer sur YouTube

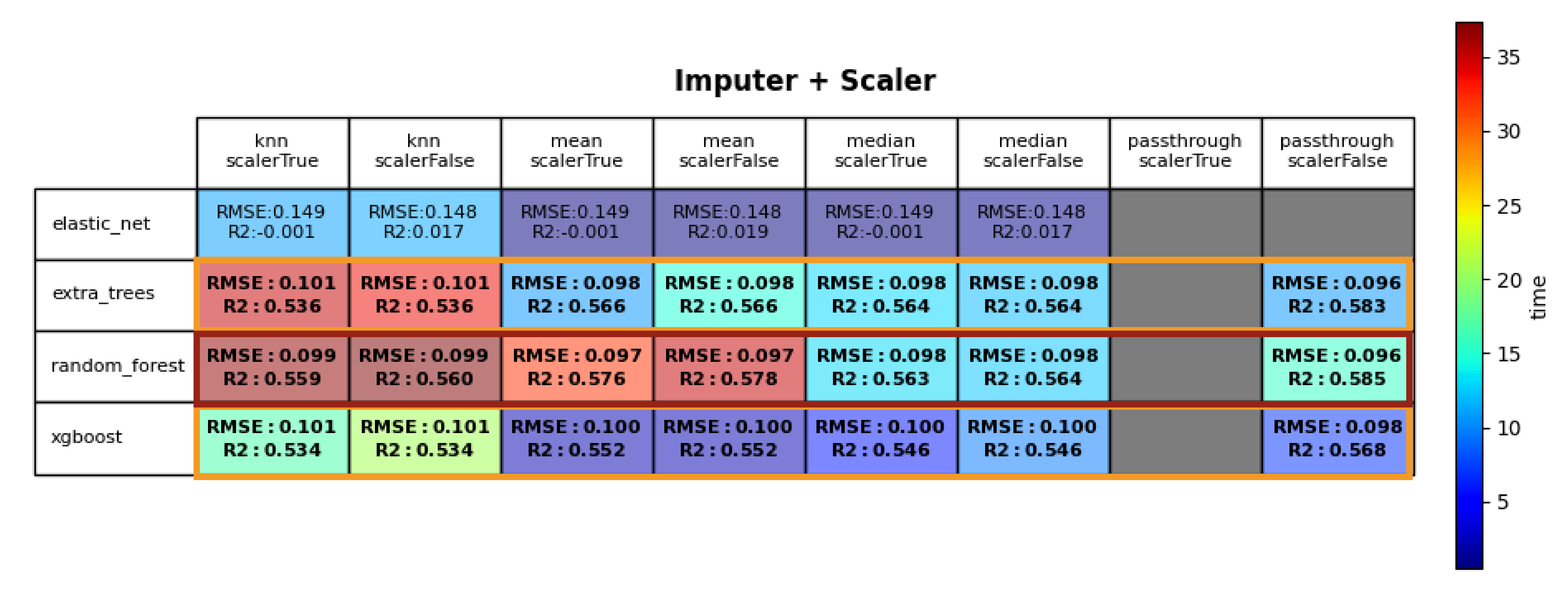
2. SELECTION DE LA MÉTHODE

b. définition des pipelines

implementation method	prediction method	scaler
passthrough (none)	extratrees	True
mean	random forest	False
median	xgboost	
knn	elastic net	

2. SELECTION DE LA MÉTHODE

c. comparaison des pipelines



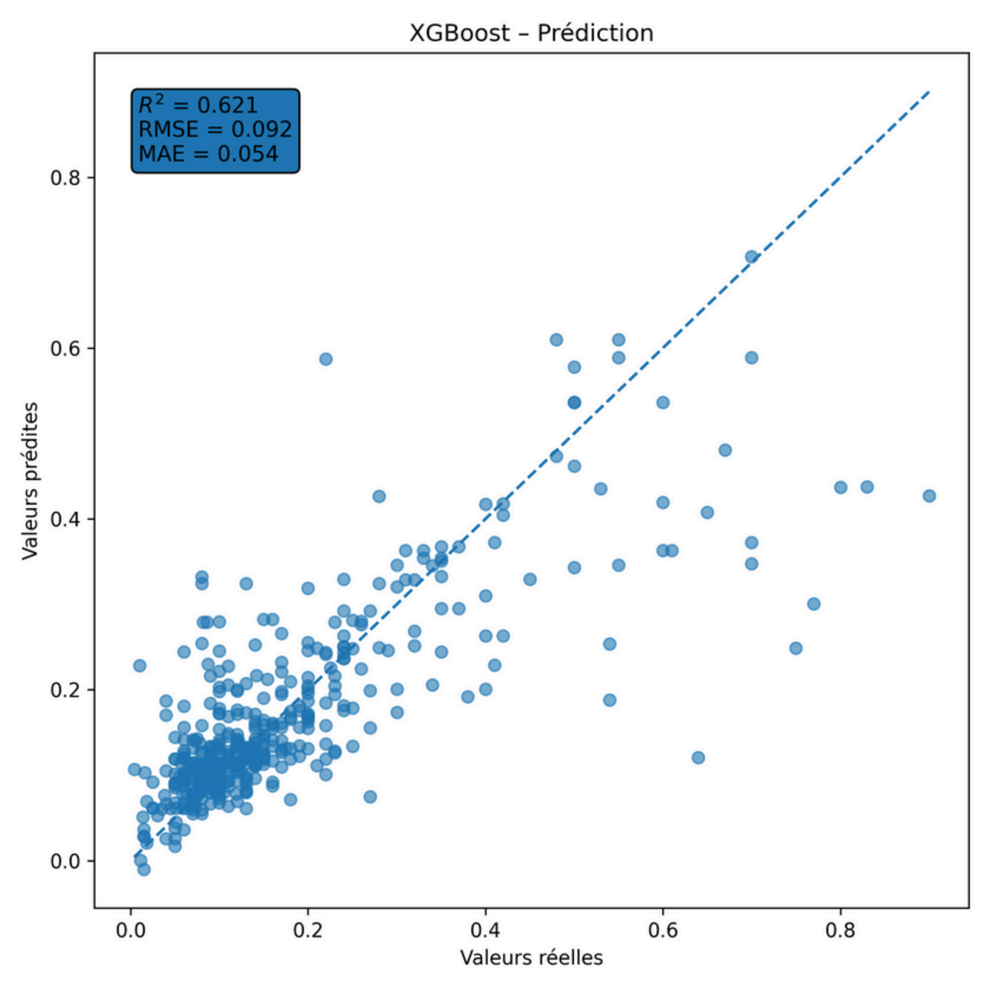
Imputer + Scaler

	knn scalerTrue	knn scalerFalse	mean scalerTrue	mean scalerFalse	median scalerTrue	median scalerFalse	passthrough scalerTrue	passthrough scalerFalse
elastic_net	RMSE:0.149 R2:-0.001	RMSE:0.148 R2:0.017	RMSE:0.149 R2:-0.001	RMSE:0.148 R2:0.019	RMSE:0.149 R2:-0.001	RMSE:0.148 R2:0.017		
extra_trees	**RMSE : 0.101 R2 : 0.536**	**RMSE : 0.101 R2 : 0.536**	**RMSE : 0.098 R2 : 0.566**	**RMSE : 0.098 R2 : 0.566**	**RMSE : 0.098 R2 : 0.564**	**RMSE : 0.098 R2 : 0.564**		**RMSE : 0.096 R2 : 0.583**
random_forest	**RMSE : 0.099 R2 : 0.559**	**RMSE : 0.099 R2 : 0.560**	**RMSE : 0.097 R2 : 0.576**	**RMSE : 0.097 R2 : 0.578**	**RMSE : 0.098 R2 : 0.563**	**RMSE : 0.098 R2 : 0.564**		**RMSE : 0.096 R2 : 0.585**
xgboost	**RMSE : 0.101 R2 : 0.534**	**RMSE : 0.101 R2 : 0.534**	**RMSE : 0.100 R2 : 0.552**	**RMSE : 0.100 R2 : 0.552**	**RMSE : 0.100 R2 : 0.546**	**RMSE : 0.100 R2 : 0.546**		**RMSE : 0.098 R2 : 0.568**

2. SELECTION DE LA MÉTHODE

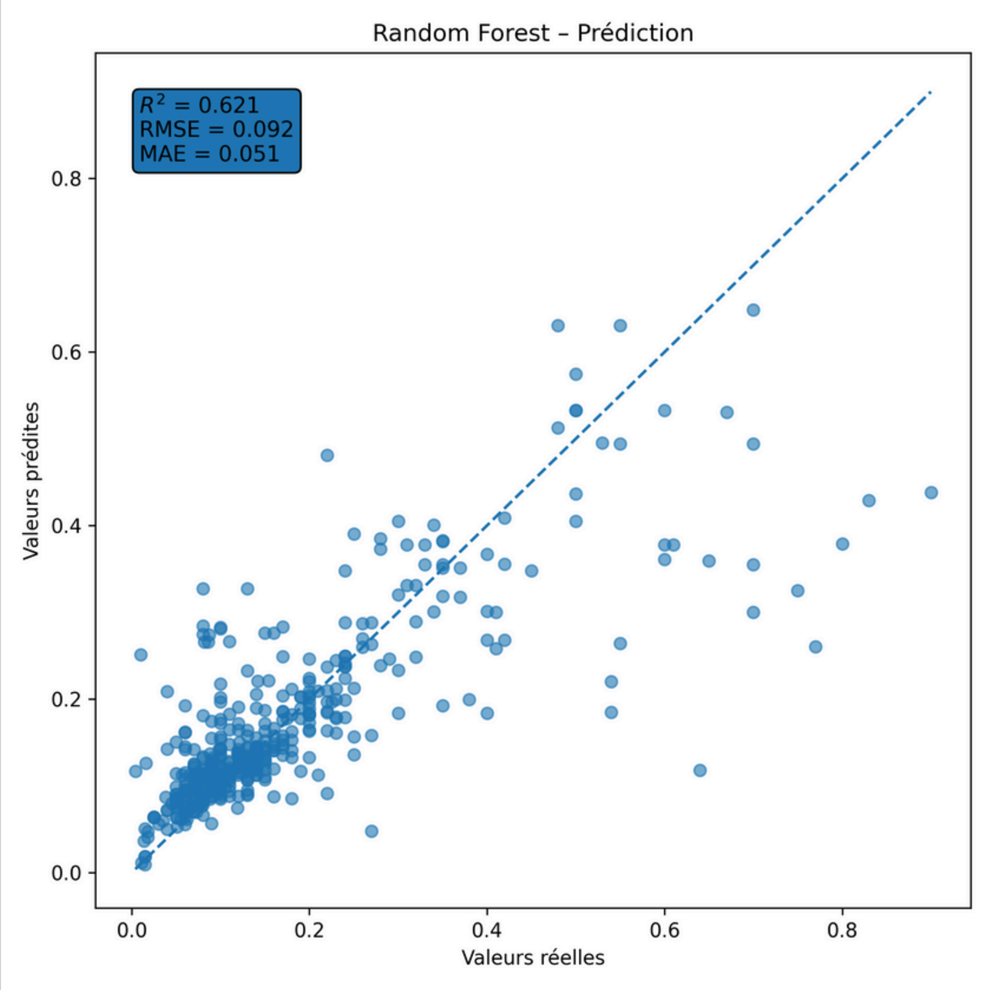
d. comparaison **CoF** après optimisation des hyperparamètres

XGBoost



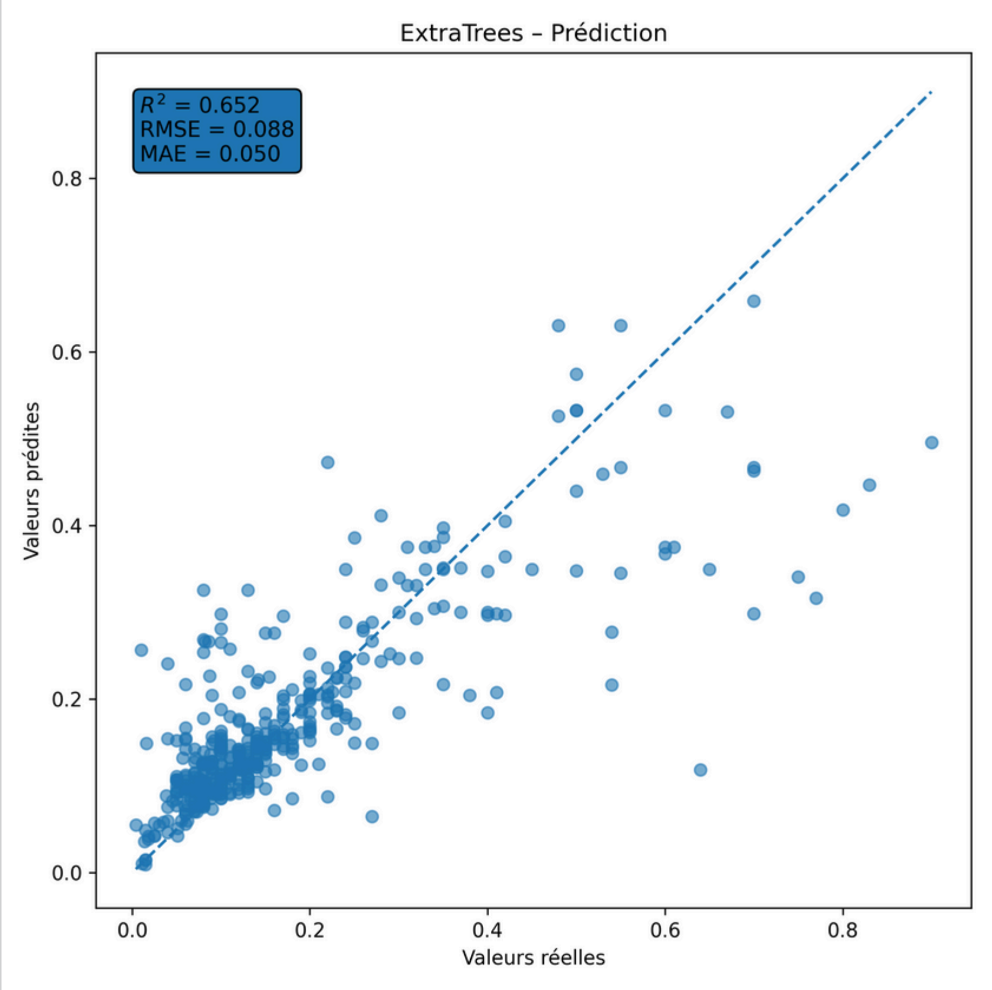
scenario 1 - RMSE

Random forest



scenario 2 - R^2

Extra Trees



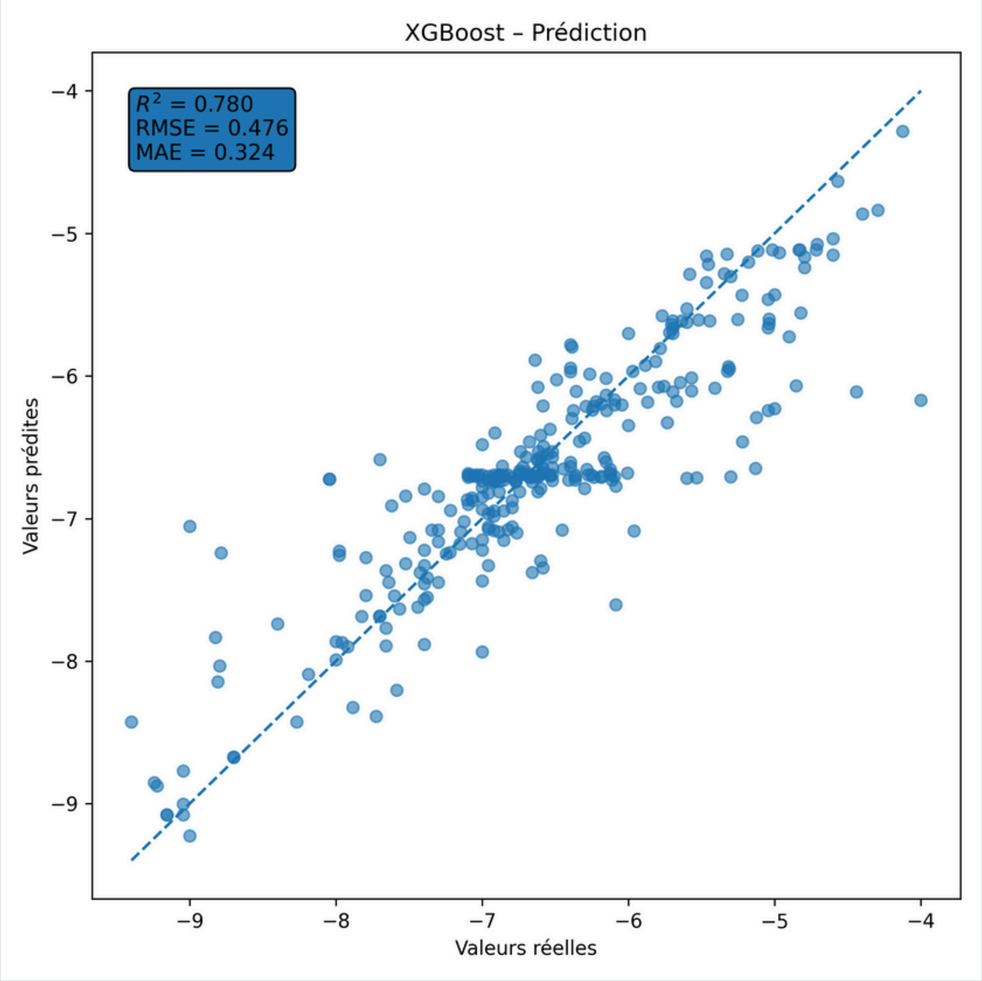
scenario 2 - RMSE

optimisation par maximisation de R^2 ou minimisation de RMSE

2. SELECTION DE LA MÉTHODE

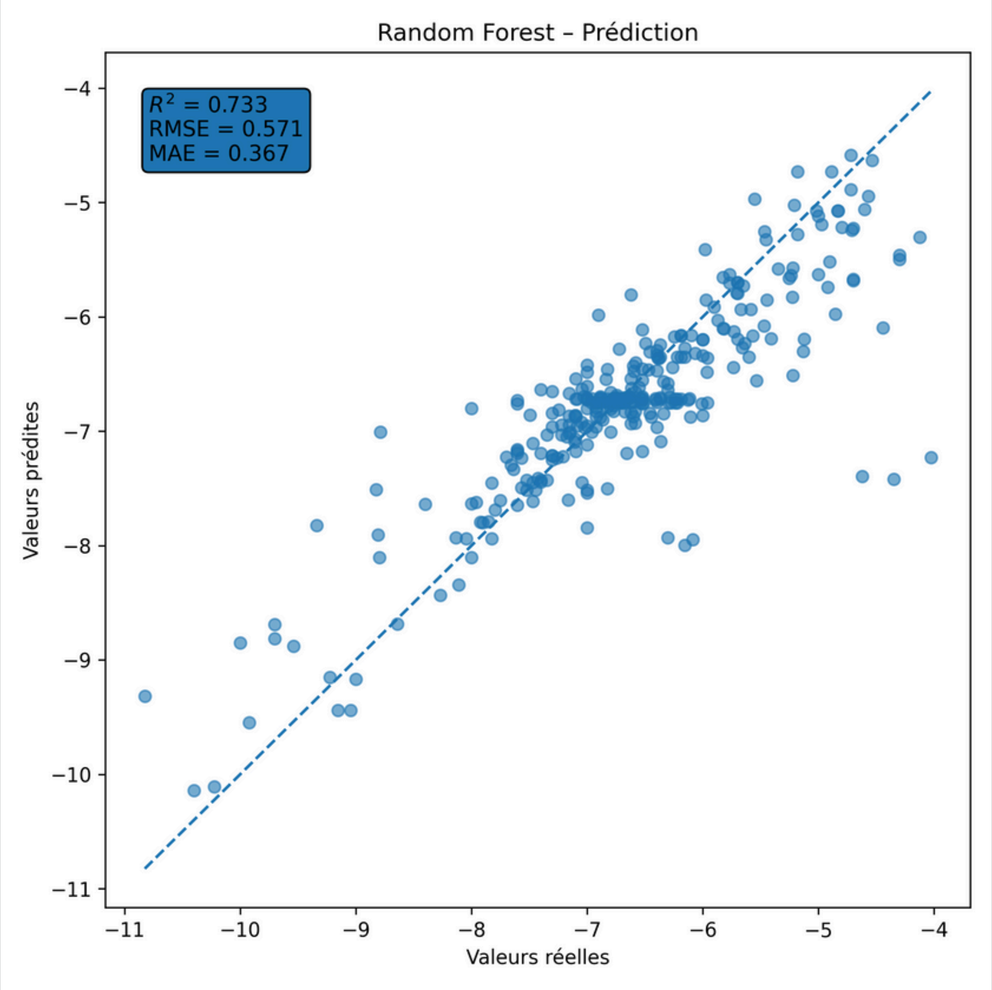
e. comparaison **Wear** après optimisation des hyperparamètres

XGBoost



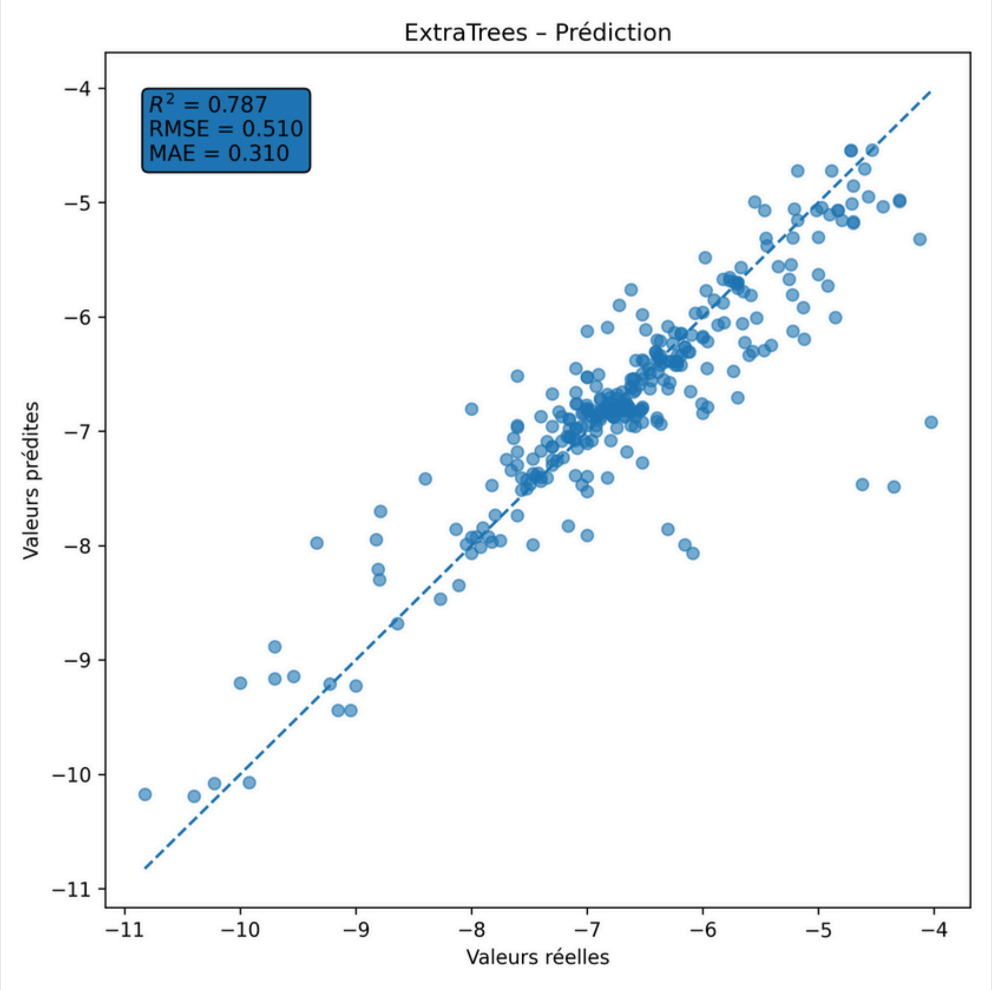
scenario 2 - RMSE

Random forest



scenario 2 - R^2

Extra Trees



scenario 2 - RMSE

optimisation par maximisation de R^2 ou minimisation de RMSE

2. SELECTION DE LA MÉTHODE

c. comparaison Wear après optimisation des hyperparamètres

=> EXTRA TREES

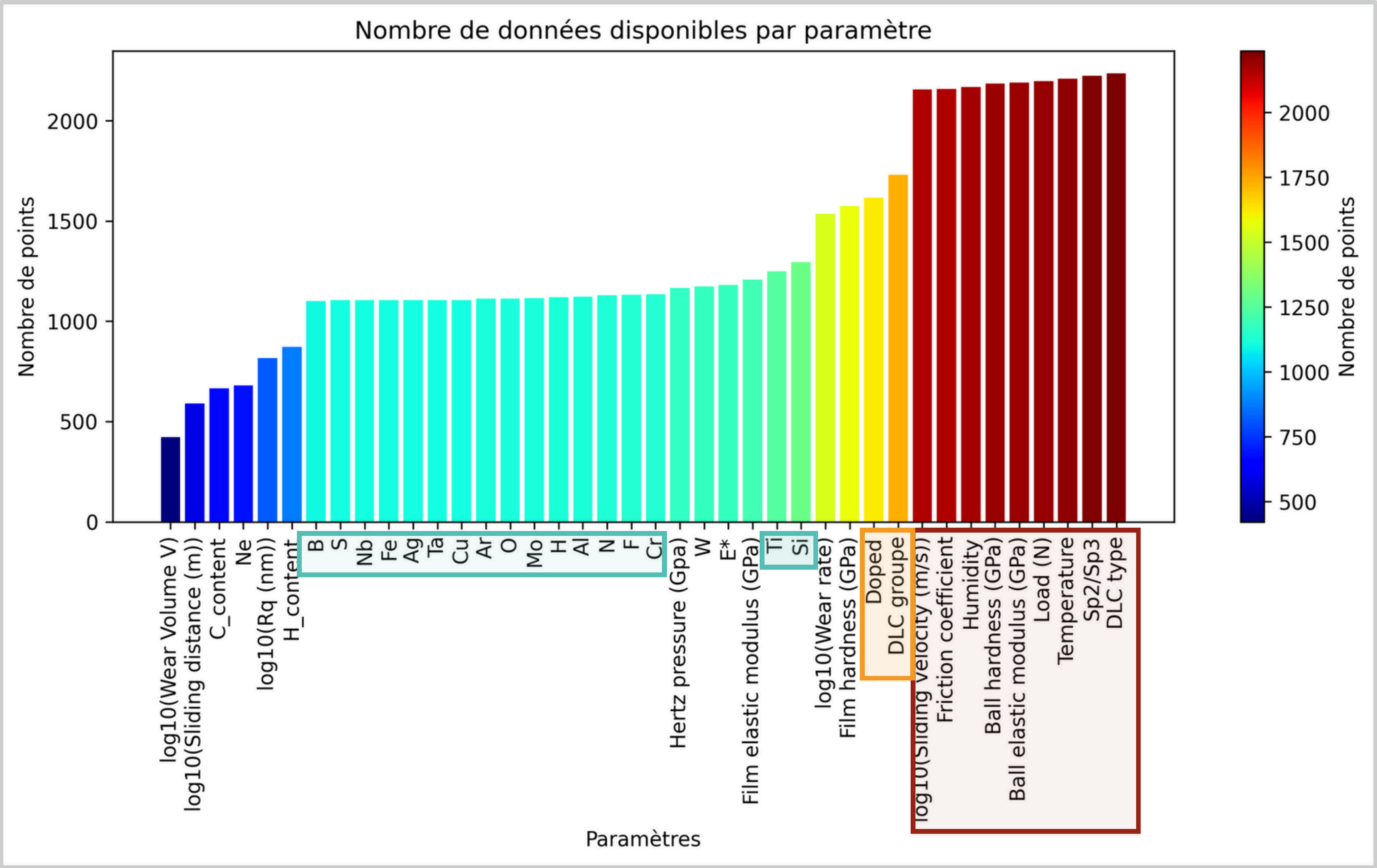
3. SELECTION DU SCENARIO

a. définition des scenarios

SCENARIO 1

SCENARIO 2

SCENARIO 3



3. SELECTION DU SCENARIO

b. rappel des formules

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

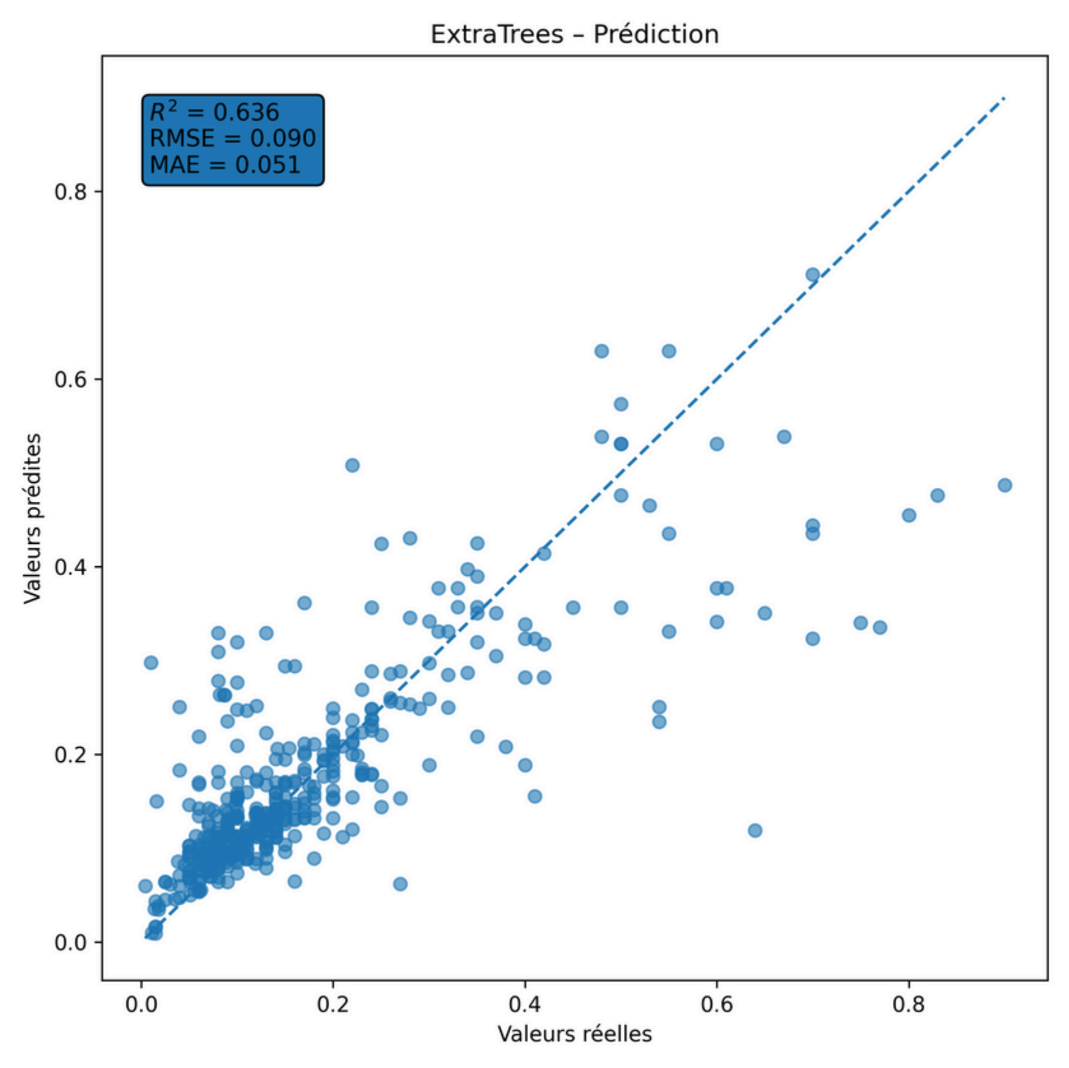
où

- y_i : valeur réelle
- $\hat{y}_i$: valeur prédite
- $\bar{y}$: moyenne des valeurs réelles
- n : nombre d'observations

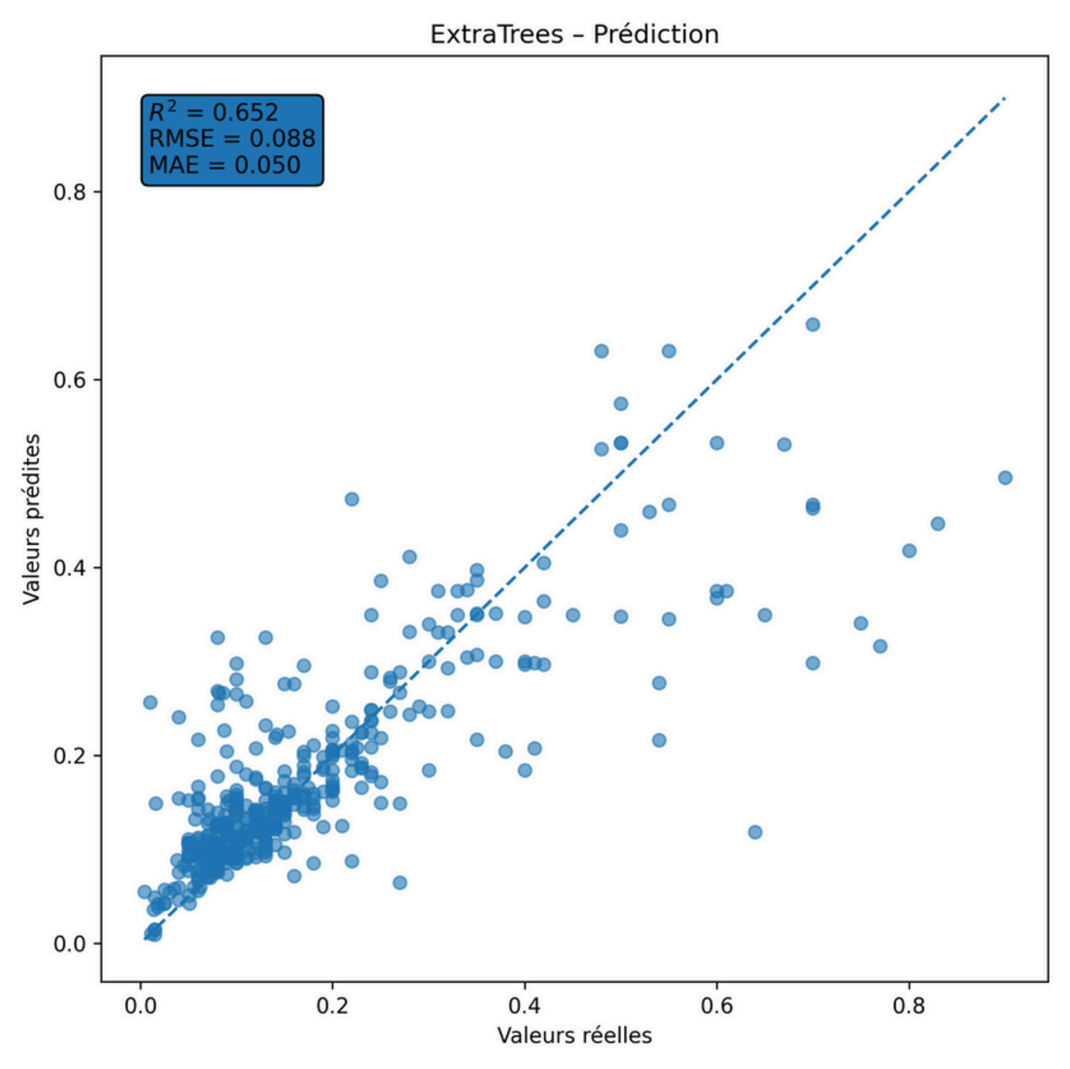
3. SELECTION DU SCENARIO

c. comparaison des scenarios - CoF

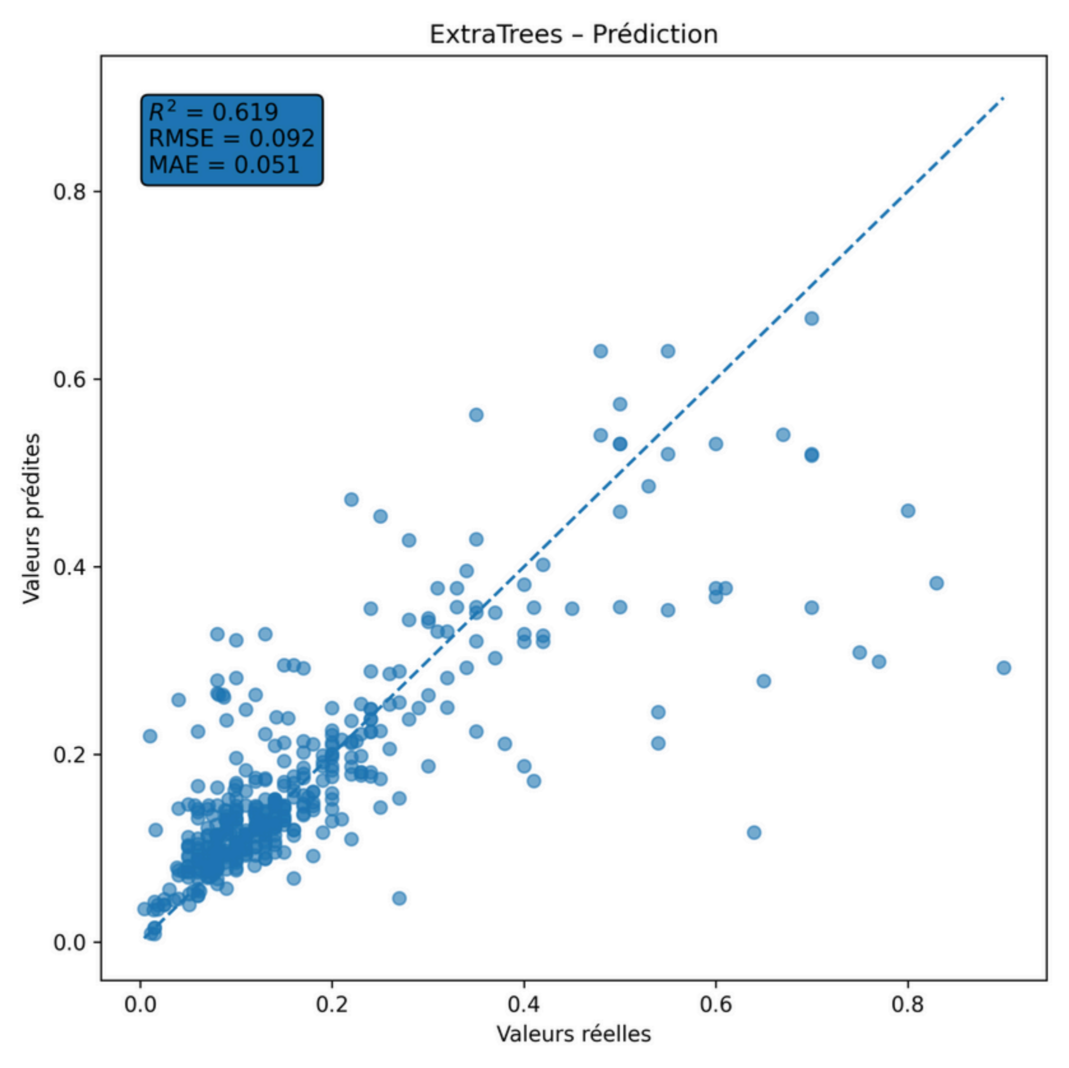
scenario 1



Scenario 2



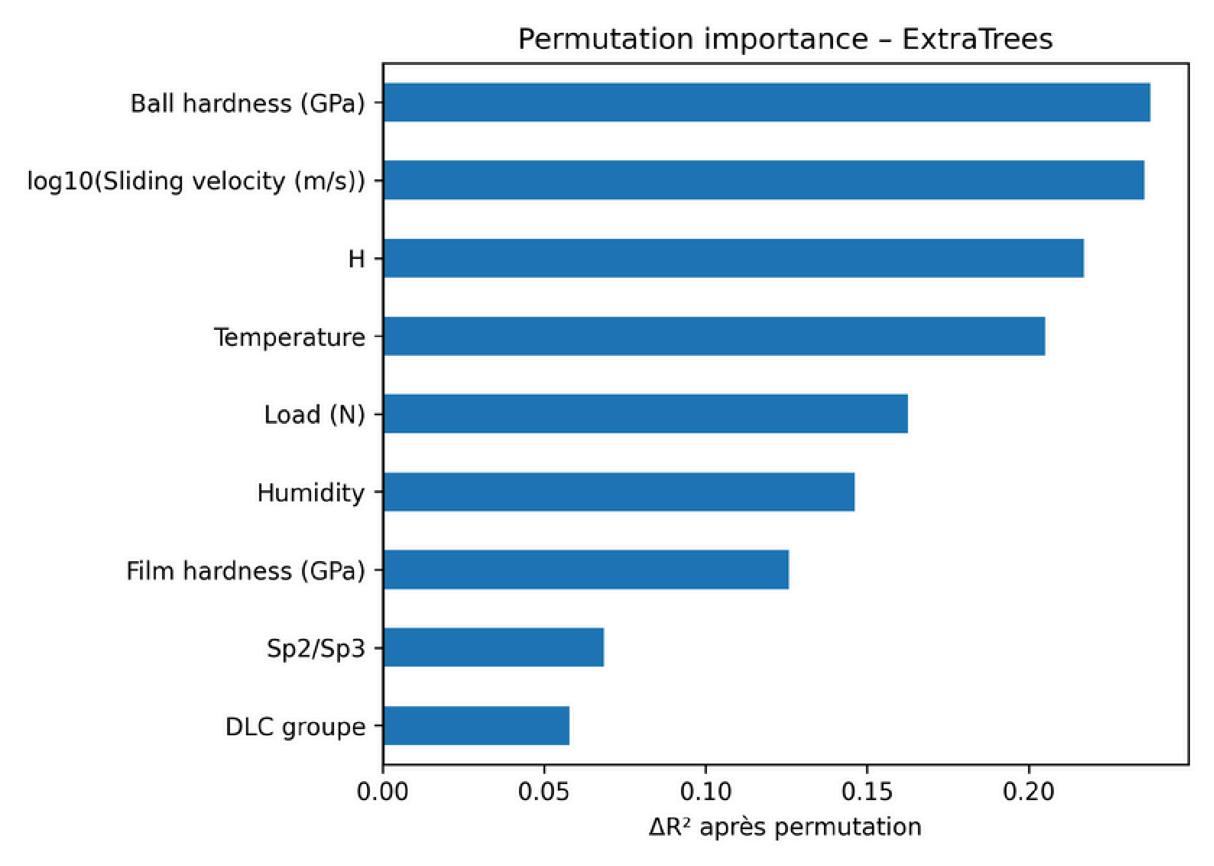
Scenario 3



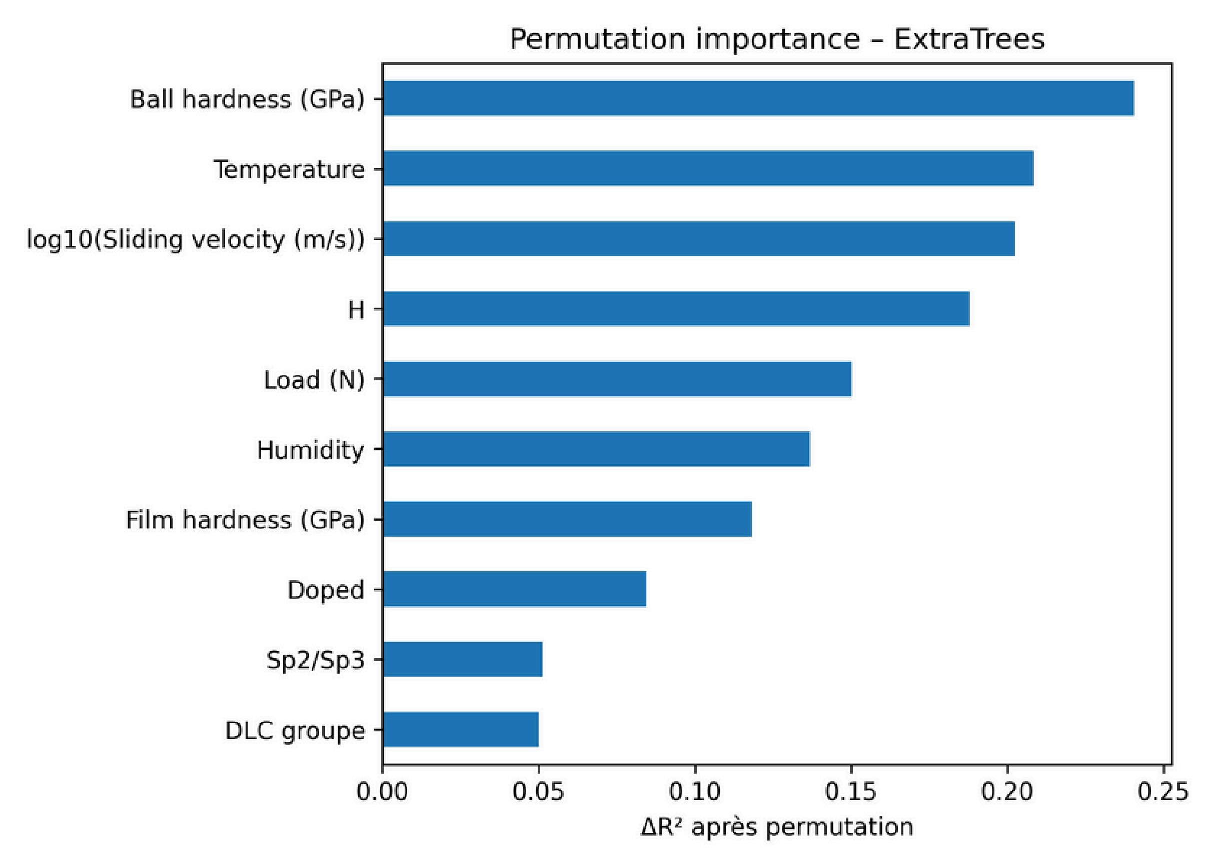
3. SELECTION DU SCENARIO

c. comparaison des scenarios - CoF

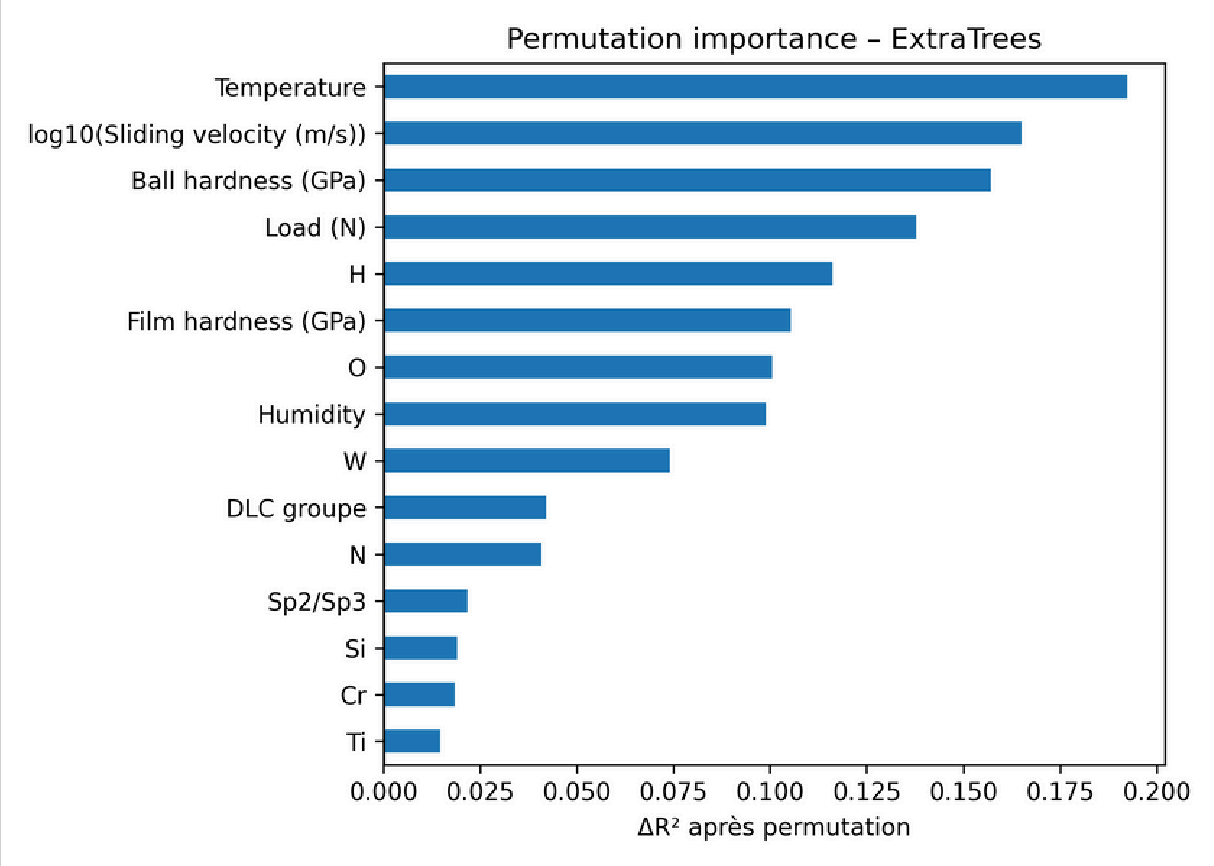
scenario 1



Scenario 2



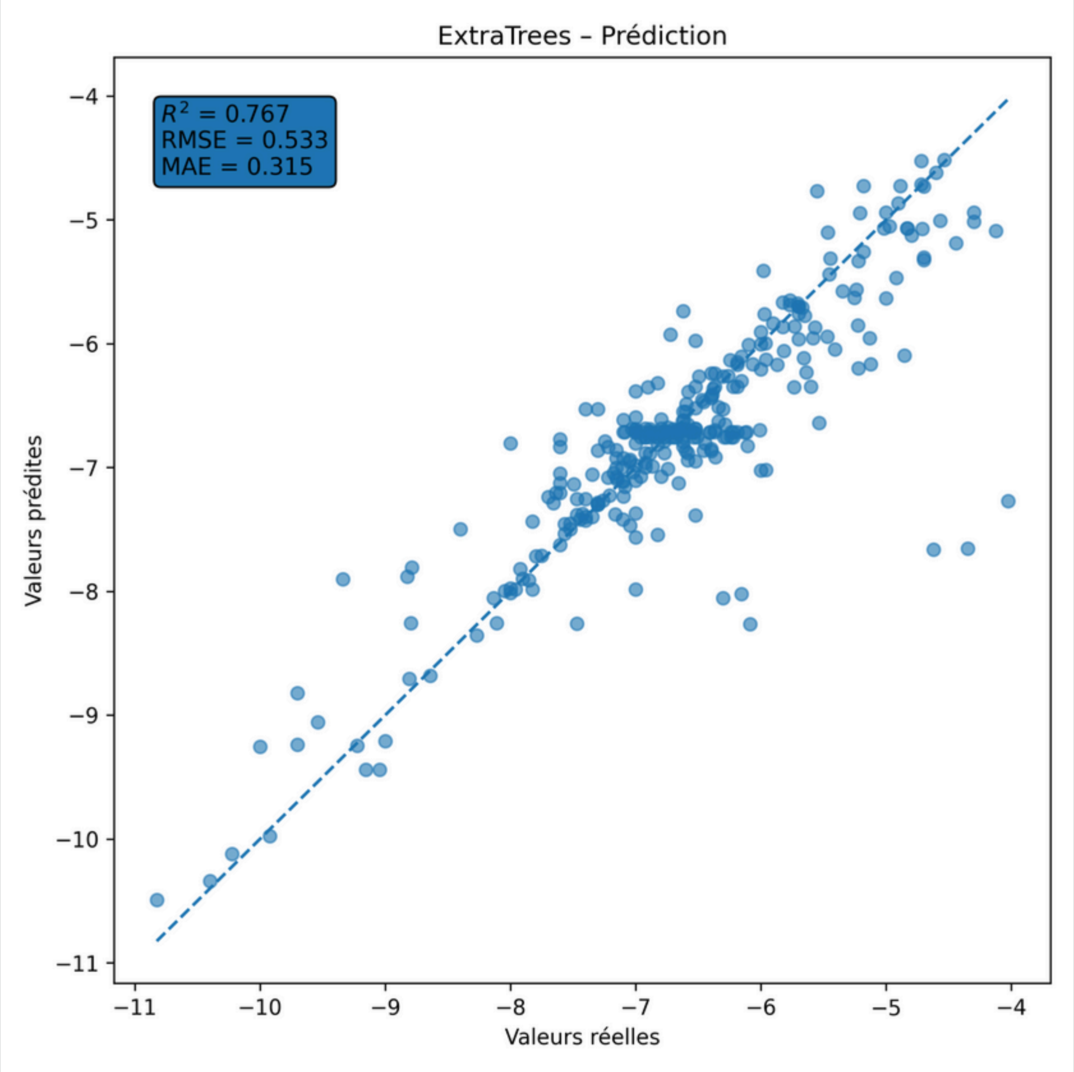
scenario 3



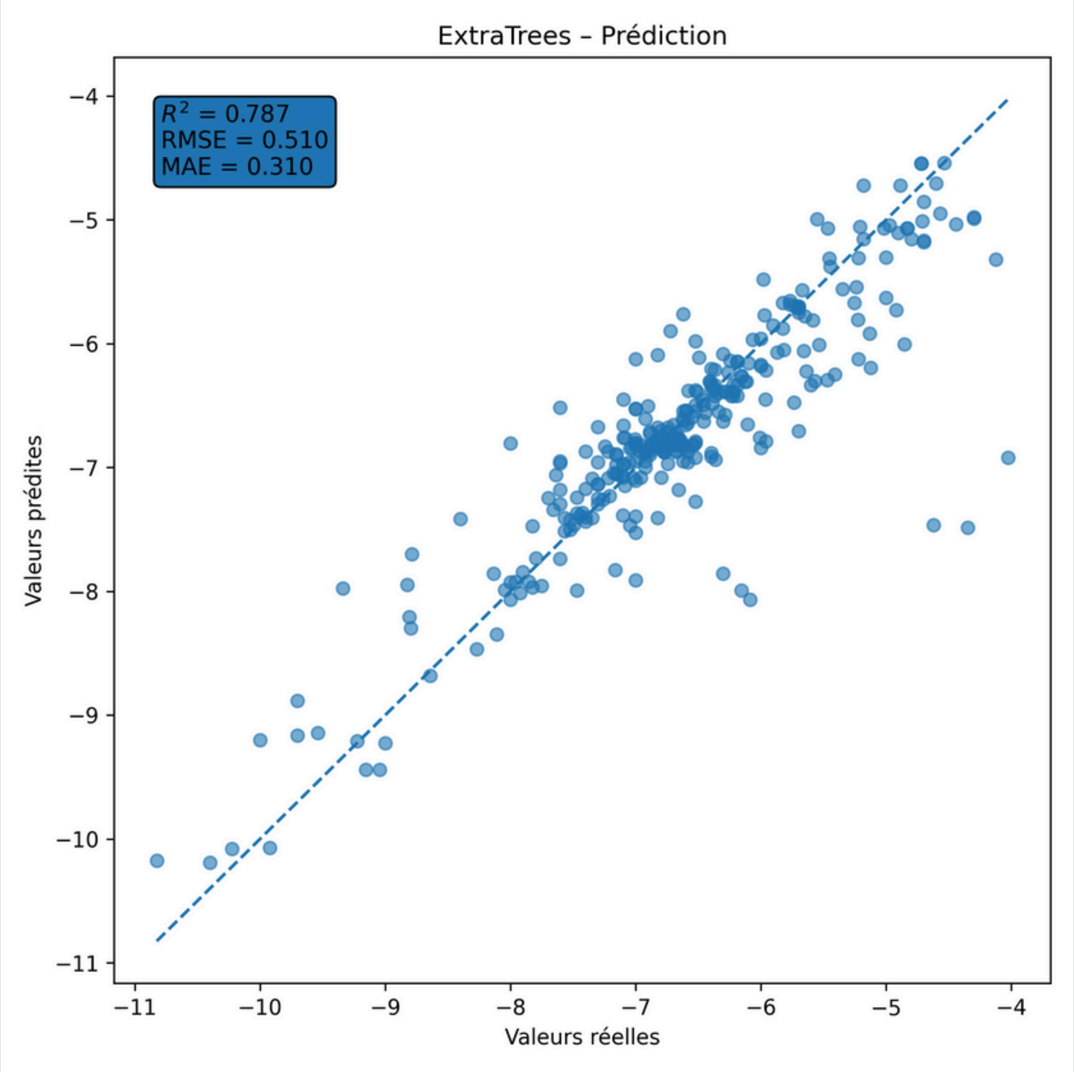
3. SELECTION DU SCENARIO

d. comparaison des scenarios - Wear

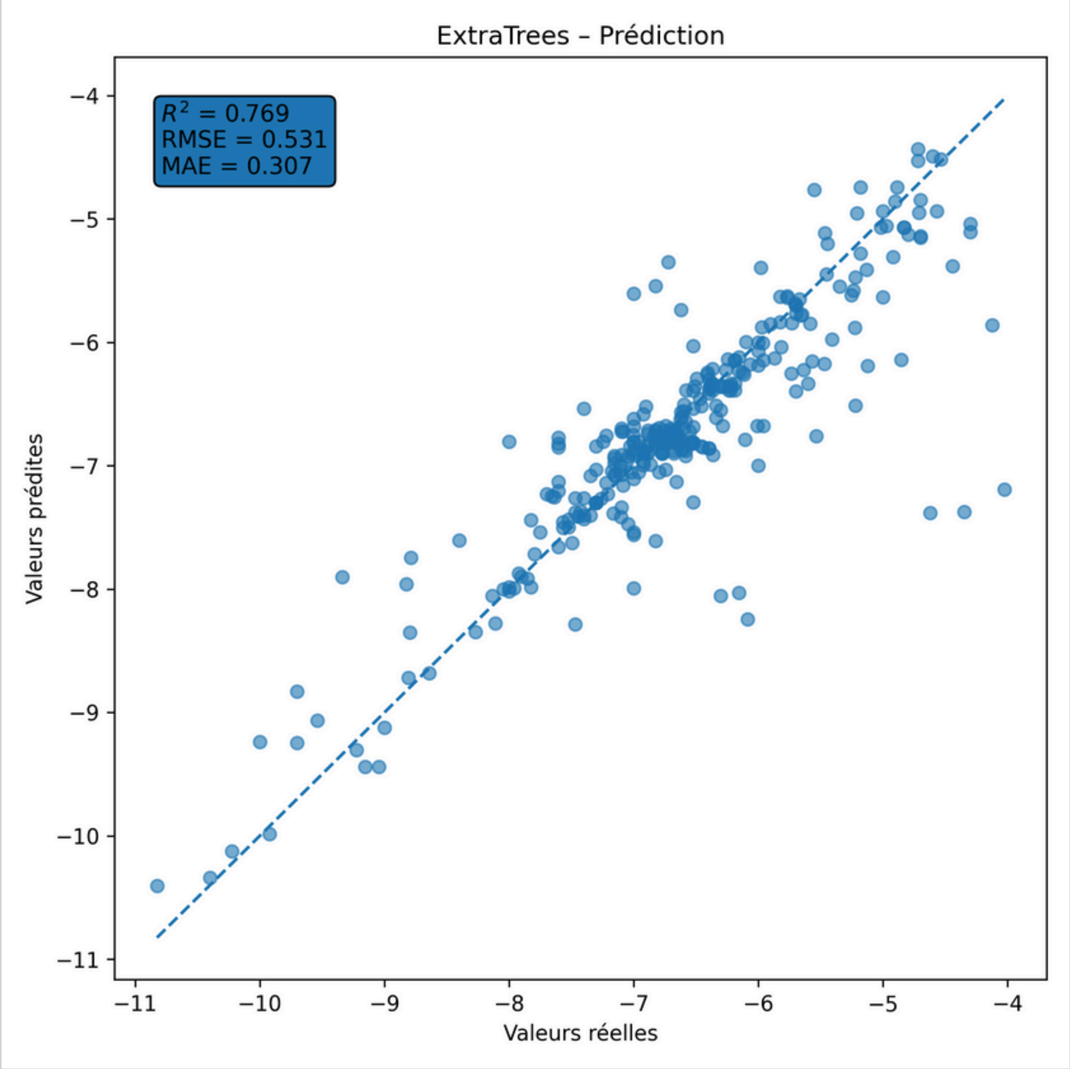
scenario 1



Scenario 2



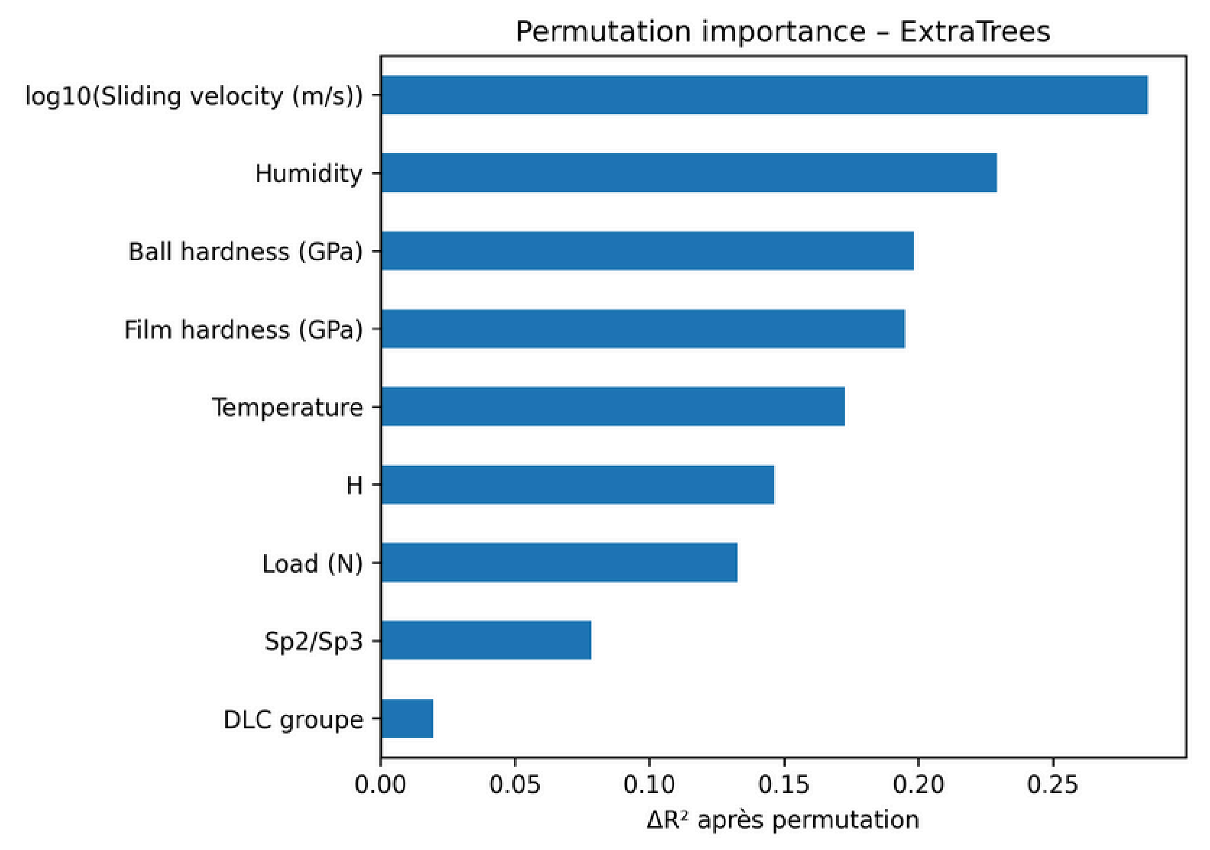
Scenario 3



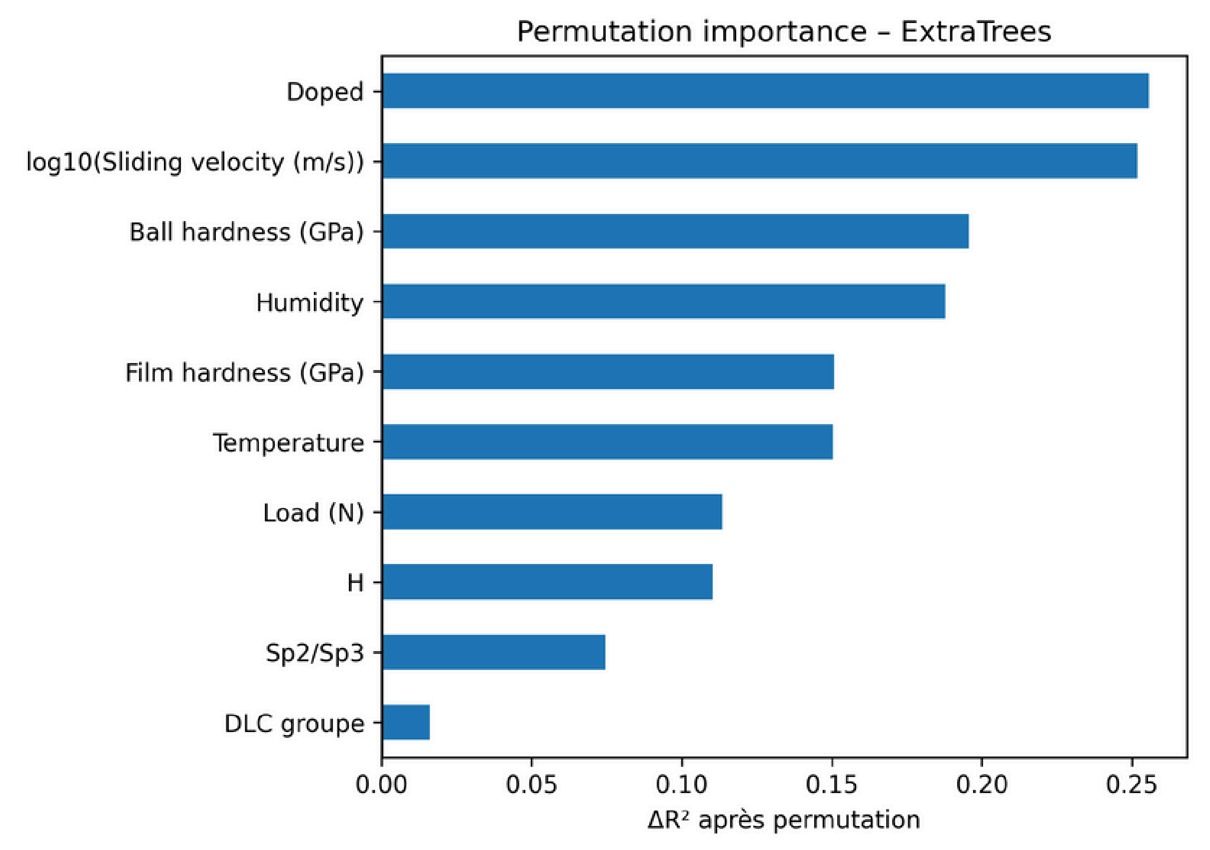
3. SELECTION DU SCENARIO

d. comparaison des scenarios - Wear

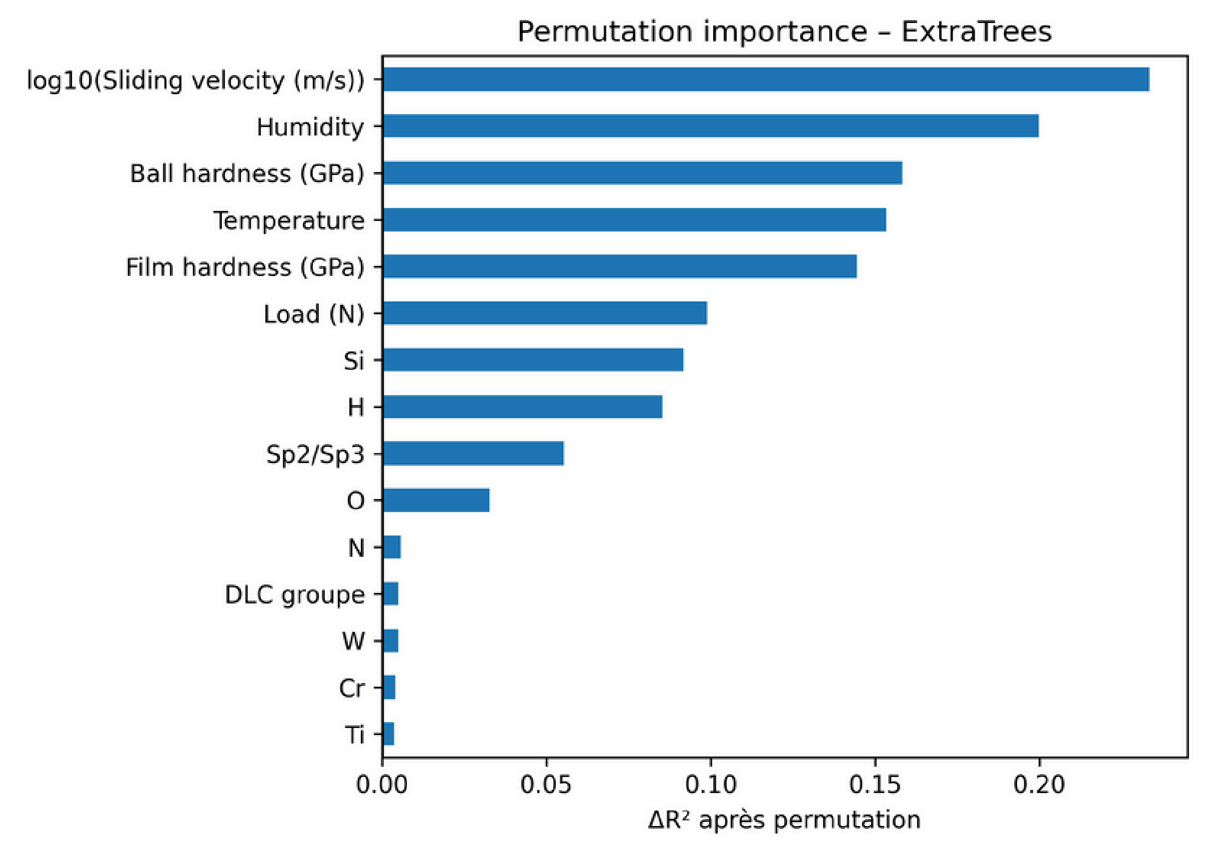
scenario 1



Scenario 2



scenario 3



3. SELECTION DU SCENARIO

b. comparaison des scenarios - Wear

=> SCENARIO 2

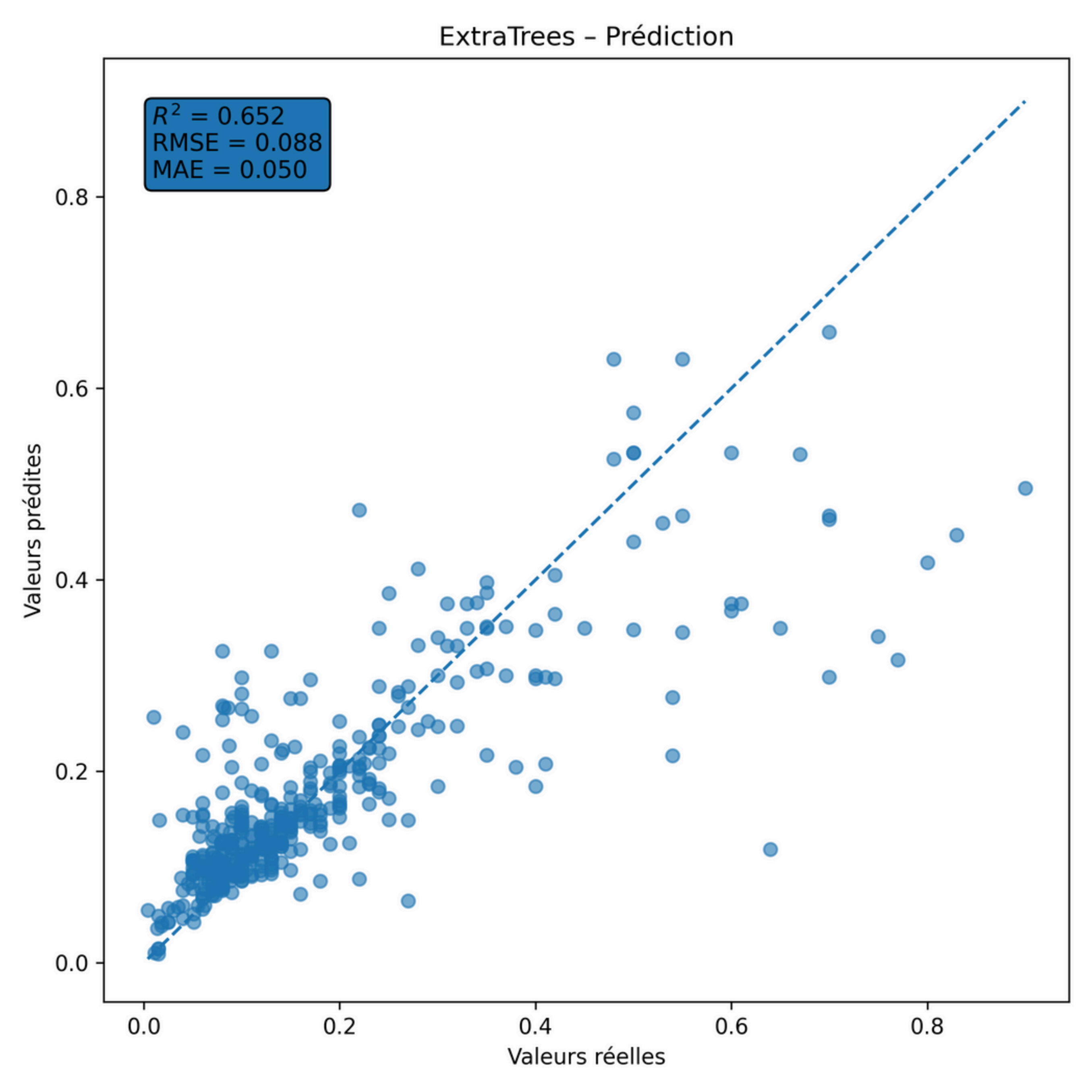
SLIDING VELOCITY - HUMIDITY - BALL HARDNESS - LOAD - TEMPERATURE - SP2/SP3 - DLC GROUPE - FILM HARDNESS - DOPED - H

4. PRÉDICTION COF ET USURE

a. Coefficient de frottement

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.652** **RMSE = 0.088** **MAE = 0.050**

Scenario 2



4. PRÉDICTION COF ET USURE

a. Coefficient de frottement

Scenario 2

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prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
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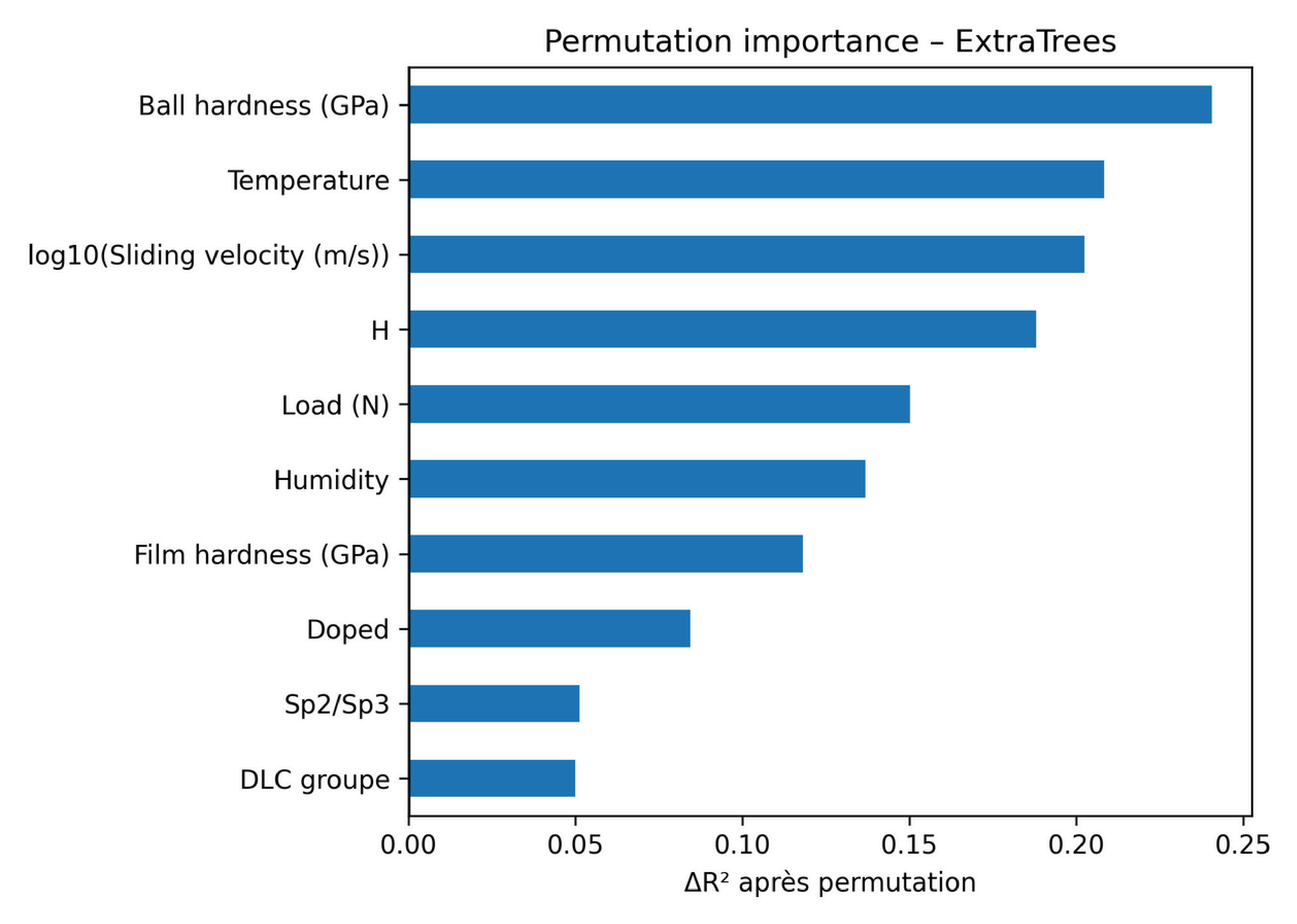
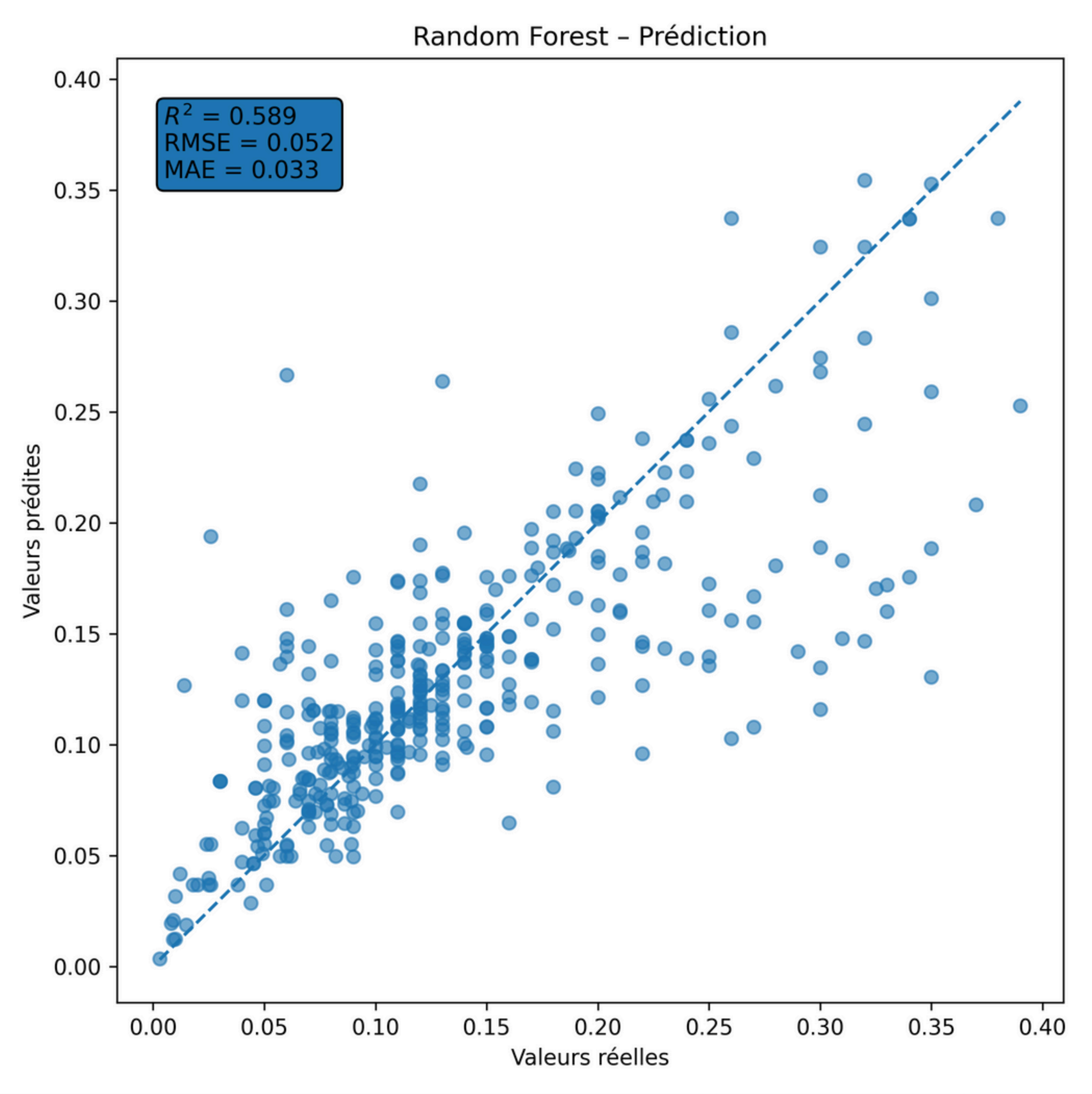


4. PRÉDICTION COF ET USURE

a. Coefficient de frottement

Scenario 2 → Reduced

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.589 (< 0.652)** **RMSE = 0.052 (< 0.088)** **MAE = 0.033 (< 0.050)**



4. PRÉDICTION COF ET USURE

a. Coefficient de frottement

Scenario 2 → Reduced

implementation method	None
prediction method	random forest
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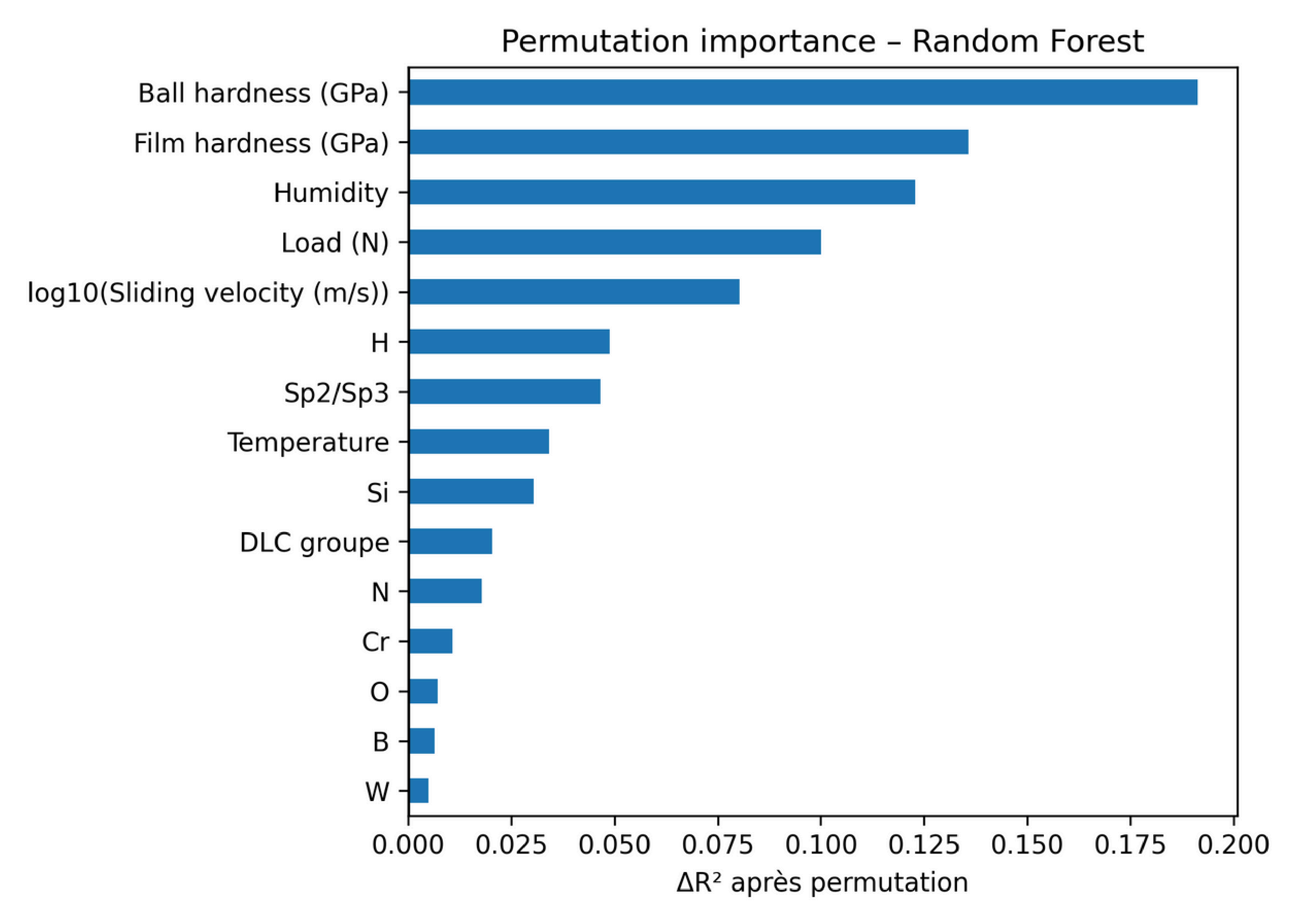
resultats	**R^2 = 0.589** **RMSE = 0.052** **MAE = 0.033**

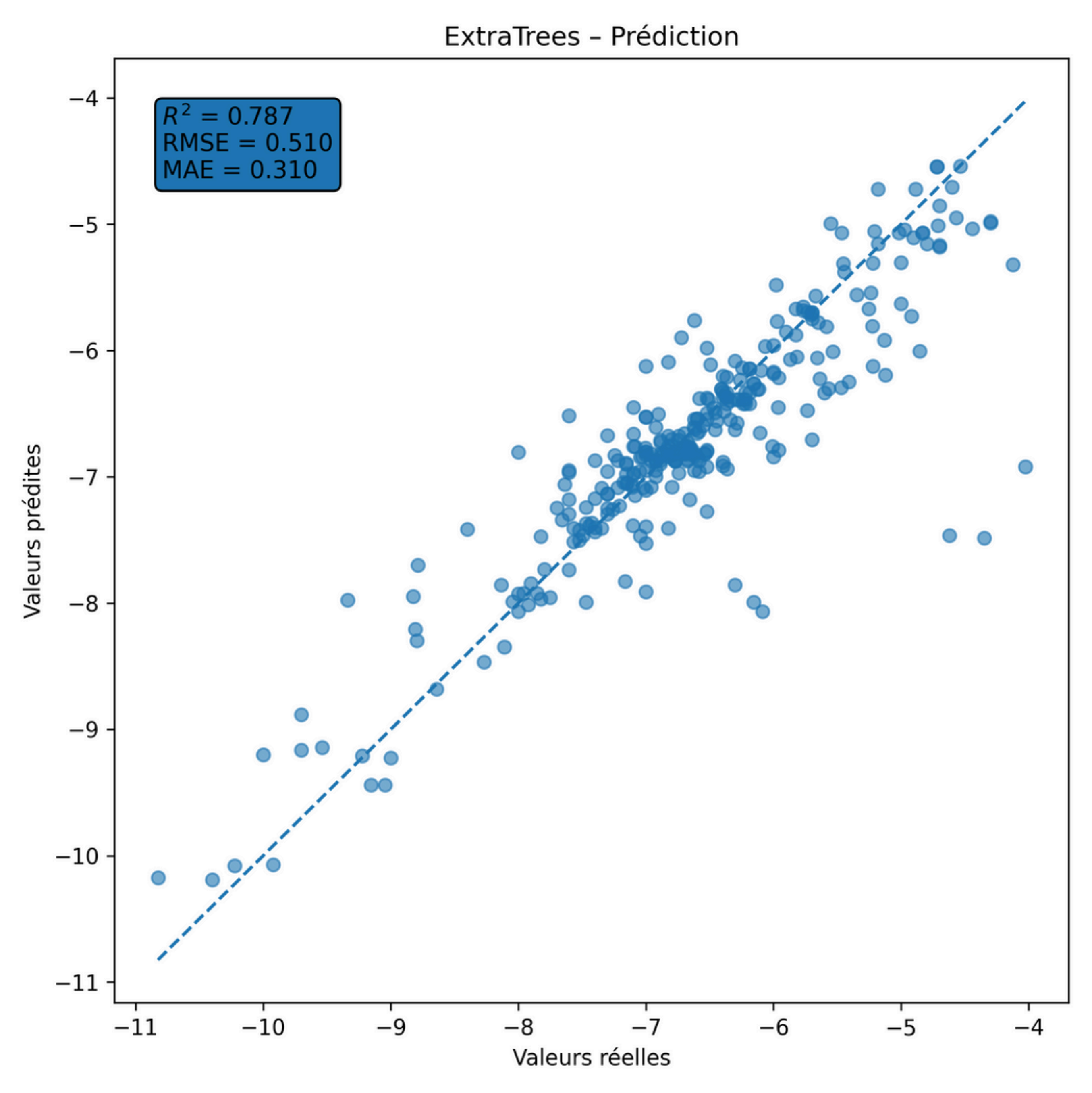


4. PRÉDICTION COF ET USURE

b. Wear rate

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.787** **RMSE = 0.510** **MAE = 0.310**

Scenario 2

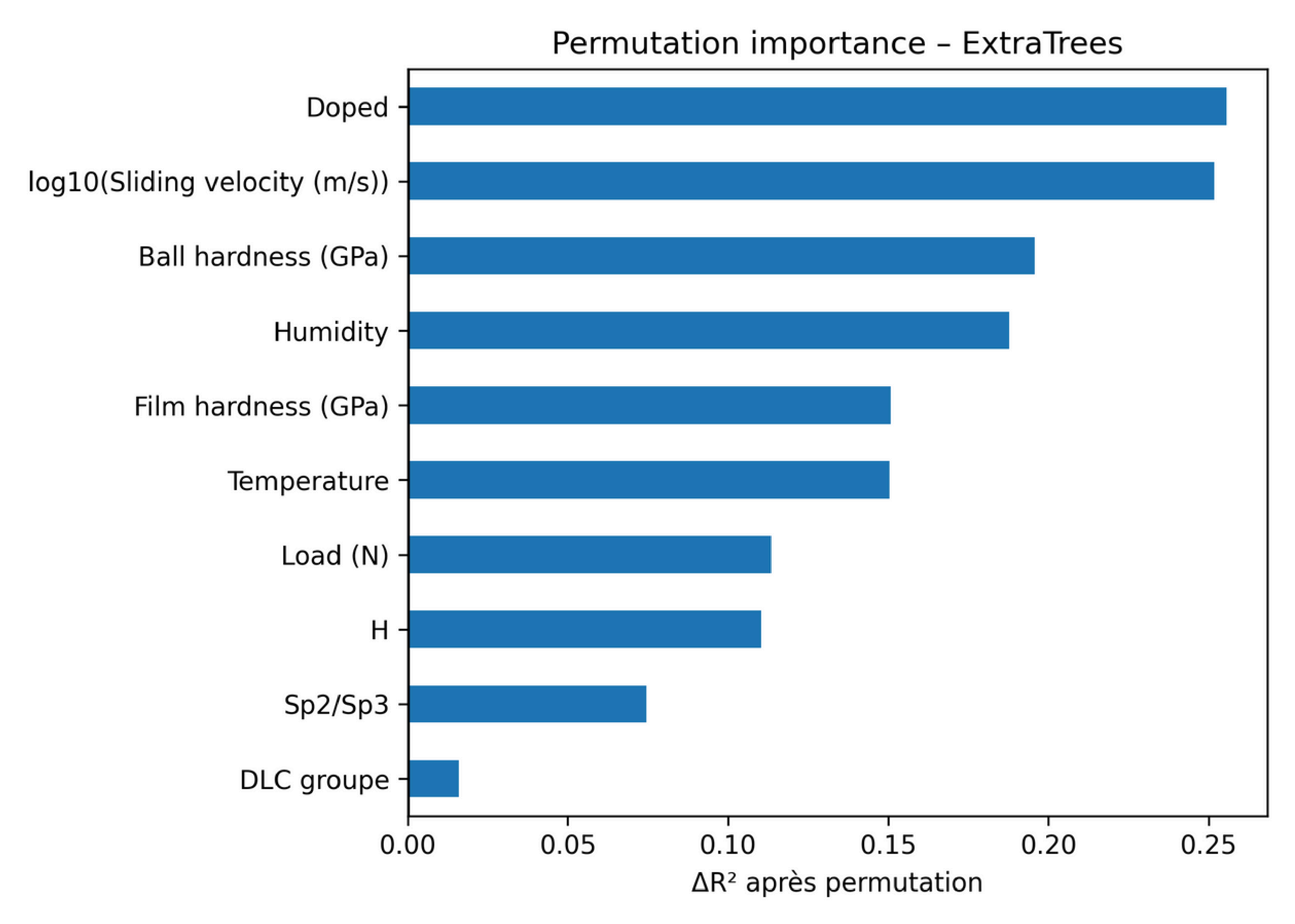


4. PRÉDICTION COF ET USURE

b. Wear rate

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.787** **RMSE = 0.510** **MAE = 0.310**

Scenario 2

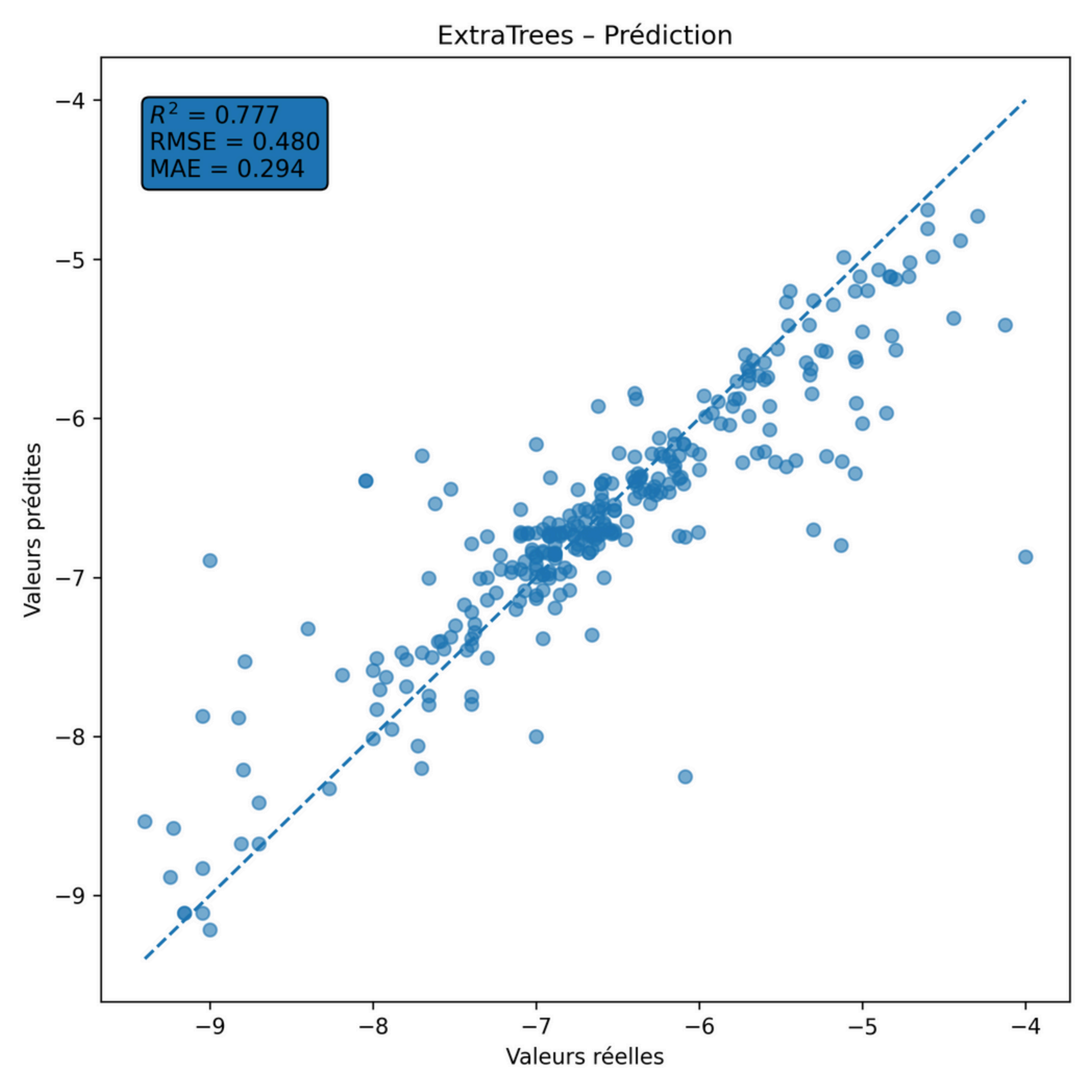


4. PRÉDICTION COF ET USURE

b. Wear rate

Scenario 2 → Reduced

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.777 (< 0.787)** **RMSE = 0.480 (< 0.510)** **MAE = 0.294 (< 0.310)**

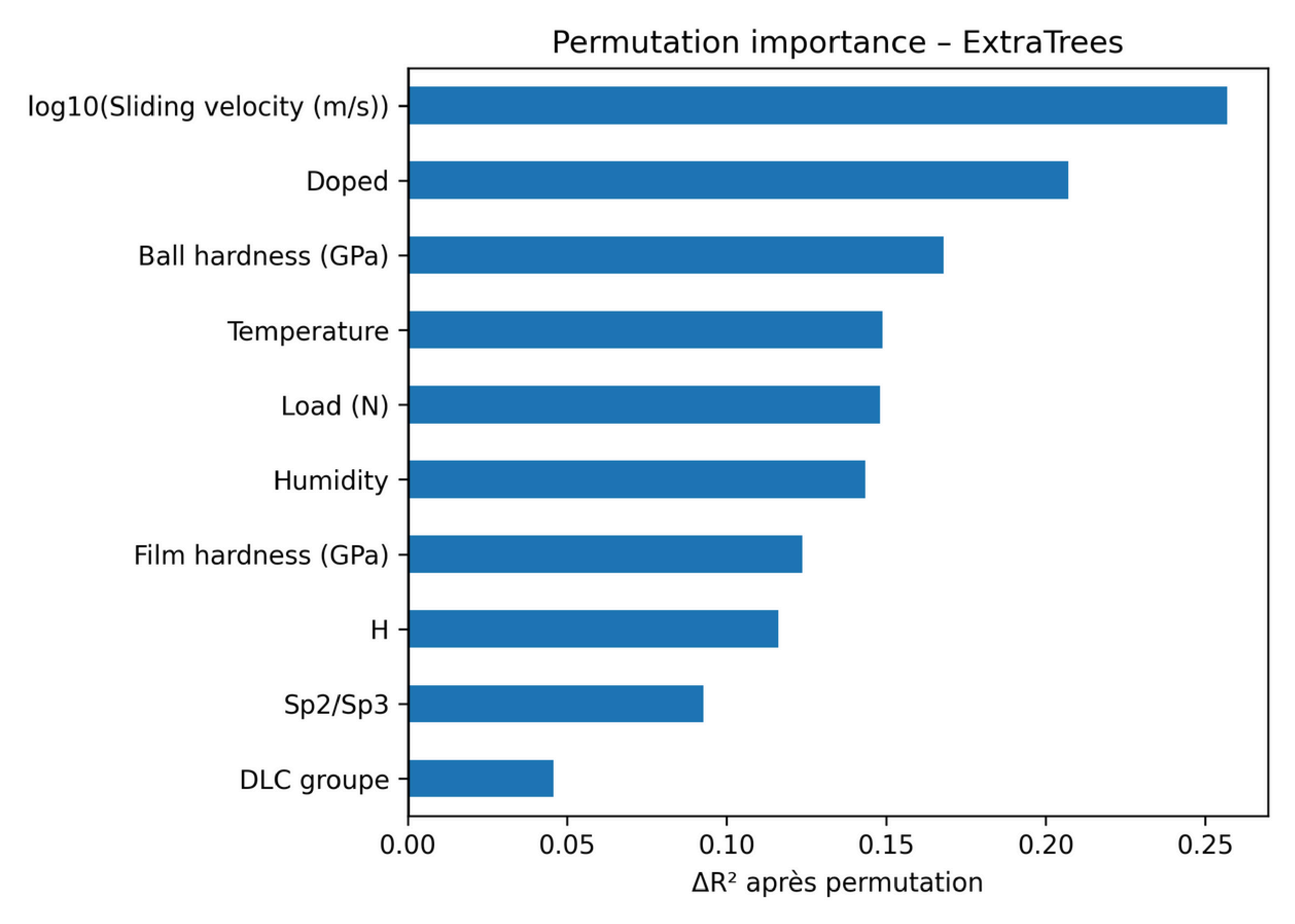


4. PRÉDICTION COF ET USURE

b. Wear rate

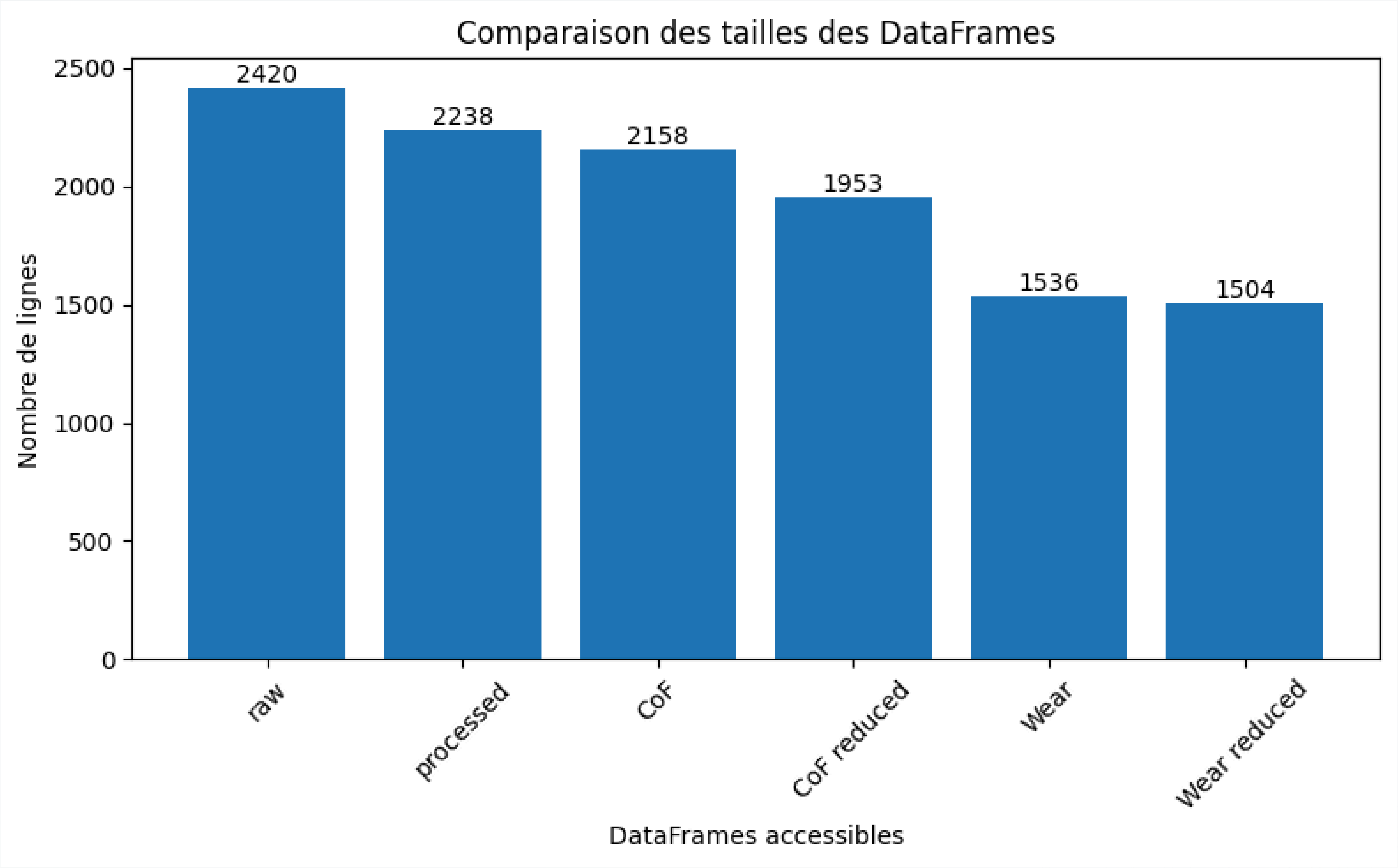
Scenario 2 → Reduced

implementation method	None
prediction method	random forest
Scaler	No
hyperparameter tuning	optuna (score = R^2)
scenario	scenario 3
resultats	**R^2 = 0.777** **RMSE = 0.480** **MAE = 0.294**



4. PRÉDICTION COF ET USURE

c. répercussions sur la qualité du dataset



5. AMÉLIORATIONS POSSIBLES

1. Utilisation optimisée des réseaux de neurones
2. Essaie d’un nouveau scenario
3. Amélioration de la prédiction de l’usure
4. Prédiction inverse