

# Anticipez les Besoins en Consommation de Bâtiments

OPENCLASSROOMS



Seattle

# ENJEUX

Seattle : 2050 → Neutralité carbone

Prédire les émissions de CO<sub>2</sub> & la consommation totale d'énergie de bâtiments non destinés à l'habitation

## SOMMAIRE

- ▶ 1. 1er Feature Engineering & Analyse Exploratoire des Datasets
- ▶ 2. Développement & Simulation d'un Premier Modèle
- ▶ 3. Simulation d'Autres Modèles & Choix d'un Modèle Final
- ▶ 4. Analyse de la "Feature Importance" Globale & Locale
- ▶ 5. Analyse de l'Influence de l'EnergyStarScore

# EXPLORATION DES DONNÉES & 1ER FEATURE ENGINEERING

## BUILDING ENERGY BENCHMARKING

- ▶ 3376 propriétés × 46 features
  - 1668 non-résidentielles
- ▶ **Compliance Status** = Compliant
- ▶ **DefaultData** = False
- ▶ **Outlier** = Null
- ▶ **PropertyGFATotal** =  
PropertyGFAParking +  
PropertyGFABuilding(s)

## FEATURE ENGINEERING:

- ▶ **Variables Cibles** =
  - ▶ **TotalGHGEmissions**
  - ▶ **SiteEnergyUseWN(kBtu)**
- ▶ **Création de nouvelles variables :**
  - ▶ **Electricity-NaturalGas-SteamUse(%)** :  
Electricity-NaturalGas-SteamUse(kBtu)  
/SiteEnergyUse
  - ▶ **Age** : DataYear - Yearbuilt

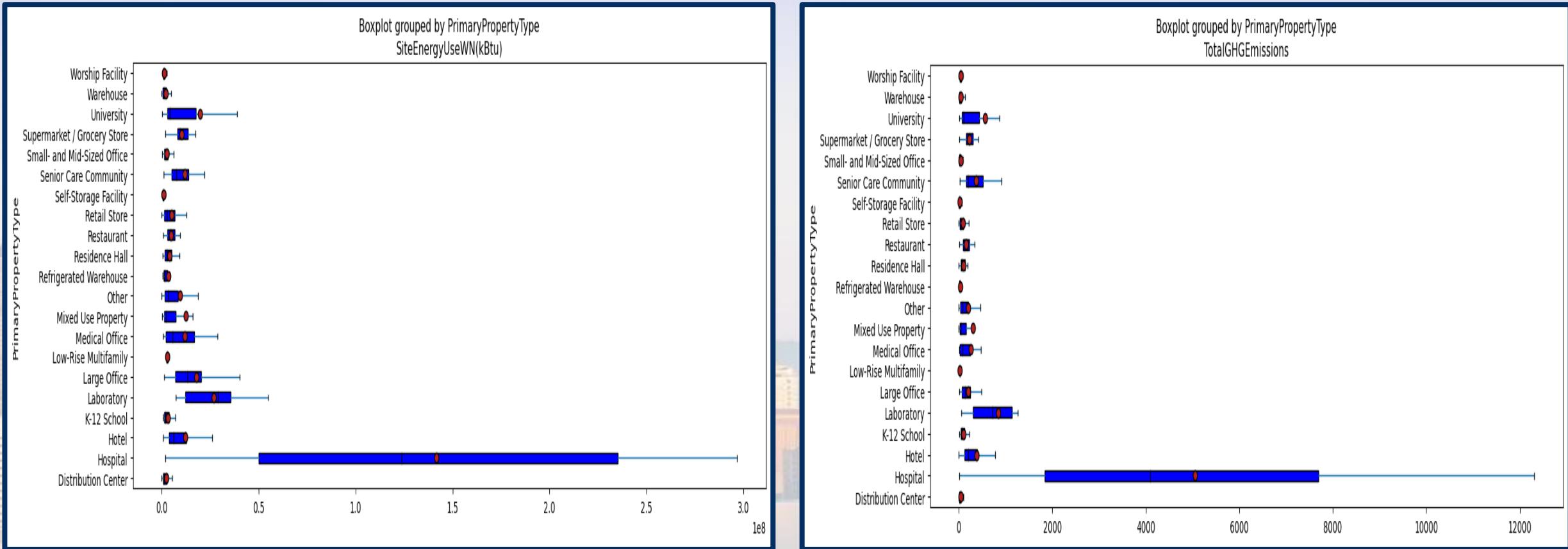
## SÉLECTION DES FEATURES

- **Caractéristiques Géographiques** : Latitude & Longitude
- **Caractéristiques Fonctionnelles** = PrimaryPropertyType
- **Caractéristiques Structurelles** = NumberofBuildings, NumberofFloors, PropertyGFABuilding(s), PropertyGFAParking, Age
- **Caractéristiques Energétiques** : Electricity(%), NaturalGas(%), SteamUse(%)

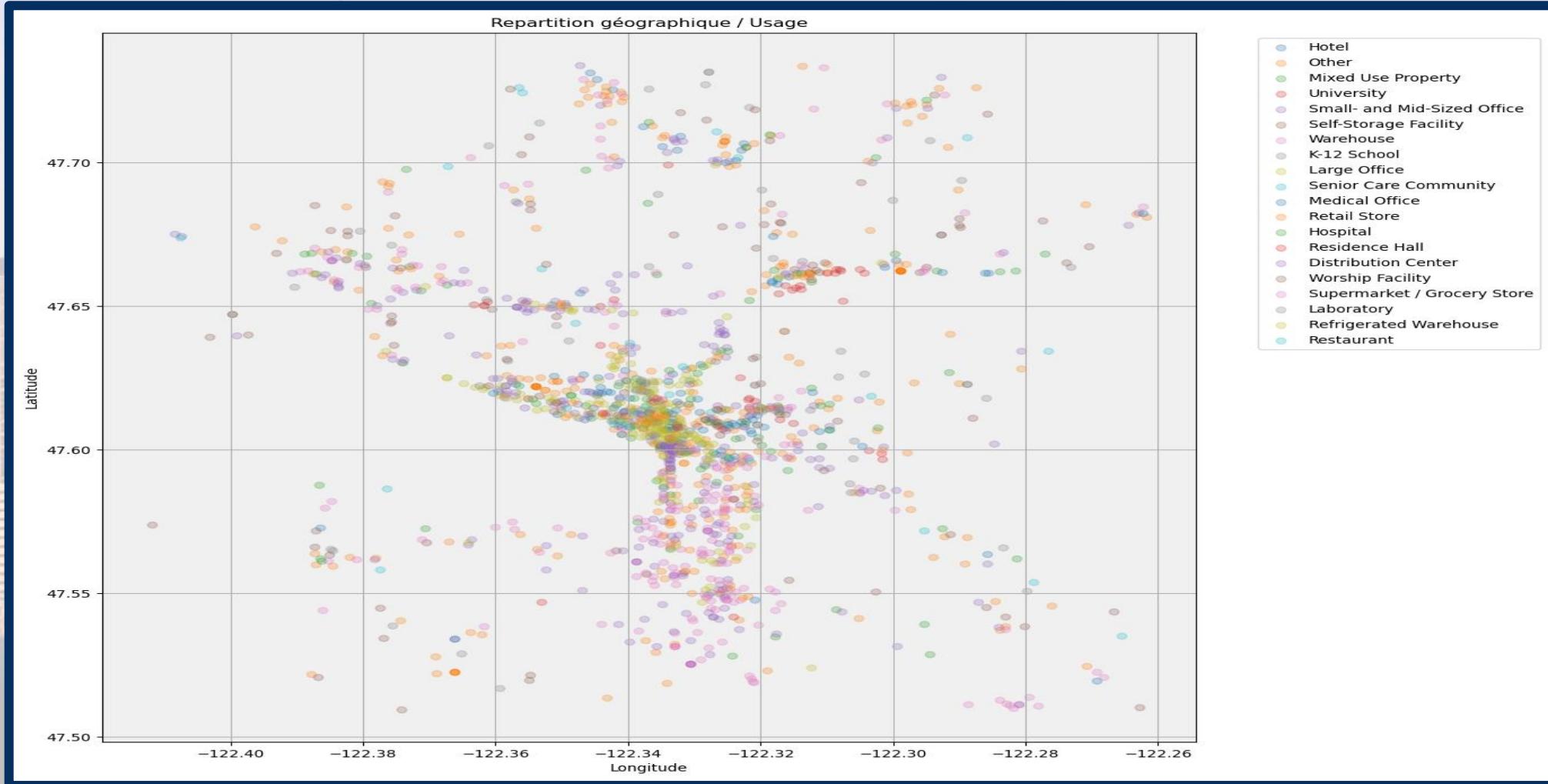


Data Leakage :  
~~GHGEmissionsIntensity, SiteEUI(kBtu/sf), etc.~~

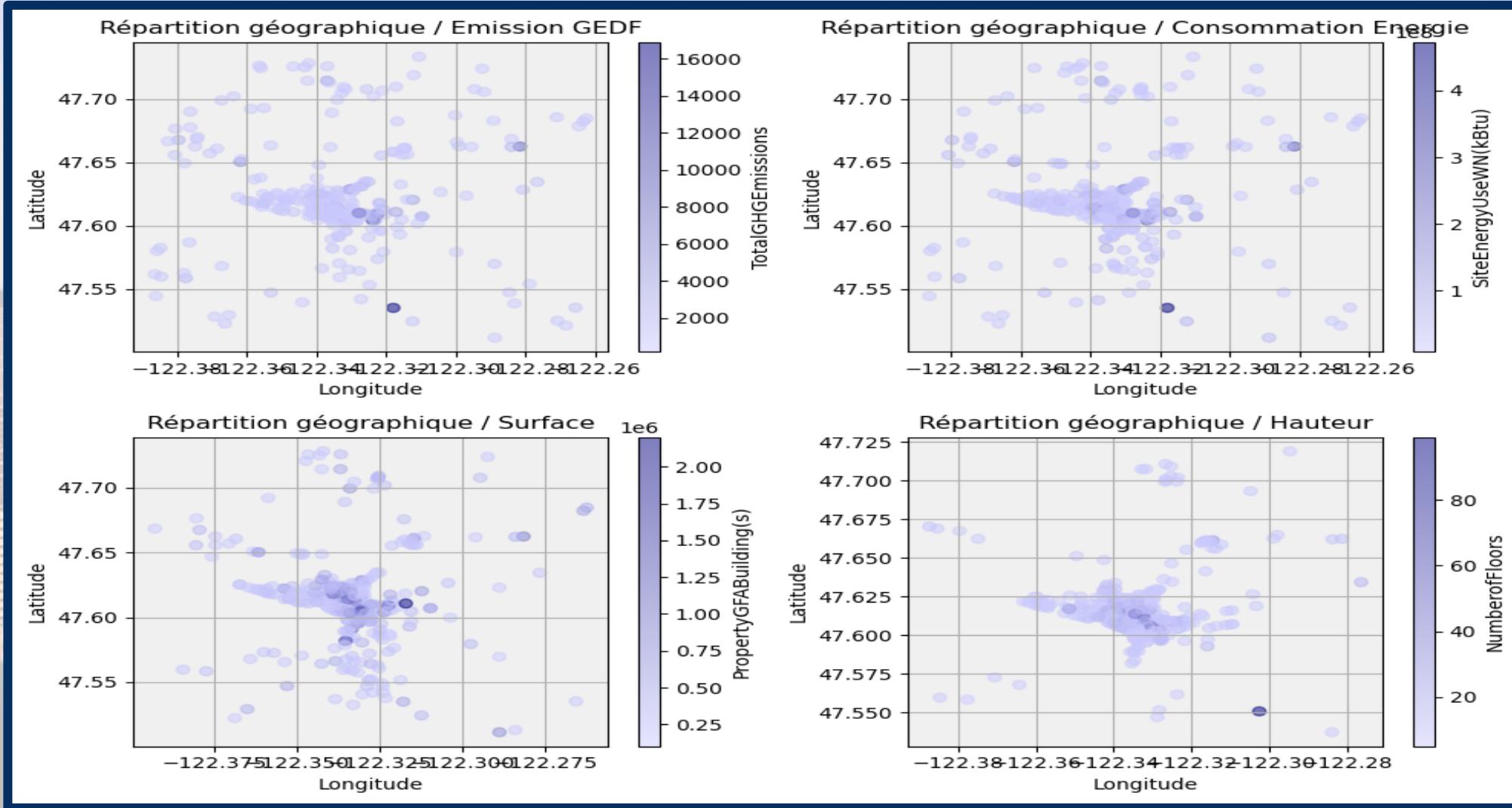
# ANALYSE EXPLORATOIRE : PROPERTY TYPE



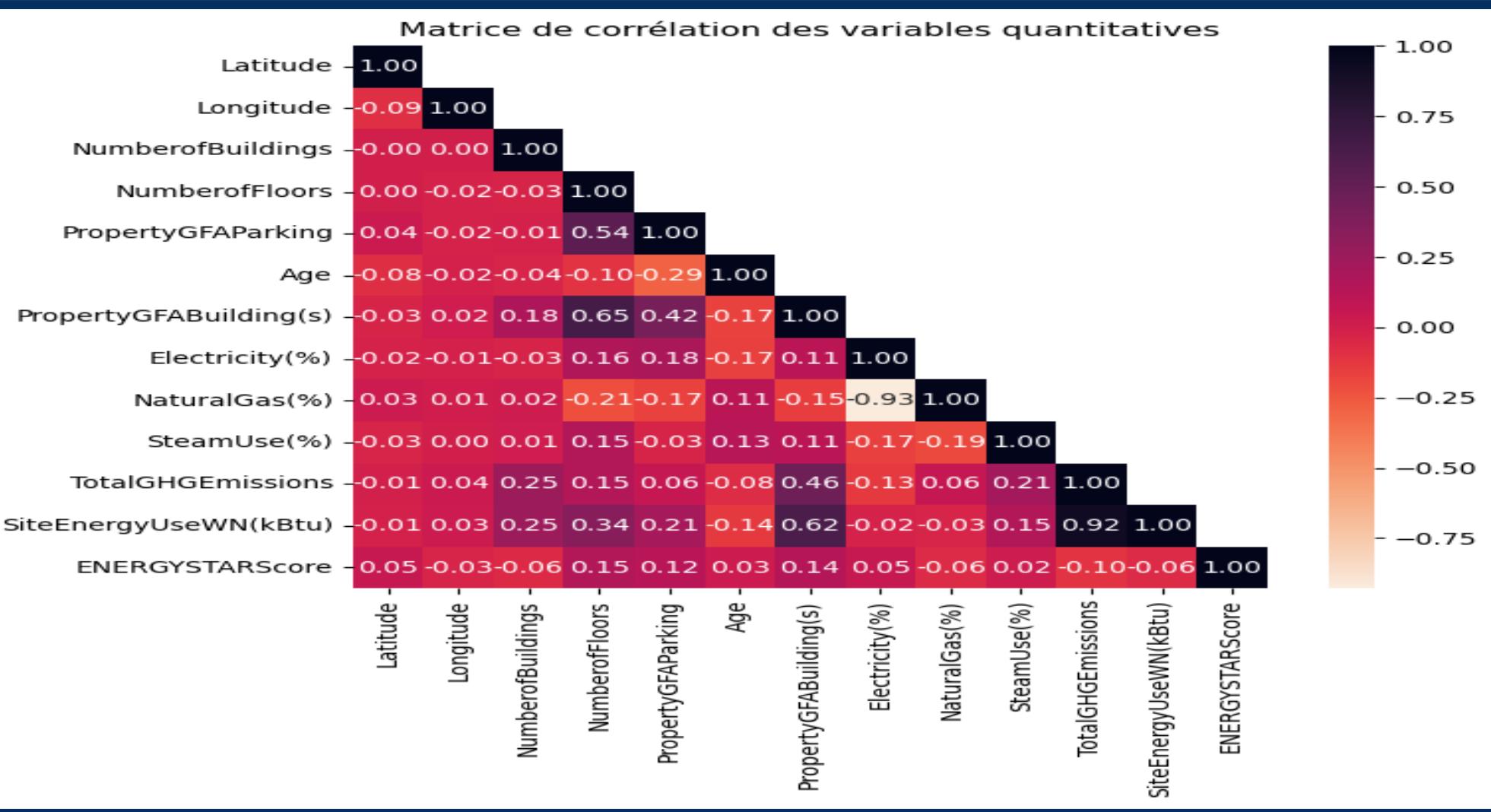
# ANALYSE EXPLORATOIRE : GEOGRAPHIE



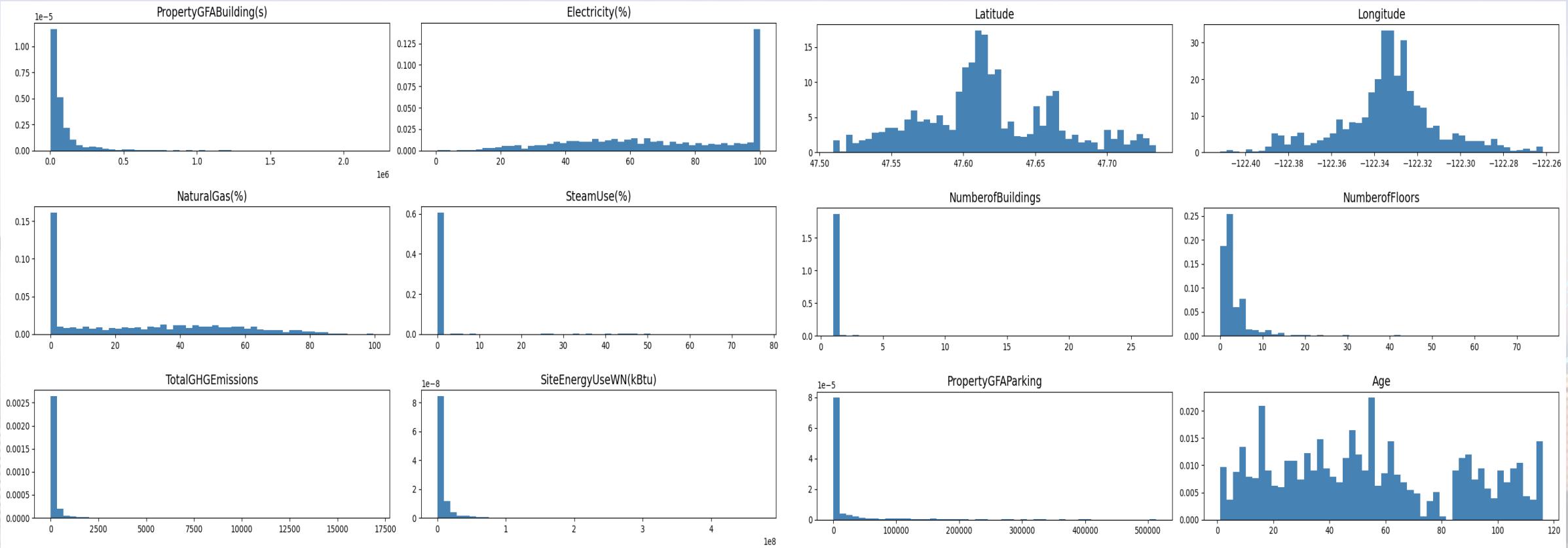
# ANALYSE EXPLORATOIRE : GEOGRAPHIE



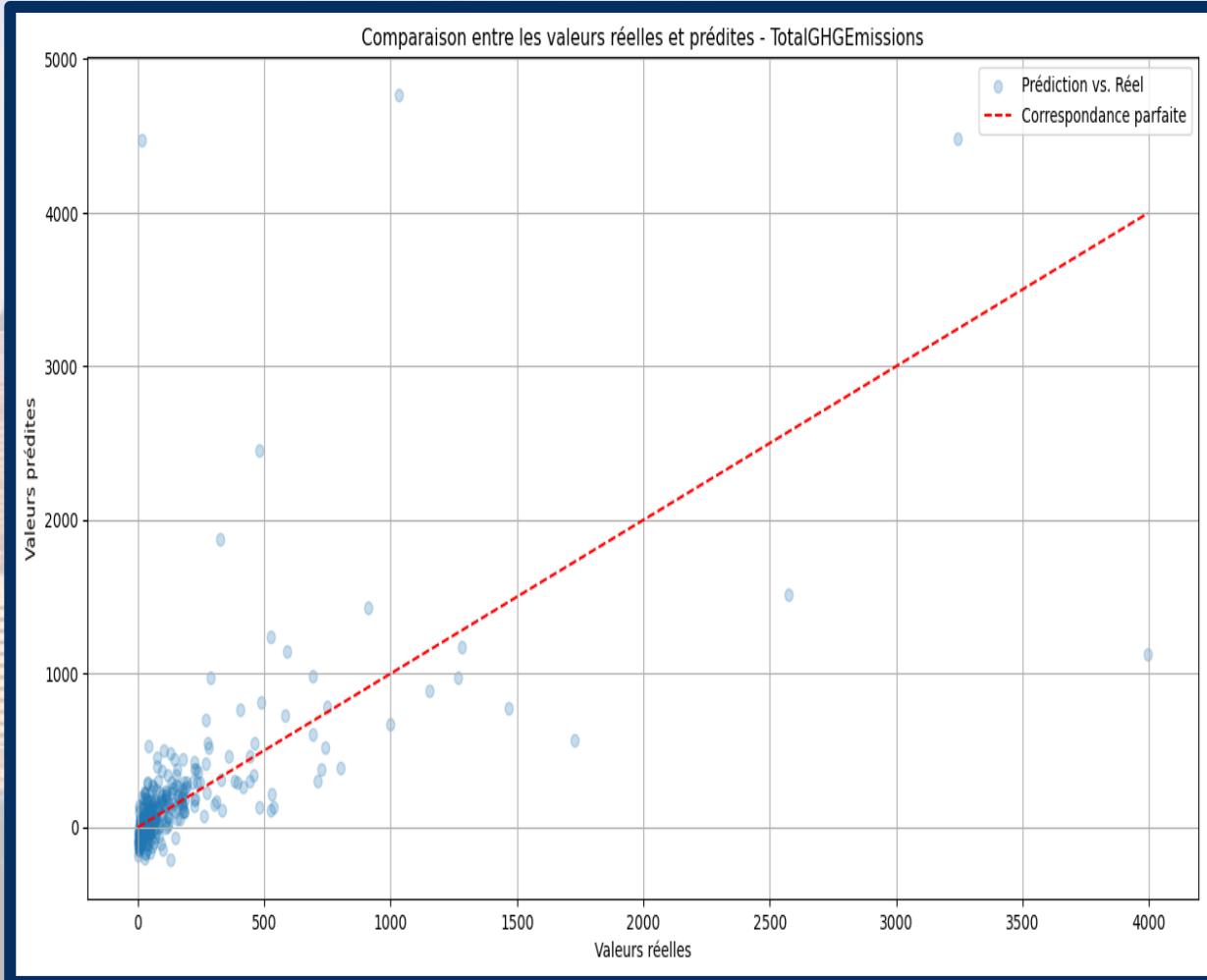
# ANALYSE EXPLORATOIRE : VARIABLES CIBLES



# ANALYSE EXPLORATOIRE : REPARTITION GLOBALE



# DÉVELOPPEMENT & SIMULATION D'UN PREMIER MODÈLE : TOTALGHGEMISSIONS



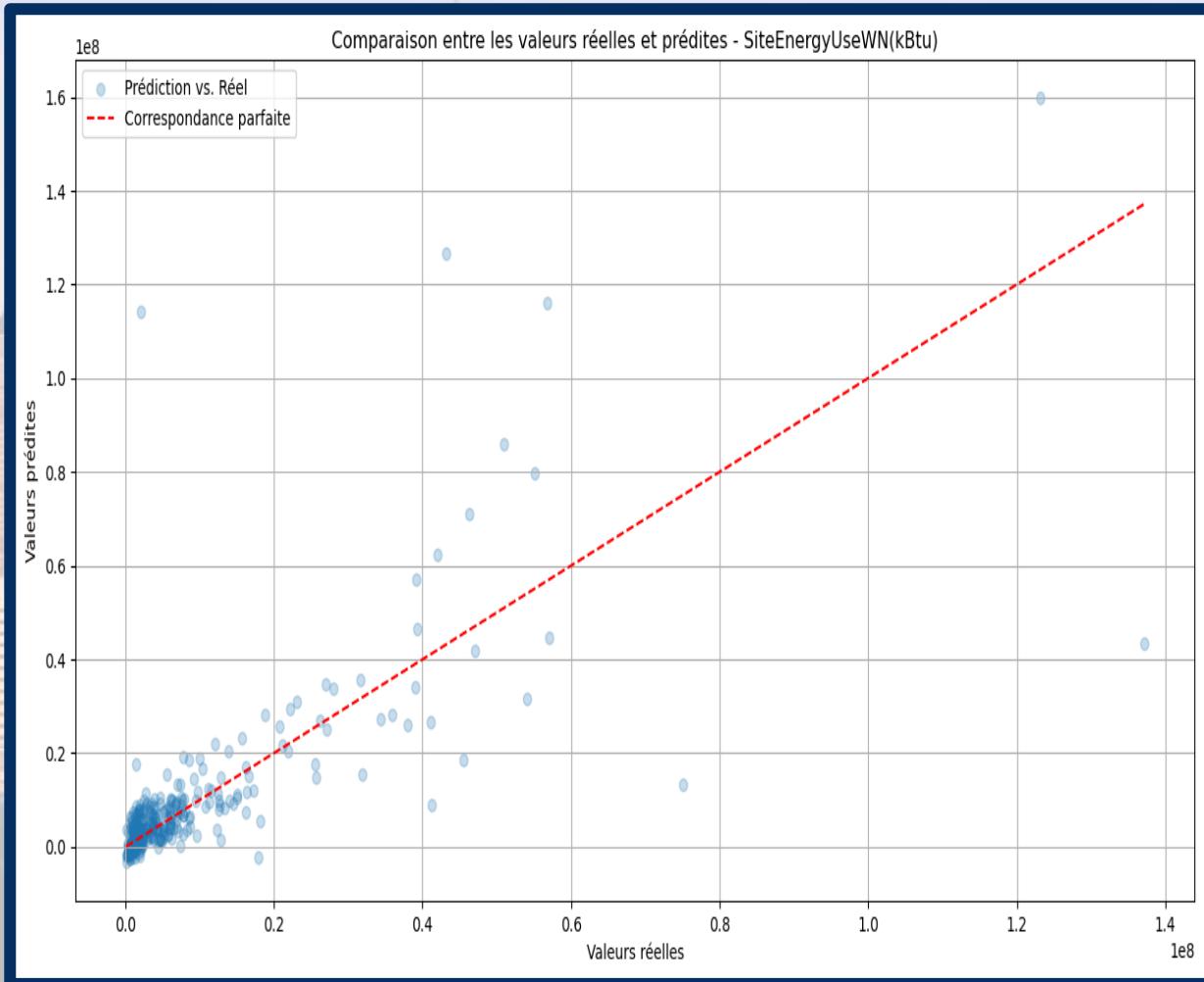
## Modèle de Départ: Régression Linéaire

### ► TotalGHGEmissions :

- $R^2 = -0.28$
- $MAE = 170.46$
- $RMSE = 442.90$

9/20

# DÉVELOPPEMENT & SIMULATION D'UN PREMIER MODÈLE : SITEENERGYUSEWN(kBtu)

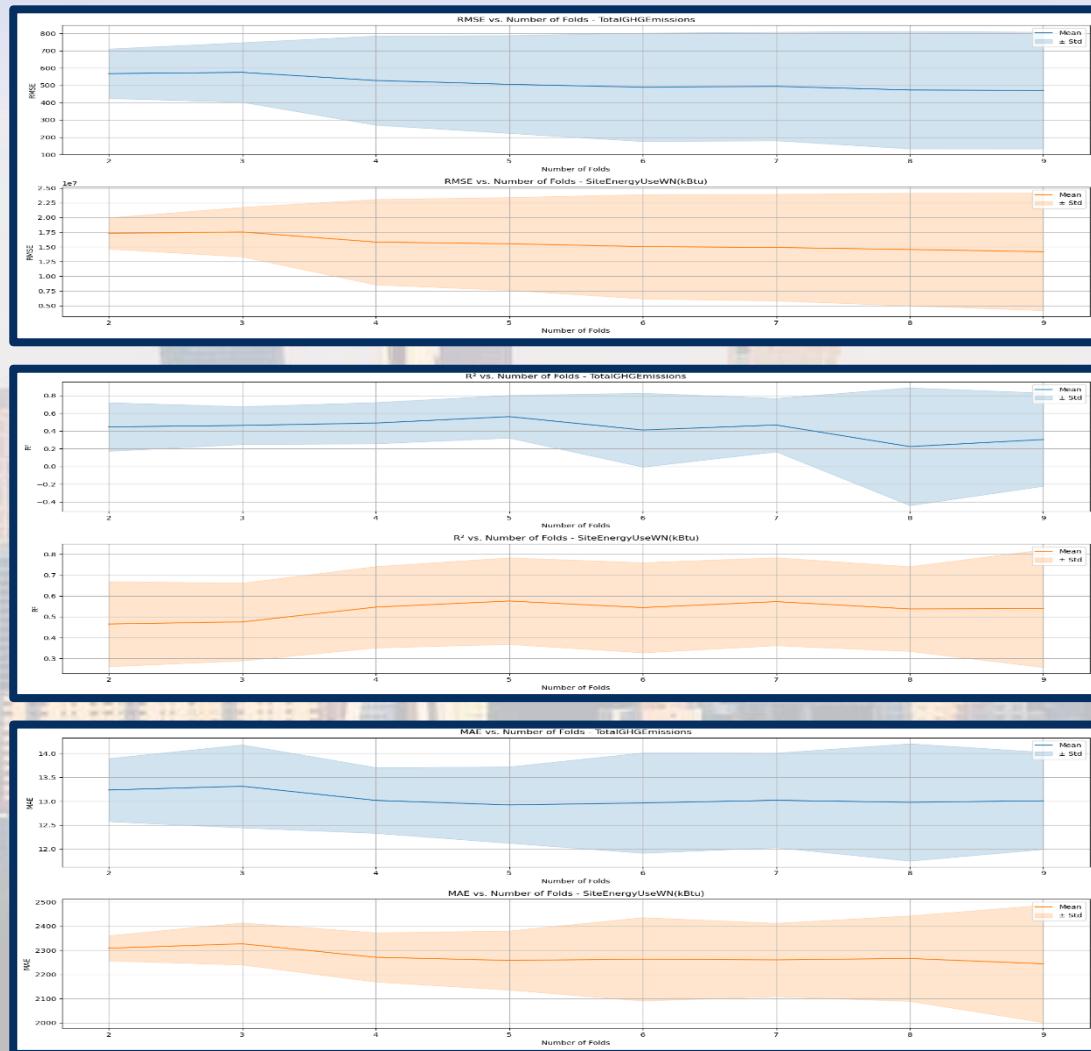


## Modèle de Départ: Régression Linéaire

► SiteEnergyUseWN(kBtu) :

- $R^2 = 0.34$
- $MAE = 5110950.26$
- $RMSE = 12500303.1$

# DÉVELOPPEMENT & SIMULATION D'UN PREMIER MODÈLE



## Méthode de Validation Croisée

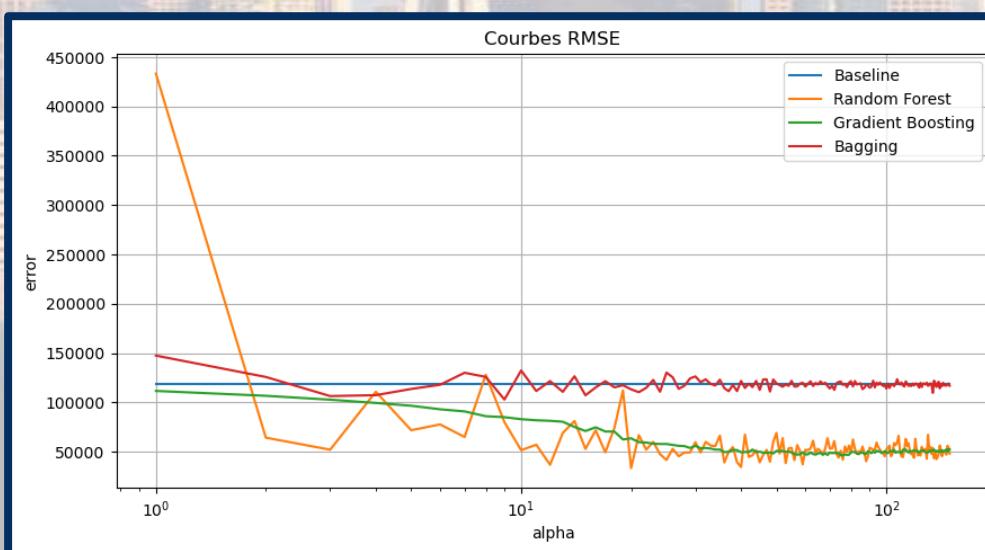
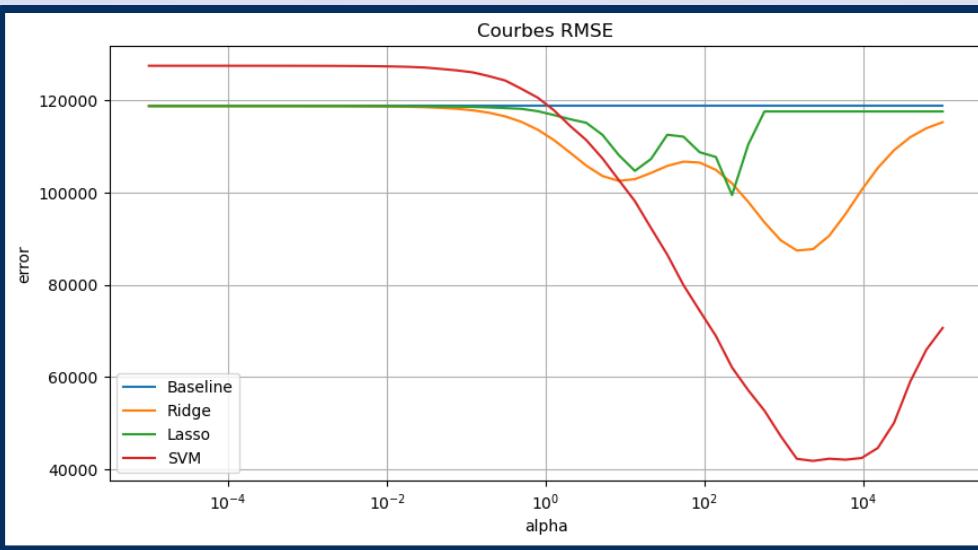
### ► TotalGHGEmissions :

- $R^2 = 0.49$
- $MAE = 13.02$
- $RMSE = 527.84$

### ► SiteEnergyUseWN(kBtu) :

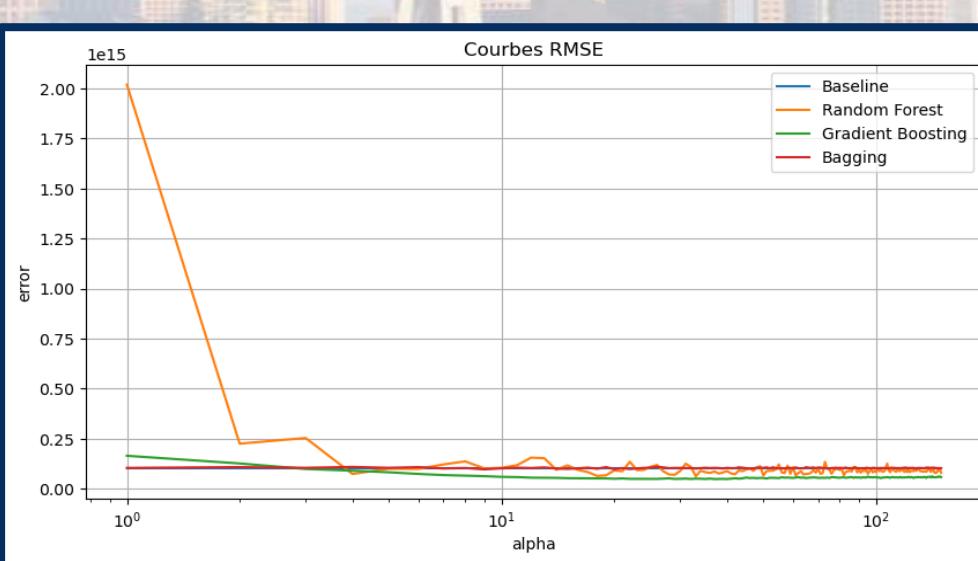
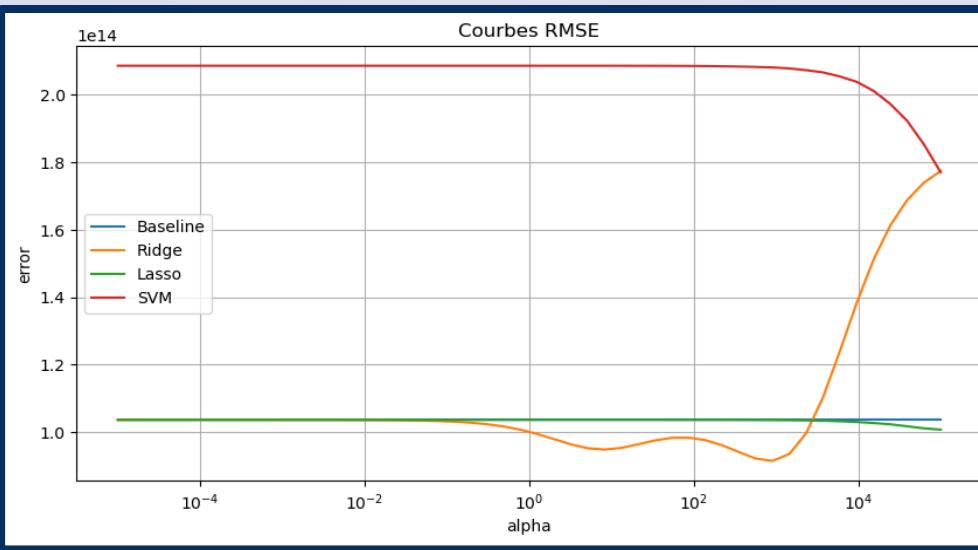
- $R^2 = 0.55$
- $MAE = 2271.22$
- $RMSE = 15823938.70$

# SIMULATION D'AUTRES MODÈLES & CHOIX D'UN MODÈLE FINAL : TOTALGHGEMISSIONS



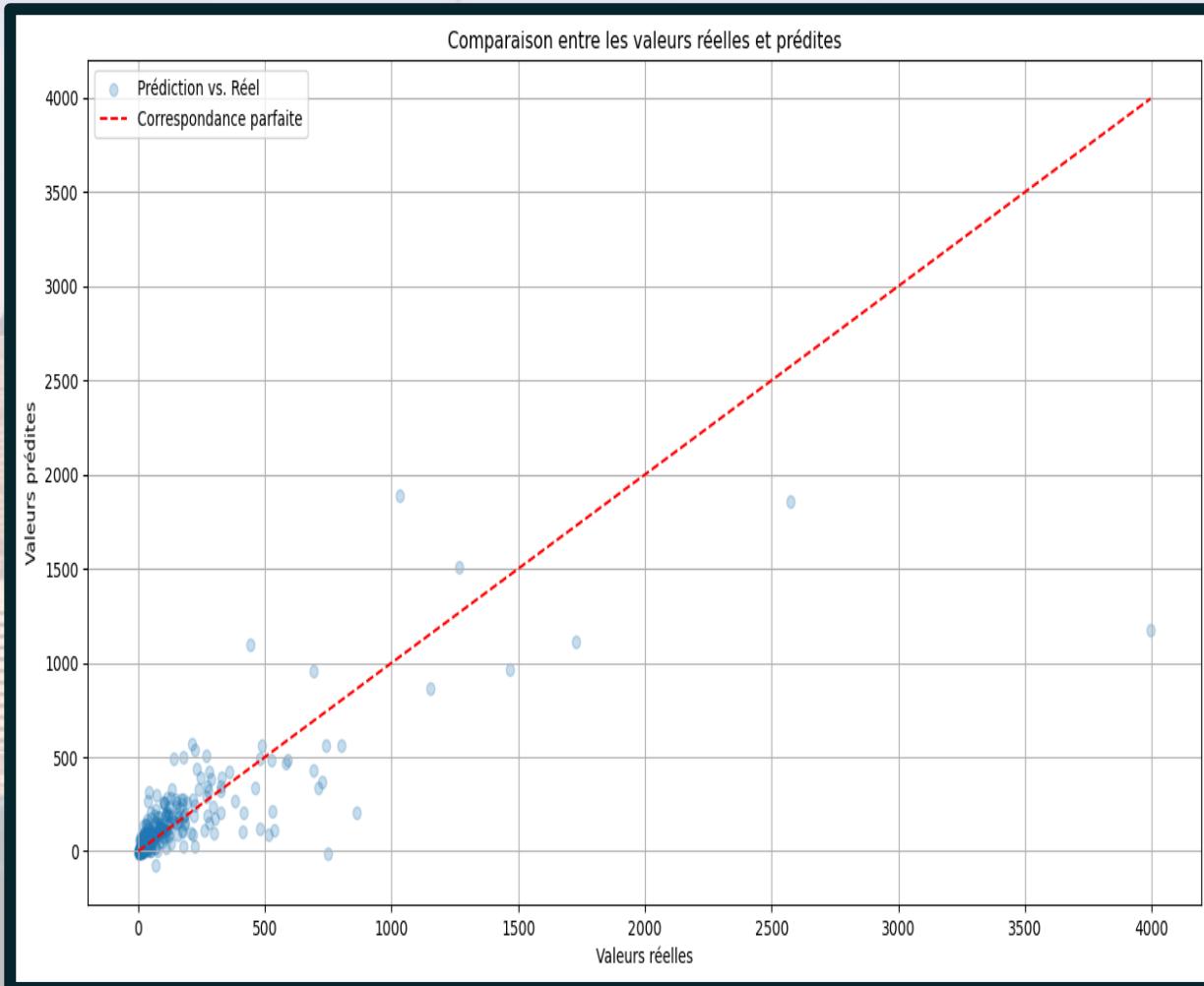
Model	Best RMSE Parameters	Training RMSE	Test RMSE
Linear Regression	{'model__fit_intercept': False}	589.47	344.58
Lasso Regression	{'model__alpha': 0.1}	741.47	315.35
Ridge Regression	{'model__alpha': 0.1}	713.05	295.68
Random Forest Regression	{'model__n_estimators': 100}	600.44	218.69
Gradient Boosting Regression	{'model__n_estimators': 200}	595.40	217.31
Bagging Regression	{'model__n_estimators': 100}	593.33	324.47
Support Vector Machine	{'model__C': 10}	699.39	204.46
Transformed Target Regression		12838.33	545.88
Stacking Regression		598.43	321.09

# SIMULATION D'AUTRES MODÈLES & CHOIX D'UN MODÈLE FINAL : SITEENERGYUSEWN(KBTU)



Model	Best RMSE Parameters	Training RMSE	Test RMSE
Linear Regression	{'model__fit_intercept': False}	1.776894e+07	1.776894e+07
Lasso Regression	{'model__alpha': 0.1}	1.776834e+07	1.018118e+07
Ridge Regression	{'model__alpha': 0.1}	1.776708e+07	1.015967e+07
Random Forest Regression	{'model__n_estimators': 100}	1.843309e+07	9.102588e+06
Gradient Boosting Regression	{'model__n_estimators': 200}	1.932904e+07	7.760410e+06
Bagging Regression	{'model__n_estimators': 100}	1.777025e+07	1.026720e+07
Support Vector Machine	{'model__C': 10}	2.533614e+07	1.444466e+07
Transformed Target Regression		3.600371e+08	5.410965e+07
Stacking Regression		2.412944e+10	1.946931e+10

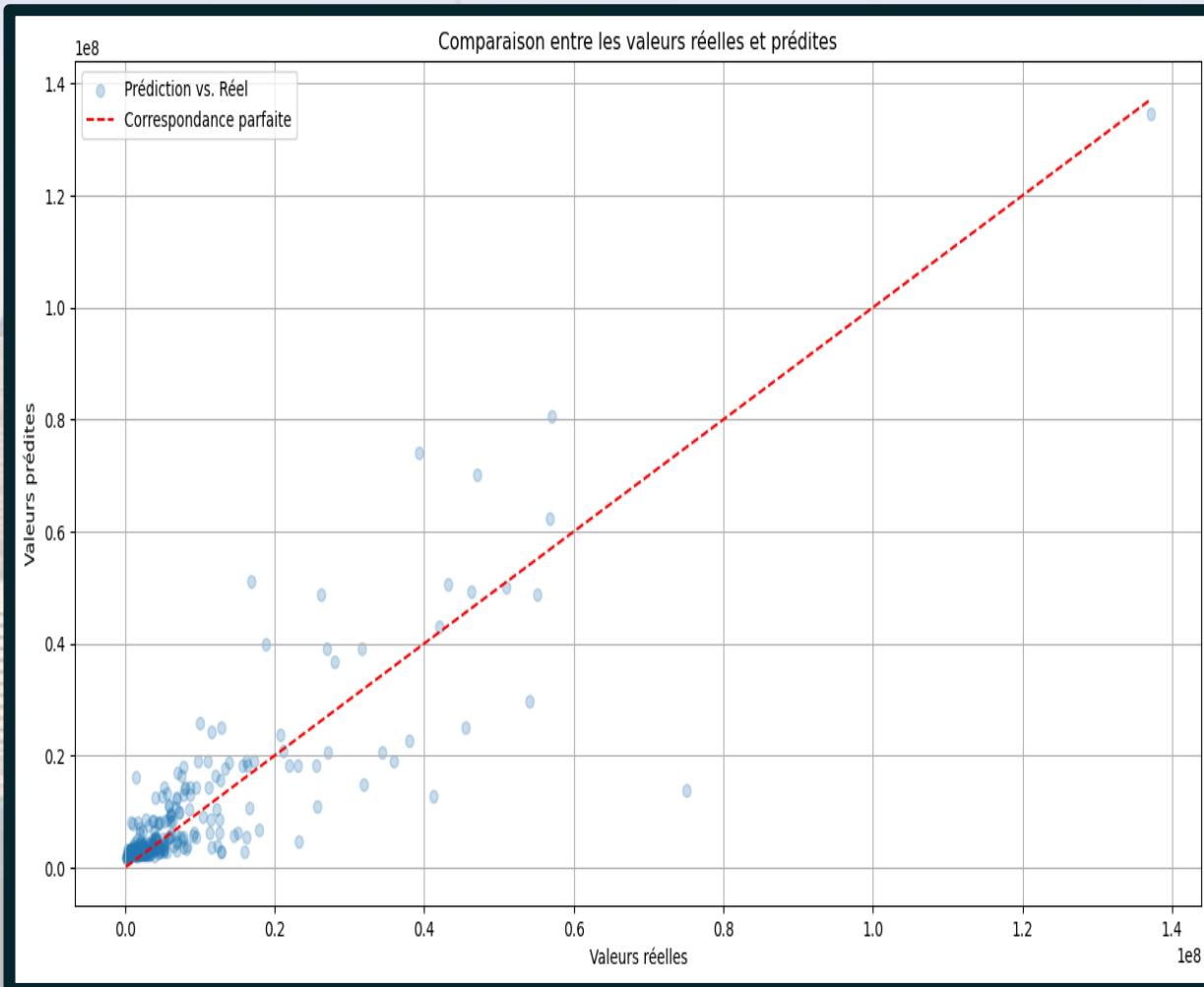
# SIMULATION D'AUTRES MODÈLES & CHOIX D'UN MODÈLE FINAL : TOTALGHGEMISSIONS



## Modèle Final: Gradient Boosting Regression

- ➡ N° of estimators = 70
- ➡  $R^2 = 0.6$
- ➡ MAE = 86.54
- ➡ RMSE = 216.81

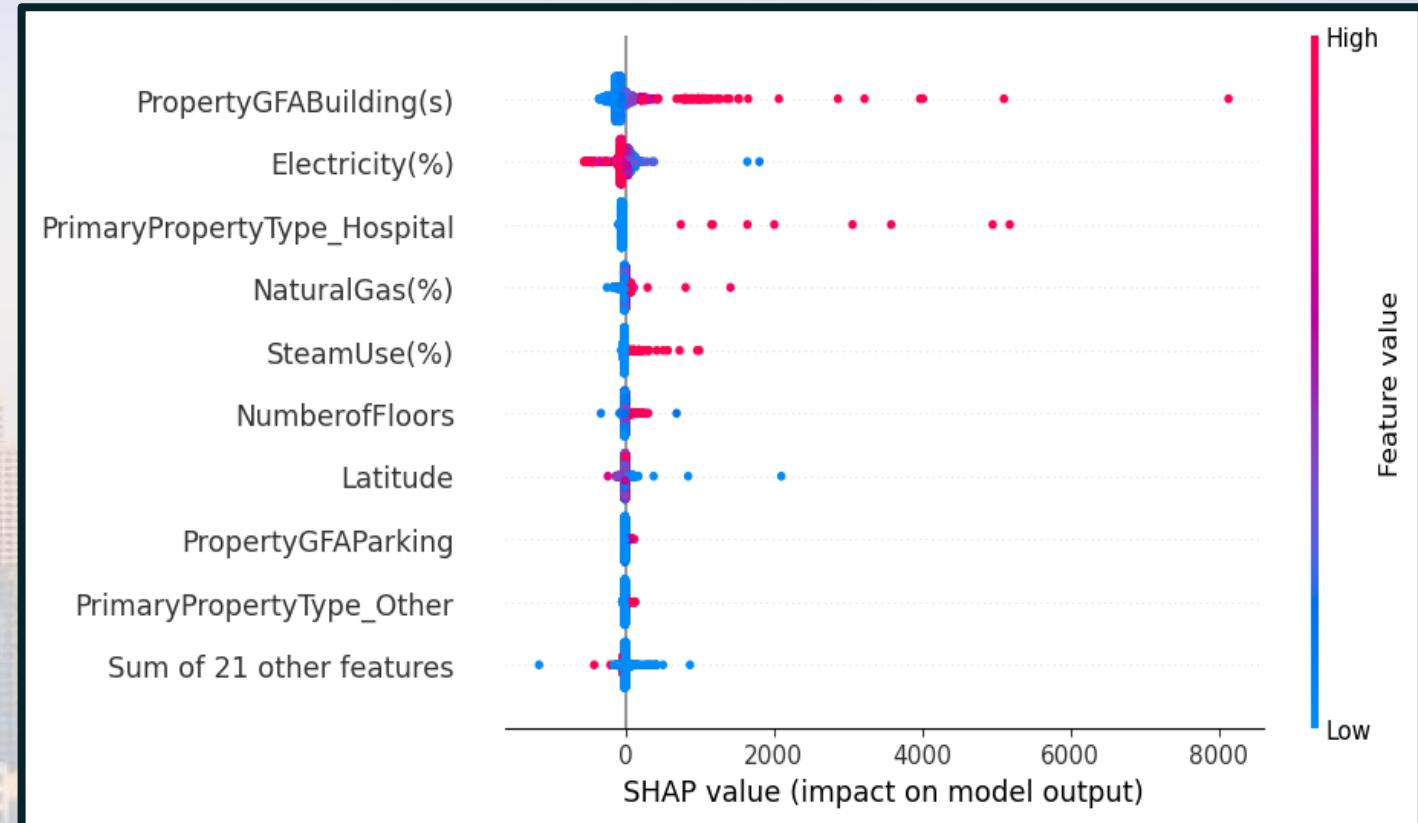
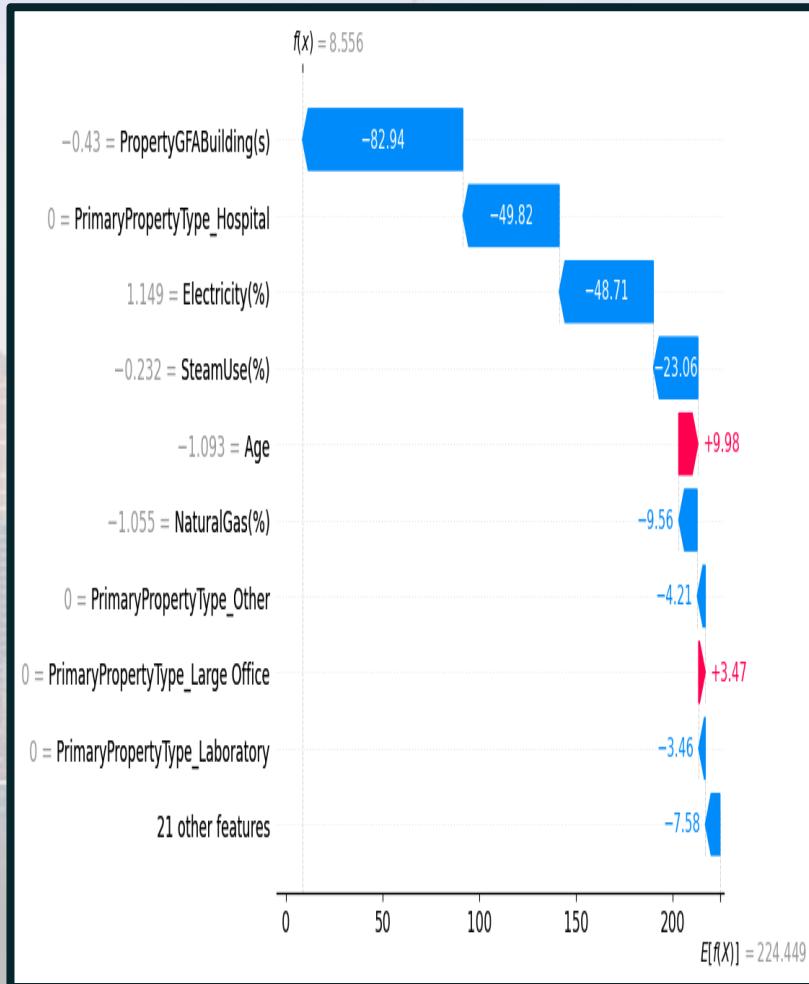
# SIMULATION D'AUTRES MODÈLES & CHOIX D'UN MODÈLE FINAL : SITEENERGYUSEWN(KBTU)



## Modèle Final: Gradient Boosting Regression

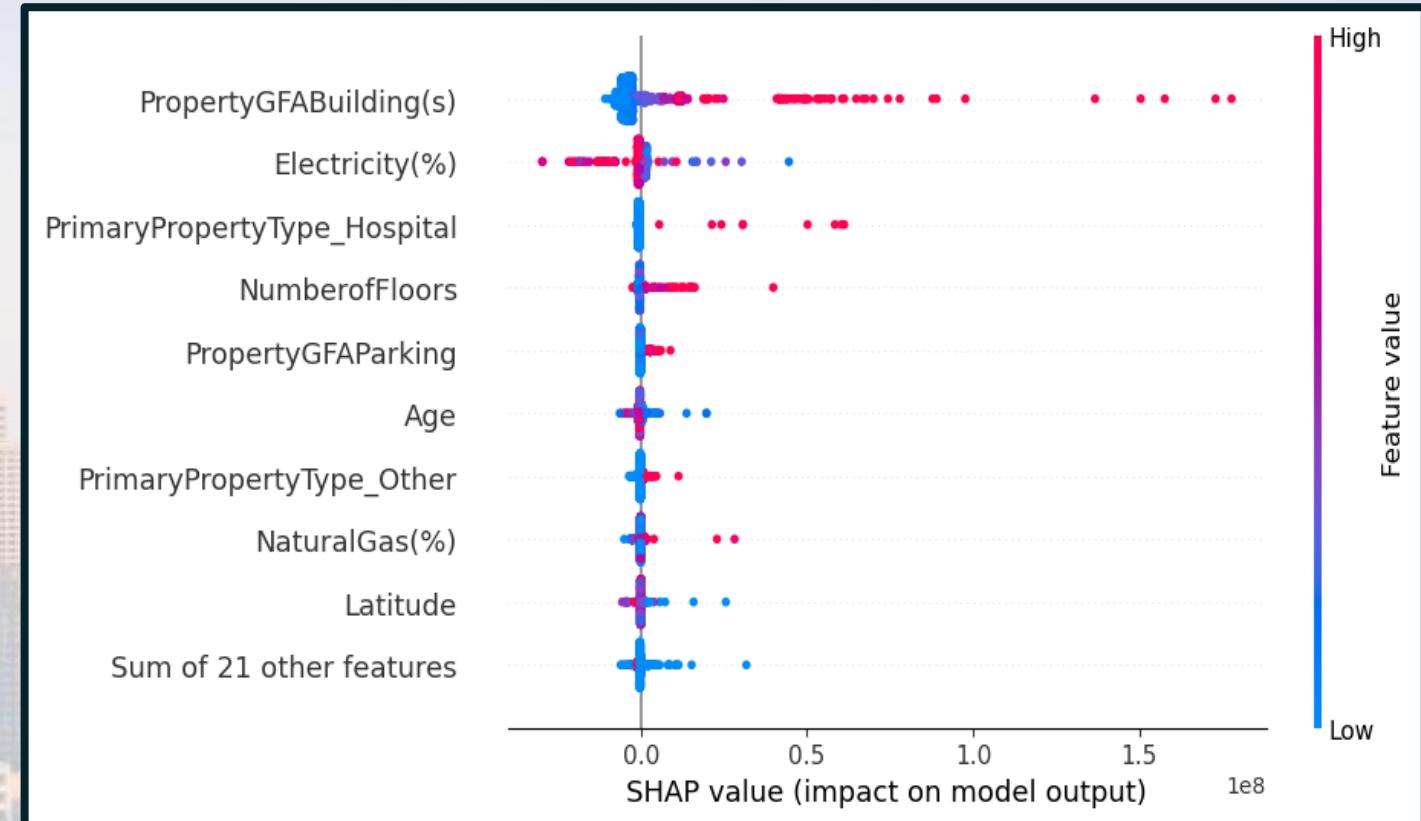
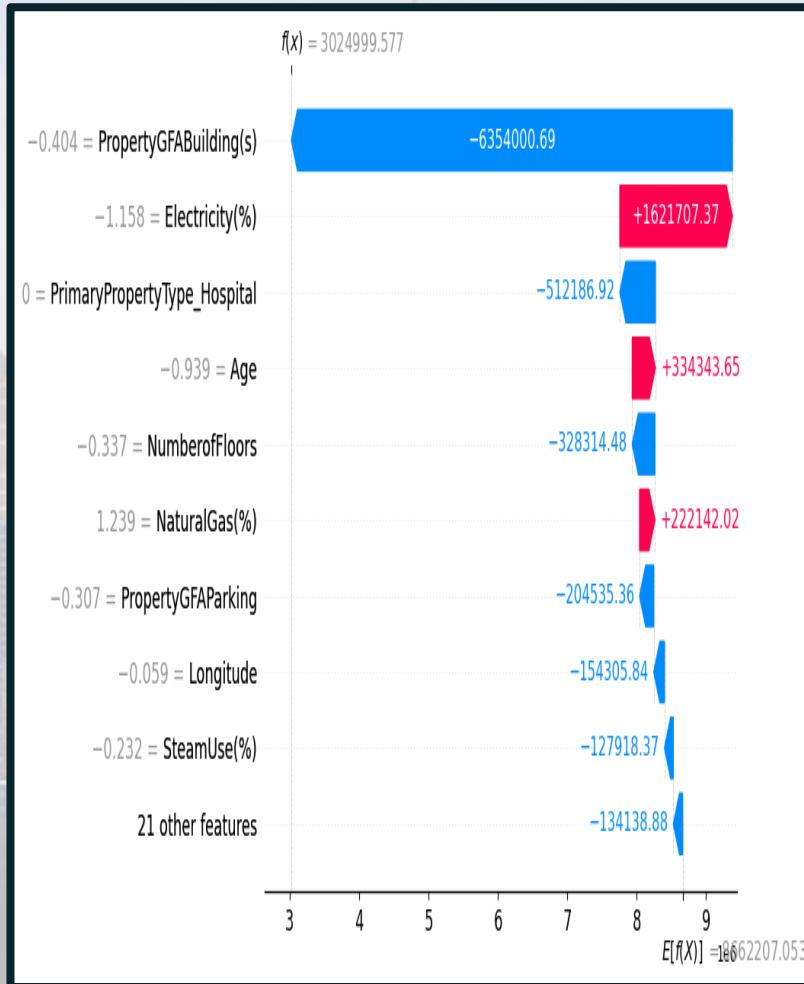
- ➡ N° of estimators = 40
- ➡  $R^2 = 0.71$
- ➡ MAE = 3858793.03
- ➡ RMSE = 7224883.46

# ANALYSE DE LA "FEATURE IMPORTANCE" GLOBALE & LOCALE : TOTALGHGEMISSIONS

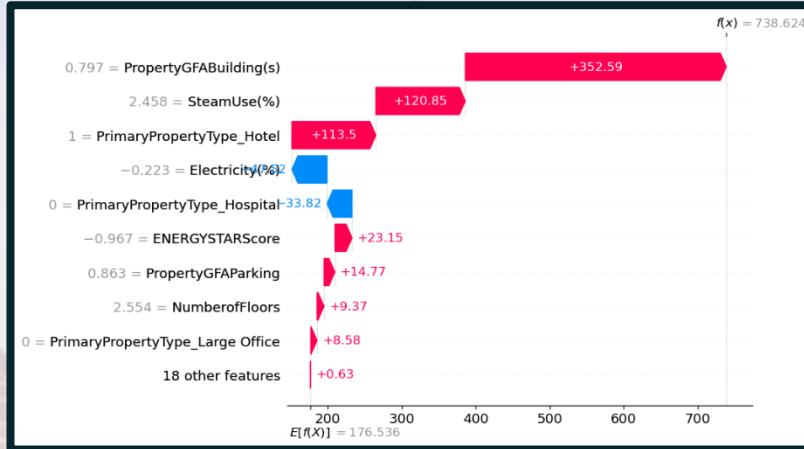


16/20

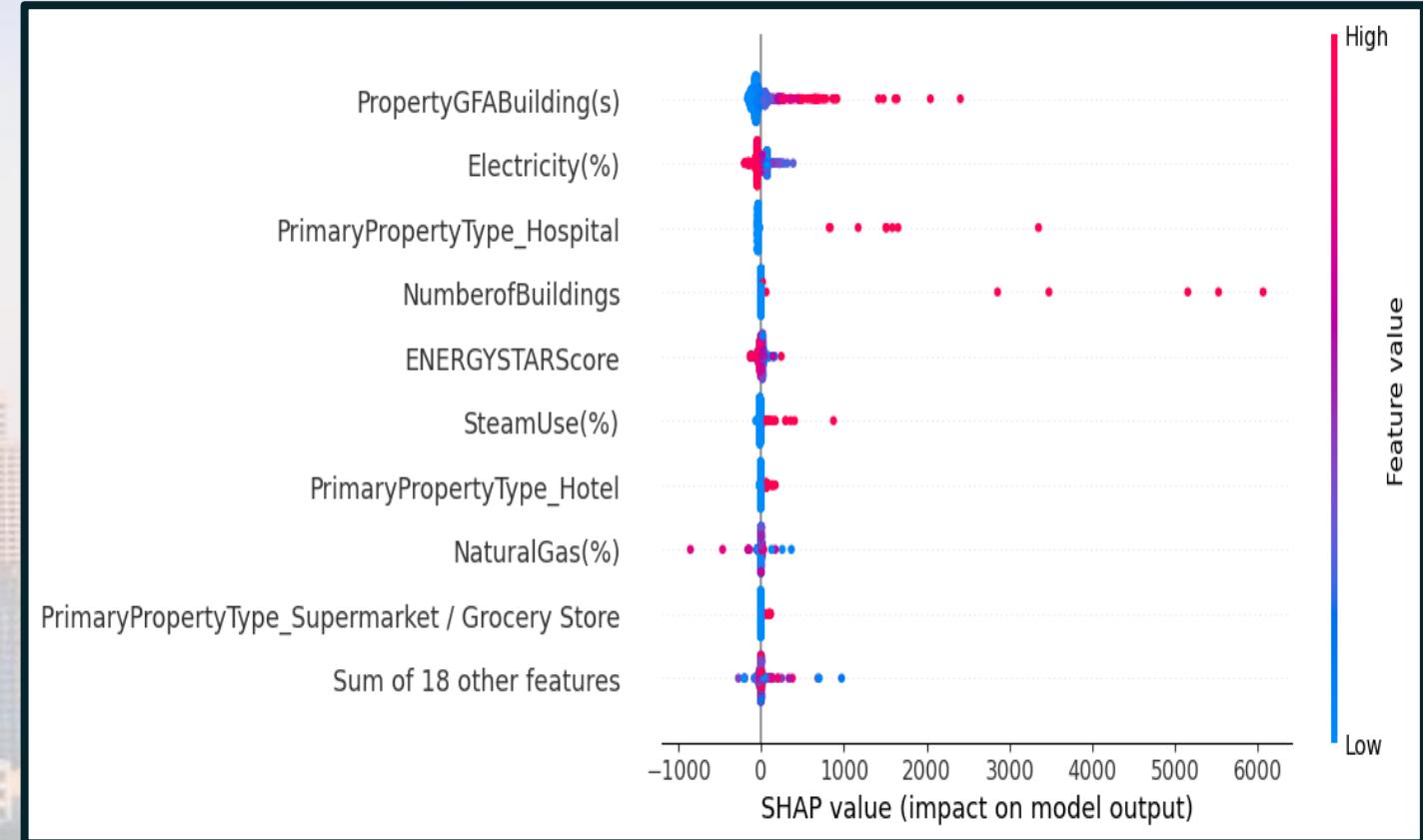
# ANALYSE DE LA "FEATURE IMPORTANCE" GLOBALE & LOCALE : SITEENERGYUSEWN(KBTU)



# ANALYSE DE L'INFLUENCE DE L'ENERGYSTARSCORE : TOTALGHGEMISSIONS

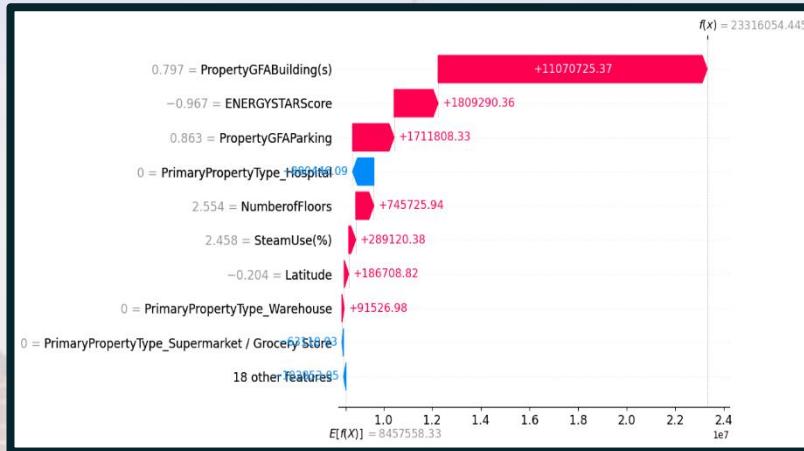


Métrique	Avec EnergyStarScore	Sans EnergyStarScore
R <sup>2</sup>	0.12	0.11
MAE	145.58	143.95
RMSE	1134.74	1144.52

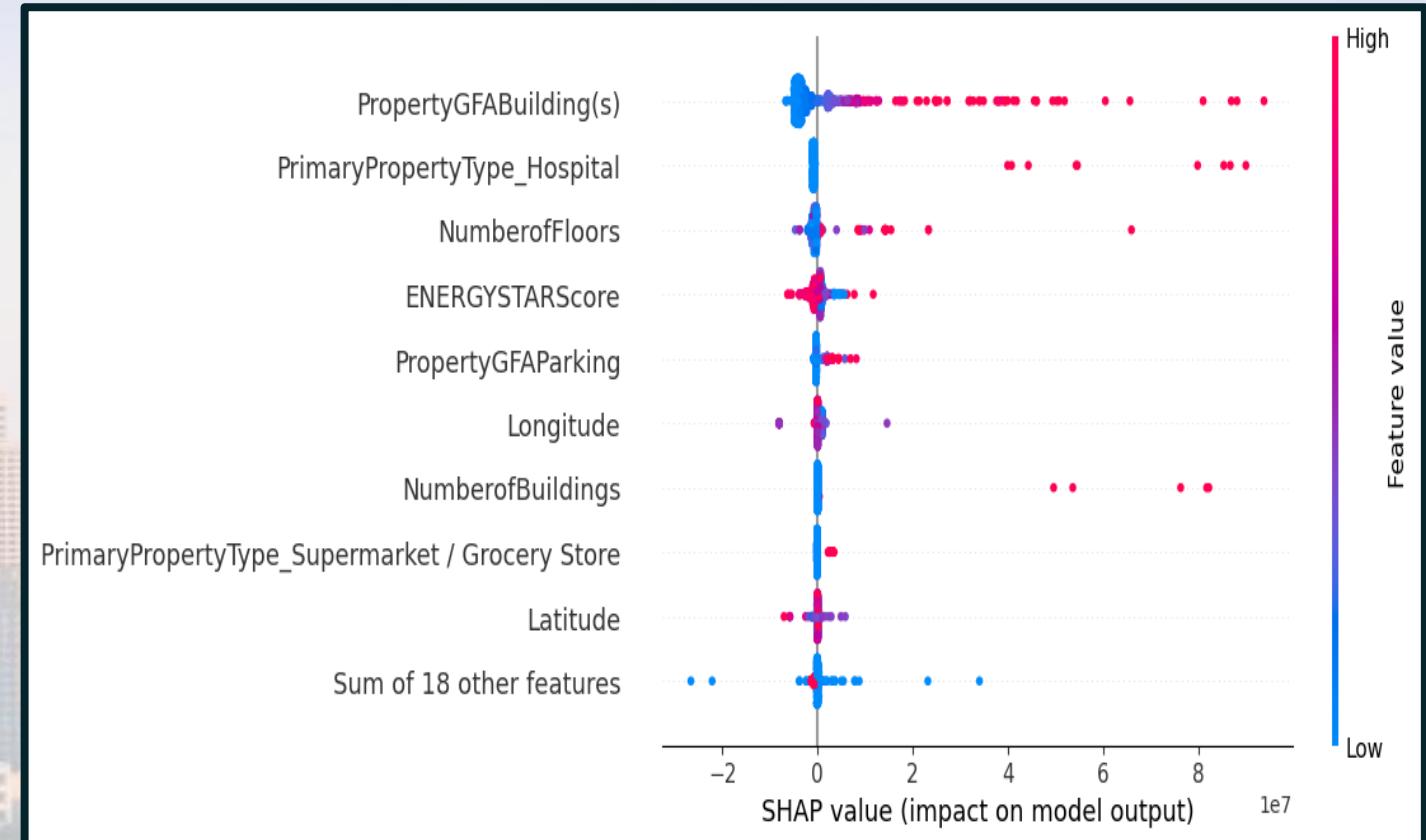


18/20

# ANALYSE DE L'INFLUENCE DE L'ENERGYSTARSCORE : SITEENERGYUSEWN(KBTU)



Métrique	Avec EnergyStarScore	Sans EnergyStarScore
R <sup>2</sup>	0.14	0.12
MAE	5131972.86	5384023.76
RMSE	31868482.04	32132763.43



19/20

# CONCLUSION

Modèle & Paramétrages Final – TotalGHGEmissions :

Gradient Boosting Regression (learning\_rate=0.1, n\_estimators= 70)

Modèle & Paramétrages Final – TotalGHGEmissions :

Gradient Boosting Regression (learning\_rate=0.1, n\_estimators= 40)



Variances particulièrement élevées

Généraliser Energy Star Score à tout le dataset = Performance++

Notifier Variables Cibles aux Valeurs Aberrantes

A blurred background image of the Seattle skyline, featuring the Space Needle and Mount Rainier in the distance.

**Merci pour votre  
attention**