In [1]:
```
# -*- coding: utf-8 -*-
"""
Created on Fri Aug 30 15:32:29 2024

@author: Thierry ALLEM
"""
# ************   ECHANGES  PHYSIQUES - MACHINE LEARNING  XGBOOST - VISUALISATIONS DES VALEURS PREDITES ET REELLES 2020-2023 ***************
```

Out[1]:
```
'\nCreated on Fri Aug 30 15:32:29 2024\n\n@author: Thierry ALLEM\n'
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import os
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Importation du fichier contenant les valeurs d'échanges physiques prédites sur les années 2020 à 2023
# Lecture du fichier CSV
df_blackout_xgb_20_23 = pd.read_csv('resultats_prev_xgb_20_23_complet.csv', sep=',',low_memory=False)
# Lecture du fichier CSV
df_blackout_xgb_20_23.head()
```

Out[3]:

	region	date_heure	annee	jour_numero	heure	jour_fractionnel	thermique	nucleaire	eolien	solaire	...	cap_prod_max_bioenergies	bioenergies_p_disp	population
0	CENTRE VAL DE LOIRE	2020-01-01 00:00:00	2020	1	00:00:00	1.0	105.0	8013.0	18.0	0.0	...	86.0	86.0	2574863
1	HAUTS DE FRANCE	2020-01-01 00:00:00	2020	1	00:00:00	1.0	2030.0	4507.0	1575.0	0.0	...	180.0	180.0	5997734
2	PAYS DE LA LOIRE	2020-01-01 00:00:00	2020	1	00:00:00	1.0	359.0	0.0	135.0	0.0	...	76.0	76.0	3832120
3	OCCITANIE	2020-01-01 00:00:00	2020	1	00:00:00	1.0	94.0	2375.0	217.0	0.0	...	146.0	146.0	5973969
4	BOURGOGNE FRANCHE COMTE	2020-01-01 00:00:00	2020	1	00:00:00	1.0	181.0	0.0	247.0	0.0	...	69.0	69.0	2801695

5 rows × 34 columns

In [4]:
```
# Suppression des colonnes non utiles aux visualisations
col_to_drop = ['thermique','nucleaire','eolien','solaire','hydraulique','bioenergies','pompage','stockage_batterie','destockage_batterie',
```

```
                    'cap_prod_max_thermique','cap_prod_max_nucleaire','eolien_p_disp','solaire_p_disp','cap_prod_max_hydraulique',
                    'cap_prod_max_bioenergies',
                    'thermique_p_disp',
                    'nucleaire_p_disp', 'hydraulique_p_disp','bioenergies_p_disp']
df_blackout_xgb_20_23 = df_blackout_xgb_20_23.drop(col_to_drop, axis=1)

df_blackout_xgb_20_23.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649152 entries, 0 to 649151
Data columns (total 15 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   region                     649152 non-null  object 
 1   date_heure                 649152 non-null  object 
 2   annee                      649152 non-null  int64  
 3   jour_numero                649152 non-null  int64  
 4   heure                      649152 non-null  object 
 5   jour_fractionnel           649152 non-null  float64
 6   ech_physiques              649152 non-null  float64
 7   population                 649152 non-null  int64  
 8   heure_decimale             649152 non-null  float64
 9   ech_physiques_pred_global  649152 non-null  float64
 10  erreur_absolue_glob        649152 non-null  float64
 11  erreur_relative_glob       649111 non-null  float64
 12  ech_physiques_pred_seg     649152 non-null  float64
 13  erreur_absolue_seg         649152 non-null  float64
 14  erreur_relative_seg        649111 non-null  float64
dtypes: float64(9), int64(3), object(3)
memory usage: 74.3+ MB
```

In [5]:
```
# Conversion de la colonne 'date_heure 'en Datetime
df_blackout_xgb_20_23['date_heure'] = pd.to_datetime(df_blackout_xgb_20_23['date_heure'])

# Ajout d'une colonne mois
df_blackout_xgb_20_23.insert(4, 'mois', df_blackout_xgb_20_23['date_heure'].dt.month)

# Création d'une colonne date au format YYYY-MM, type Object

df_blackout_xgb_20_23.insert(6, 'mois_annee', df_blackout_xgb_20_23['date_heure'].dt.strftime('%m-%Y'))
```

In [6]:
```
# Ajout de colonnes attribuant un indice de confiance aux prévisions

# On définit une petite valeur epsilon pour éviter la division par zéro
epsilon = 1e-10

# Définition des indices de confiance
df_blackout_xgb_20_23['indice_confiance_glob'] = np.where(
    df_blackout_xgb_20_23['ech_physiques'] == 0,
    0,  # Indice de confiance de 0 si la valeur réelle est nulle
    np.maximum(0, 1 - df_blackout_xgb_20_23['erreur_absolue_glob'] / (np.abs(df_blackout_xgb_20_23['ech_physiques']) + epsilon))*100
```

```
)

df_blackout_xgb_20_23['indice_confiance_seg'] = np.where(
    df_blackout_xgb_20_23['ech_physiques'] == 0,
    0,  # Indice de confiance de 0 si la valeur réelle est nulle
    np.maximum(0, 1 - df_blackout_xgb_20_23['erreur_absolue_seg'] / (np.abs(df_blackout_xgb_20_23['ech_physiques']) + epsilon))*100
)

df_blackout_xgb_20_23.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649152 entries, 0 to 649151
Data columns (total 19 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   region                     649152 non-null  object
 1   date_heure                 649152 non-null  datetime64[ns]
 2   annee                      649152 non-null  int64
 3   jour_numero                649152 non-null  int64
 4   mois                       649152 non-null  int32
 5   heure                      649152 non-null  object
 6   mois_annee                 649152 non-null  object
 7   jour_fractionnel           649152 non-null  float64
 8   ech_physiques              649152 non-null  float64
 9   population                 649152 non-null  int64
 10  heure_decimale             649152 non-null  float64
 11  ech_physiques_pred_global  649152 non-null  float64
 12  erreur_absolue_glob        649152 non-null  float64
 13  erreur_relative_glob       649111 non-null  float64
 14  ech_physiques_pred_seg     649152 non-null  float64
 15  erreur_absolue_seg         649152 non-null  float64
 16  erreur_relative_seg        649111 non-null  float64
 17  indice_confiance_glob      649152 non-null  float64
 18  indice_confiance_seg       649152 non-null  float64
dtypes: datetime64[ns](1), float64(11), int32(1), int64(3), object(3)
memory usage: 91.6+ MB
```

In [7]:
```
# Réorganisation des colonnes
ordre_desire = ['region','date_heure','annee','mois_annee','mois','jour_numero','jour_fractionnel','ech_physiques','ech_physiques_pred_global',
                'erreur_absolue_glob','erreur_relative_glob','indice_confiance_glob', 'ech_physiques_pred_seg','erreur_absolue_seg',
                'erreur_relative_seg','indice_confiance_seg']
df_blackout_xgb_20_23 = df_blackout_xgb_20_23[ordre_desire]

df_blackout_xgb_20_23.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 649152 entries, 0 to 649151
Data columns (total 16 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   region                      649152 non-null  object
 1   date_heure                  649152 non-null  datetime64[ns]
 2   annee                       649152 non-null  int64
 3   mois_annee                  649152 non-null  object
 4   mois                        649152 non-null  int32
 5   jour_numero                 649152 non-null  int64
 6   jour_fractionnel            649152 non-null  float64
 7   ech_physiques               649152 non-null  float64
 8   ech_physiques_pred_global   649152 non-null  float64
 9   erreur_absolue_glob         649152 non-null  float64
 10  erreur_relative_glob        649111 non-null  float64
 11  indice_confiance_glob       649152 non-null  float64
 12  ech_physiques_pred_seg      649152 non-null  float64
 13  erreur_absolue_seg          649152 non-null  float64
 14  erreur_relative_seg         649111 non-null  float64
 15  indice_confiance_seg        649152 non-null  float64
dtypes: datetime64[ns](1), float64(10), int32(1), int64(2), object(2)
memory usage: 76.8+ MB
```

In [8]:
```
# Recherche de valeurs manquantes
df_blackout_xgb_20_23.isna().sum()
```

Out[8]:
```
region                       0
date_heure                   0
annee                        0
mois_annee                   0
mois                         0
jour_numero                  0
jour_fractionnel             0
ech_physiques                0
ech_physiques_pred_global    0
erreur_absolue_glob          0
erreur_relative_glob        41
indice_confiance_glob        0
ech_physiques_pred_seg       0
erreur_absolue_seg           0
erreur_relative_seg         41
indice_confiance_seg         0
dtype: int64
```

In [9]:
```
# Brèves statistiques
describe =  df_blackout_xgb_20_23.describe()
```

In [10]:
```
# VISUALISATION GRAPHIQUE DES PREDICTIONS - VALEURS DES ECHANGES REELS ET PREDITES SELON LES 2 METHODES ET ERREURS ABSOLUES
```

In [31]:
```
# Import des métriques des modélisations régionales (spar segmentation), par année
df_metric_seg_annee = pd.read_csv('resultats_xgb_seg_metrics_20_23.csv', sep=';', encoding='latin-1')
df_metric_seg_annee.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48 entries, 0 to 47
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   region  48 non-null     object
 1   annee   48 non-null     int64
 2   MSE     48 non-null     float64
 3   RMSE    48 non-null     float64
 4   MAE     48 non-null     float64
 5   R²      48 non-null     float64
dtypes: float64(4), int64(1), object(1)
memory usage: 2.4+ KB
```

In [32]:
```
# Création des colonnes vides pour les nouvelles métriques
df_metric_seg_annee['mediane_ech_phys'] = np.nan
df_metric_seg_annee['irq_ech_phys'] = np.nan


df_metric_seg_annee['mediane_ech_phys_glob'] = np.nan
df_metric_seg_annee['irq_ech_phys_glob'] = np.nan

df_metric_seg_annee['mae_err_abs_glob'] = np.nan
df_metric_seg_annee['ecart_type_err_abs_glob'] = np.nan
df_metric_seg_annee['variance_err_abs_glob'] = np.nan

df_metric_seg_annee['mediane_erreur_absolue_glob'] = np.nan
df_metric_seg_annee['irq_err_abs_glob'] = np.nan

df_metric_seg_annee['mae_indice_confiance_global'] = np.nan
df_metric_seg_annee['mediane_indice_confiance_global'] = np.nan

df_metric_seg_annee['mediane_ech_phys_seg'] = np.nan
df_metric_seg_annee['irq_ech_phys_seg'] = np.nan

df_metric_seg_annee['mae_err_abs_seg'] = np.nan
df_metric_seg_annee['ecart_type_err_abs_seg'] = np.nan
df_metric_seg_annee['variance_err_abs_seg'] = np.nan

df_metric_seg_annee['mediane_erreur_absolue_seg'] = np.nan
df_metric_seg_annee['irq_err_abs_seg'] = np.nan

df_metric_seg_annee['mae_indice_confiance_seg'] = np.nan
df_metric_seg_annee['mediane_indice_confiance_seg'] = np.nan
```

In [33]:
```python
# Fonction pour ajouter des barres de saisons
def barre_saisons(ax):
    saisons = {'Hiver': (1, 79),
               'Printemps': (80, 171),
               'Été': (172, 265),
               'Automne': (266, 354),
               'Hiver (suite)': (355, 365)}
    colors = ['lightblue', 'lightgreen', 'lightyellow', 'orange', 'lightblue']
    for (saison, (start, end)), color in zip(saisons.items(), colors):
        ax.axvspan(start, end, color=color, alpha=0.3)
        ax.text((start + end) / 2, 1.00, saison, ha='center', va='bottom', fontsize=8, color='gray', transform=ax.get_xaxis_transform())
```

In [34]:
```python
# Création du répertoire de sauvegarde des graphiques
output_dir = "Ech_Phys_XGB_combined_graphs_Ind_Conf"
if not os.path.exists(output_dir):
    os.makedirs(output_dir)
```

In [35]:
```python
for region in df_blackout_xgb_20_23['region'].unique():
    df_region = df_blackout_xgb_20_23[df_blackout_xgb_20_23['region'] == region]

    for annee in df_region['annee'].unique():
        df_annee = df_region[df_region['annee'] == annee]

        # Calcul des métriques
        mediane_ech_phys = df_annee['ech_physiques'].median()
        irq_ech_phys = stats.iqr(df_annee['ech_physiques'])

        mediane_ech_phys_glob = df_annee['ech_physiques_pred_global'].median()
        irq_ech_phys_glob = stats.iqr(df_annee['ech_physiques_pred_global'])

        mediane_ech_phys_seg = df_annee['ech_physiques_pred_seg'].median()
        irq_ech_phys_seg = stats.iqr(df_annee['ech_physiques_pred_seg'])

        mae_err_abs_glob = df_annee['erreur_absolue_glob'].mean()
        mediane_erreur_absolue_glob = (np.abs(df_annee['erreur_absolue_glob'])).median()
        irq_err_abs_glob = stats.iqr(df_annee['erreur_absolue_glob'])
        ecart_type_err_abs_glob = df_annee['erreur_absolue_glob'].std()
        variance_err_abs_glob = df_annee['erreur_absolue_glob'].var()

        mae_err_abs_seg = df_annee['erreur_absolue_seg'].mean()
        mediane_erreur_absolue_seg = (np.abs(df_annee['erreur_absolue_seg'])).median()
        irq_err_abs_seg = stats.iqr(df_annee['erreur_absolue_seg'])
        ecart_type_err_abs_seg = df_annee['erreur_absolue_seg'].std()
        variance_err_abs_seg = df_annee['erreur_absolue_seg'].var()

        # Moyennes et médianes des indices de confiance
        mae_indice_confiance_global = df_annee['indice_confiance_glob'].mean()
        mae_indice_confiance_seg = df_annee['indice_confiance_seg'].mean()
        mediane_indice_confiance_global = df_annee['indice_confiance_glob'].median()
        mediane_indice_confiance_seg = df_annee['indice_confiance_seg'].median()
```

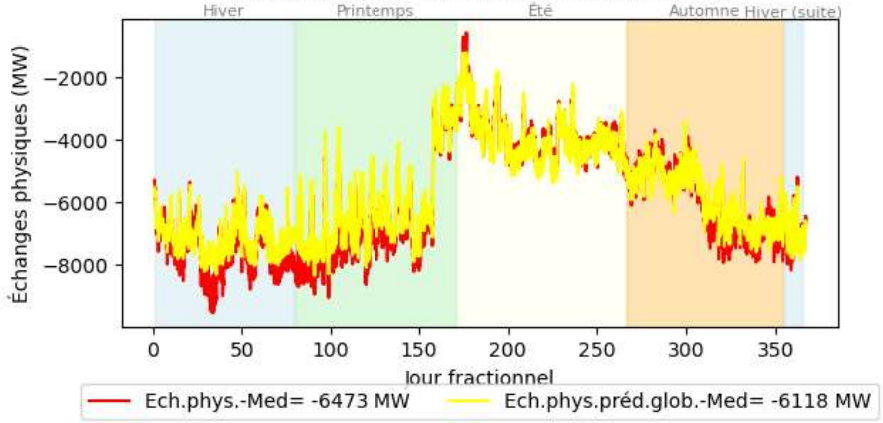
```python
# Mise à jour du DataFrame avec les nouvelles métriques
df_metric_seg_annee.loc[
    (df_metric_seg_annee['region'] == region) & (df_metric_seg_annee['annee'] == annee),
    ['mediane_ech_phys', 'irq_ech_phys', 'mediane_ech_phys_glob', 'irq_ech_phys_glob','mae_err_abs_glob',
     'ecart_type_err_abs_glob', 'variance_err_abs_glob','mediane_erreur_absolue_glob', 'irq_err_abs_glob',
     'mae_indice_confiance_global', 'mediane_indice_confiance_glob',
     'mediane_ech_phys_seg', 'irq_ech_phys_seg','mae_err_abs_seg', 'ecart_type_err_abs_seg', 'variance_err_abs_seg',
     'mediane_erreur_absolue_seg', 'irq_err_abs_seg', 'mae_indice_confiance_seg', 'mediane_indice_confiance_seg']
    ] = [mediane_ech_phys, irq_ech_phys, mediane_ech_phys_glob, irq_ech_phys_glob,
         mae_err_abs_glob, ecart_type_err_abs_glob, variance_err_abs_glob,
         mediane_erreur_absolue_glob, irq_err_abs_glob, mae_indice_confiance_global,
         mediane_indice_confiance_global, mediane_ech_phys_seg, irq_ech_phys_seg,
         mae_err_abs_seg, ecart_type_err_abs_seg, variance_err_abs_seg, mediane_erreur_absolue_seg,
         irq_err_abs_seg, mae_indice_confiance_seg, mediane_indice_confiance_seg]


    # Création du graphique
fig, axs = plt.subplots(4, 2, figsize=(15, 15))

# 1ère ligne, 1ère colonne
axs[0, 0].plot(df_annee['jour_fractionnel'], df_annee['ech_physiques'], color='red', label=f'Ech.phys.-Med= {mediane_ech_phys:.0f} MW')
axs[0, 0].plot(df_annee['jour_fractionnel'], df_annee['ech_physiques_pred_global'], color='yellow', label=f'Ech.phys.préd.glob.-Med= {mediane_ech_phys_glo
axs[0, 0].set_title("Ech. physiques - prévisions -Modèle global", y = 1.05)
axs[0, 0].set_xlabel("Jour fractionnel")
axs[0, 0].set_ylabel("Échanges physiques (MW)")
axs[0, 0].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[0, 0])  # Ajout des barres de saisons

# 1ère ligne, 2ème colonne
axs[0, 1].plot(df_annee['jour_fractionnel'], df_annee['ech_physiques'], color='red', label=f'Ech.phys.-Med.= {mediane_ech_phys:.0f} MW')
axs[0, 1].plot(df_annee['jour_fractionnel'], df_annee['ech_physiques_pred_seg'], color='blue', label=f'Ech.phys.préd.seg.-Med.= {mediane_ech_phys_seg:.0f}
axs[0, 1].set_title("Ech. physiques - prévision - Modèle régional", y = 1.05)
axs[0, 1].set_xlabel("Jour fractionnel")
axs[0, 1].set_ylabel("Échanges physiques (MW)")
axs[0, 1].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[0, 1])  # Ajout des barres de saisons

# 2ème ligne, 1ère colonne
window_size = 144
axs[1, 0].plot(df_annee['jour_numero'], df_annee['ech_physiques'].rolling(window=window_size).mean(), color='red', label='Ech. physiques (moy.mob.)')
axs[1, 0].plot(df_annee['jour_numero'], df_annee['ech_physiques_pred_global'].rolling(window=window_size).mean(), color='yellow', label='Ech. physiques pr
axs[1, 0].set_title("Moyennes mobiles WS144- Modèle global", y = 1.05)
axs[1, 0].set_xlabel("Jour numero")
axs[1, 0].set_ylabel("Échanges physiques (MW)")
axs[1, 0].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[1, 0])  # Ajout des barres de saisons

# 2ème ligne, 2ème colonne
axs[1, 1].plot(df_annee['jour_numero'], df_annee['ech_physiques'].rolling(window=window_size).mean(), color='red', label='Ech. physiques (moy.mob.)')
axs[1, 1].plot(df_annee['jour_numero'], df_annee['ech_physiques_pred_seg'].rolling(window=window_size).mean(), color='blue', label='Ech. physiques préd.se
```

```
axs[1, 1].set_title("Moyennes mobiles WS144 - Modèle régional", y = 1.05)
axs[1, 1].set_xlabel("Jour numero")
axs[1, 1].set_ylabel("Échanges physiques (MW)")
axs[1, 1].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[1, 1])  # Ajout des barres de saisons

# 3ème ligne, 1ère colonne (Erreurs absolues- Préd. global)
axs[2, 0].plot(df_annee['jour_fractionnel'], df_annee['indice_confiance_glob'], color='yellow', label='indice_confiance_glob.')
axs[2, 0].axhline(mae_indice_confiance_global, color='red', linestyle='--', label=f'MAE: {mae_indice_confiance_global:.1f} %')
axs[2, 0].axhline(mediane_indice_confiance_global, color='magenta', linestyle='--', label=f'Med.: {mediane_indice_confiance_global:.1f} %')
axs[2, 0].set_title("Indices de confiance (100-|erreur relative|) - Modèle global", y = 1.05)
axs[2, 0].set_xlabel("Jour fractionnel")
axs[2, 0].set_ylabel("Indice de confiance (%)")
axs[2, 0].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[2, 0])  # Ajout des barres de saisons

# 3ème ligne, 2ème colonne (Erreurs absolues - Préd. segmenté)
axs[2, 1].plot(df_annee['jour_fractionnel'], df_annee['indice_confiance_seg'], color='blue', label='indice_confiance_seg')
axs[2, 1].axhline(mae_indice_confiance_seg, color='red', linestyle='--', label=f'MAE: {mae_indice_confiance_seg:.1f} %')
axs[2, 1].axhline(mediane_indice_confiance_seg, color='magenta', linestyle='--', label=f'Med.: {mediane_indice_confiance_seg:.1f} %')
axs[2, 1].set_title("Indice de confiance (100-|erreur relative|)- Modèle régional", y = 1.05)
axs[2, 1].set_xlabel("Jour fractionnel")
axs[2, 1].set_ylabel("Indices de confiance (%)")
axs[2, 1].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
barre_saisons(axs[2, 1])  # Ajout des barres de saisons

# 4ème ligne, 1ère colonne (Distribution des erreurs absolues des 2 méthodes)
if df_annee['indice_confiance_glob'].var() > 0 and df_annee['indice_confiance_seg'].var() > 0:
    sns.kdeplot(df_annee['indice_confiance_seg'], color='blue', label='indice_confiance_seg', fill=True, ax=axs[3, 0])
    sns.kdeplot(df_annee['indice_confiance_glob'], color='yellow', label='indice_confiance_global', fill=True, alpha = 0.4, ax=axs[3, 0])

else:
    axs[3, 0].text(0.5, 0.5, "Variabilité insuffisante\npour KDE", fontsize=12, ha='center', va='center')

axs[3, 0].set_title("Distribution des indices de confiance des prévisions")
axs[3, 0].set_xlabel("Indice de confiance (%)")
axs[3, 0].set_ylabel("Densité")
axs[3, 0].legend(loc='upper center', bbox_to_anchor=(0.5, -0.15), ncol=2)
# 4ème ligne, 2ème colonne (Ajout des métriques de prévisions)
metrics = df_metric_seg_annee[(df_metric_seg_annee['region'] == region) & (df_metric_seg_annee['annee'] == annee)]
if not metrics.empty:
    # Texte pour chaque colonne
    col1_text = (
        f"Médiane: {mediane_ech_phys:.0f} MW\n"
        f"IQR: {irq_ech_phys:.0f} MW\n"
        )
    col2_text = (
        f"Médiane: {mediane_ech_phys_glob:.0f} MW\n"
        f"IQR: {irq_ech_phys_glob:.0f} MW\n"
        f"Ind.Conf.Moy.: {mae_indice_confiance_global:.1f} %\n"
        )
```

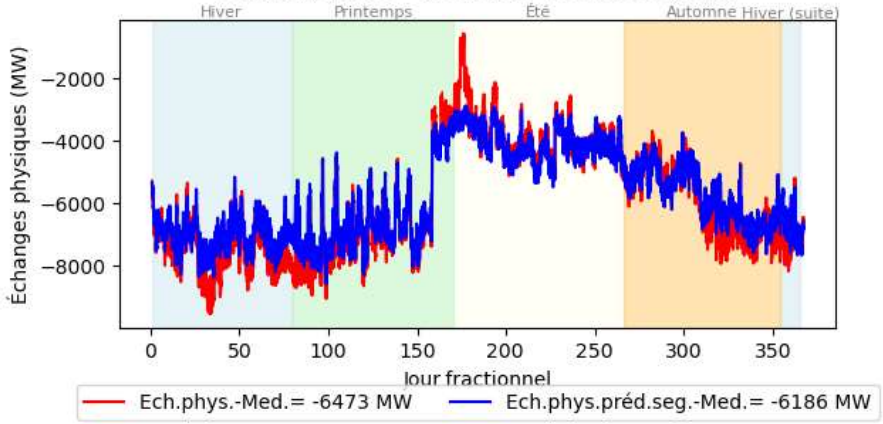
```
            col3_text = (
                f"Médiane: {mediane_ech_phys_seg:.0f} MW\n"
                f"IQR: {irq_ech_phys_seg:.0f} MW\n"
                f"Ind.Conf.Moy.: {mae_indice_confiance_seg:.1f} %\n"
                )

            # Affichage des textes dans les colonnes
            axs[3, 1].text(0.5, 0.93, f"Métriques {annee}", fontsize=14, ha='left', va='bottom',
                           bbox=dict(facecolor='white', edgecolor='brown', boxstyle='round4,pad=0.3'))

            axs[3, 1].text(0.17, 0.7, "Valeurs réelles", fontsize=12, ha='left', va='top')
            axs[3, 1].text(0.5, 0.7, "Modèle global", fontsize=12, ha='left', va='top')
            axs[3, 1].text(0.83, 0.7, "Modèle régional", fontsize=12, ha='left', va='top')


            # Ajout des résultats
            axs[3, 1].text(0.17, 0.5, col1_text, fontsize=10, ha='left', va='top')
            axs[3, 1].text(0.5, 0.5, col2_text, fontsize=10, ha='left', va='top')
            axs[3, 1].text(0.83, 0.5, col3_text, fontsize=10, ha='left', va='top')

        else:
            axs[3, 1].text(0.5, 0.5, "Aucune métrique disponible", fontsize=12, ha='center', va='center')

        # Masquage du sous-graphe vide
        axs[3, 1].axis('off')

        # Ajustement de l'espacement entre les sous-graphes
        plt.subplots_adjust(hspace=0.6, wspace=0.3, top=0.92, bottom=0.08)

        # Ajout du titre principal
        fig.suptitle(f"Prévisions des échanges physiques par XGBoost sans transformation cible \n{region}, {annee}", fontsize=16)
        fig.text(0.5,0.01,"XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7", ha='center', font

        # Sauvegarde du graphique
        filename = f"{region}_{annee}_combined.png"
        plt.savefig(os.path.join(output_dir, filename), dpi=300)
        plt.show()
```

Prévisions des échanges physiques par XGBoost sans transformation cible
CENTRE VAL DE LOIRE, 2020

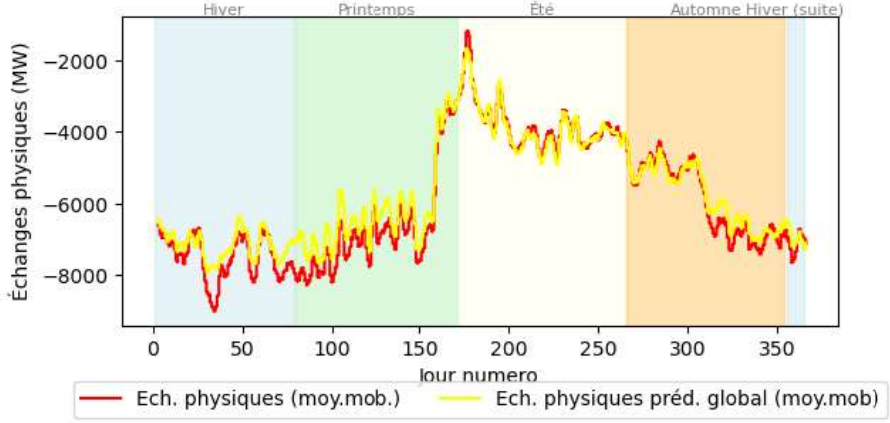
Ech. physiques - prévisions -Modèle global



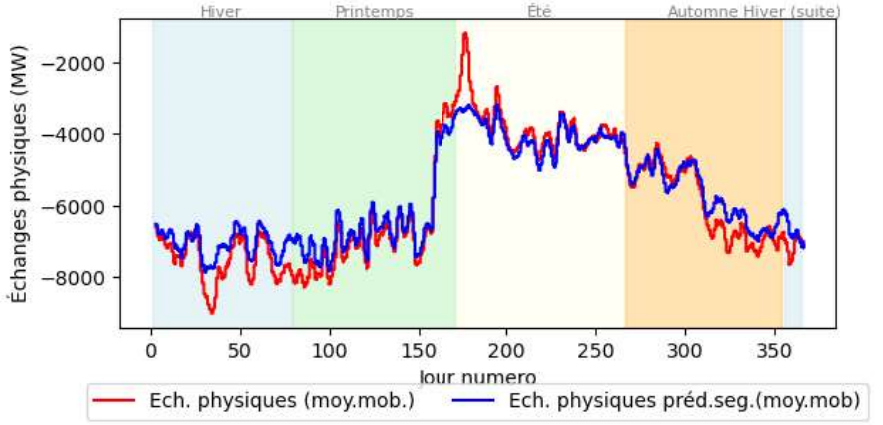
Ech. physiques - prévision - Modèle régional



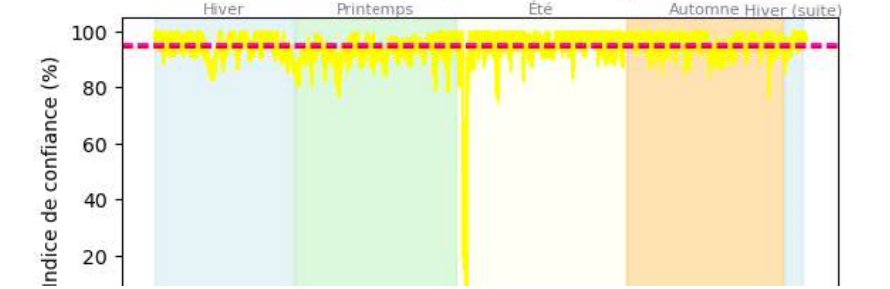
Moyennes mobiles WS144- Modèle global



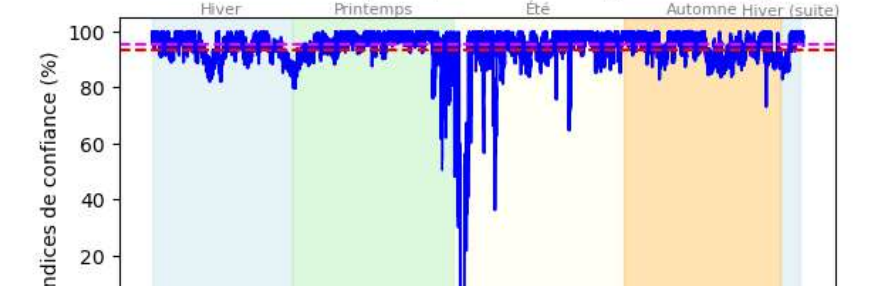
Moyennes mobiles WS144 - Modèle régional

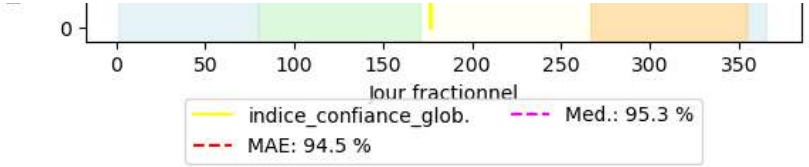


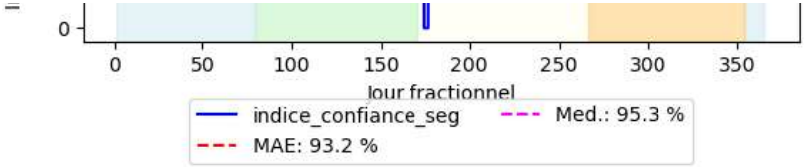
Indices de confiance (100-|erreur relative|) - Modèle global

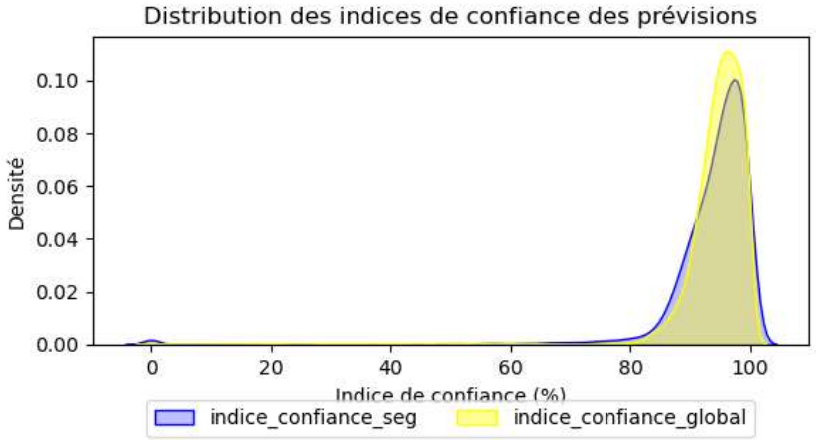


Indice de confiance (100-|erreur relative|)- Modèle régional









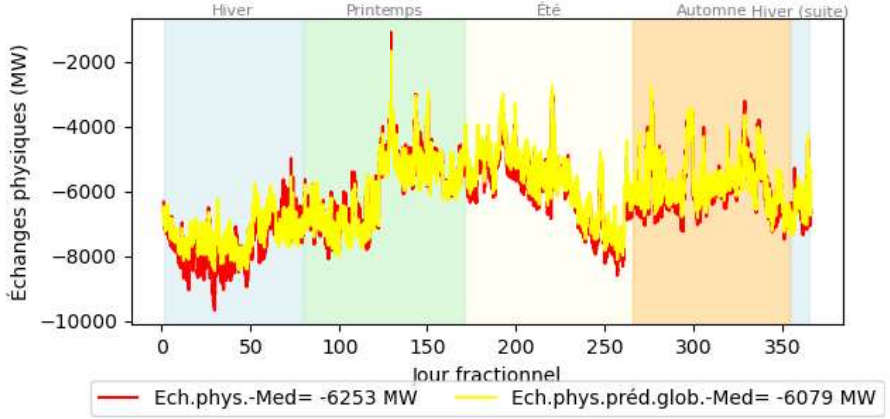
Métriques 2020

Valeurs réelles	Modèle global	Modèle régional
Médiane: -6473 MW	Médiane: -6118 MW	Médiane: -6186 MW
IQR: 2939 MW	IQR: 2557 MW	IQR: 2468 MW
	Ind.Conf.Moy.: 94.5 %	Ind.Conf.Moy.: 93.2 %

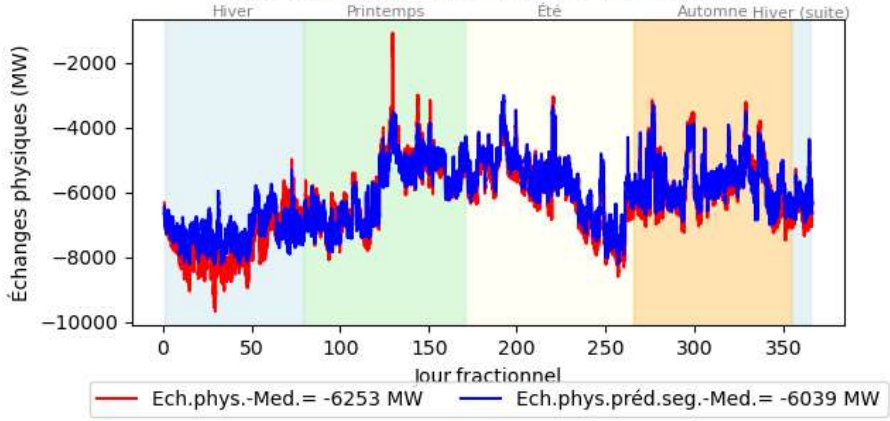
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

Prévisions des échanges physiques par XGBoost sans transformation cible
CENTRE VAL DE LOIRE, 2021

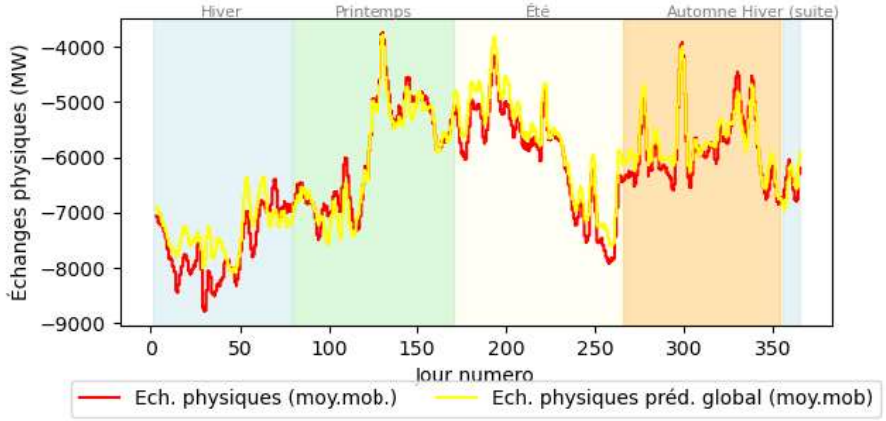
Ech. physiques - prévisions -Modèle global



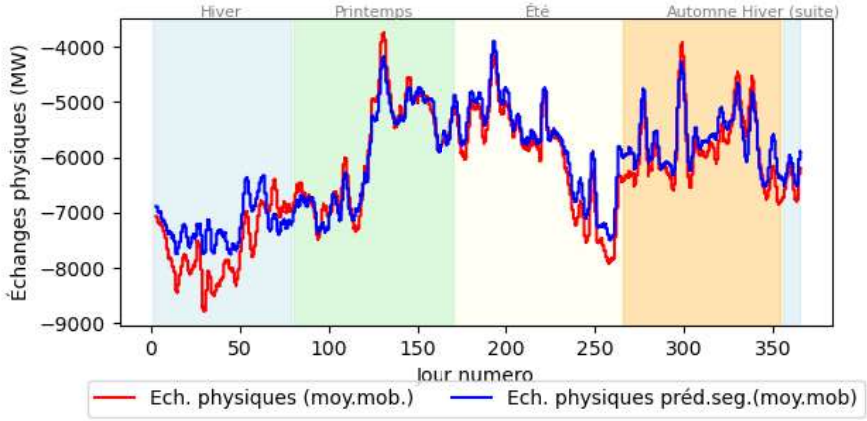
Ech. physiques - prévision - Modèle régional



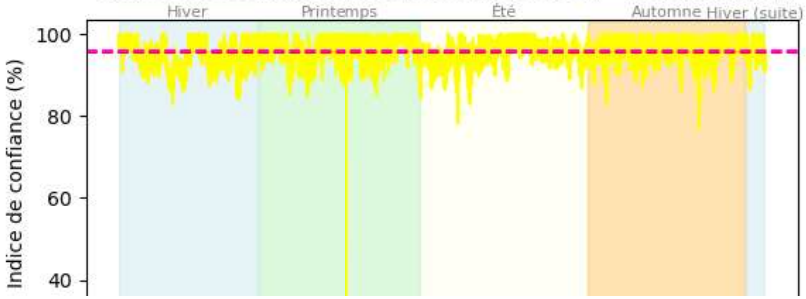
Moyennes mobiles WS144- Modèle global



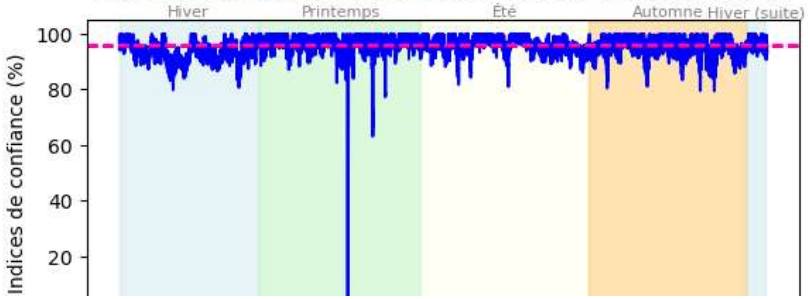
Moyennes mobiles WS144 - Modèle régional

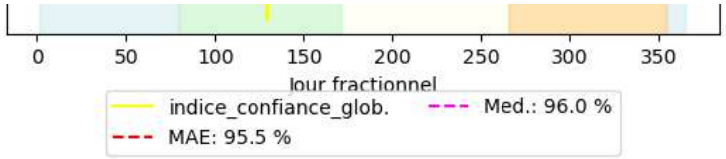


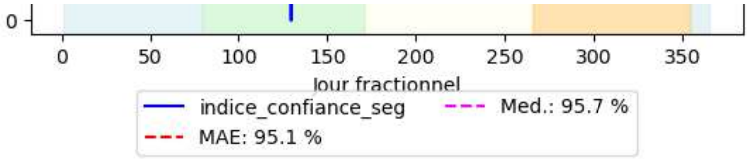
Indices de confiance (100-|erreur relative|) - Modèle global

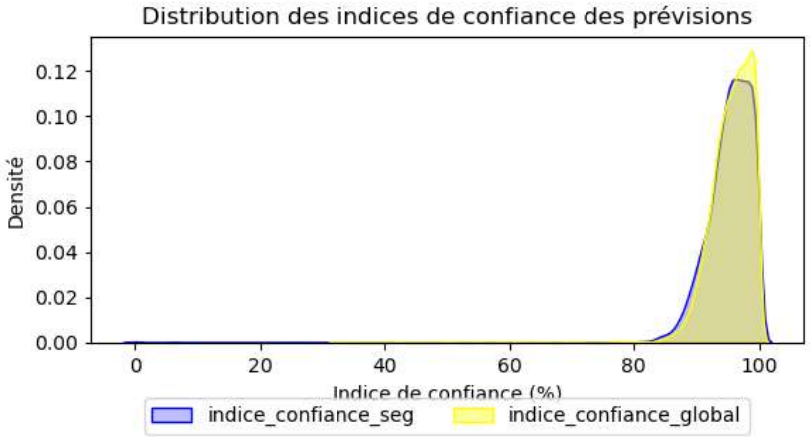


Indice de confiance (100-|erreur relative|)- Modèle régional







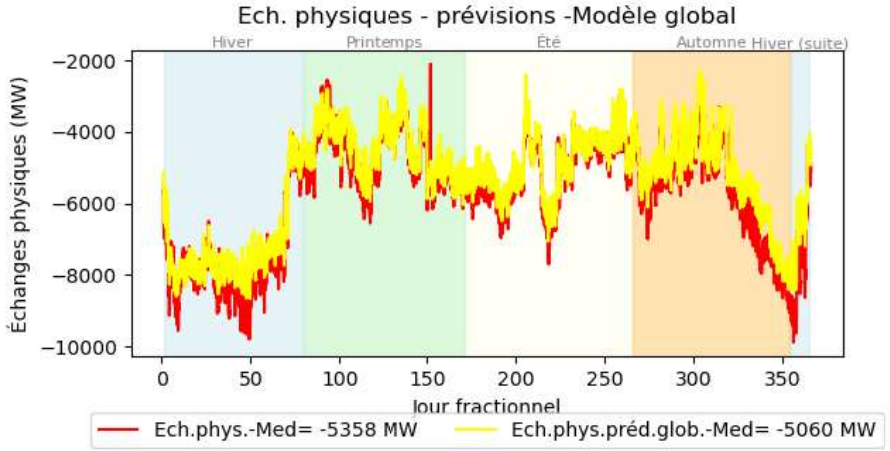


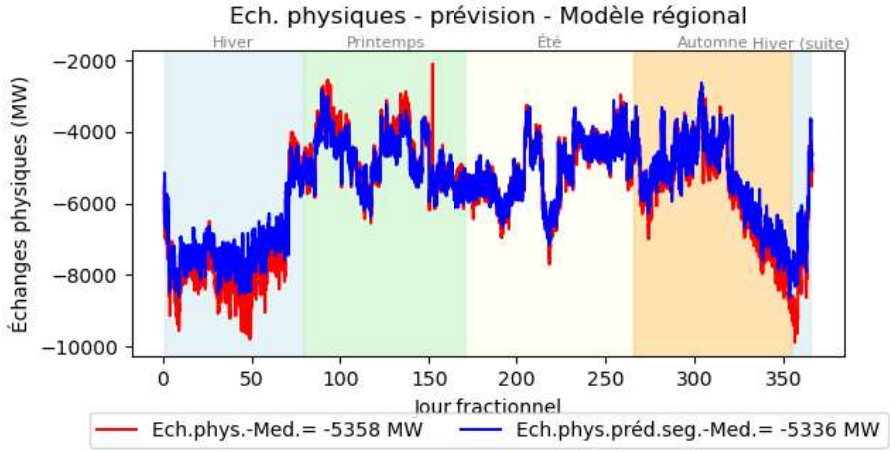
Métriques 2021

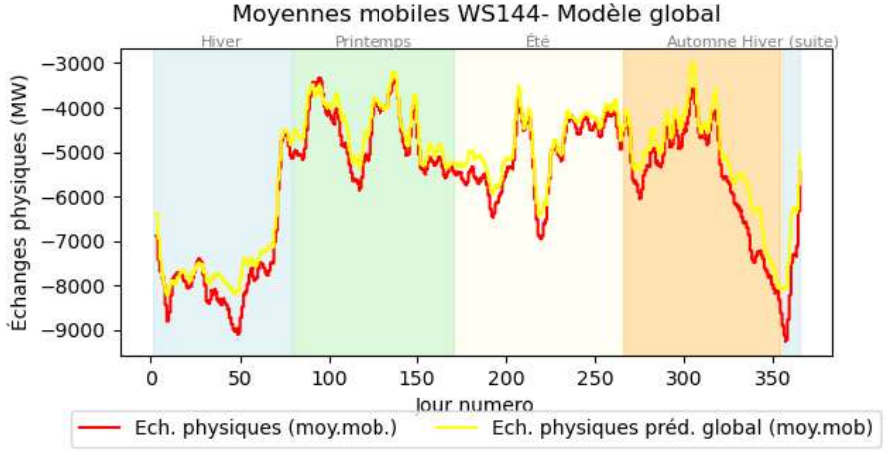
Valeurs réelles	Modèle global	Modèle régional
Médiane: -6253 MW	Médiane: -6079 MW	Médiane: -6039 MW
IQR: 1622 MW	IQR: 1656 MW	IQR: 1596 MW
	Ind.Conf.Moy.: 95.5 %	Ind.Conf.Moy.: 95.1 %

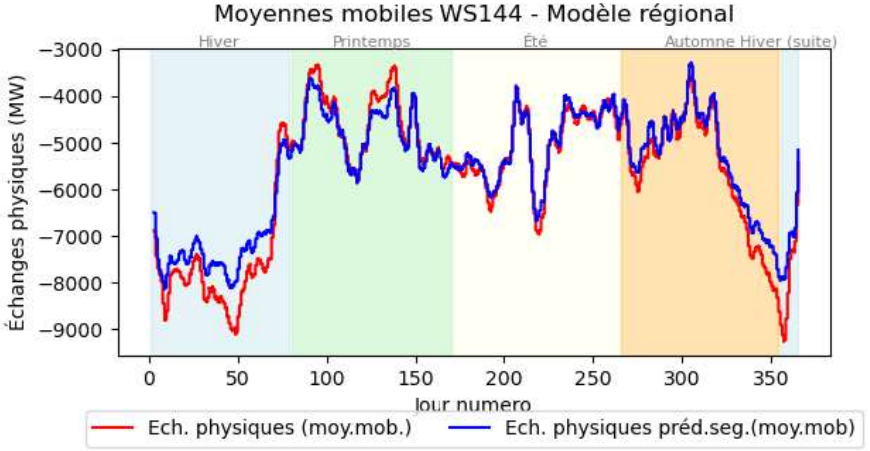
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

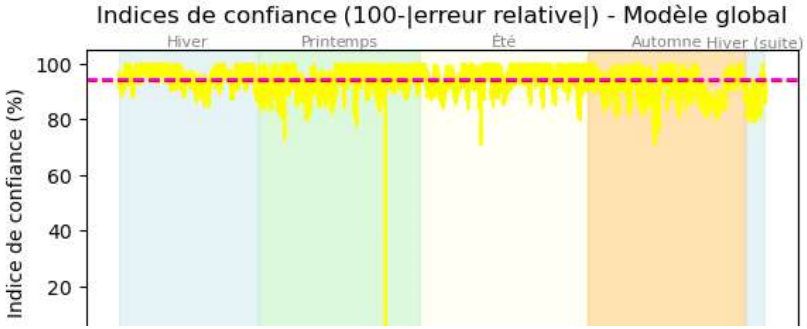
Prévisions des échanges physiques par XGBoost sans transformation cible
CENTRE VAL DE LOIRE, 2022

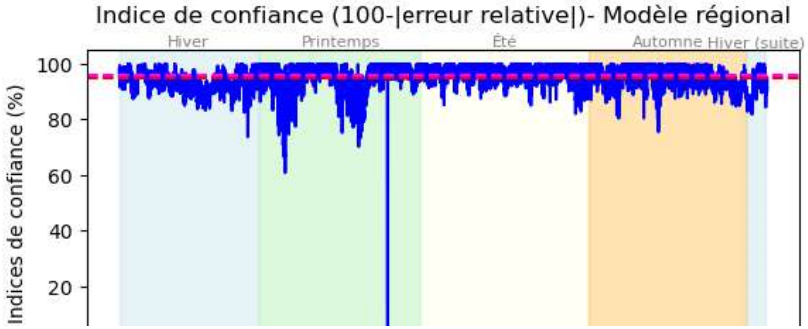


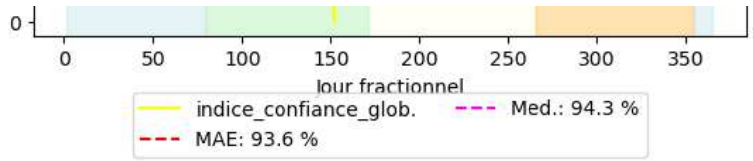


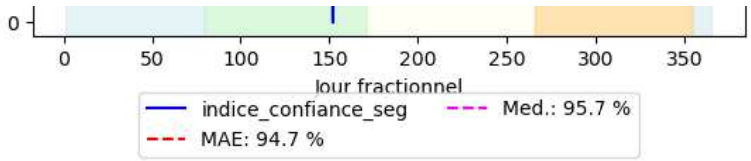


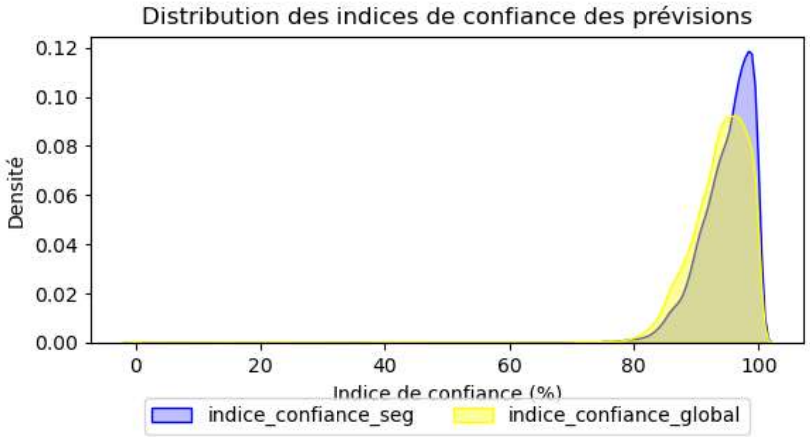










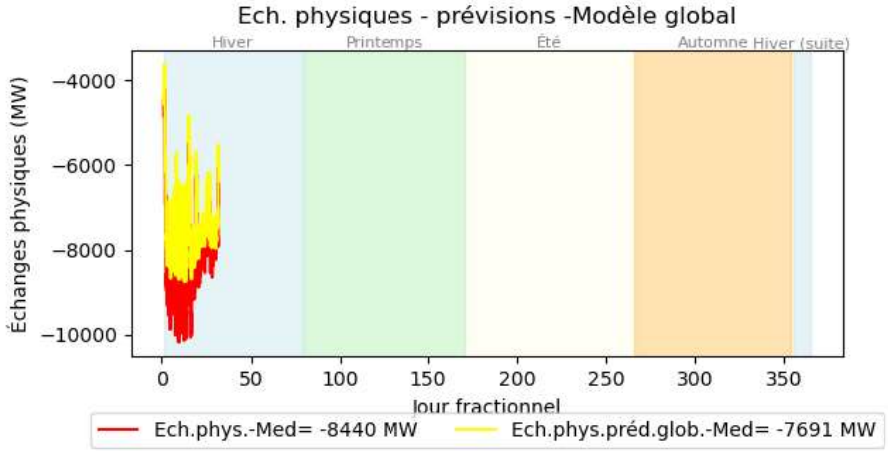


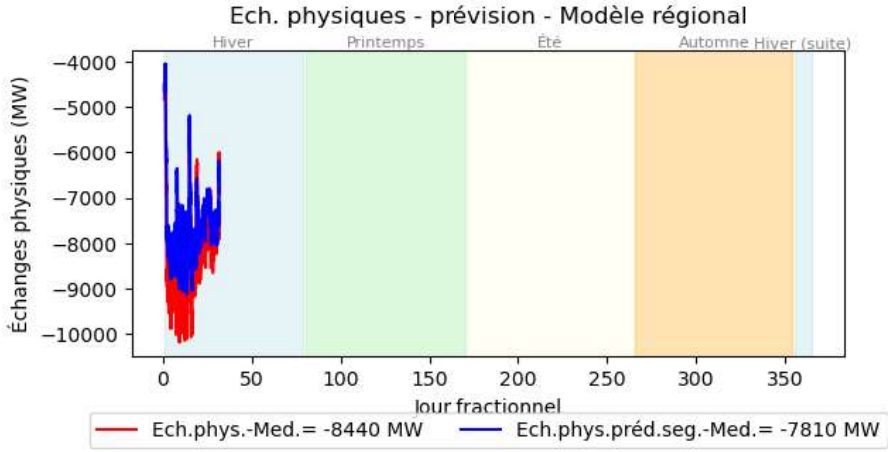
Métriques 2022

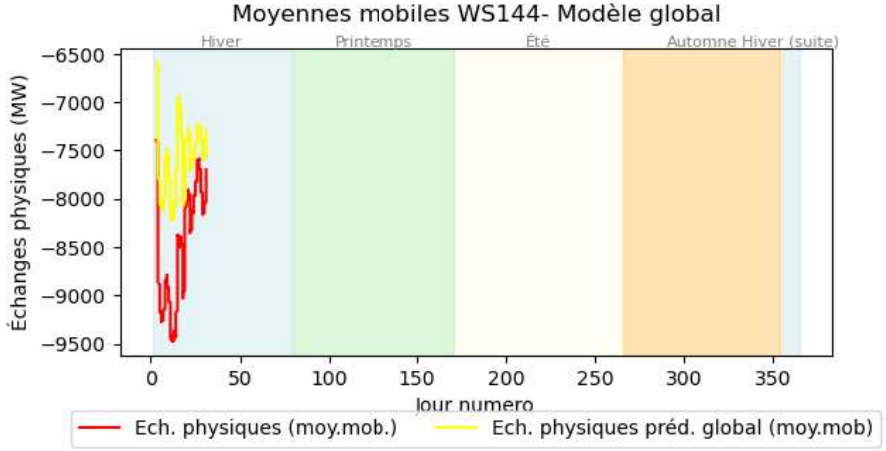
Valeurs réelles	Modèle global	Modèle régional
Médiane: -5358 MW	Médiane: -5060 MW	Médiane: -5336 MW
IQR: 2566 MW	IQR: 2041 MW	IQR: 2105 MW
	Ind.Conf.Moy.: 93.6 %	Ind.Conf.Moy.: 94.7 %

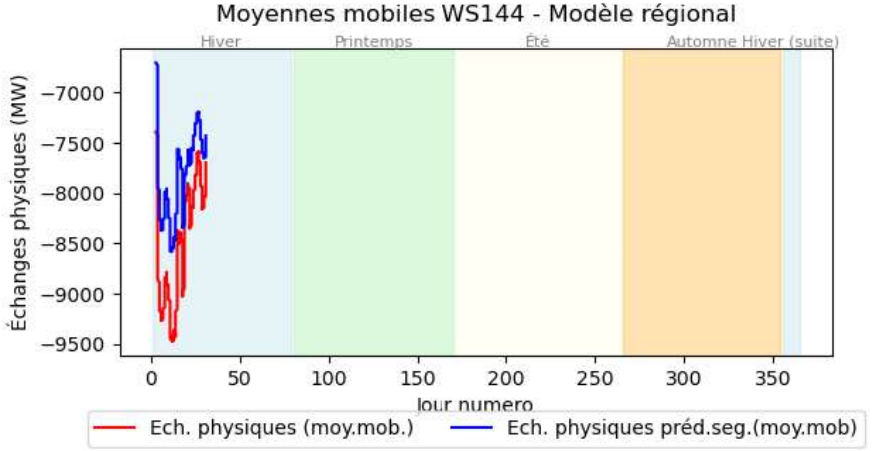
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

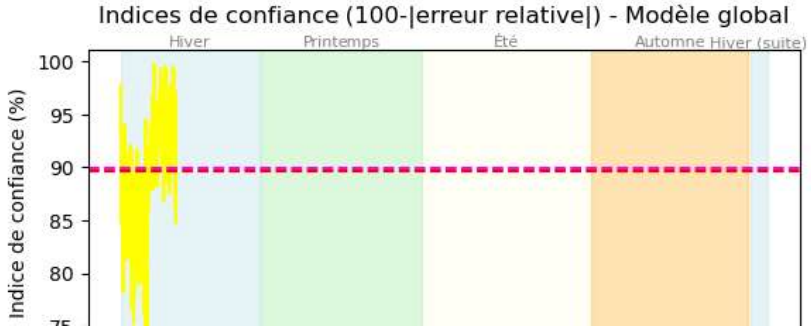
Prévisions des échanges physiques par XGBoost sans transformation cible
CENTRE VAL DE LOIRE, 2023

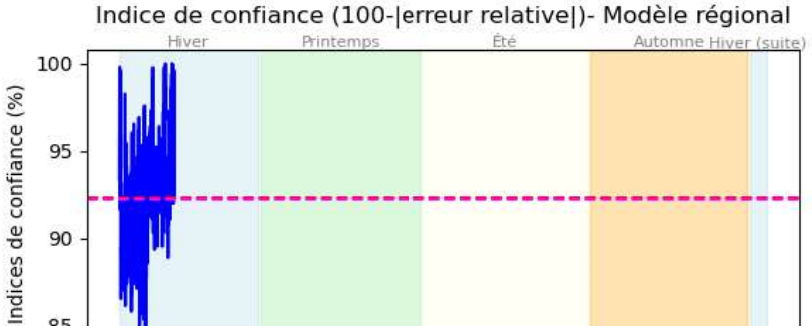


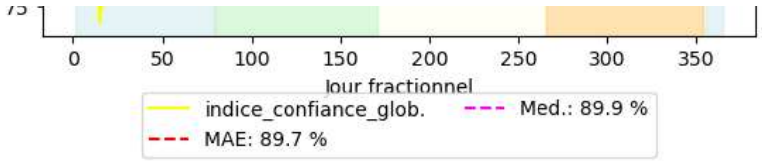


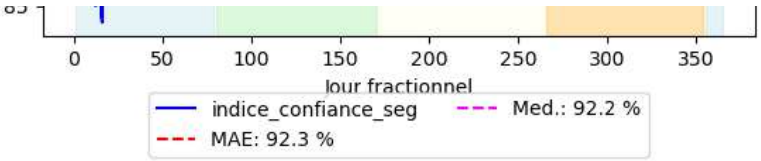


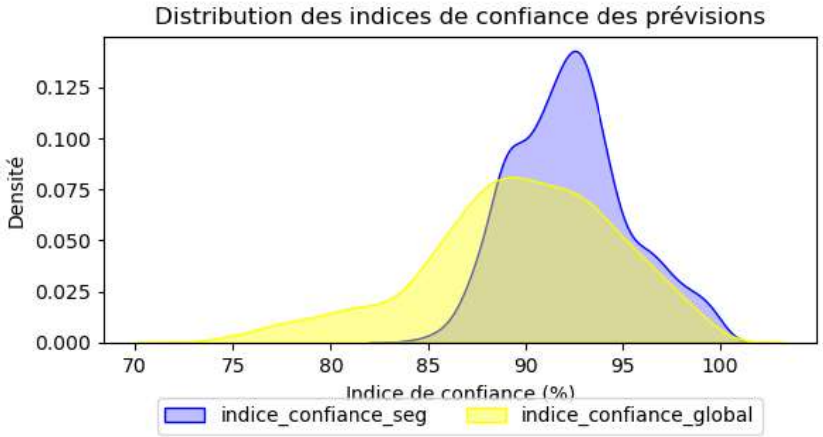










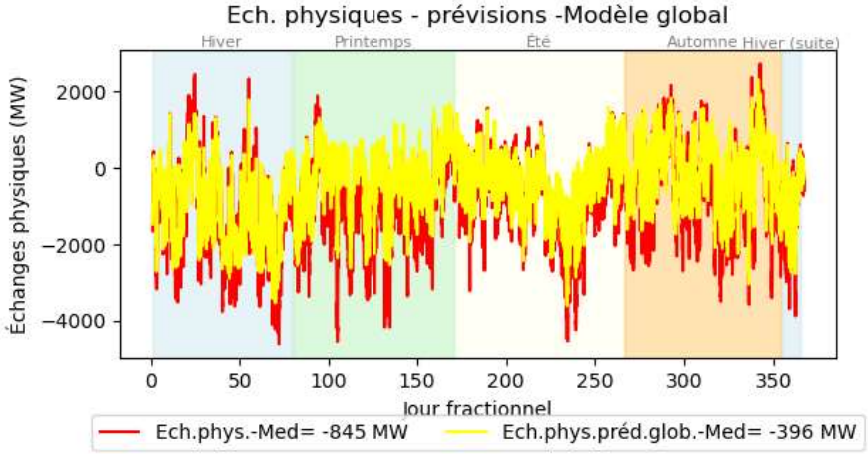


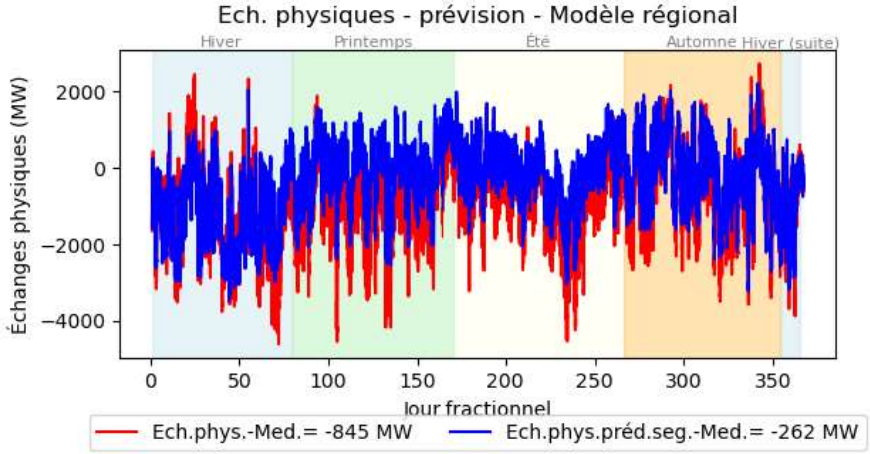
Métriques 2023

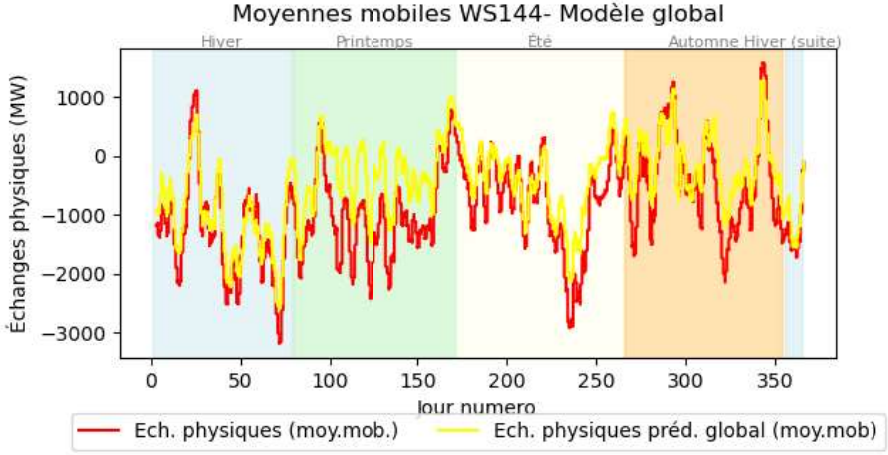
Valeurs réelles	Modèle global	Modèle régional
Médiane: -8440 MW	Médiane: -7691 MW	Médiane: -7810 MW
IQR: 1369 MW	IQR: 939 MW	IQR: 967 MW
	Ind.Conf.Moy.: 89.7 %	Ind.Conf.Moy.: 92.3 %

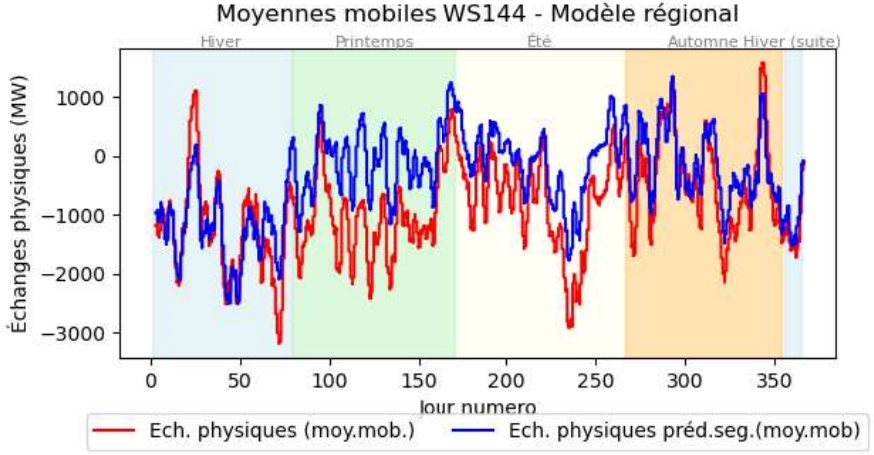
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

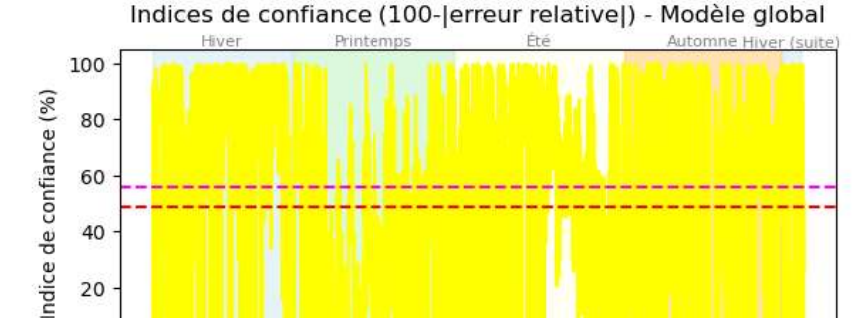
Prévisions des échanges physiques par XGBoost sans transformation cible
HAUTS DE FRANCE, 2020

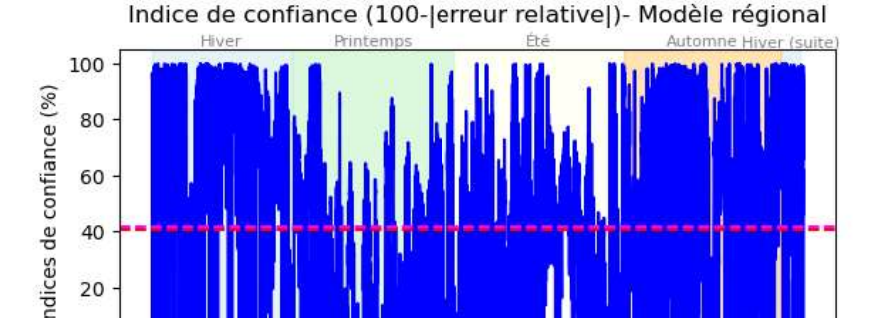


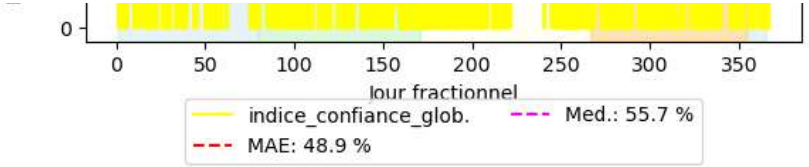


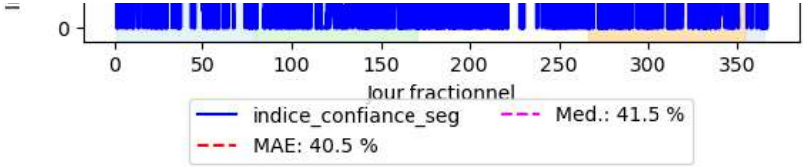


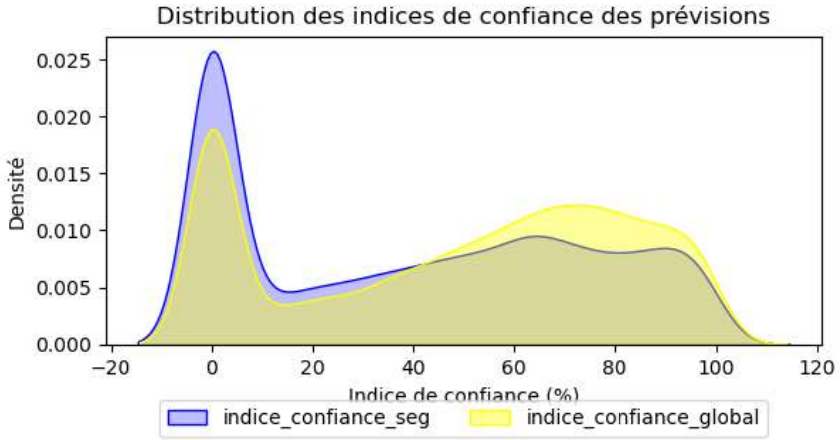










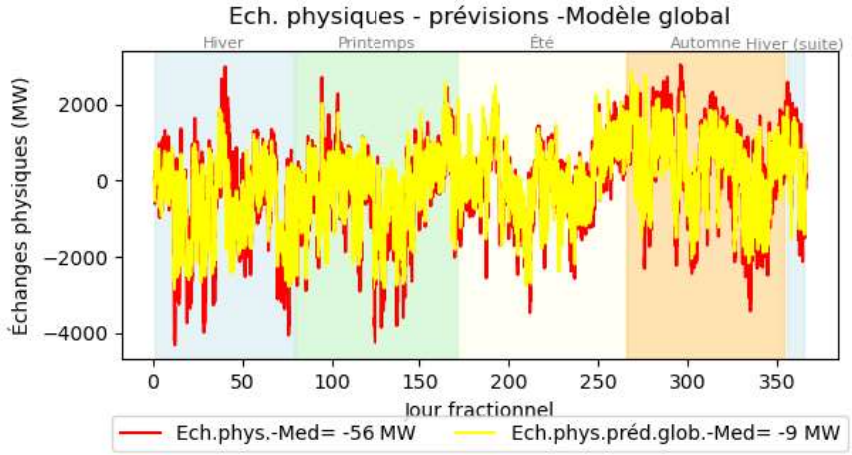


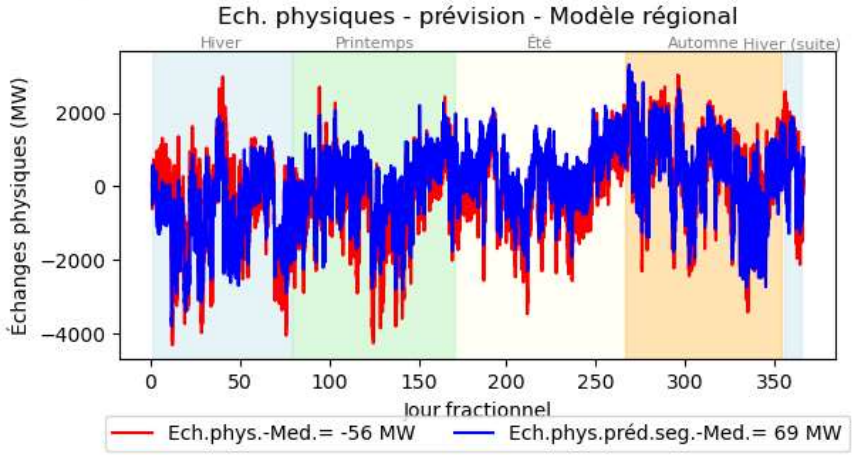
Métriques 2020

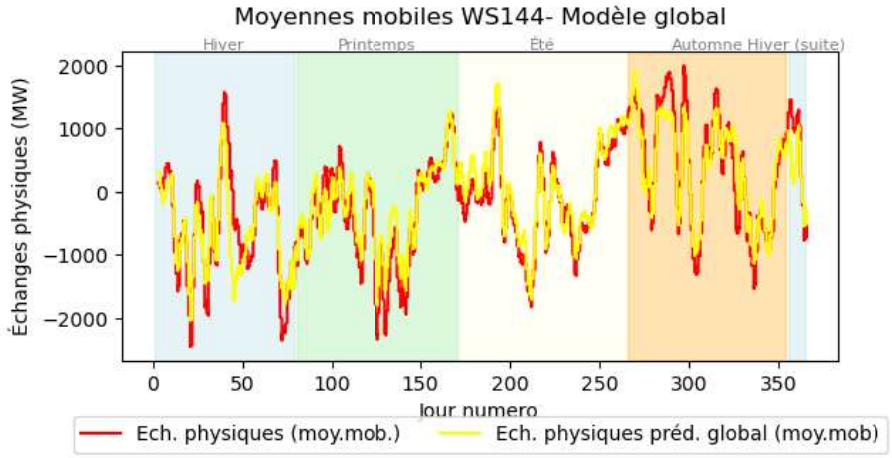
Valeurs réelles	Modèle global	Modèle régional
Médiane: -845 MW	Médiane: -396 MW	Médiane: -262 MW
IQR: 1521 MW	IQR: 1323 MW	IQR: 1396 MW
	Ind.Conf.Moy.: 48.9 %	Ind.Conf.Moy.: 40.5 %

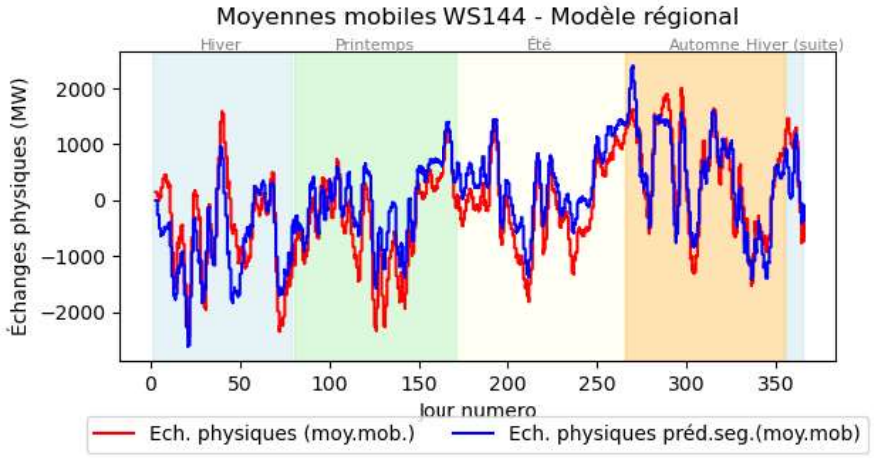
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

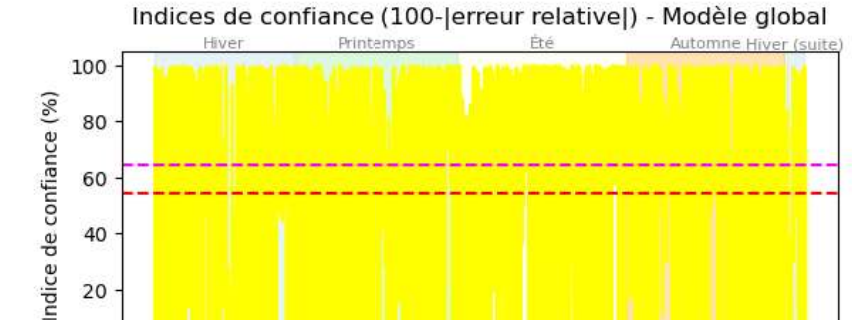
Prévisions des échanges physiques par XGBoost sans transformation cible
HAUTS DE FRANCE, 2021

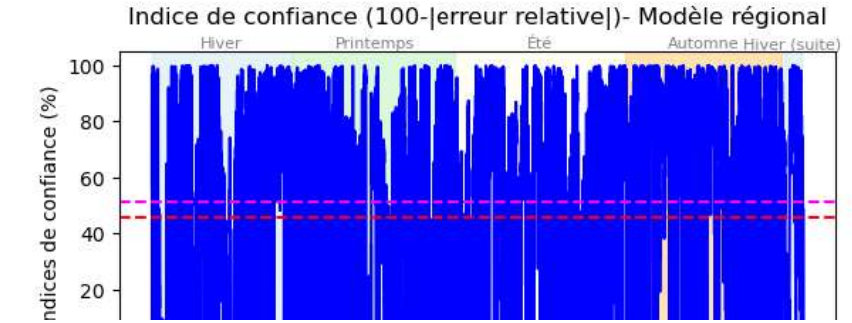


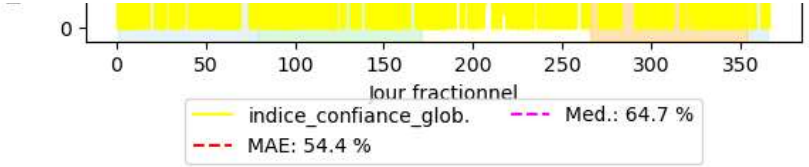


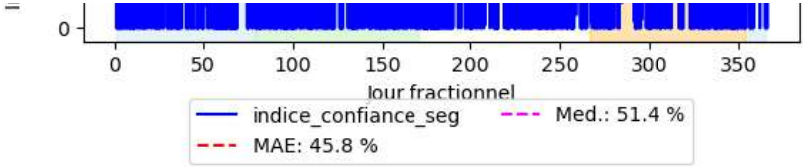


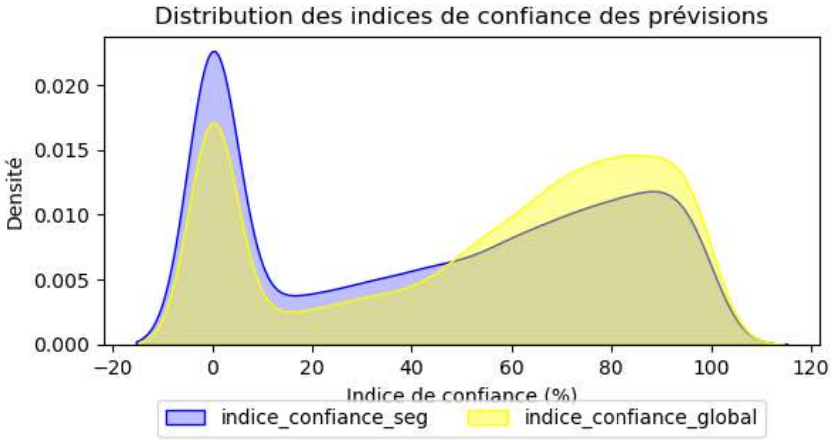










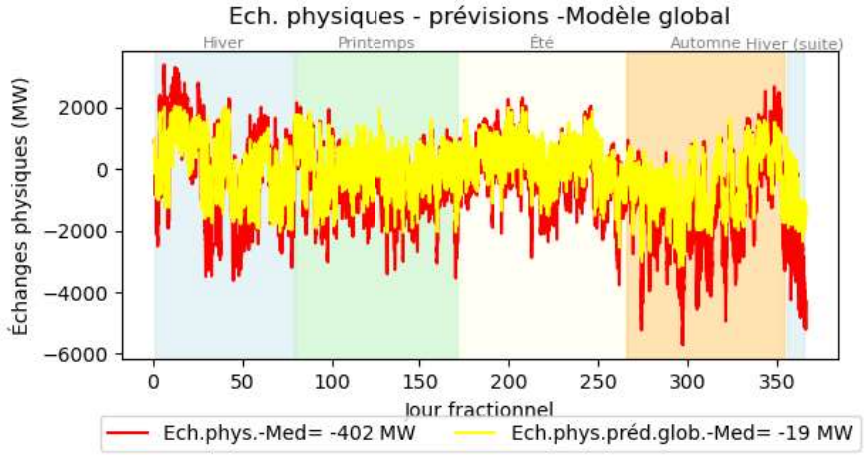


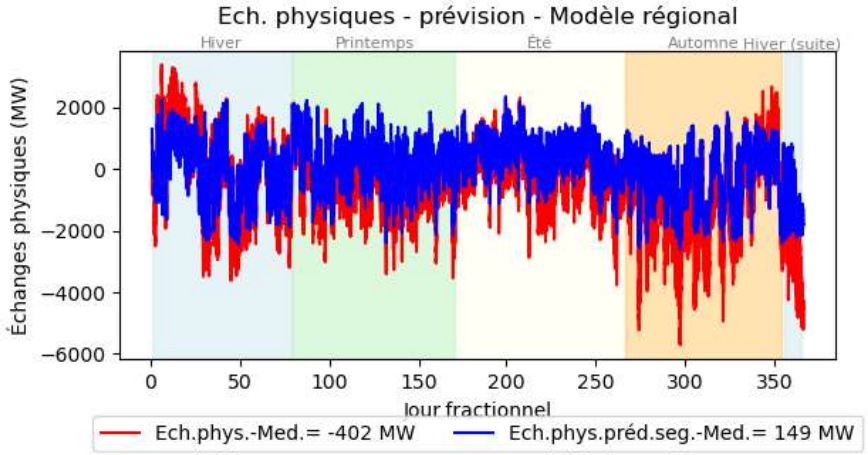
Métriques 2021

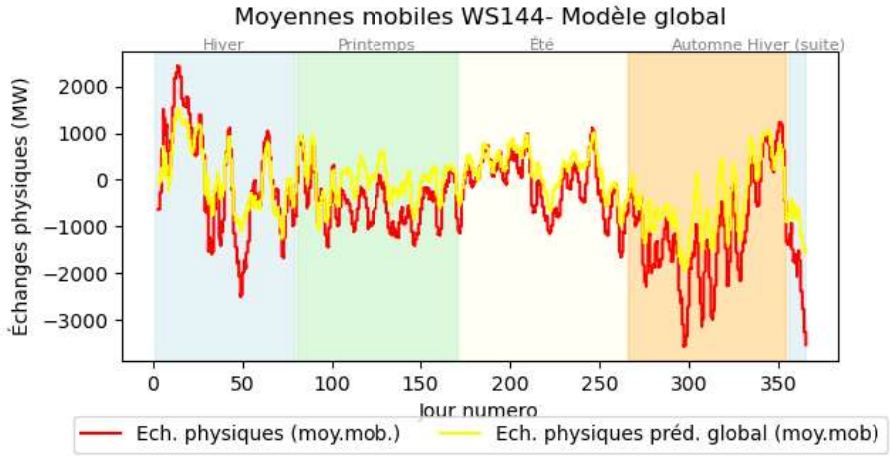
Valeurs réelles	Modèle global	Modèle régional
Médiane: -56 MW	Médiane: -9 MW	Médiane: 69 MW
IQR: 1572 MW	IQR: 1404 MW	IQR: 1444 MW
	Ind.Conf.Moy.: 54.4 %	Ind.Conf.Moy.: 45.8 %

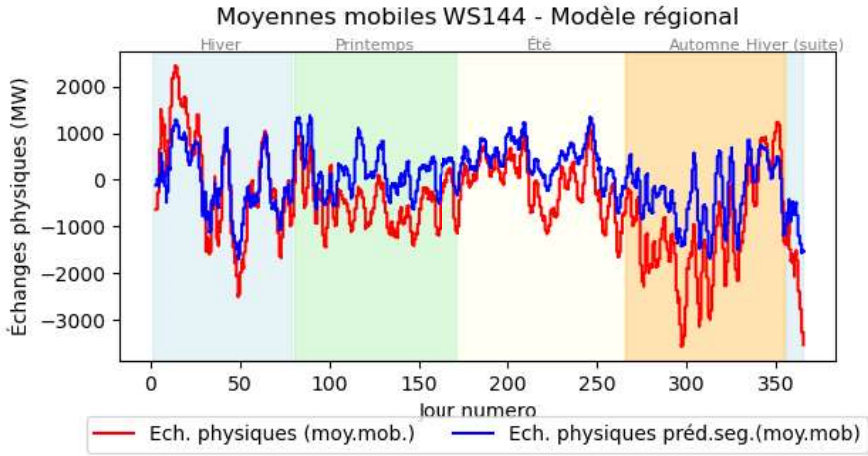
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

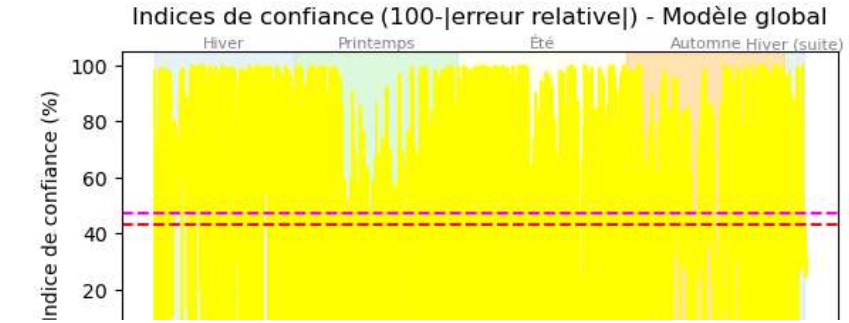
Prévisions des échanges physiques par XGBoost sans transformation cible
HAUTS DE FRANCE, 2022

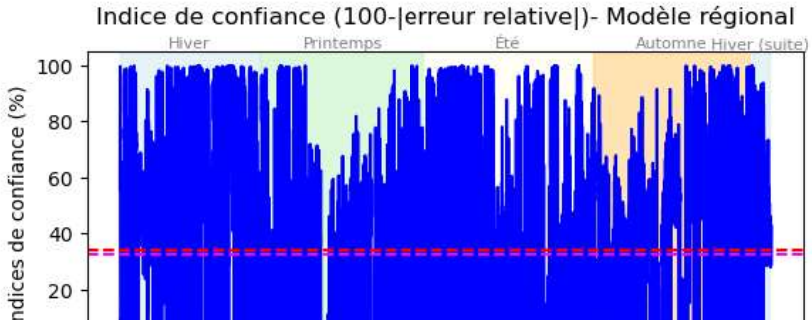


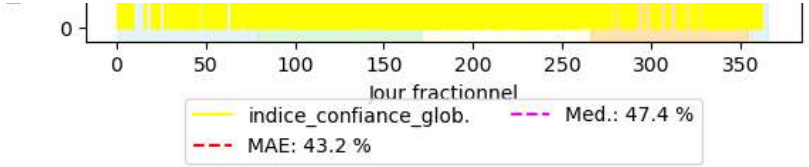


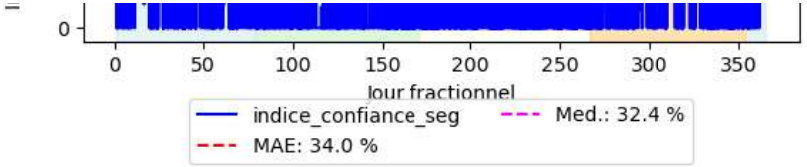


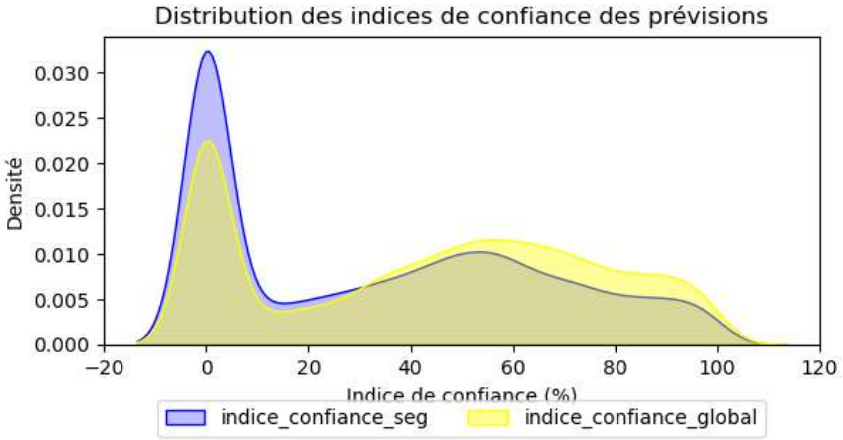










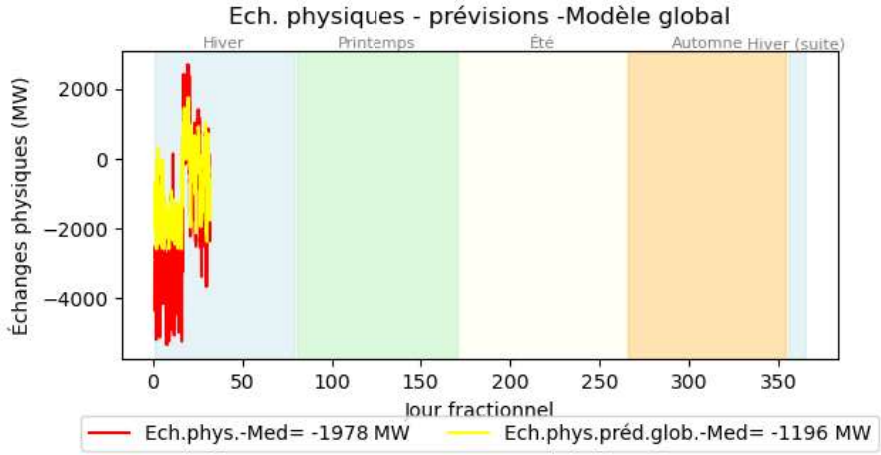


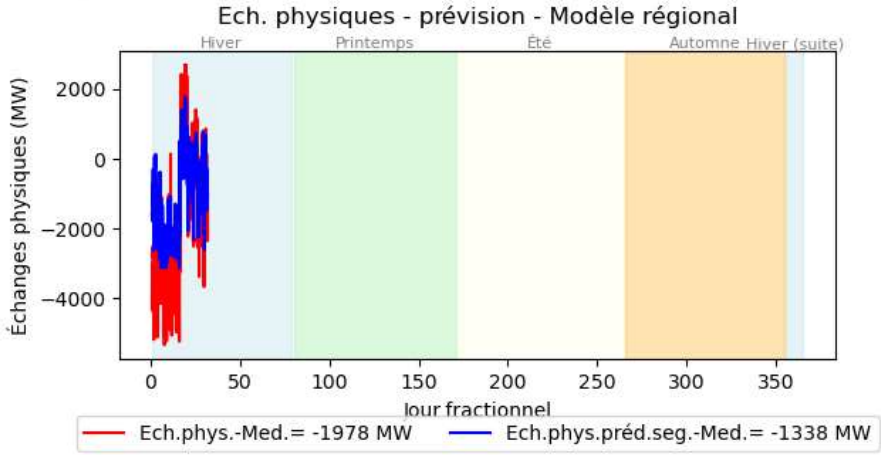
Métriques 2022

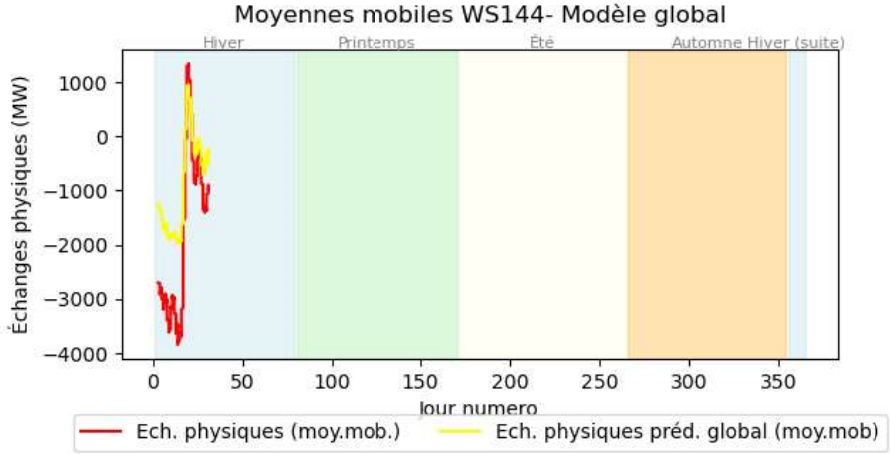
Valeurs réelles	Modèle global	Modèle régional
Médiane: -402 MW	Médiane: -19 MW	Médiane: 149 MW
IQR: 1665 MW	IQR: 1289 MW	IQR: 1302 MW
	Ind.Conf.Moy.: 43.2 %	Ind.Conf.Moy.: 34.0 %

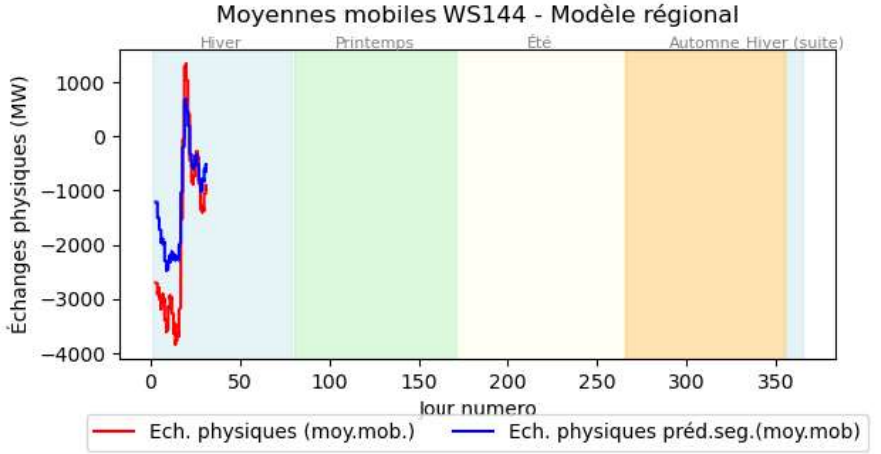
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

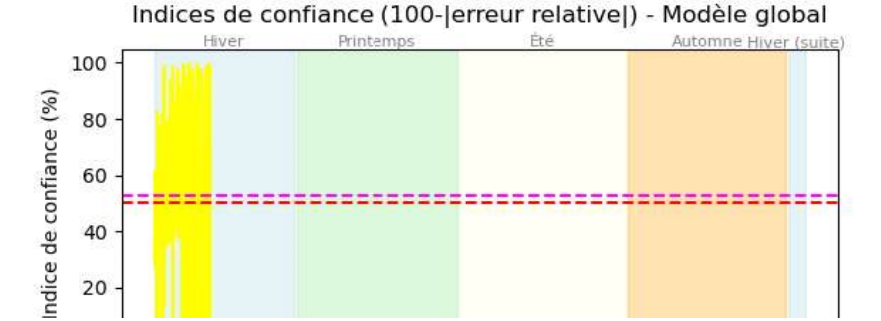
Prévisions des échanges physiques par XGBoost sans transformation cible
HAUTS DE FRANCE, 2023

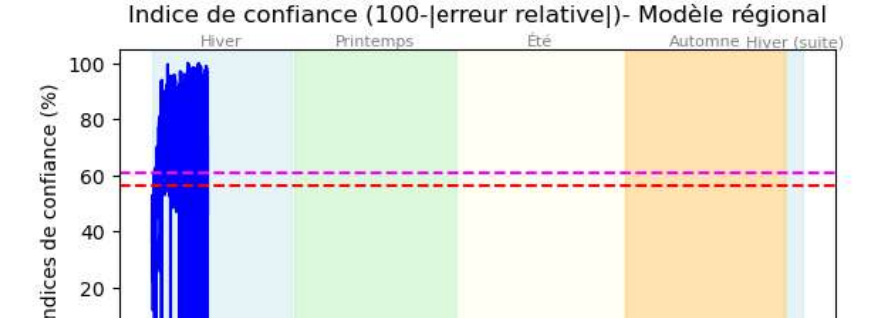


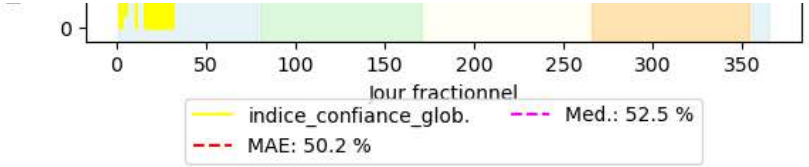


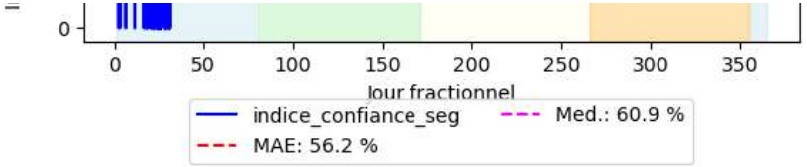


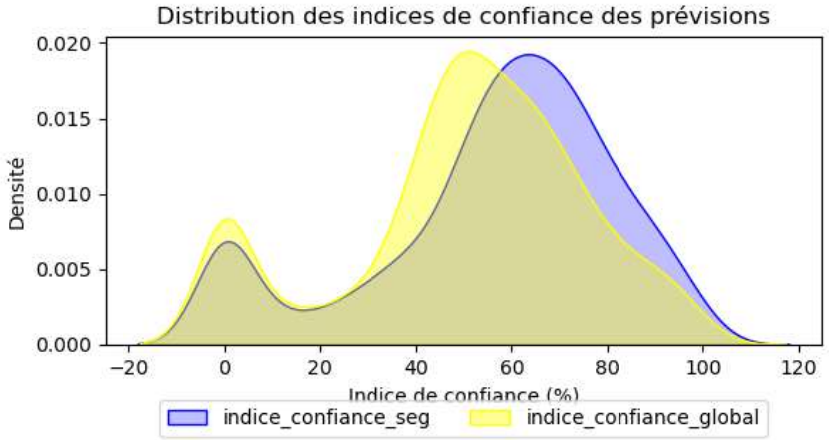










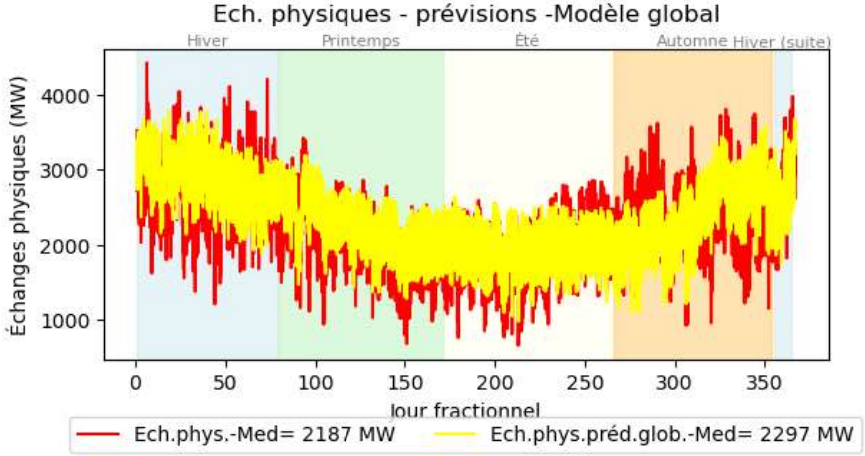


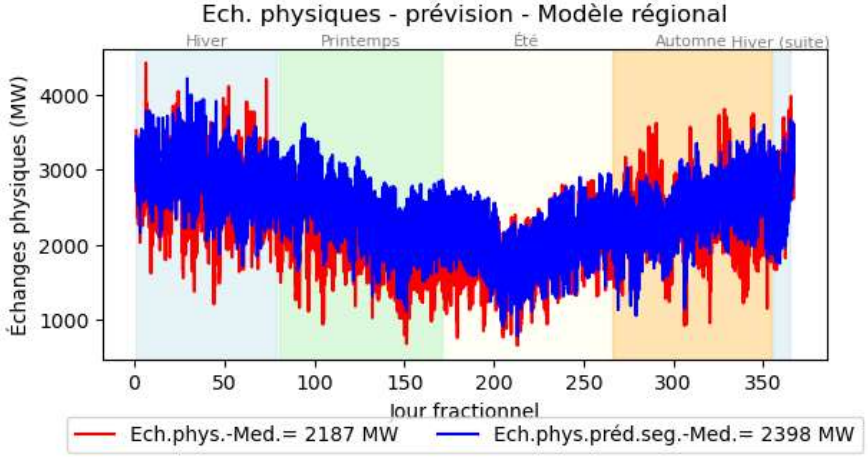
Métriques 2023

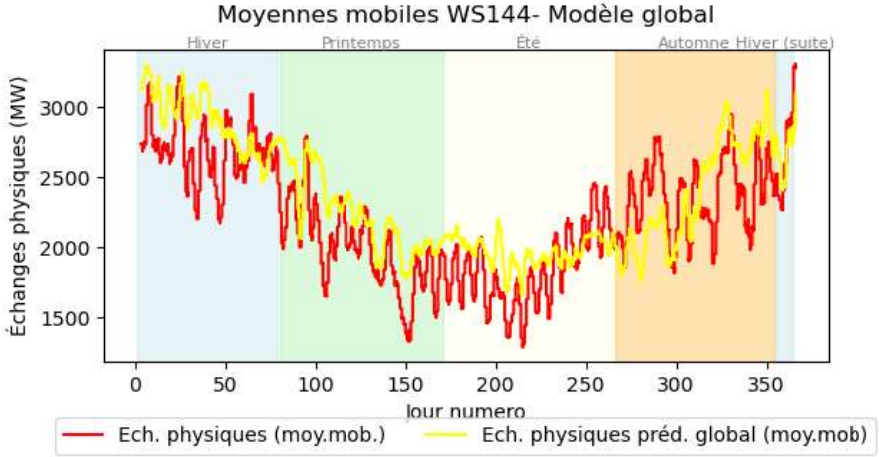
Valeurs réelles	Modèle global	Modèle régional
Médiane: -1978 MW	Médiane: -1196 MW	Médiane: -1338 MW
IQR: 2938 MW	IQR: 1856 MW	IQR: 1928 MW
	Ind.Conf.Moy.: 50.2 %	Ind.Conf.Moy.: 56.2 %

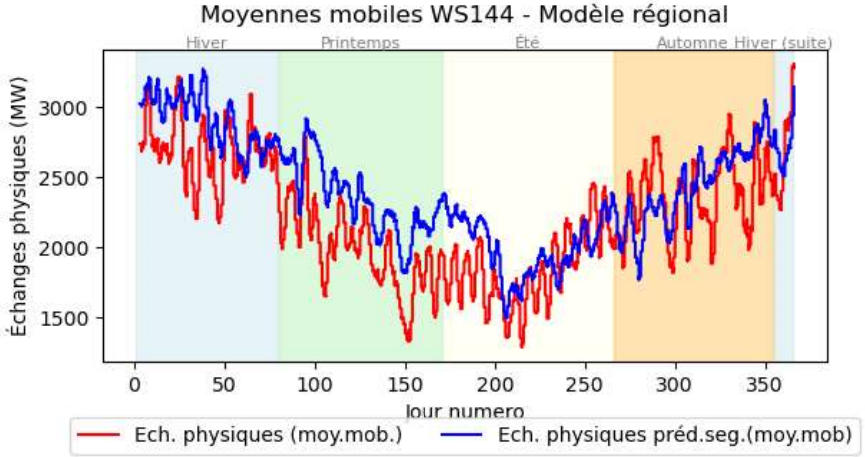
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

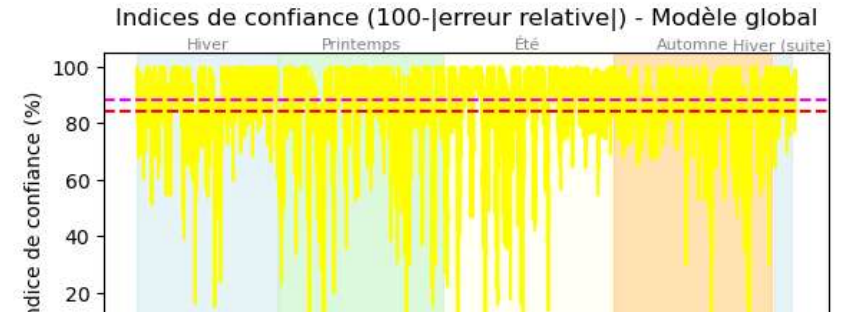
Prévisions des échanges physiques par XGBoost sans transformation cible
PAYS DE LA LOIRE, 2020

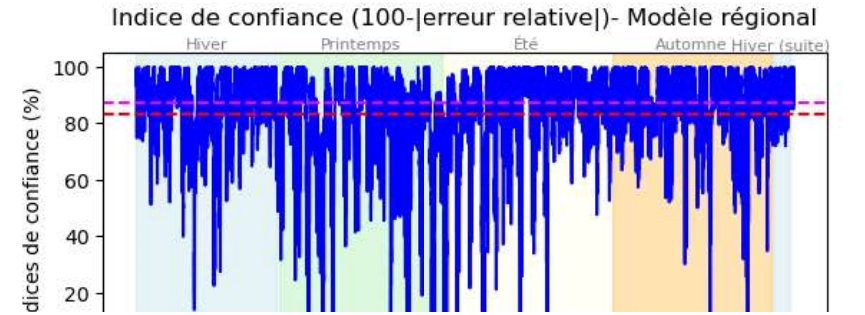


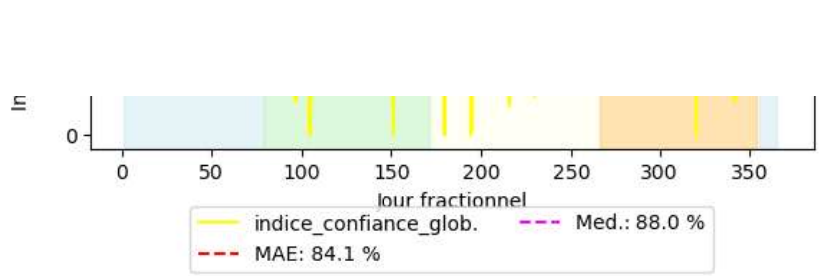


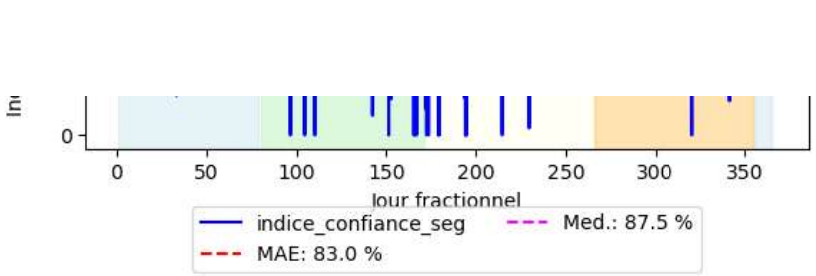


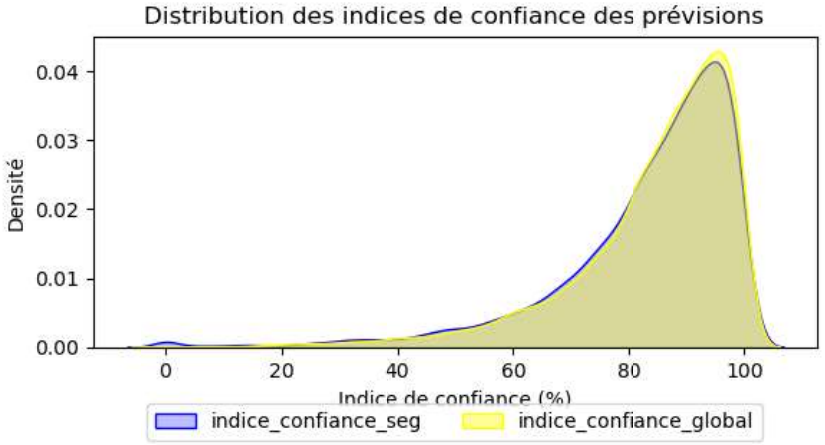










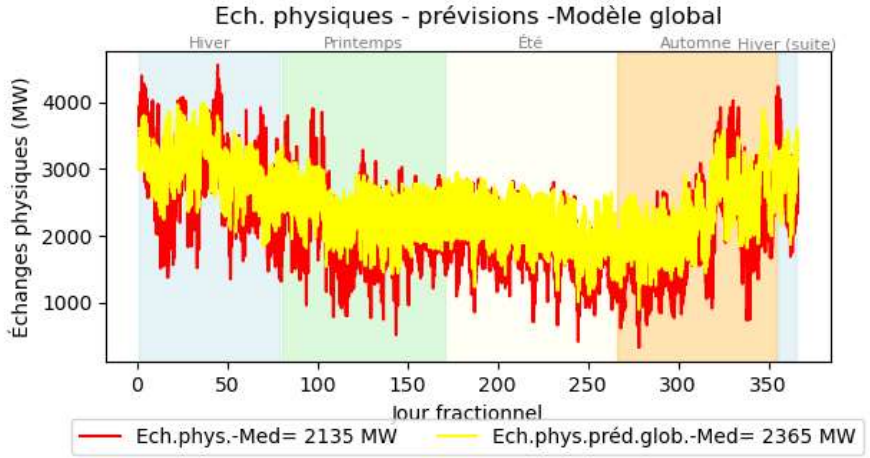


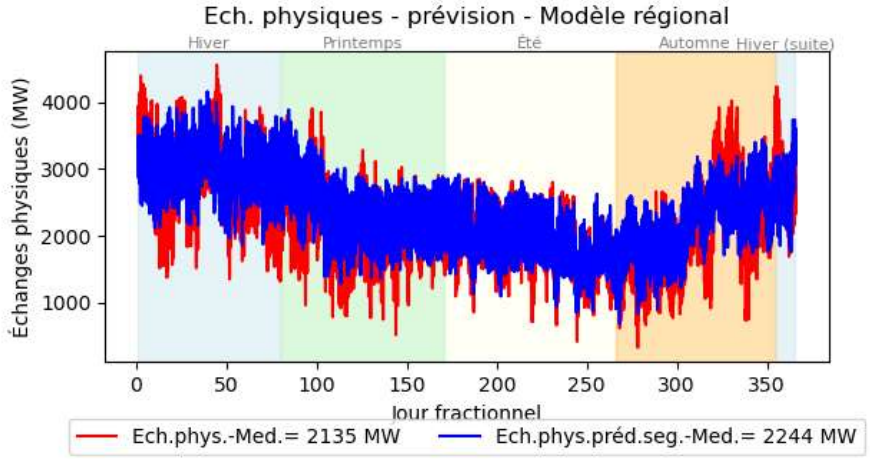
Métriques 2020

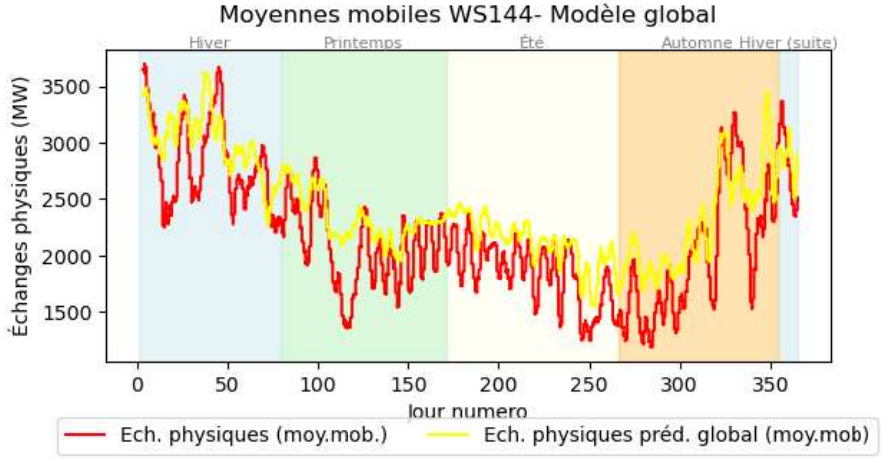
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2187 MW	Médiane: 2297 MW	Médiane: 2398 MW
IQR: 787 MW	IQR: 746 MW	IQR: 683 MW
	Ind.Conf.Moy.: 84.1 %	Ind.Conf.Moy.: 83.0 %

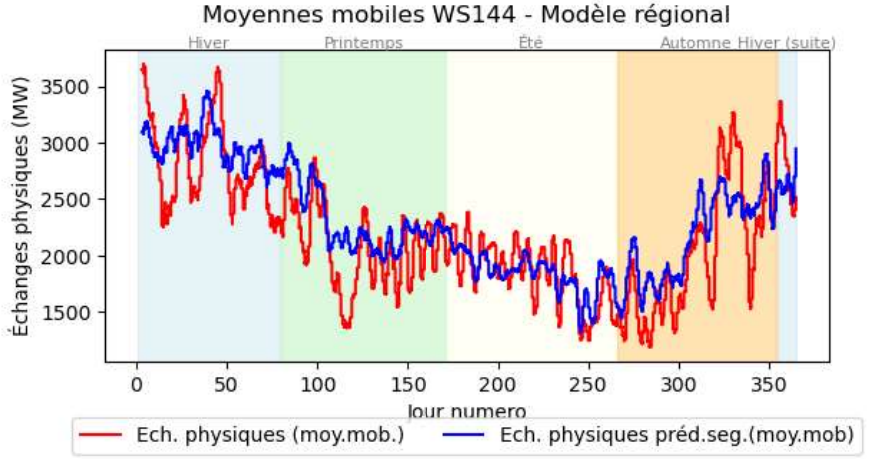
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

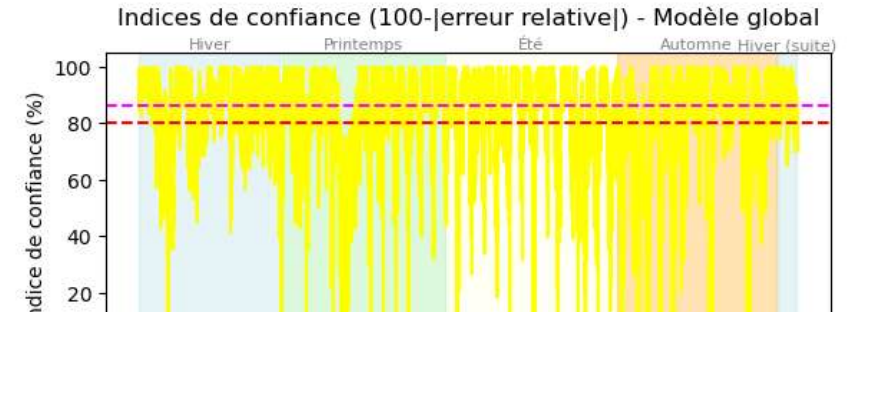
Prévisions des échanges physiques par XGBoost sans transformation cible
PAYS DE LA LOIRE, 2021

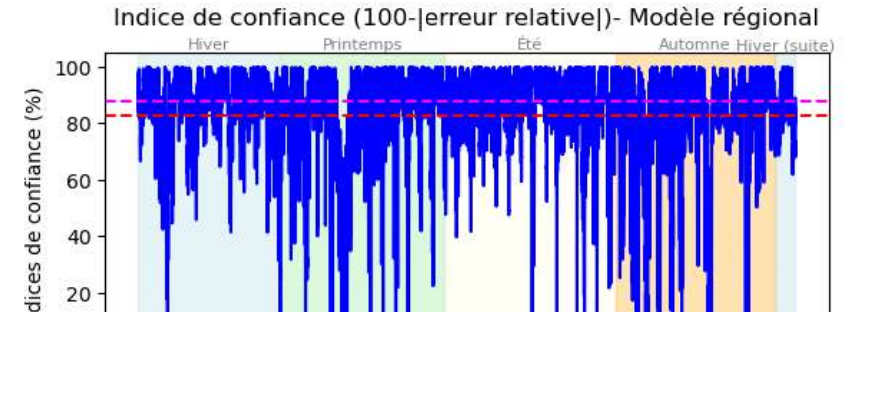


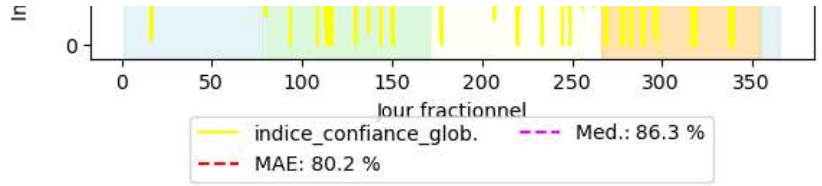


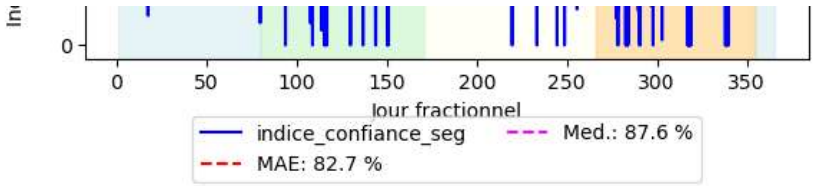


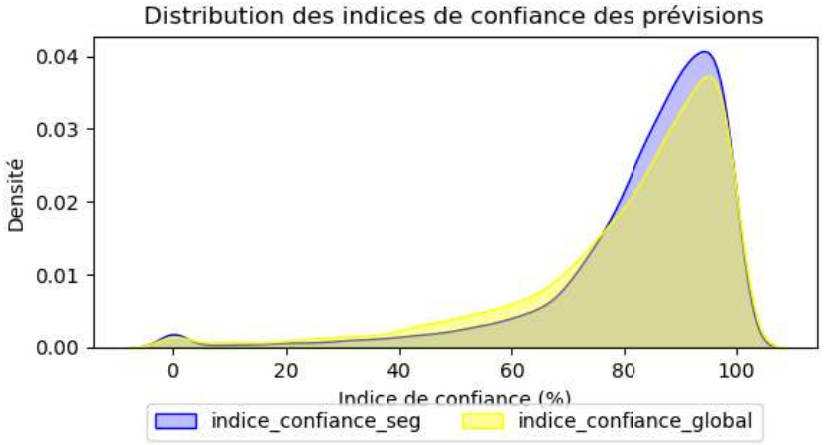










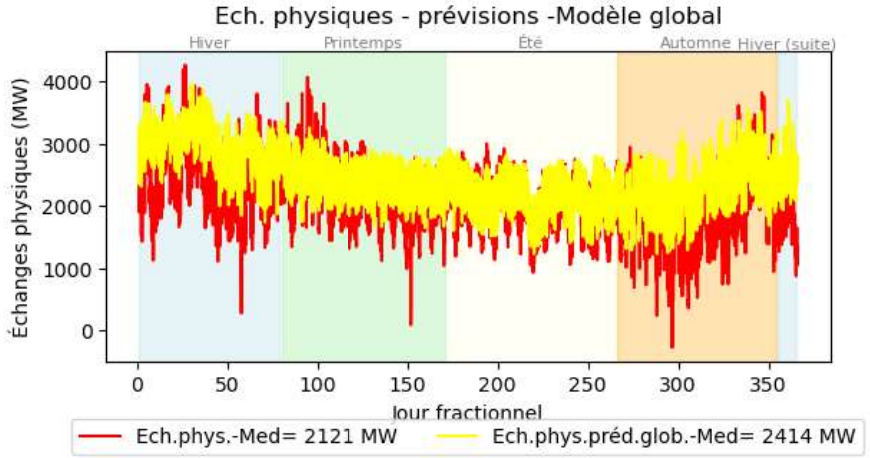


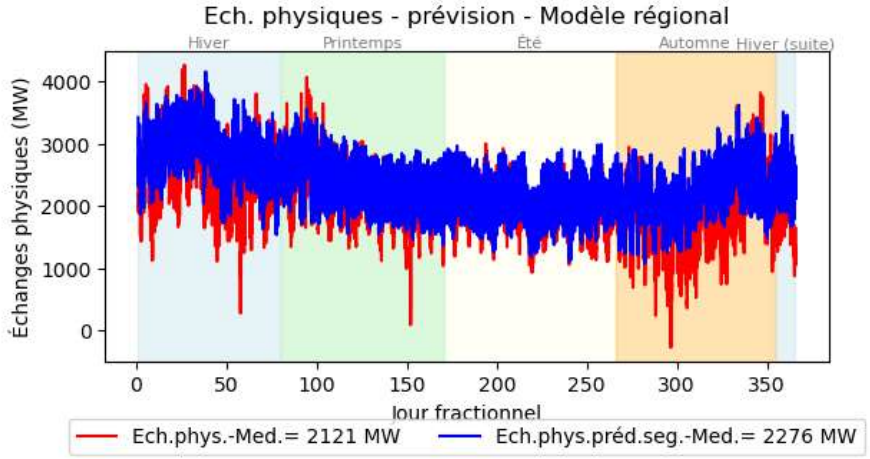
Métriques 2021

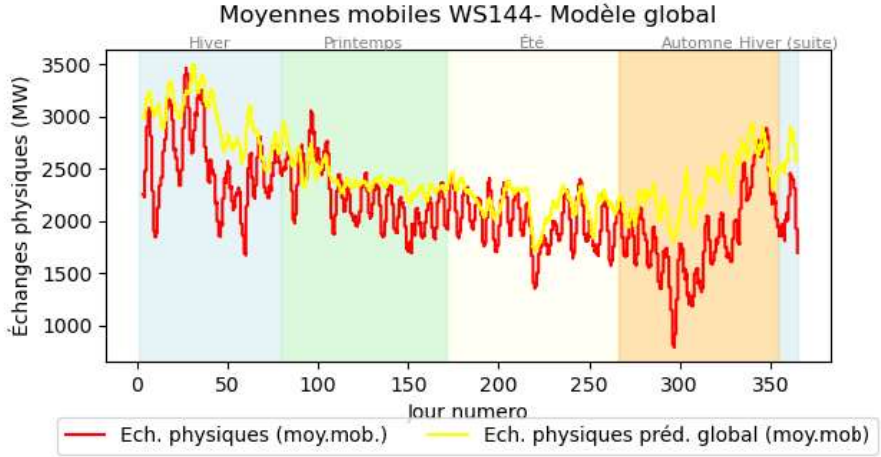
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2135 MW	Médiane: 2365 MW	Médiane: 2244 MW
IQR: 927 MW	IQR: 711 MW	IQR: 801 MW
	Ind.Conf.Moy.: 80.2 %	Ind.Conf.Moy.: 82.7 %

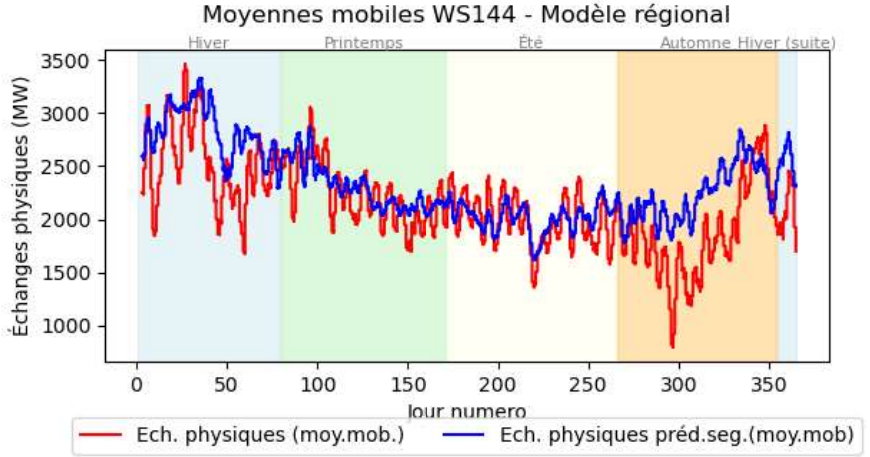
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

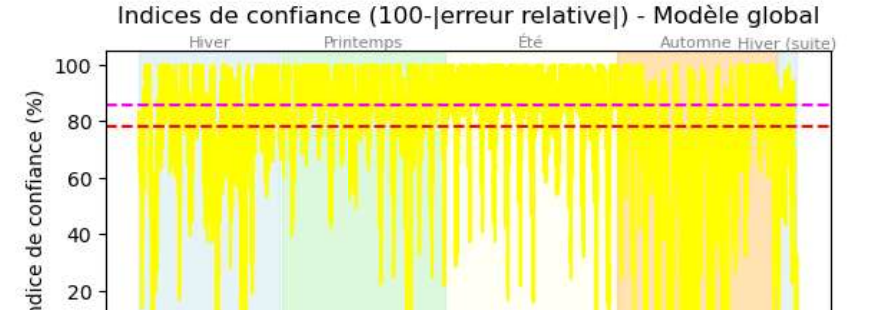
Prévisions des échanges physiques par XGBoost sans transformation cible
PAYS DE LA LOIRE, 2022

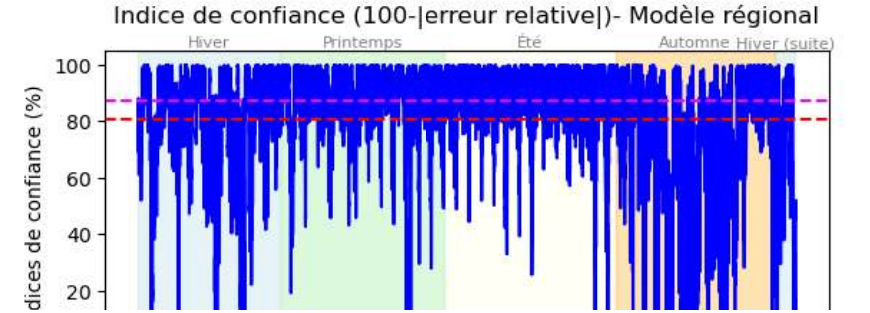


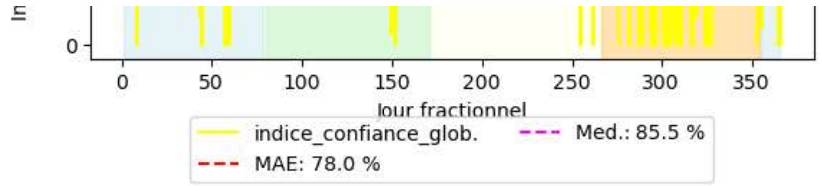


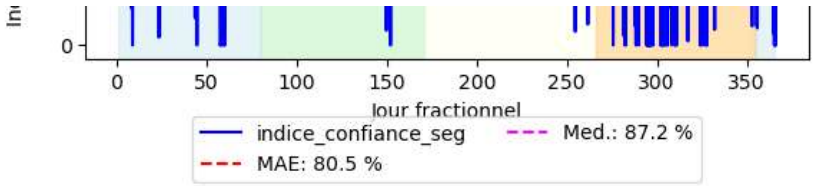


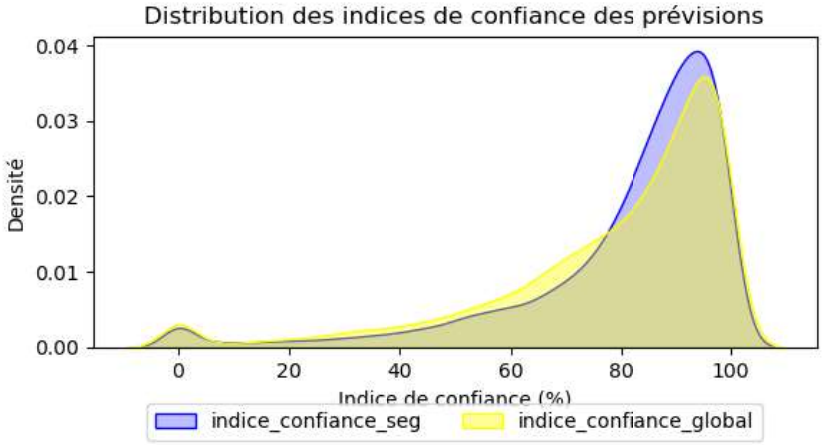










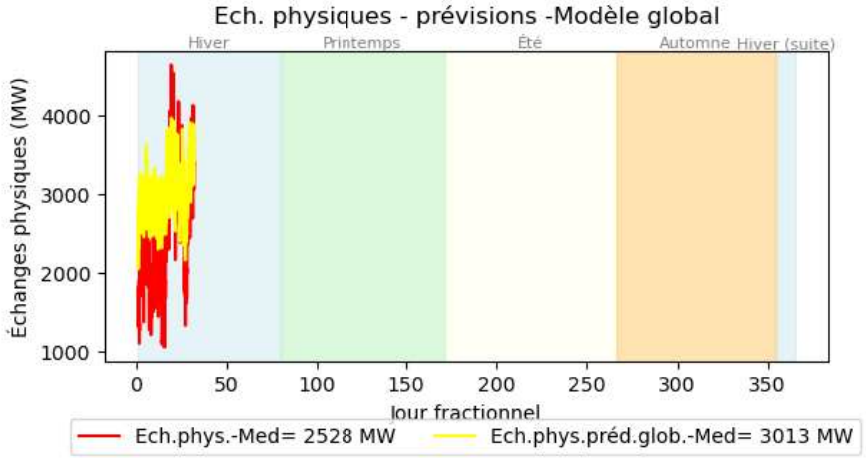


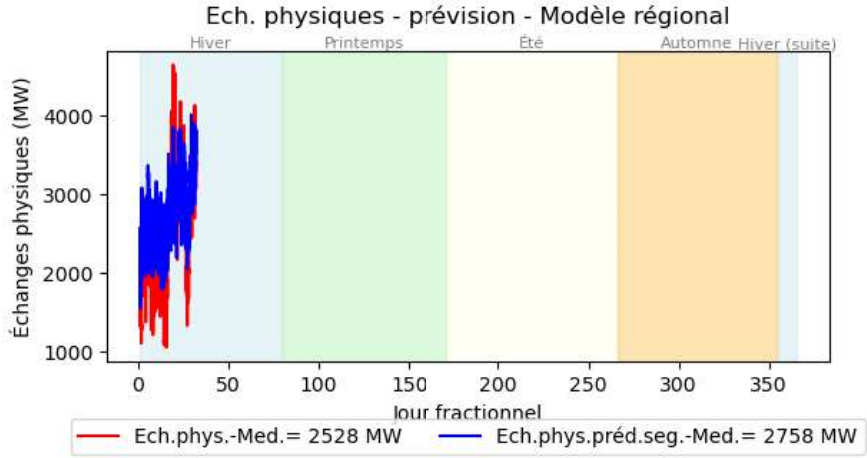
Métriques 2022

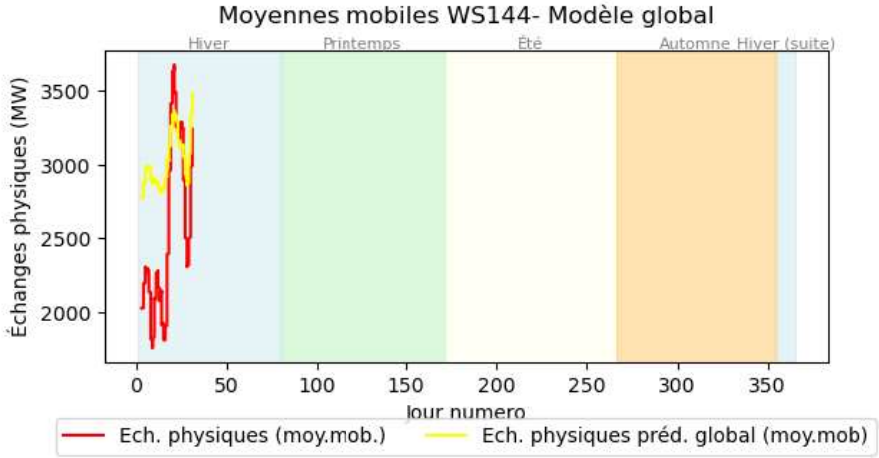
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2121 MW	Médiane: 2414 MW	Médiane: 2276 MW
IQR: 721 MW	IQR: 564 MW	IQR: 625 MW
	Ind.Conf.Moy.: 78.0 %	Ind.Conf.Moy.: 80.5 %

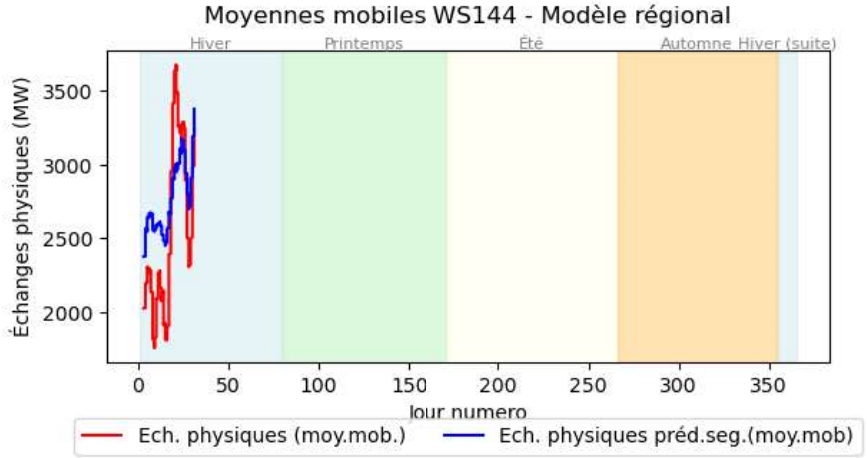
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

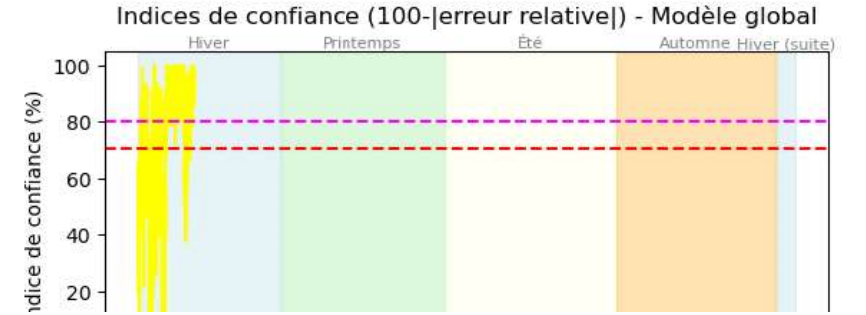
Prévisions des échanges physiques par XGBoost sans transformation cible
PAYS DE LA LOIRE, 2023

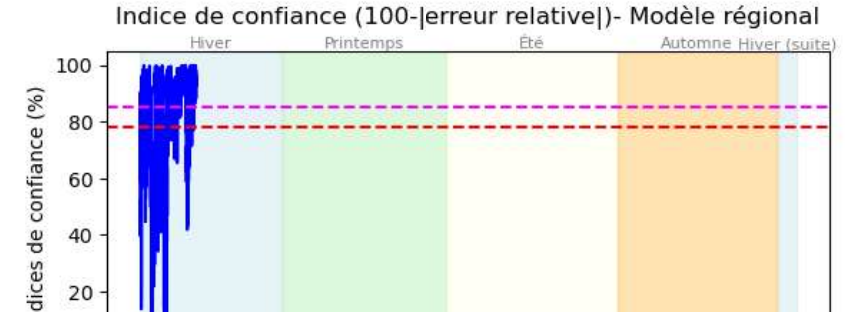


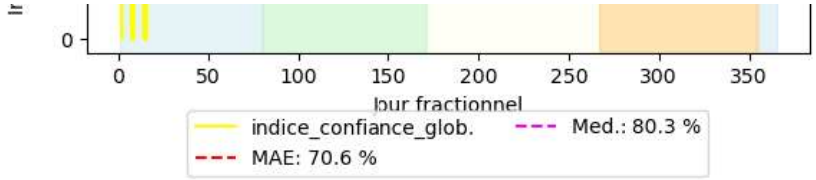


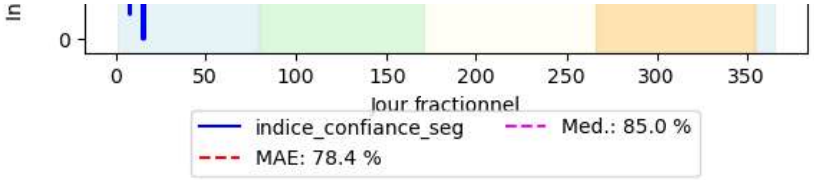


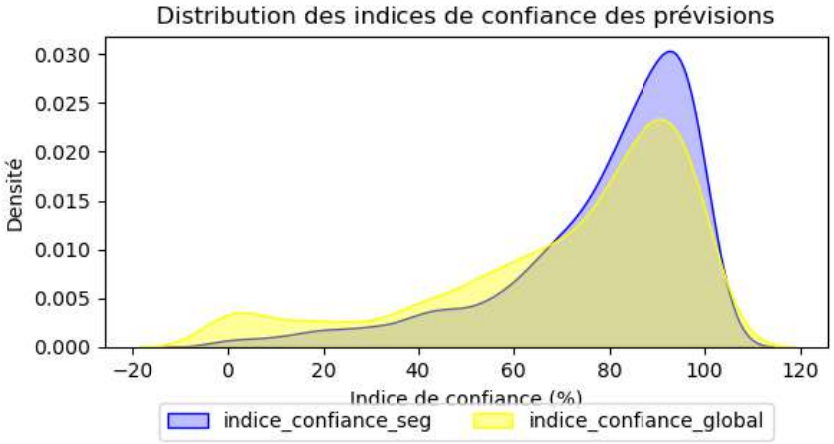










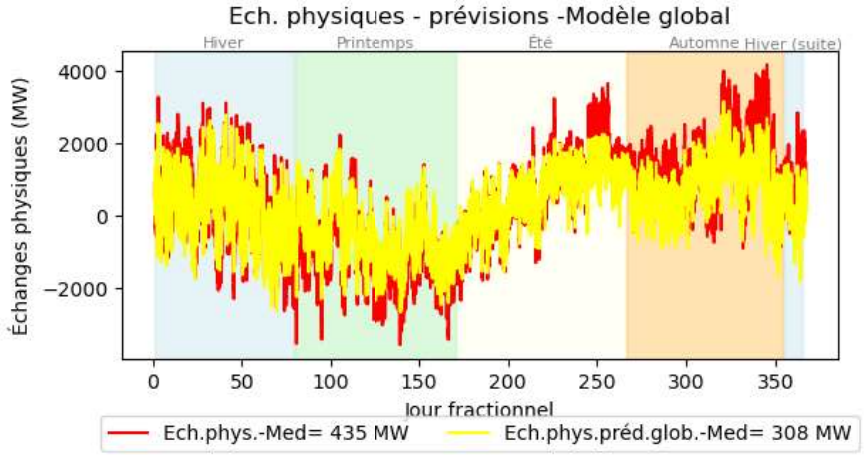


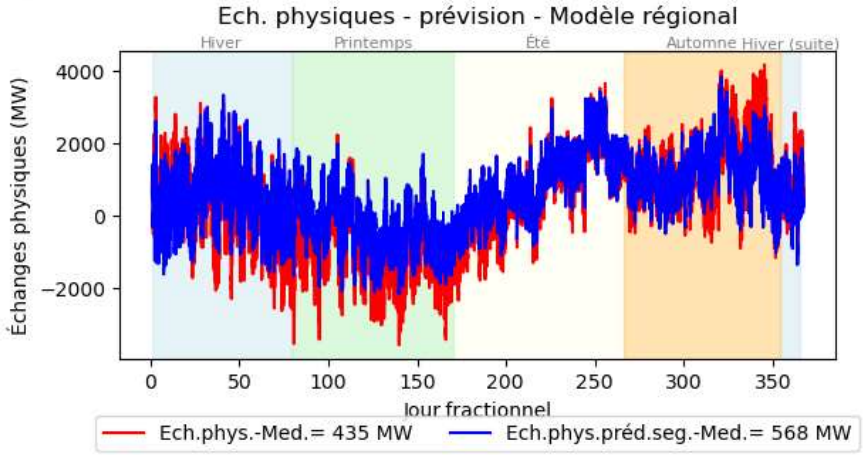
Métriques 2023

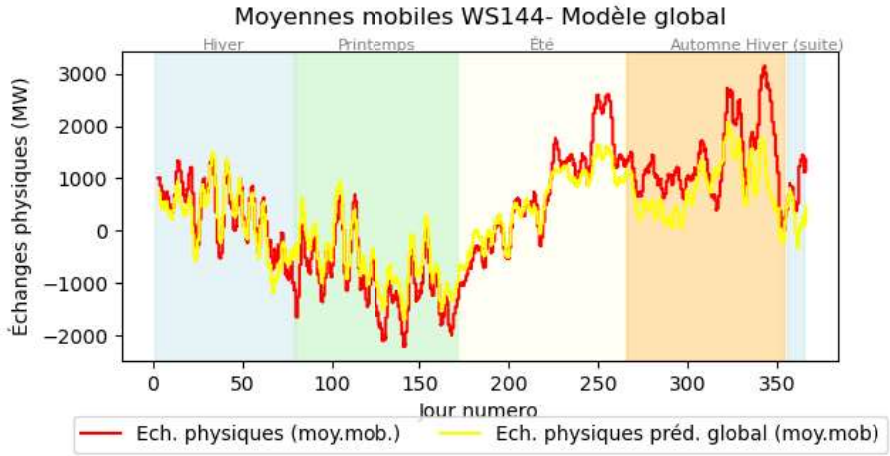
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2528 MW	Médiane: 3013 MW	Médiane: 2758 MW
IQR: 1189 MW	IQR: 456 MW	IQR: 567 MW
	Ind.Conf.Moy.: 70.6 %	Ind.Conf.Moy.: 78.4 %

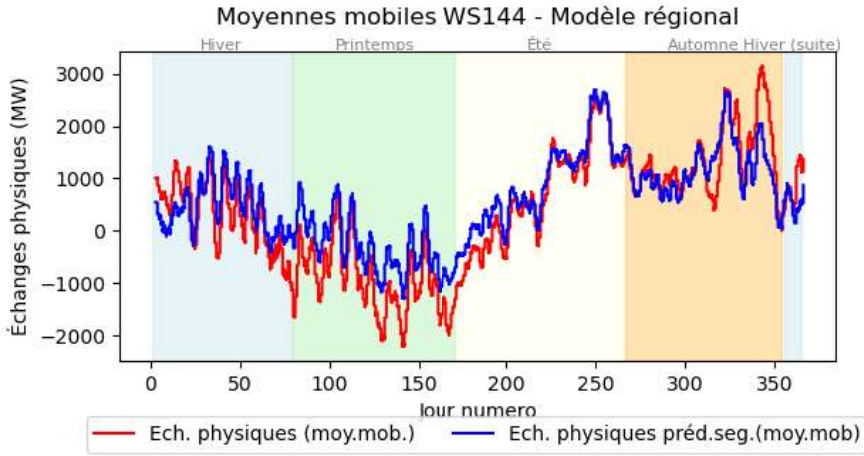
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

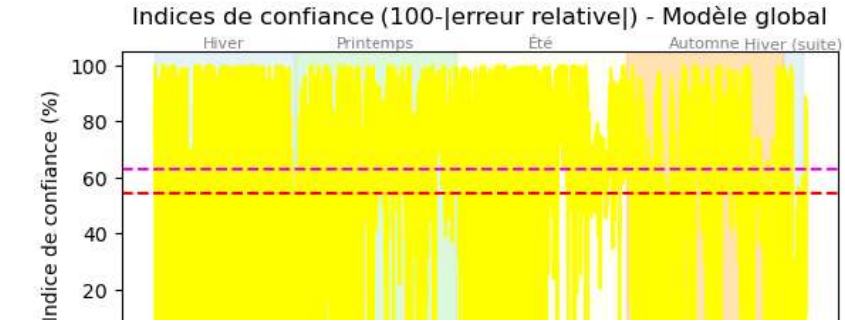
Prévisions des échanges physiques par XGBoost sans transformation cible
OCCITANIE, 2020

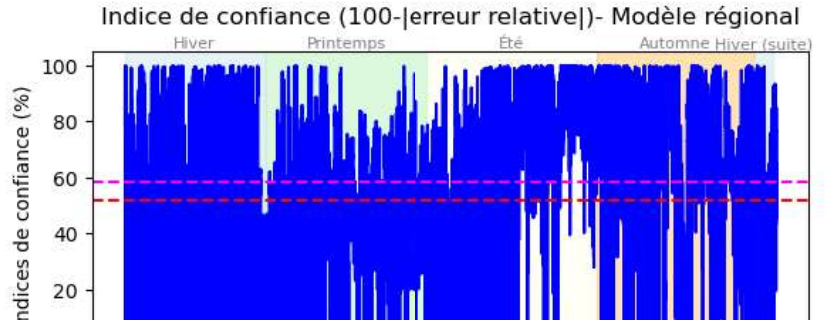


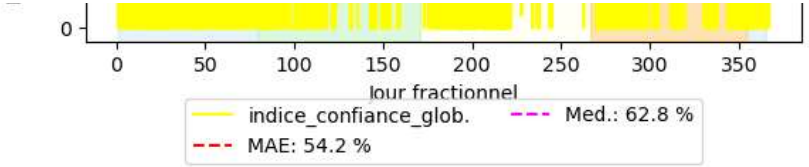


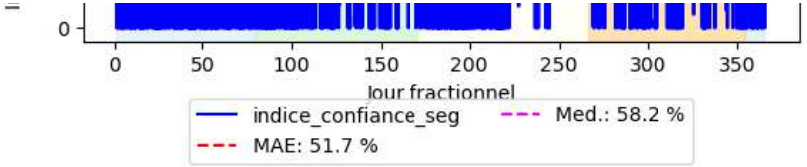


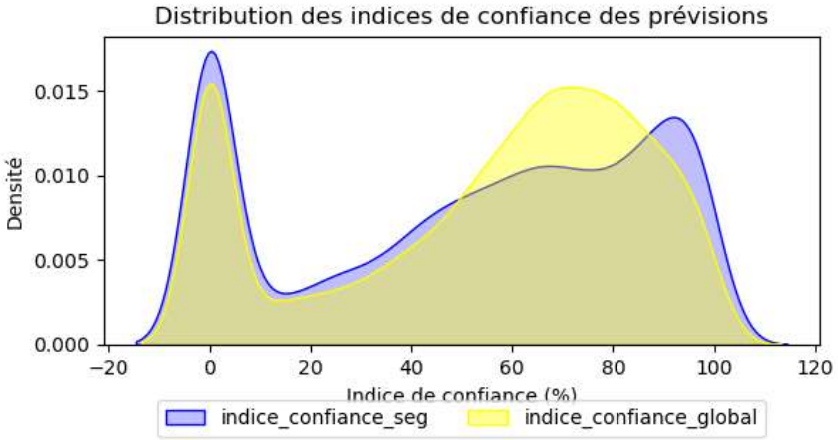










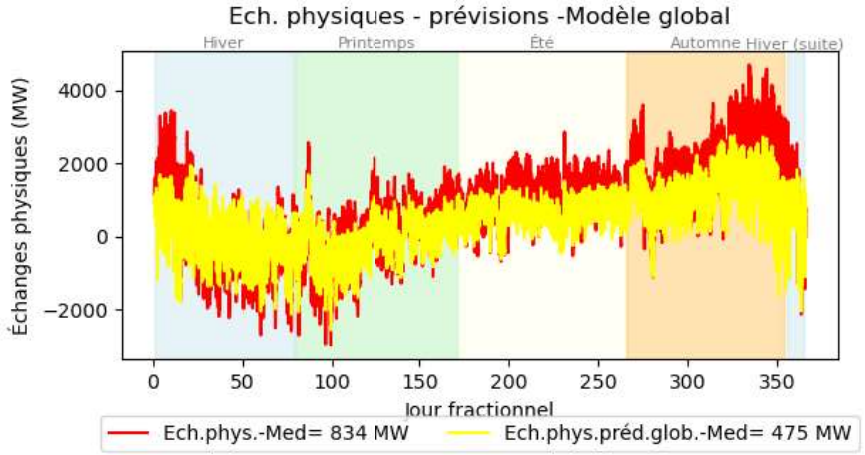


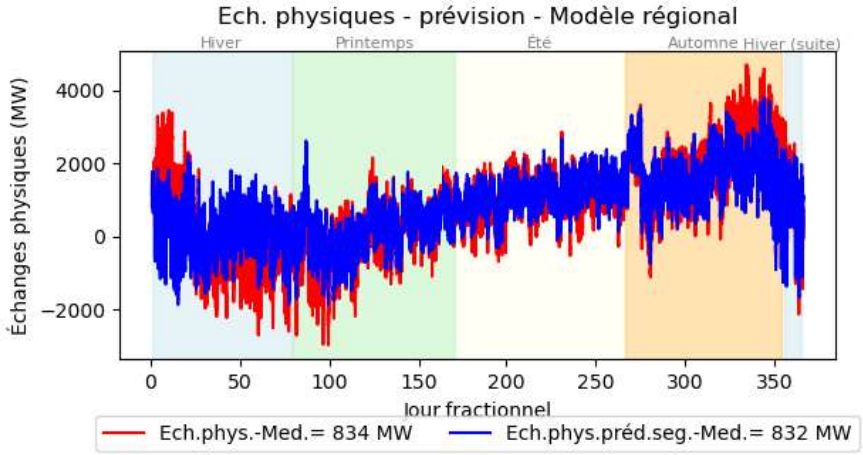
Métriques 2020

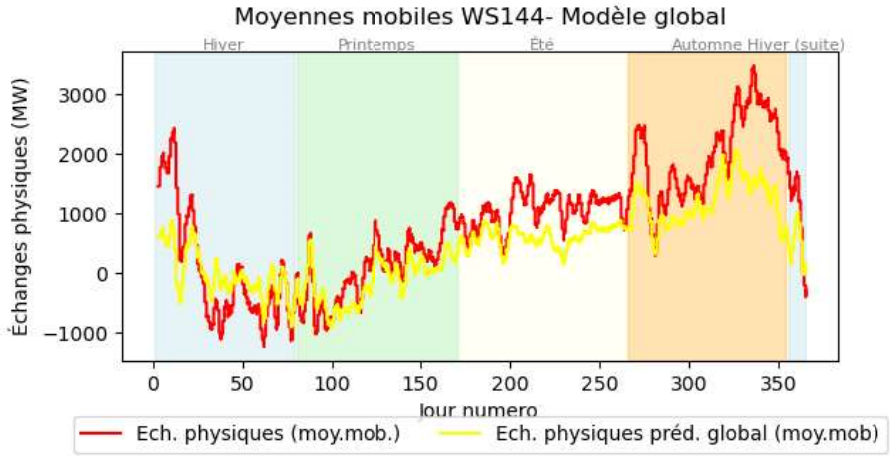
Valeurs réelles	Modèle global	Modèle régional
Médiane: 435 MW	Médiane: 308 MW	Médiane: 568 MW
IQR: 1882 MW	IQR: 1466 MW	IQR: 1440 MW
	Ind.Conf.Moy.: 54.2 %	Ind.Conf.Moy.: 51.7 %

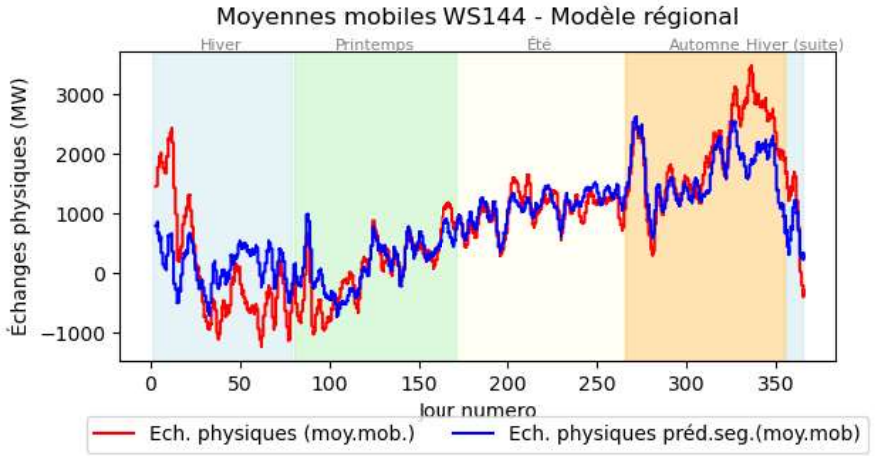
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

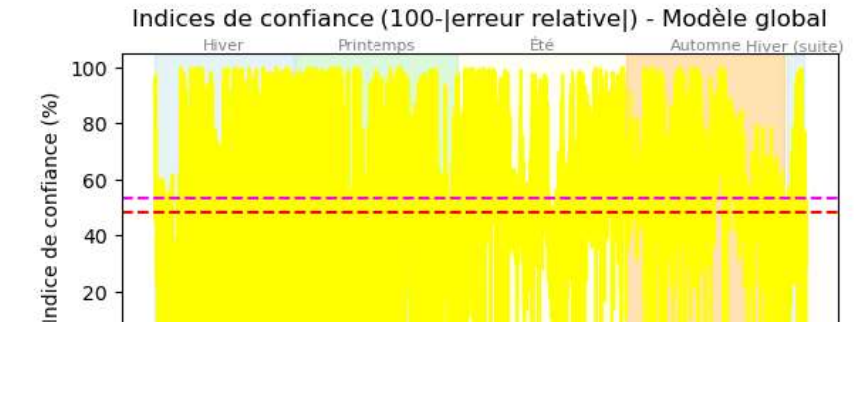
Prévisions des échanges physiques par XGBoost sans transformation cible
OCCITANIE, 2021

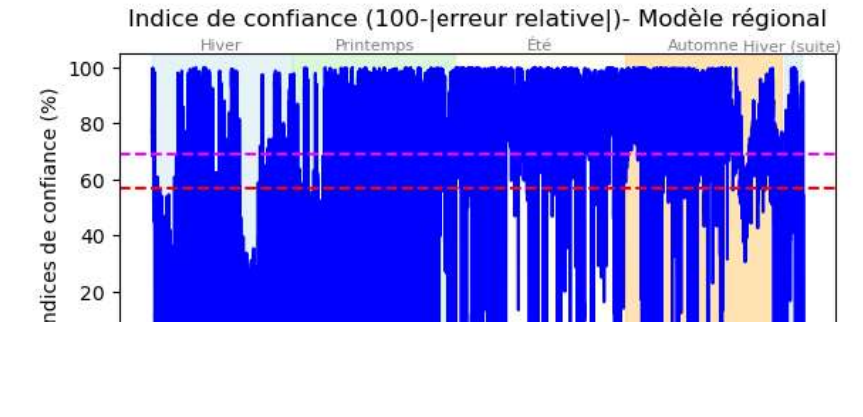


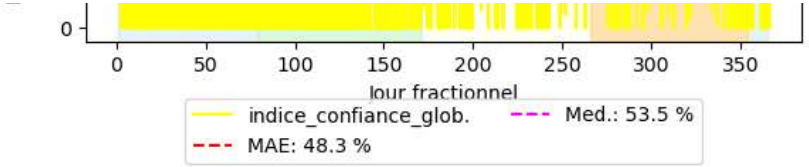


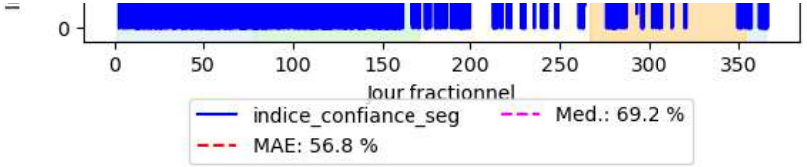


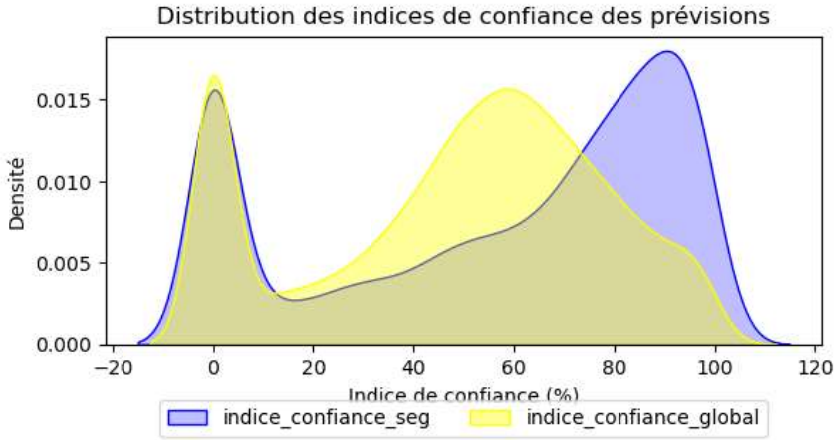










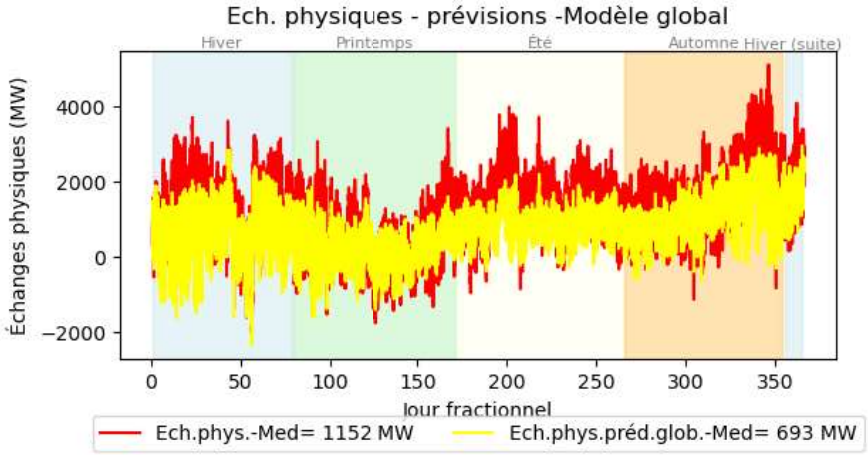


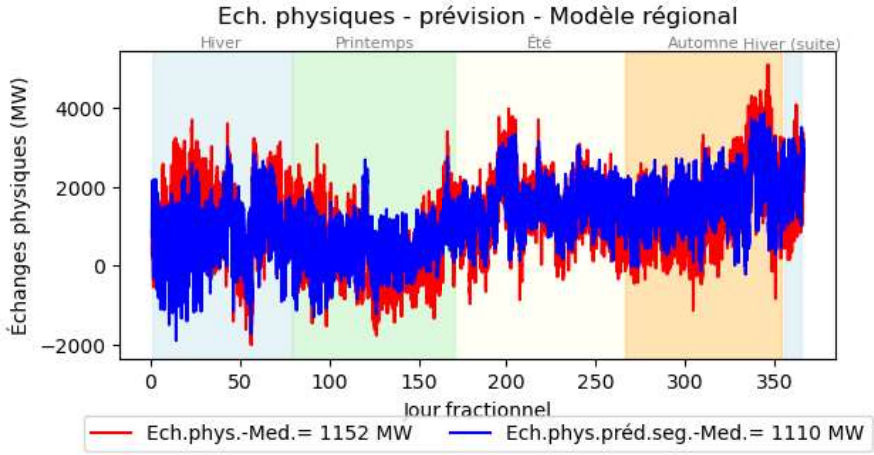
Métriques 2021

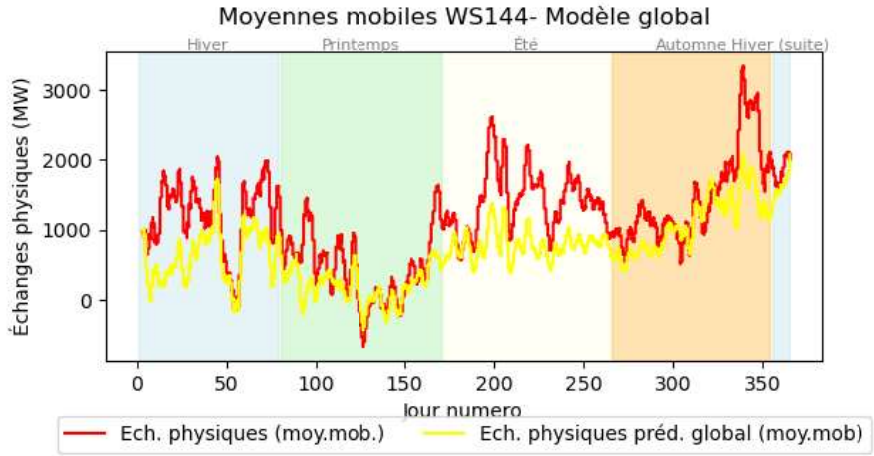
Valeurs réelles	Modèle global	Modèle régional
Médiane: 834 MW	Médiane: 475 MW	Médiane: 832 MW
IQR: 1524 MW	IQR: 976 MW	IQR: 1232 MW
	Ind.Conf.Moy.: 48.3 %	Ind.Conf.Moy.: 56.8 %

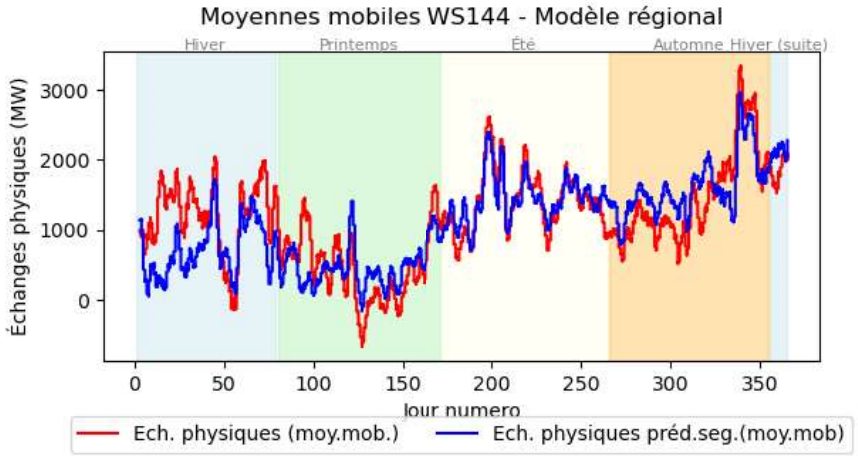
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

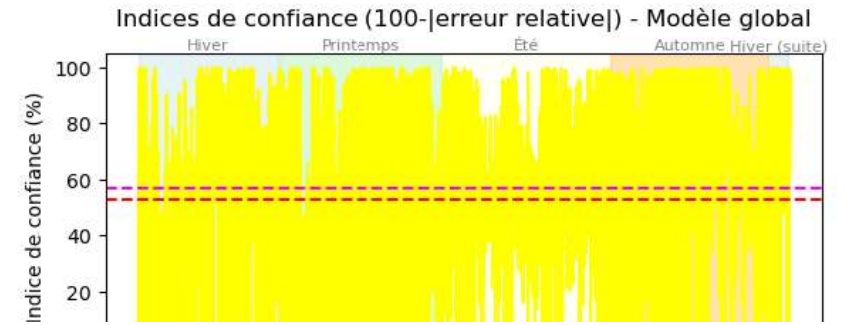
Prévisions des échanges physiques par XGBoost sans transformation cible
OCCITANIE, 2022

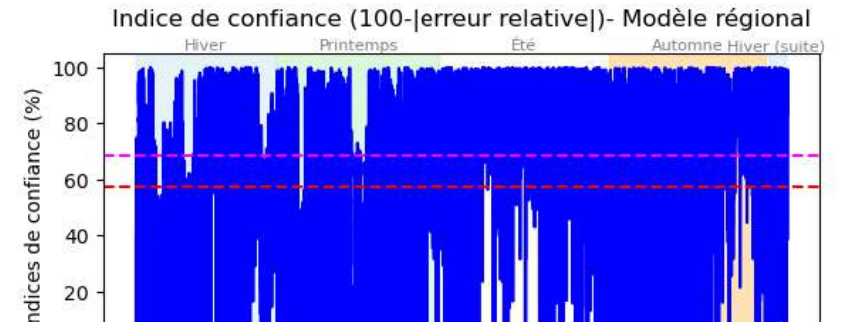


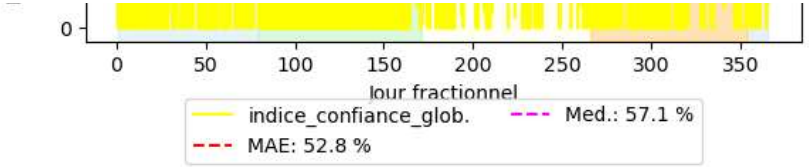


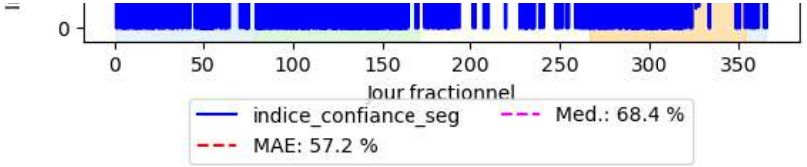


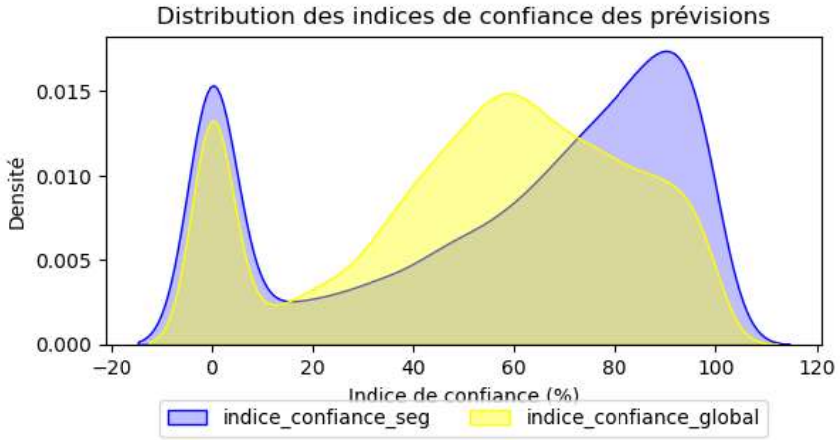










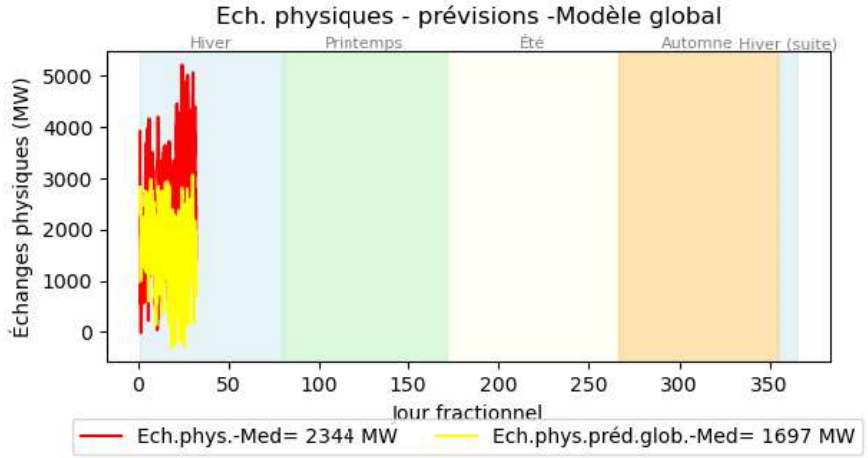


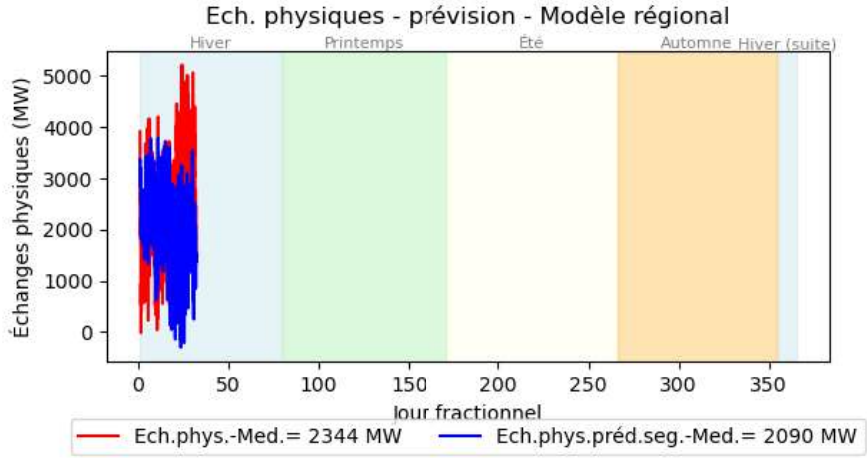
Métriques 2022

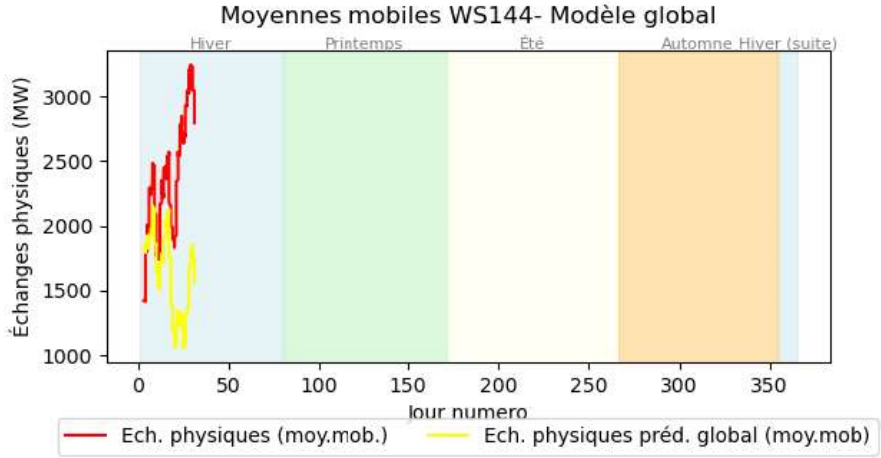
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1152 MW	Médiane: 693 MW	Médiane: 1110 MW
IQR: 1265 MW	IQR: 878 MW	IQR: 1121 MW
	Ind.Conf.Moy.: 52.8 %	Ind.Conf.Moy.: 57.2 %

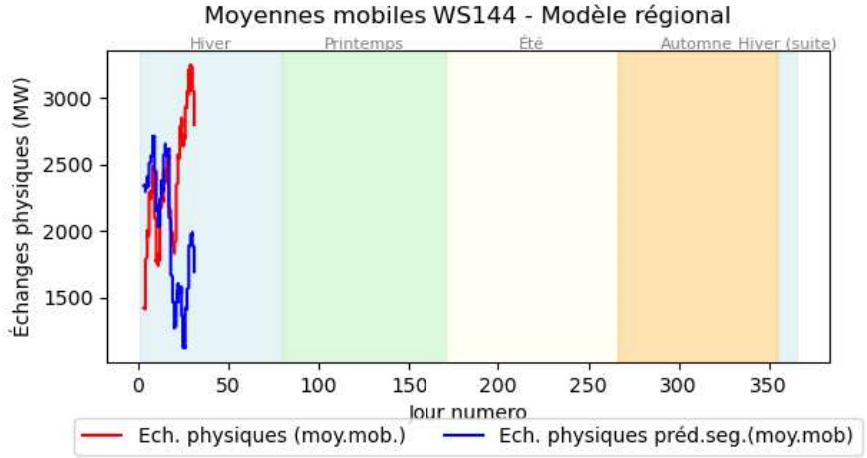
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

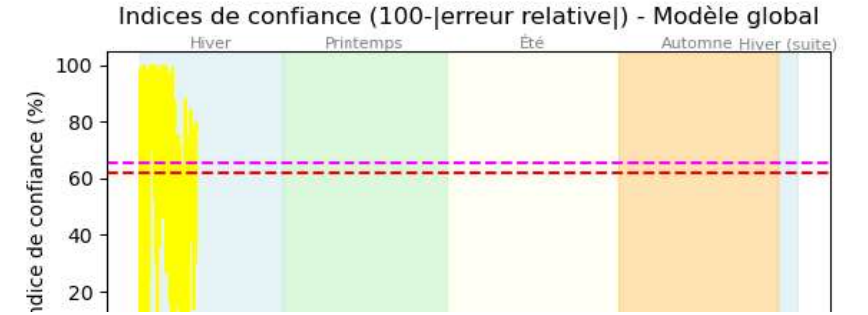
Prévisions des échanges physiques par XGBoost sans transformation cible
OCCITANIE, 2023

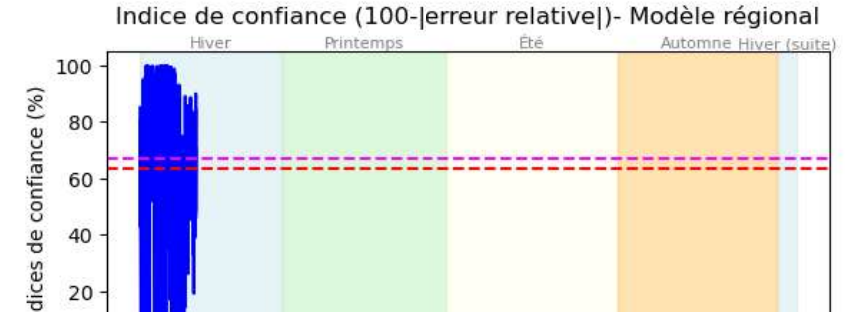


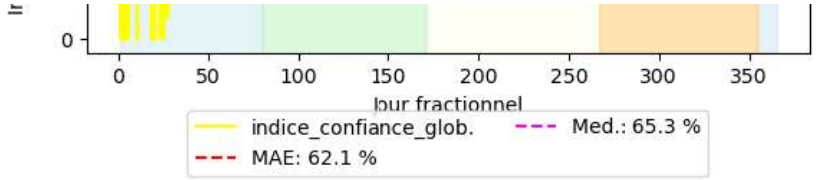


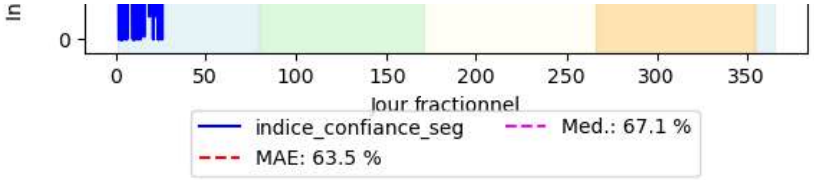


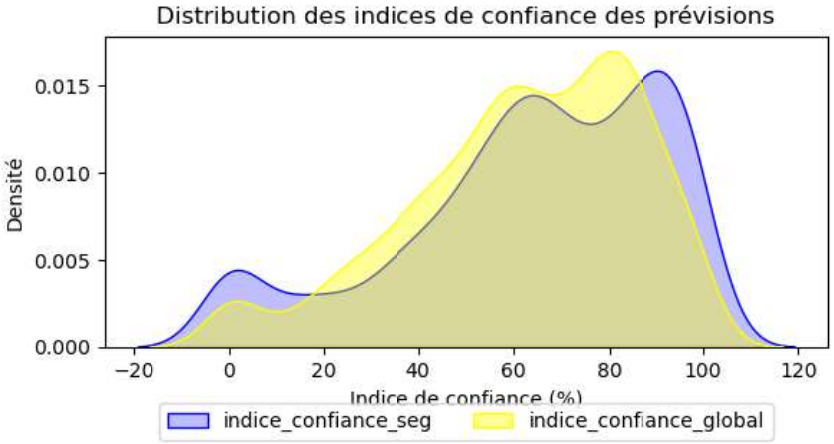










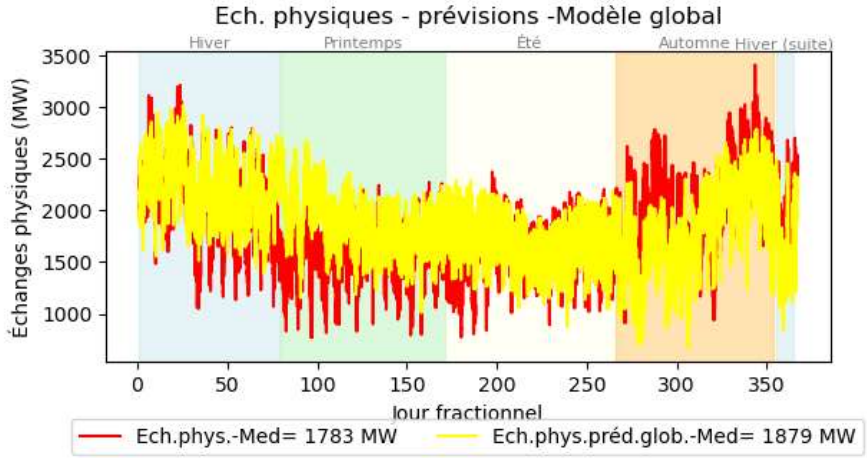


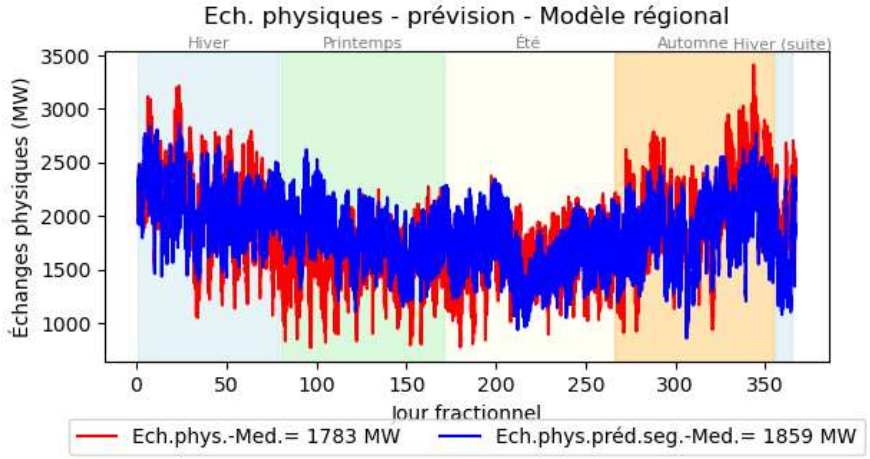
Métriques 2023

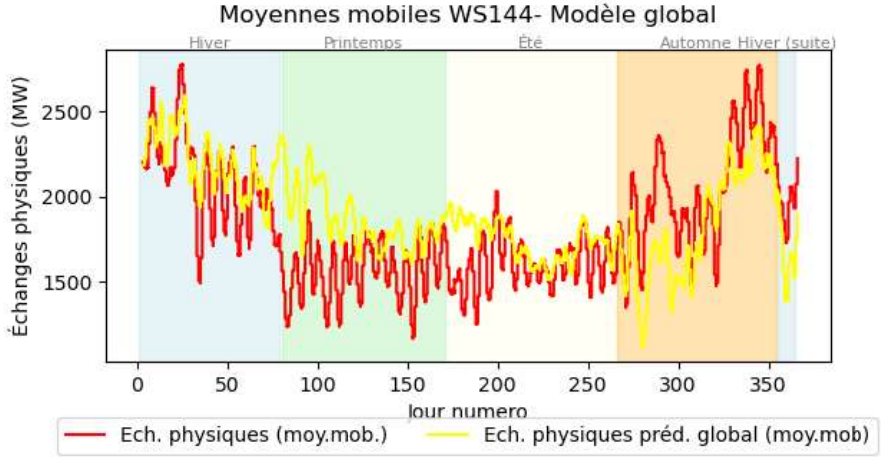
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2344 MW	Médiane: 1697 MW	Médiane: 2090 MW
IQR: 1383 MW	IQR: 1178 MW	IQR: 1376 MW
	Ind.Conf.Moy.: 62.1 %	Ind.Conf.Moy.: 63.5 %

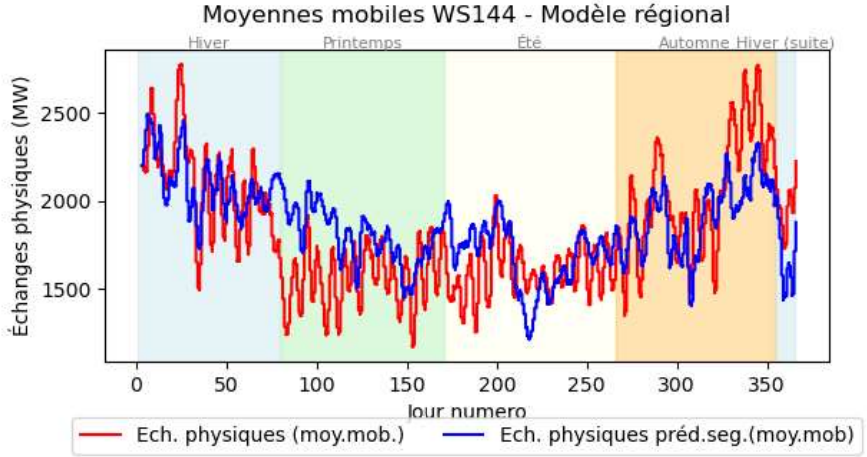
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

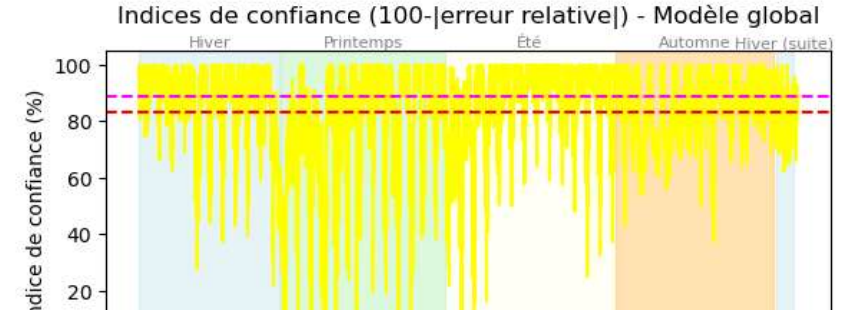
Prévisions des échanges physiques par XGBoost sans transformation cible
BOURGOGNE FRANCHE COMTE, 2020

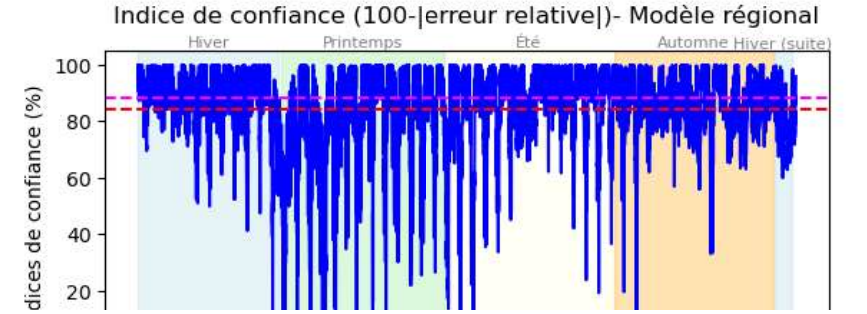


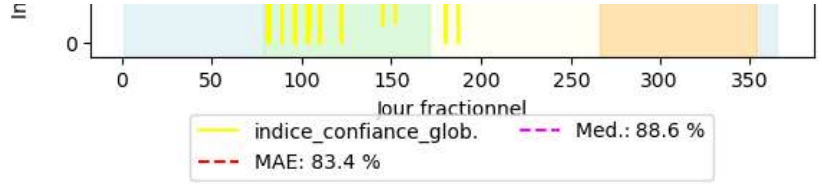


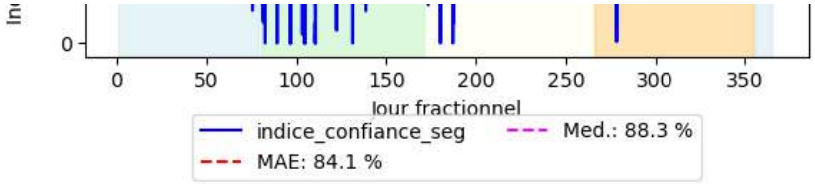


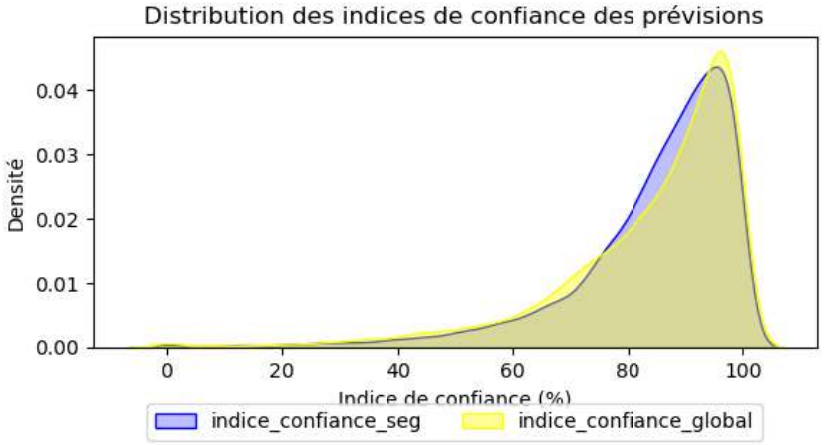










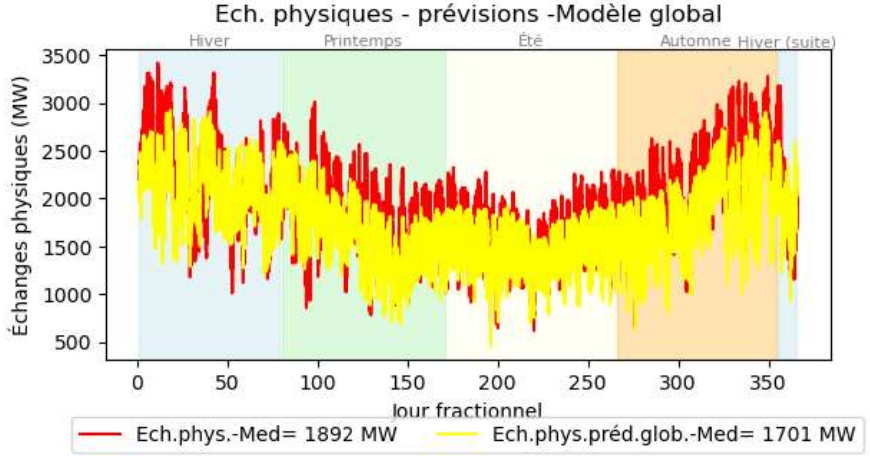


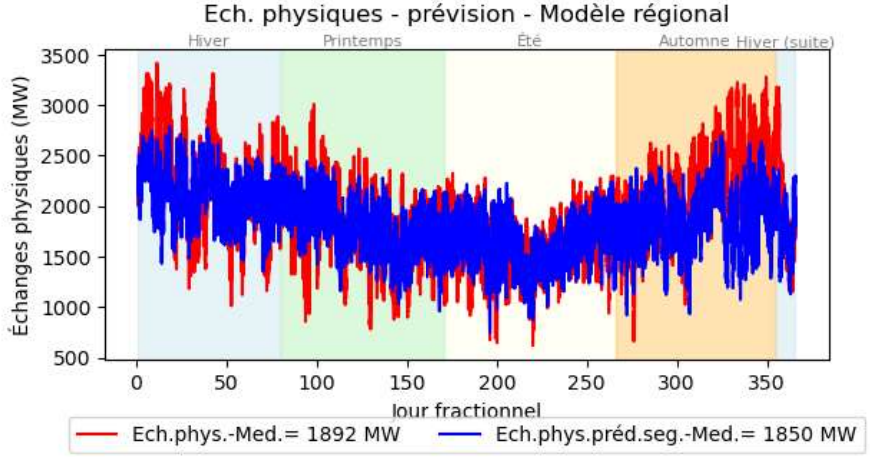
Métriques 2020

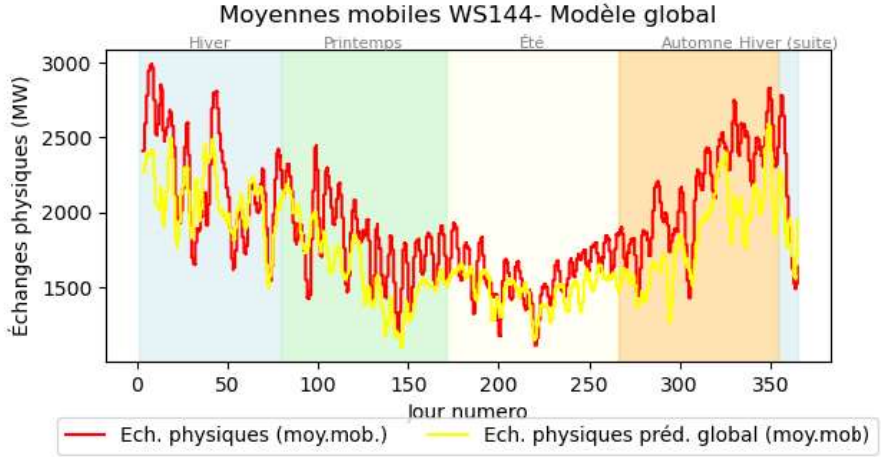
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1783 MW	Médiane: 1879 MW	Médiane: 1859 MW
IQR: 589 MW	IQR: 458 MW	IQR: 424 MW
	Ind.Conf.Moy.: 83.4 %	Ind.Conf.Moy.: 84.1 %

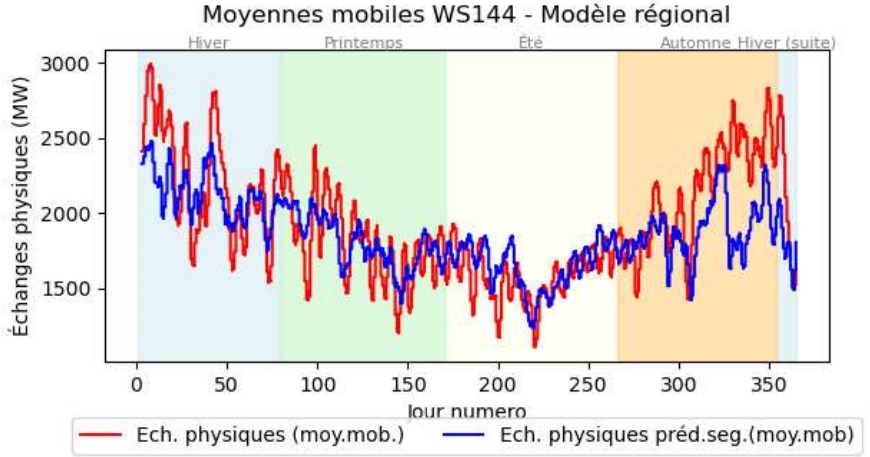
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

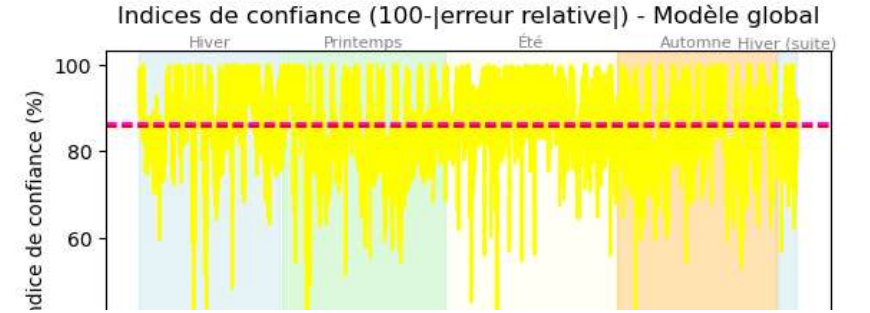
Prévisions des échanges physiques par XGBoost sans transformation cible
BOURGOGNE FRANCHE COMTE, 2021

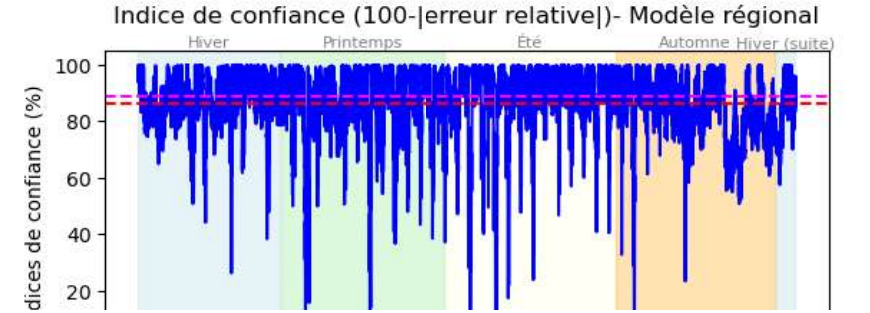


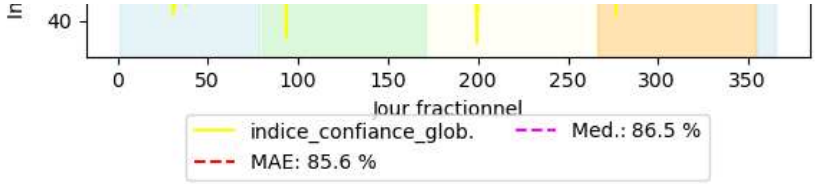


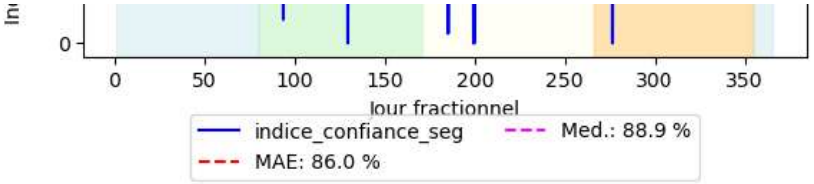


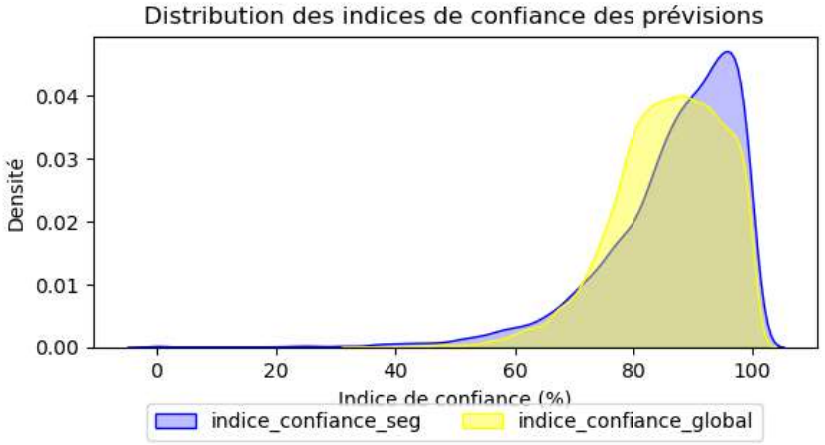










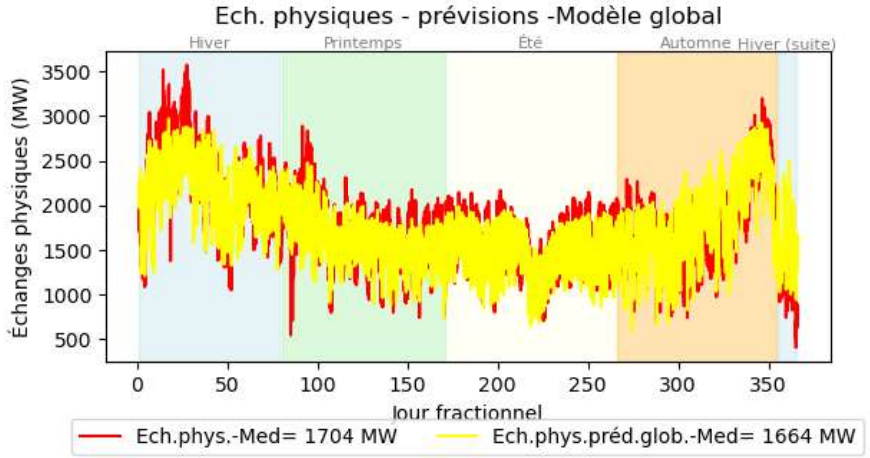


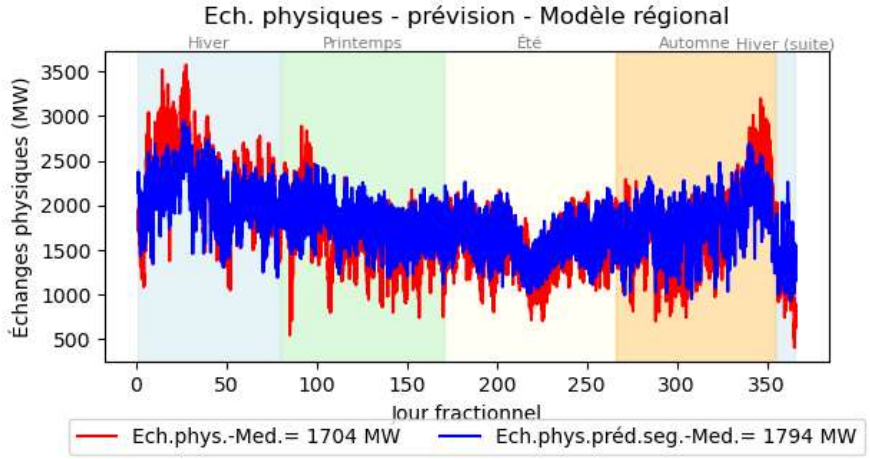
Métriques 2021

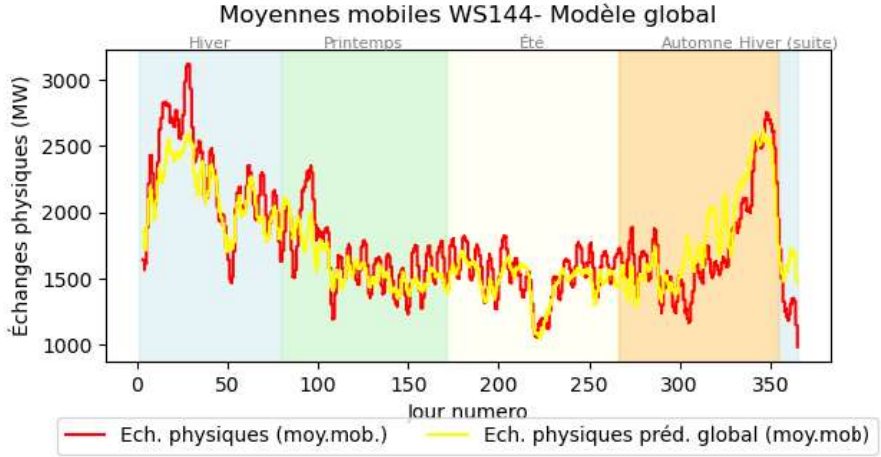
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1892 MW	Médiane: 1701 MW	Médiane: 1850 MW
IQR: 653 MW	IQR: 536 MW	IQR: 429 MW
	Ind.Conf.Moy.: 85.6 %	Ind.Conf.Moy.: 86.0 %

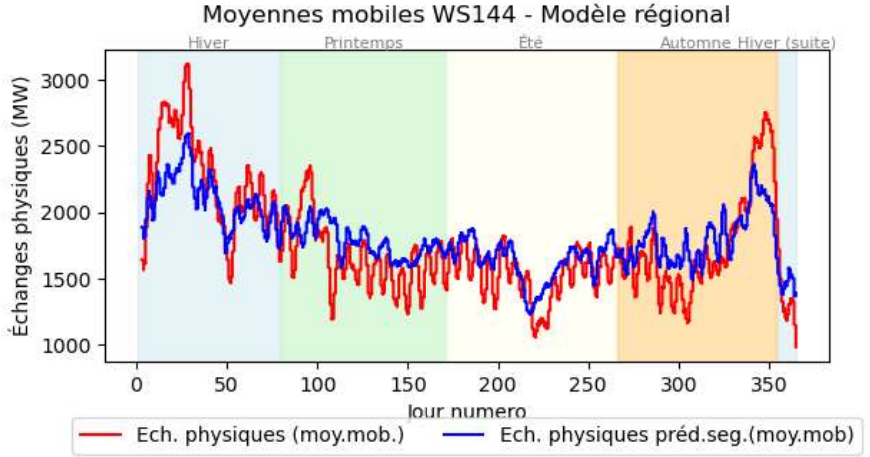
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

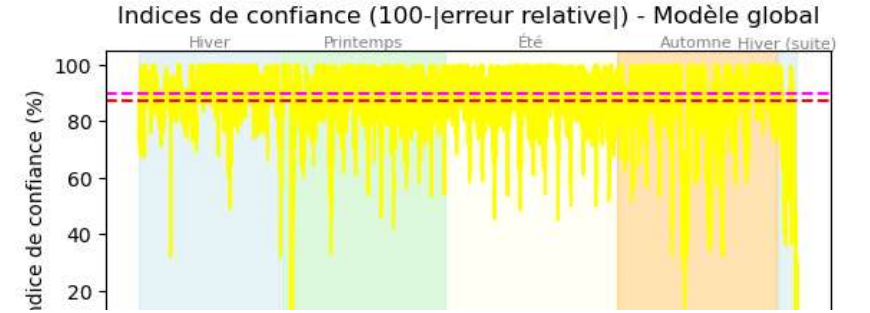
Prévisions des échanges physiques par XGBoost sans transformation cible
BOURGOGNE FRANCHE COMTE, 2022

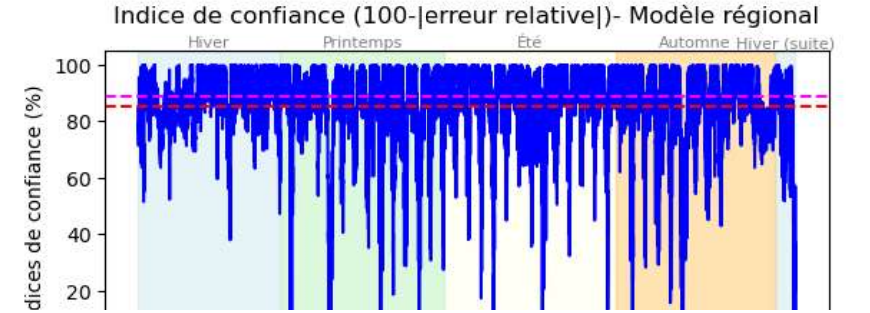


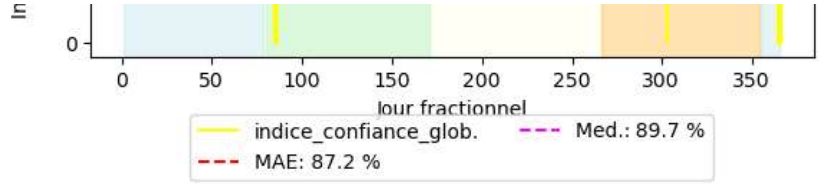


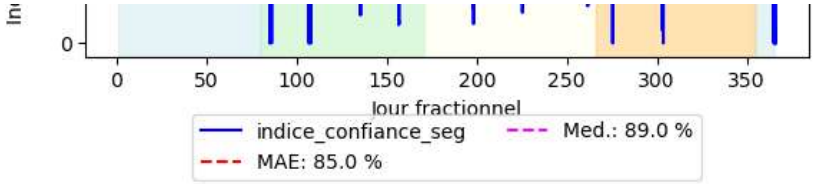


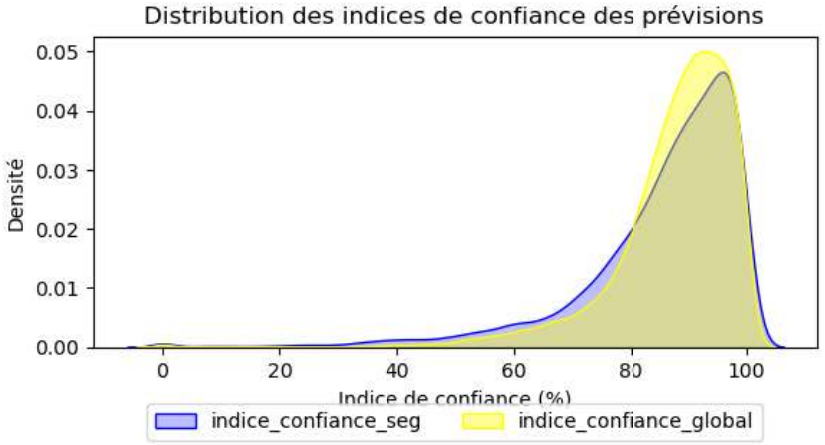










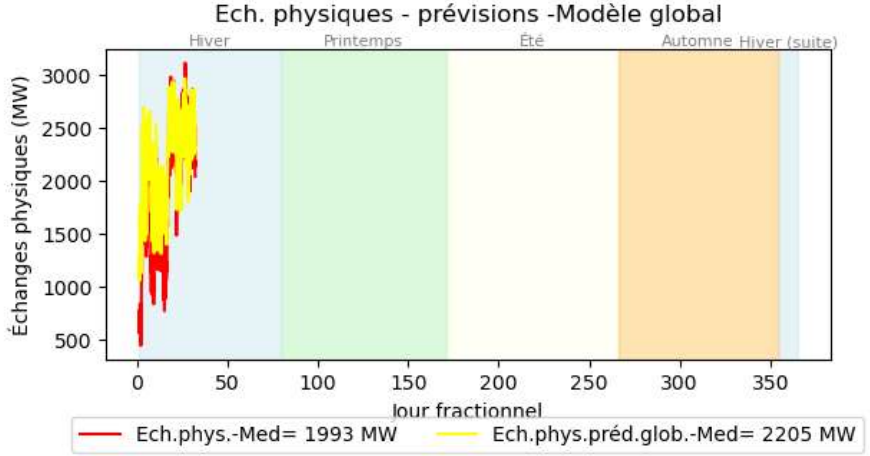


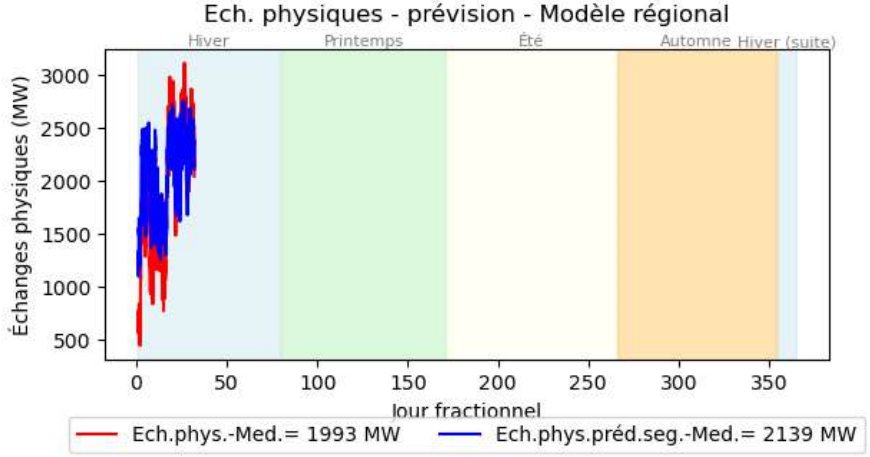
Métriques 2022

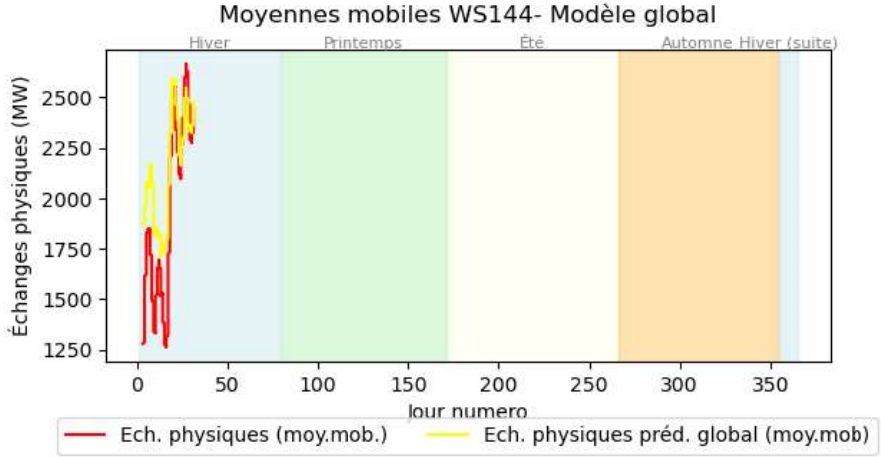
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1704 MW	Médiane: 1664 MW	Médiane: 1794 MW
IQR: 585 MW	IQR: 530 MW	IQR: 419 MW
	Ind.Conf.Moy.: 87.2 %	Ind.Conf.Moy.: 85.0 %

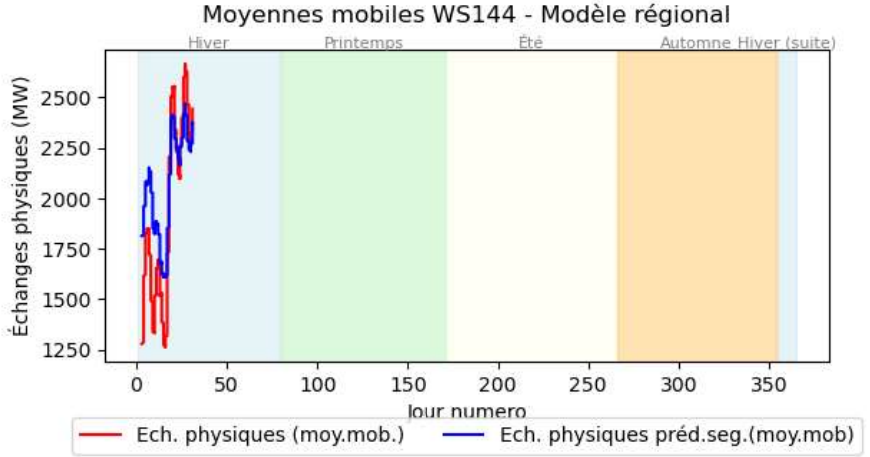
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

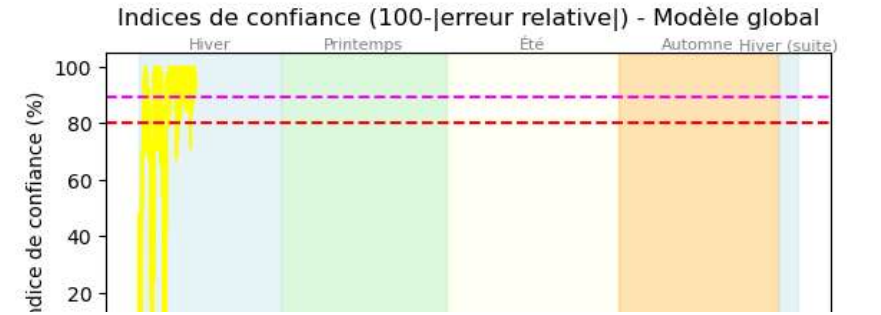
Prévisions des échanges physiques par XGBoost sans transformation cible
BOURGOGNE FRANCHE COMTE, 2023

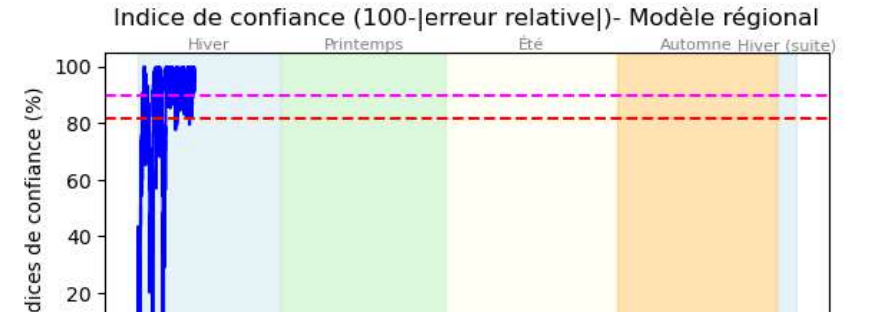


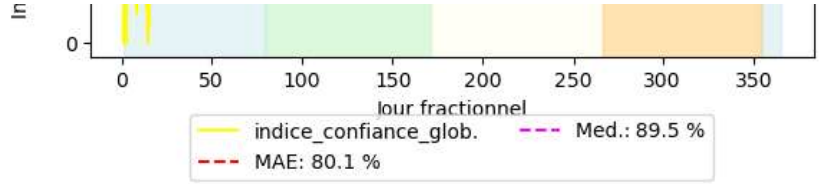


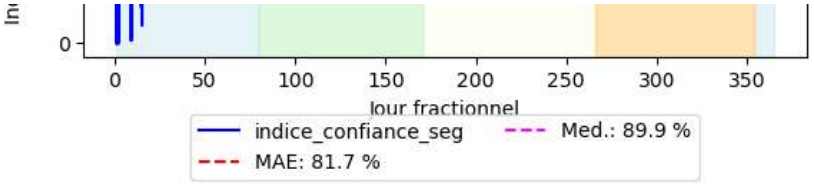


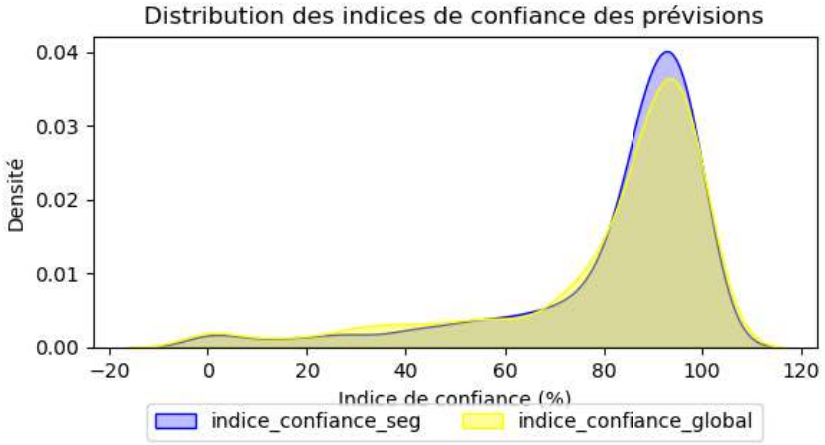










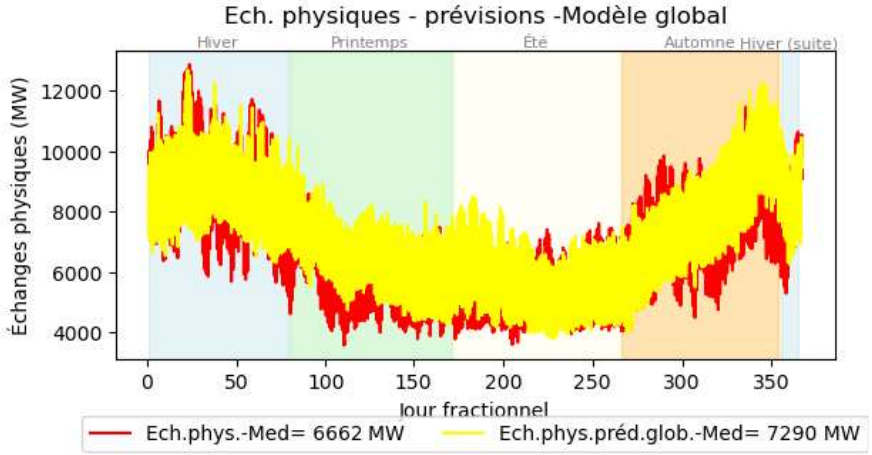


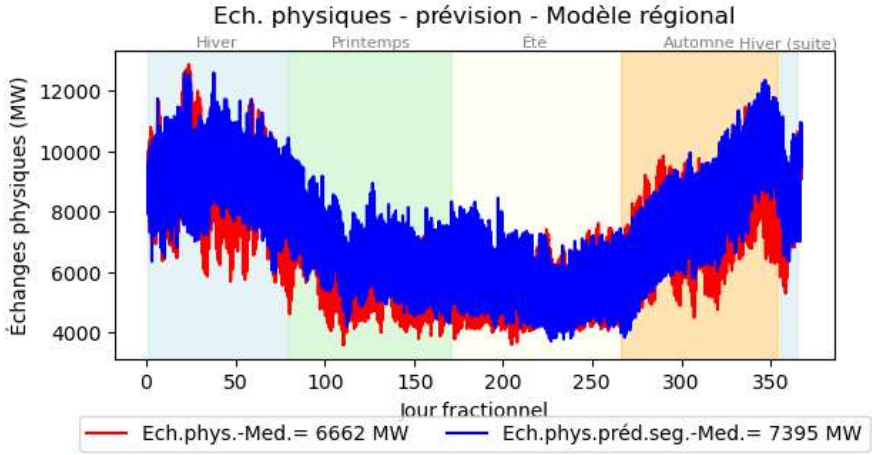
Métriques 2023

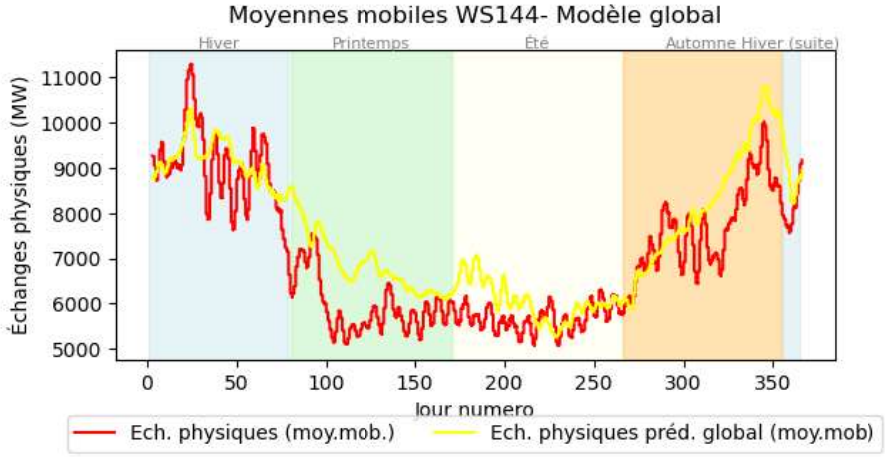
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1993 MW	Médiane: 2205 MW	Médiane: 2139 MW
IQR: 896 MW	IQR: 673 MW	IQR: 621 MW
	Ind.Conf.Moy.: 80.1 %	Ind.Conf.Moy.: 81.7 %

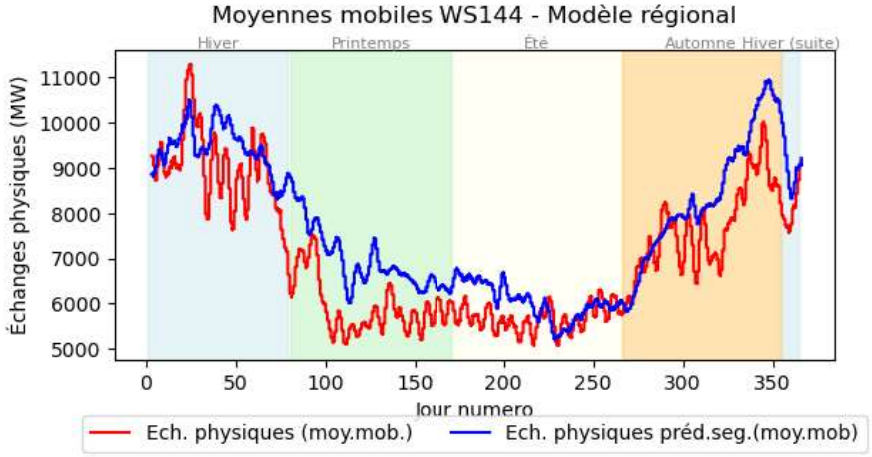
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

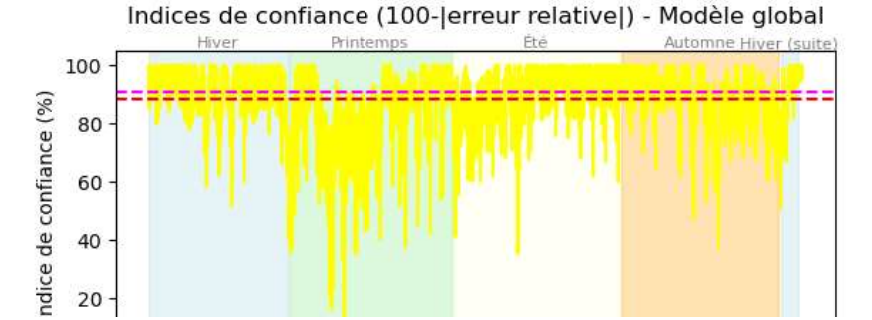
Prévisions des échanges physiques par XGBoost sans transformation cible
ILE DE FRANCE, 2020

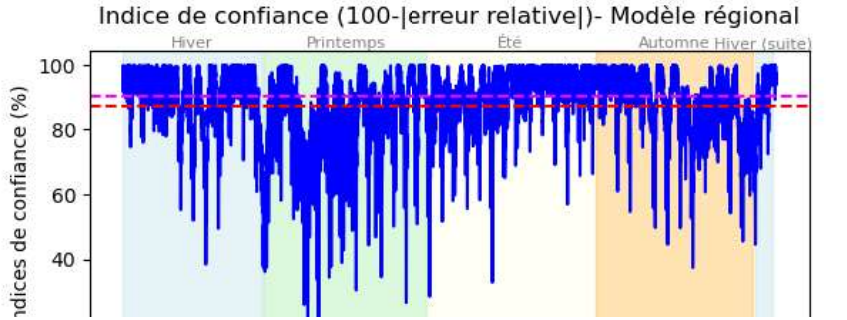


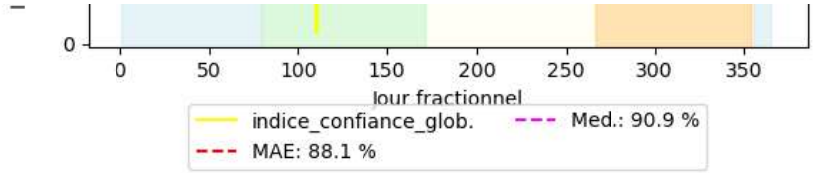


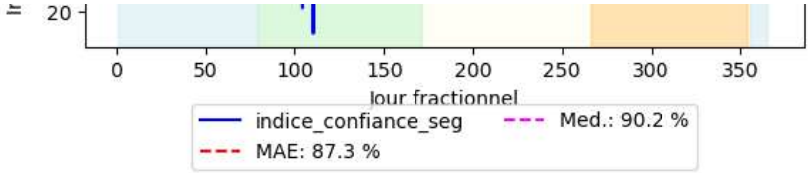


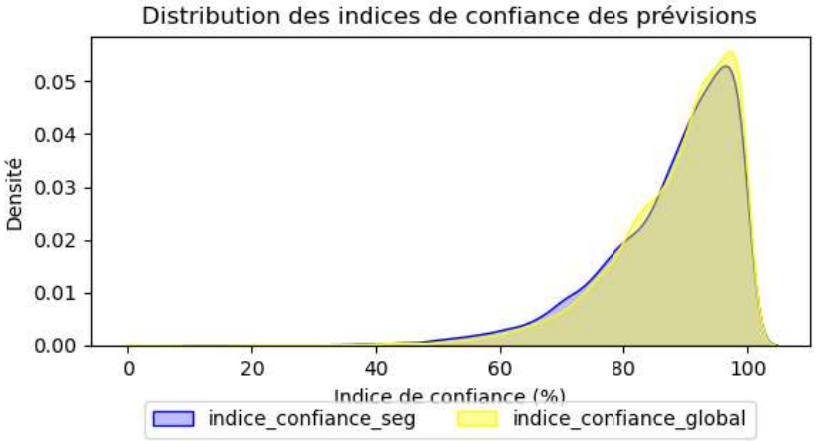










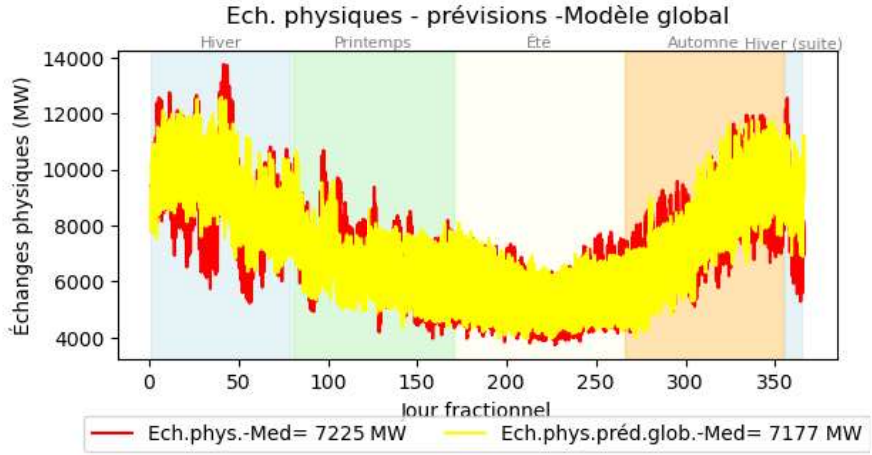


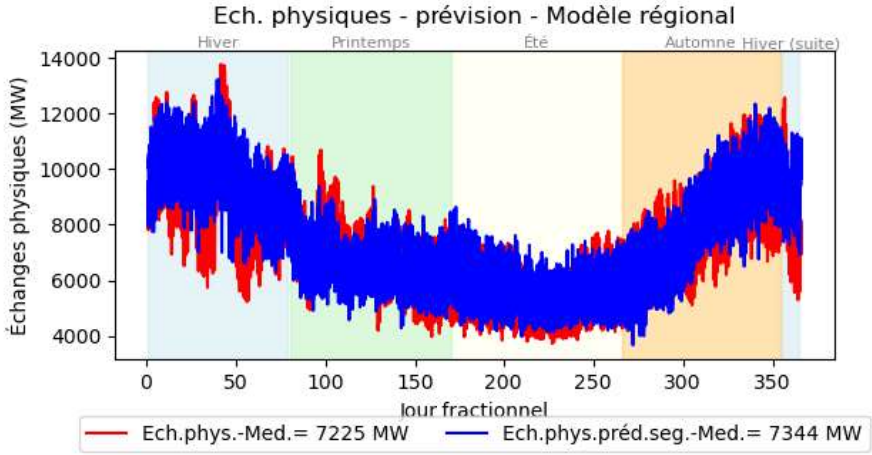
Métriques 2020

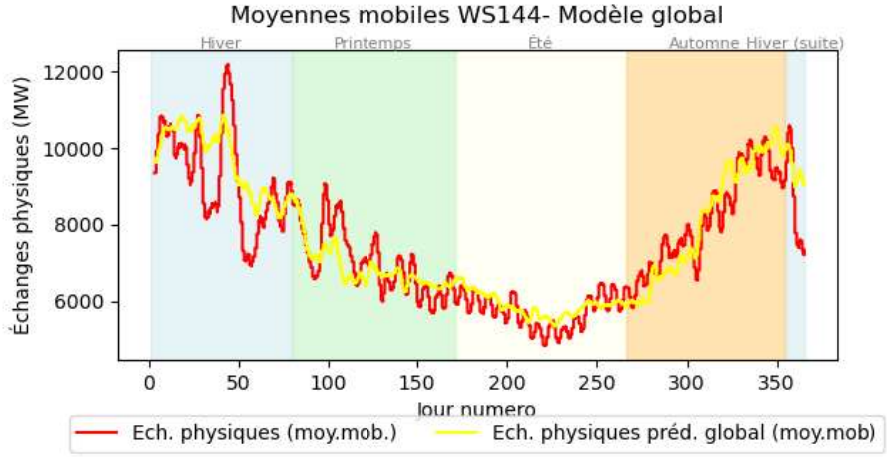
Valeurs réelles	Modèle global	Modèle régional
Médiane: 6662 MW IQR: 2502 MW	Médiane: 7290 MW IQR: 2424 MW Ind.Conf.Moy.: 88.1 %	Médiane: 7395 MW IQR: 2611 MW Ind.Conf.Moy.: 87.3 %

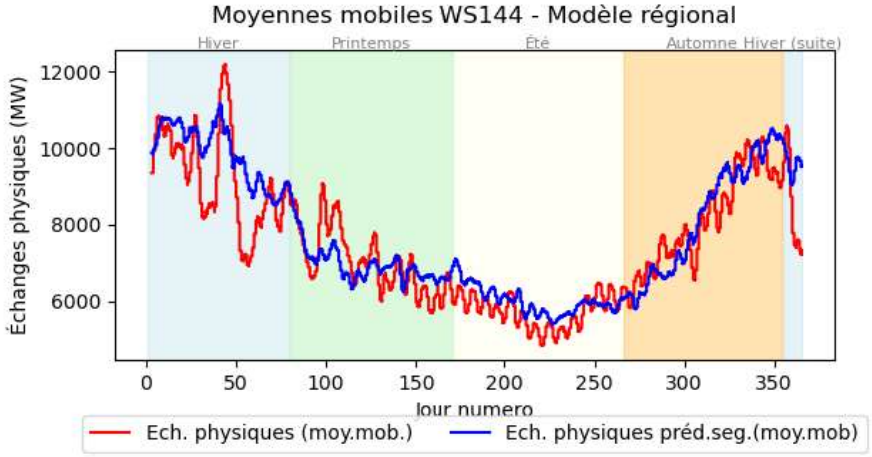
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

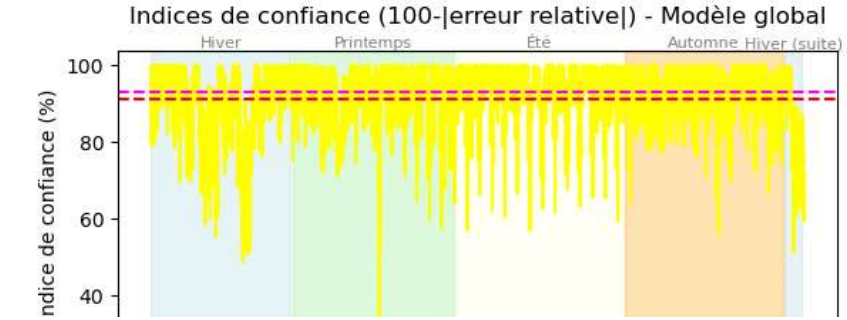
Prévisions des échanges physiques par XGBoost sans transformation cible
ILE DE FRANCE, 2021

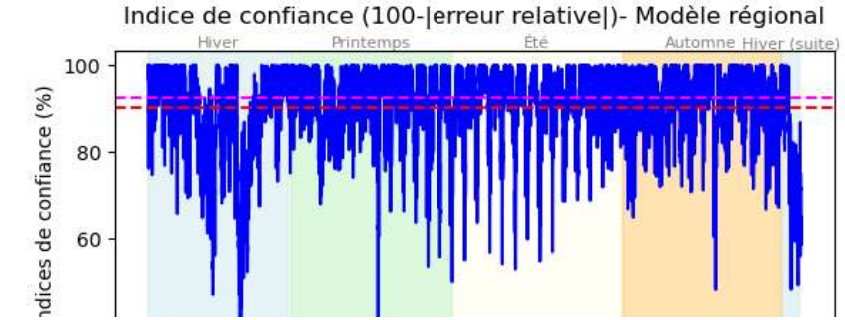


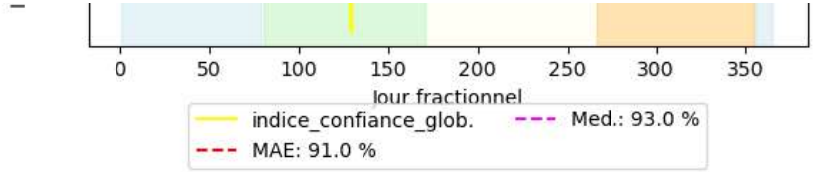


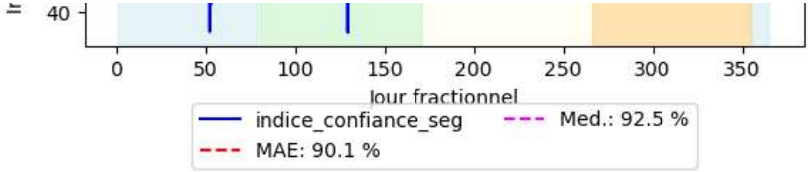


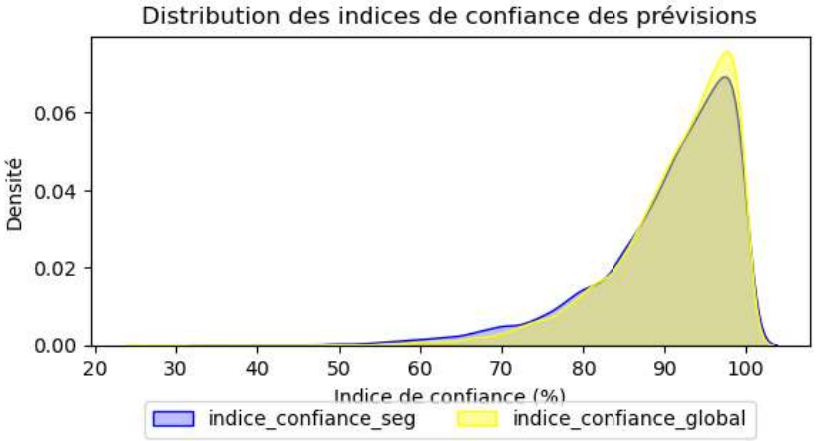










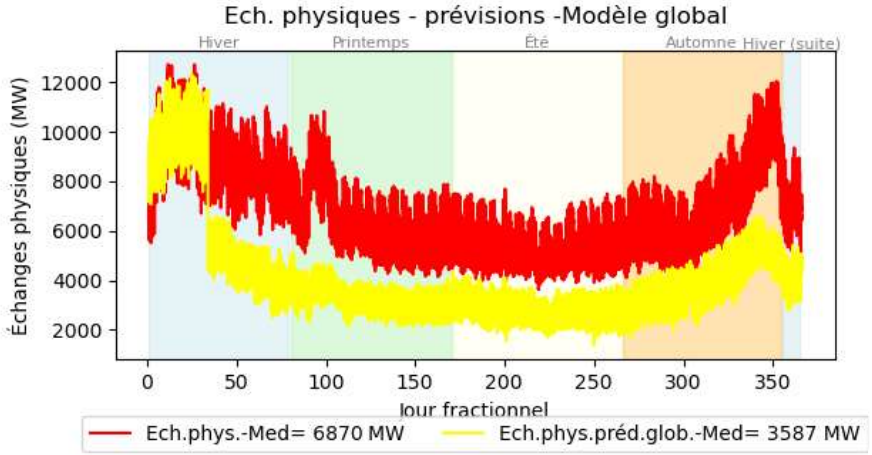


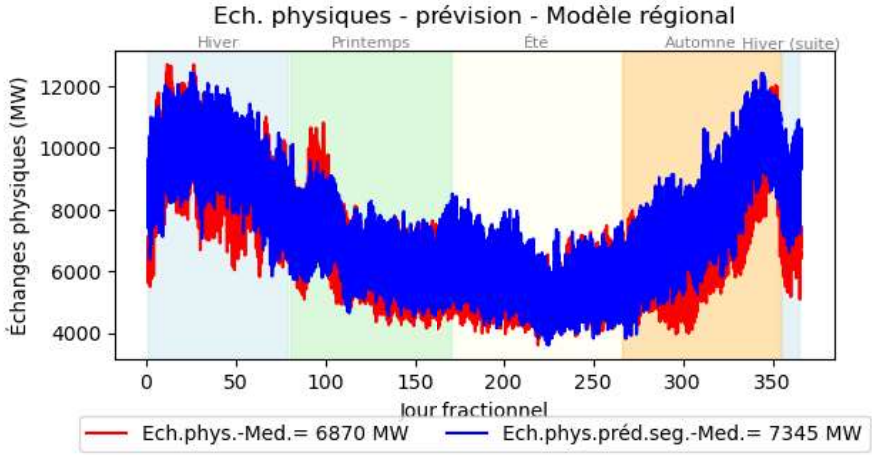
Métriques 2021

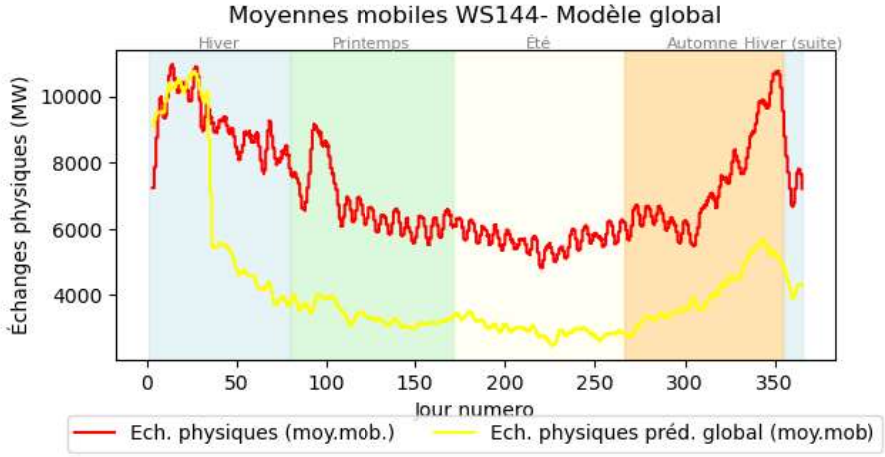
Valeurs réelles	Modèle global	Modèle régional
Médiane: 7225 MW	Médiane: 7177 MW	Médiane: 7344 MW
IQR: 2610 MW	IQR: 2776 MW	IQR: 2862 MW
	Ind.Conf.Moy.: 91.0 %	Ind.Conf.Moy.: 90.1 %

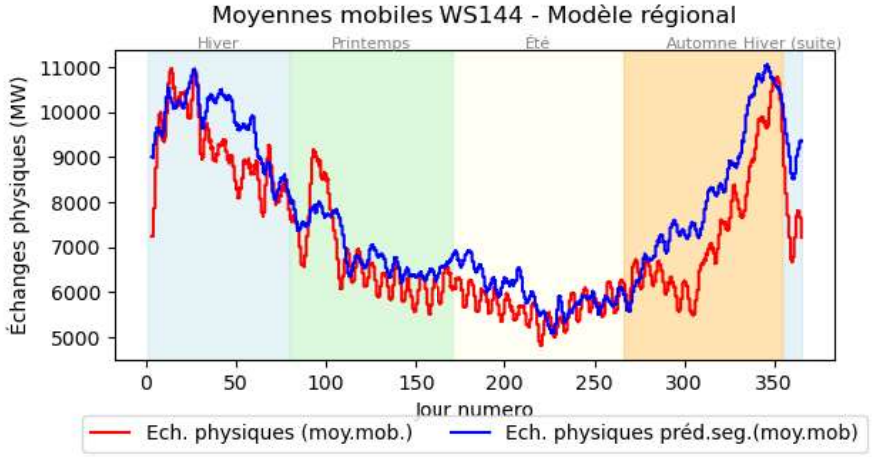
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

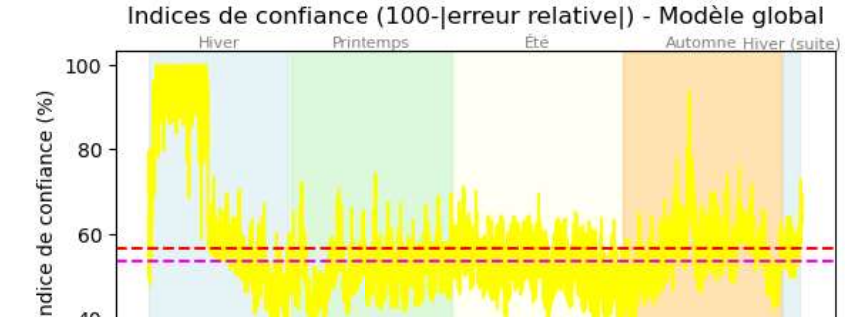
Prévisions des échanges physiques par XGBoost sans transformation cible
ILE DE FRANCE, 2022

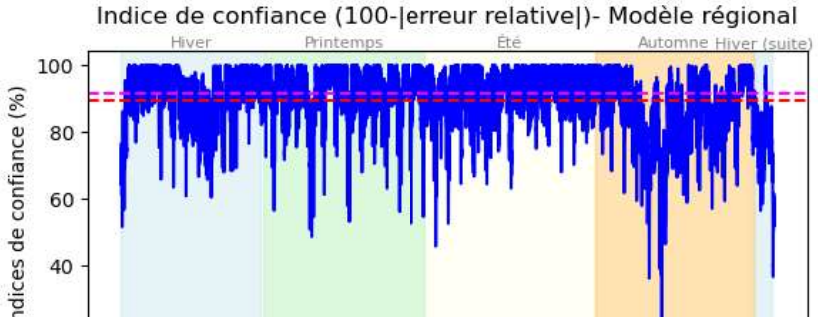


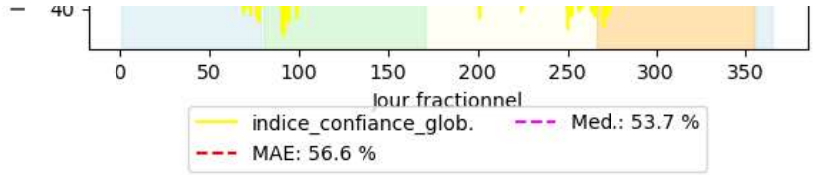


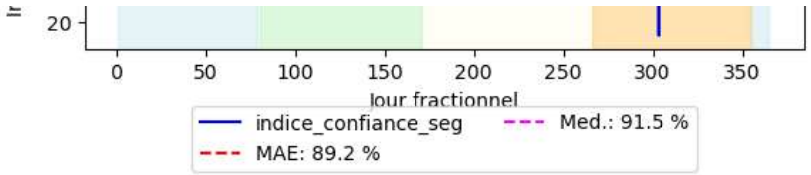


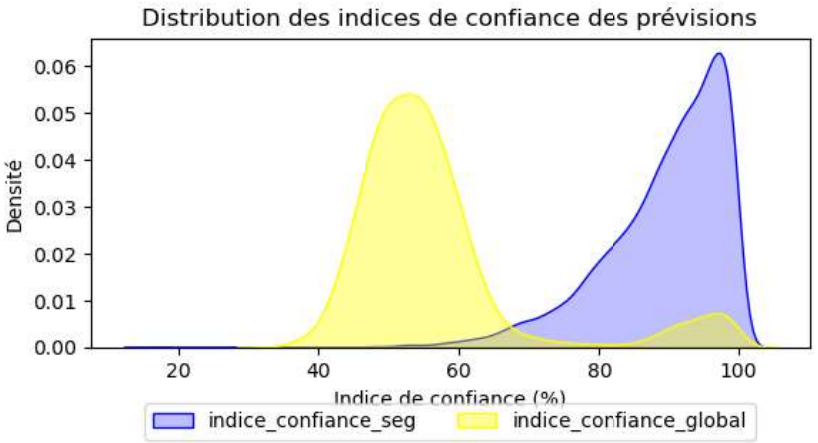










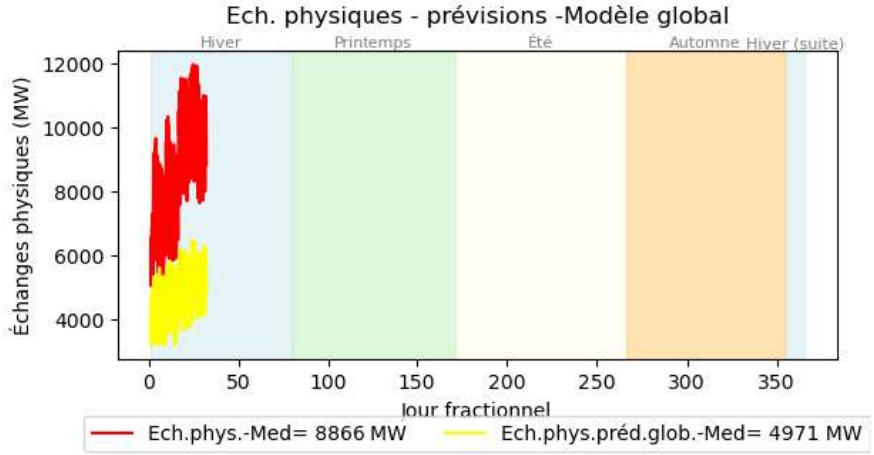


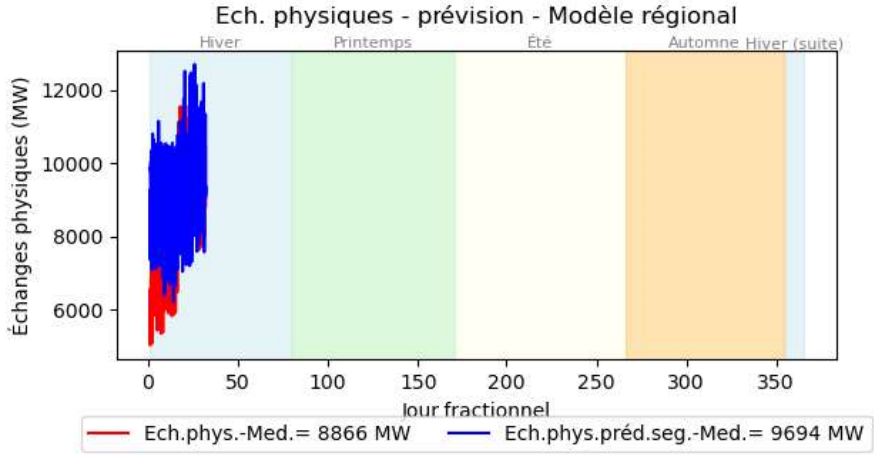
Métriques 2022

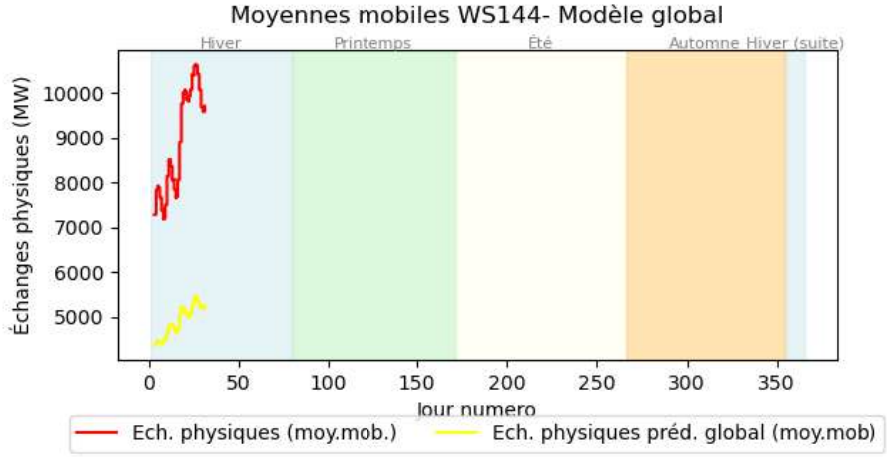
Valeurs réelles	Modèle global	Modèle régional
Médiane: 6870 MW	Médiane: 3587 MW	Médiane: 7345 MW
IQR: 2456 MW	IQR: 1420 MW	IQR: 2667 MW
	Ind.Conf.Moy.: 56.6 %	Ind.Conf.Moy.: 89.2 %

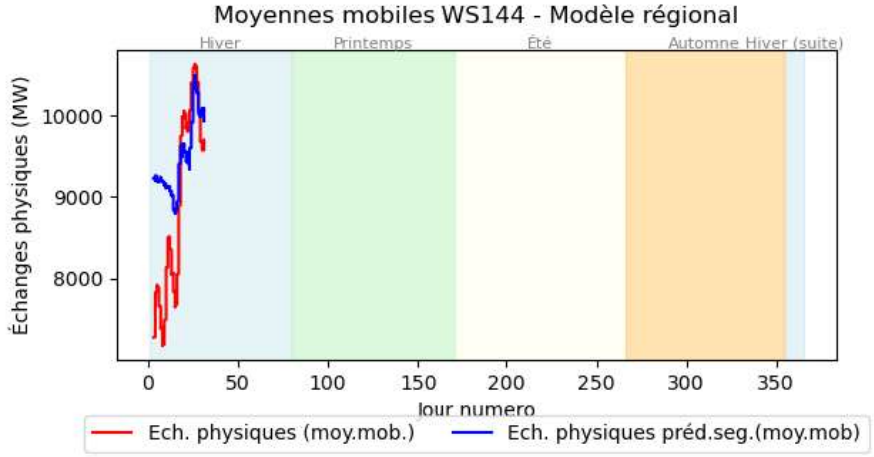
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

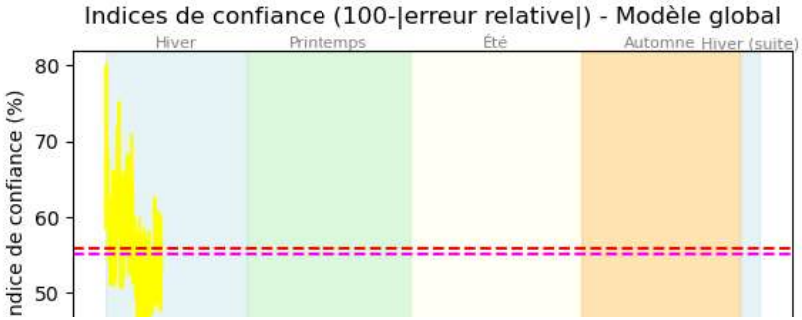
Prévisions des échanges physiques par XGBoost sans transformation cible
ILE DE FRANCE, 2023

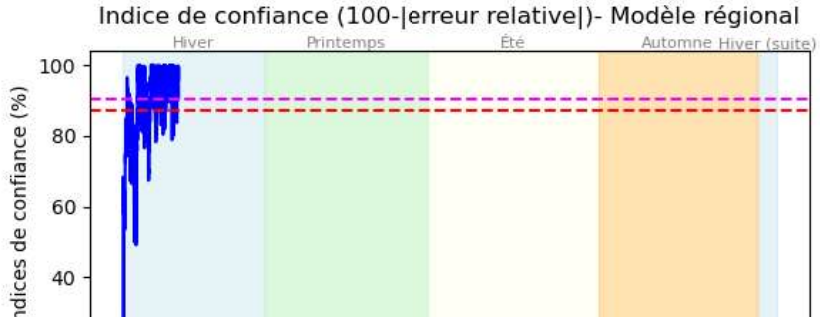


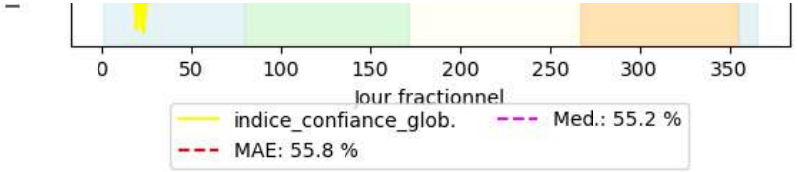


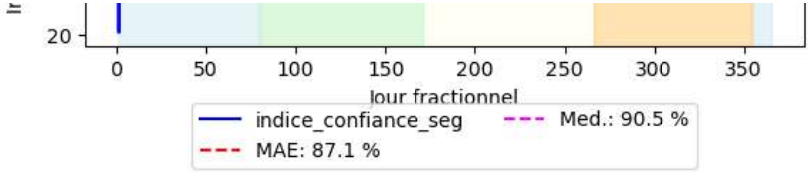


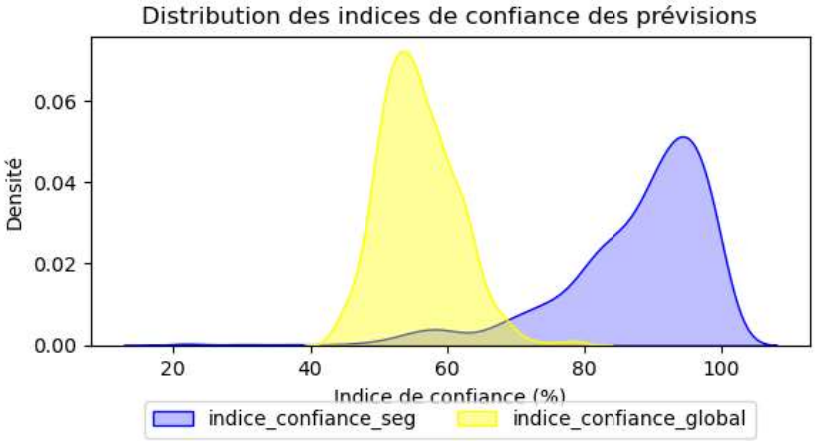












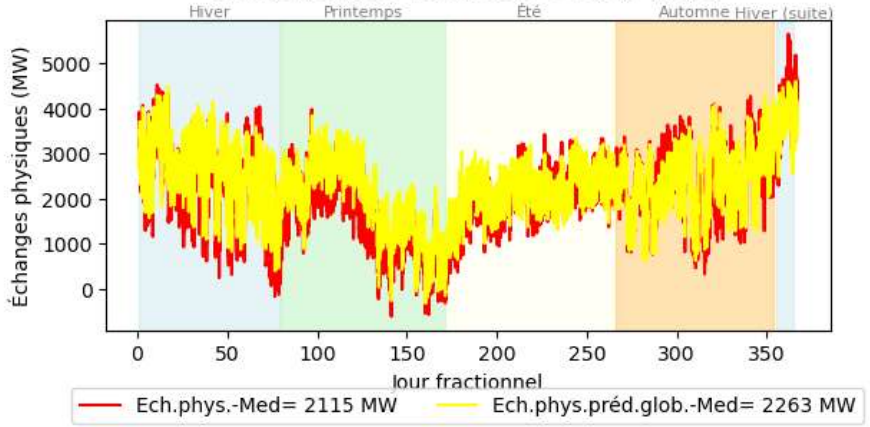
Métriques 2023

Valeurs réelles	Modèle global	Modèle régional
Médiane: 8866 MW	Médiane: 4971 MW	Médiane: 9694 MW
IQR: 2440 MW	IQR: 976 MW	IQR: 1746 MW
	Ind.Conf.Moy.: 55.8 %	Ind.Conf.Moy.: 87.1 %

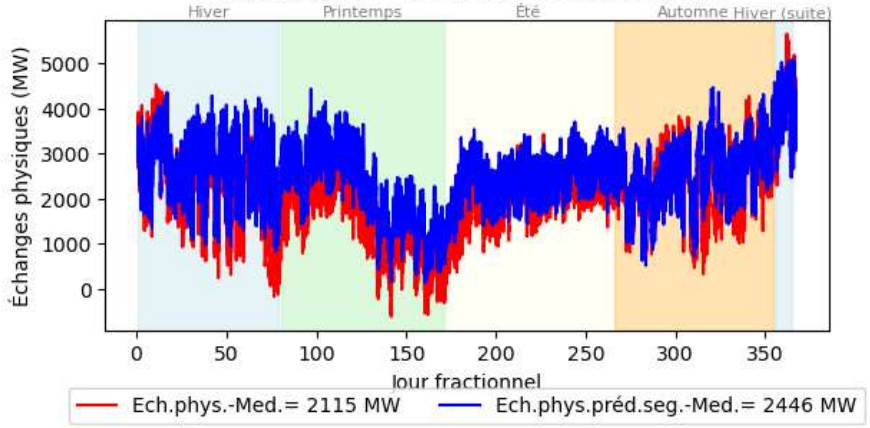
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

Prévisions des échanges physiques par XGBoost sans transformation cible
PROVENCE ALPES COTE D AZUR, 2020

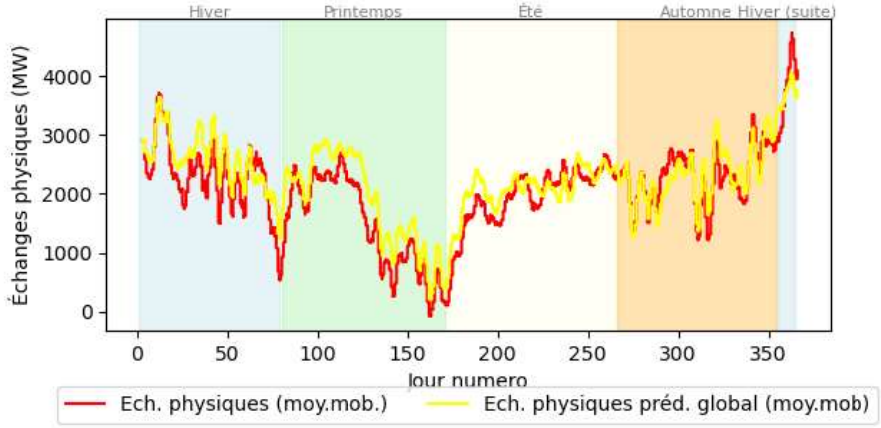
Ech. physiques - prévisions -Modèle global



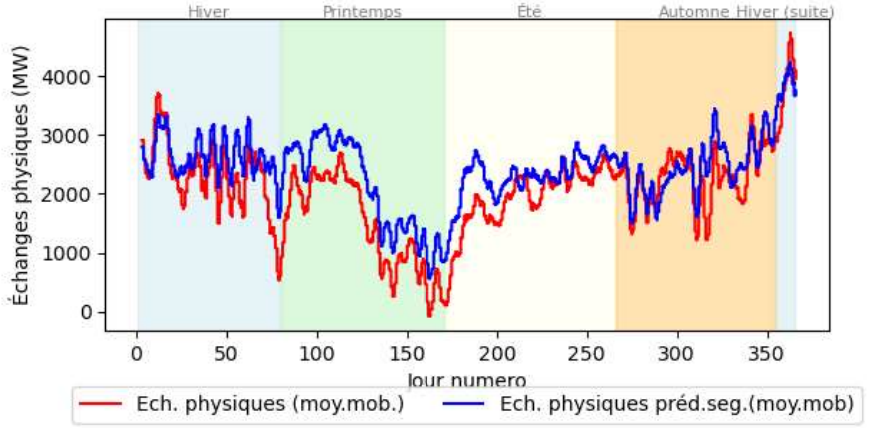
Ech. physiques - prévision - Modèle régional



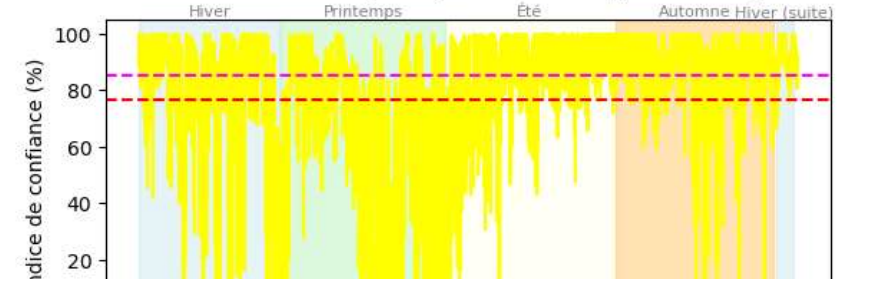
Moyennes mobiles WS144- Modèle global



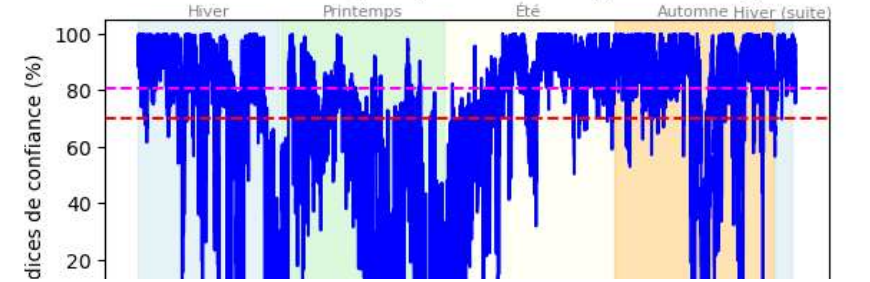
Moyennes mobiles WS144 - Modèle régional

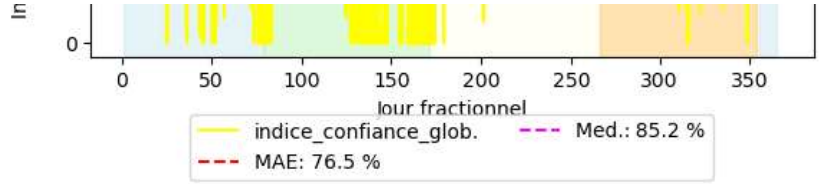


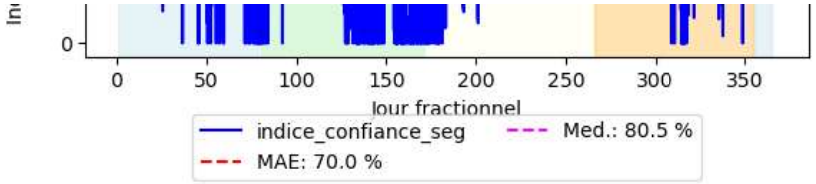
Indices de confiance (100-|erreur relative|) - Modèle global

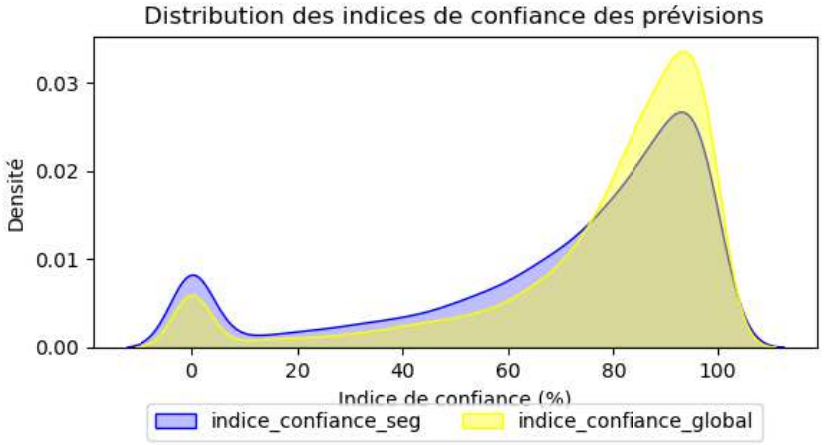


Indice de confiance (100-|erreur relative|)- Modèle régional









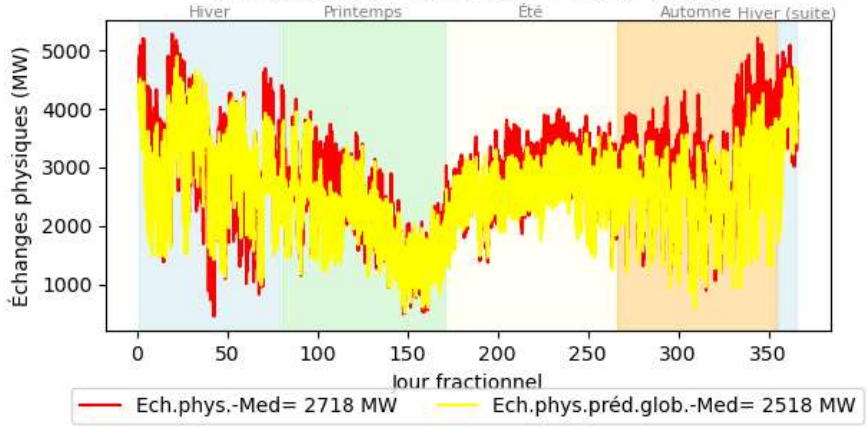
Métriques 2020

Valeurs réelles	Modèle global	Modèle régional
Médiane: 2115 MW	Médiane: 2263 MW	Médiane: 2446 MW
IQR: 1092 MW	IQR: 930 MW	IQR: 945 MW
	Ind.Conf.Moy.: 76.5 %	Ind.Conf.Moy.: 70.0 %

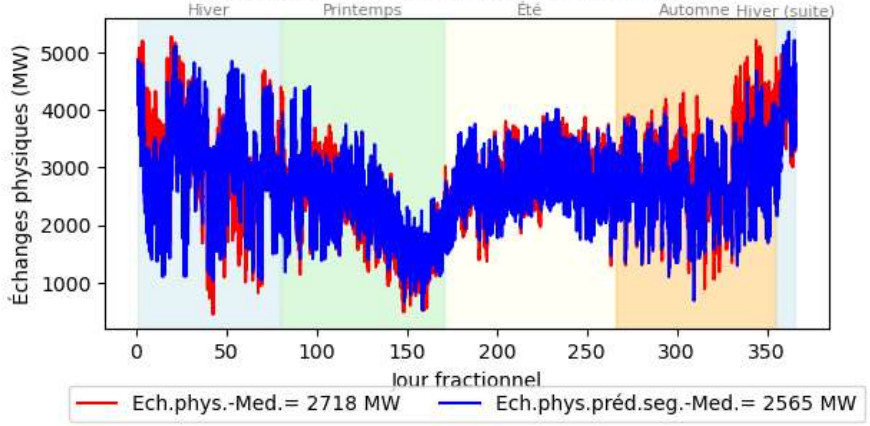
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

Prévisions des échanges physiques par XGBoost sans transformation cible
PROVENCE ALPES COTE D AZUR, 2021

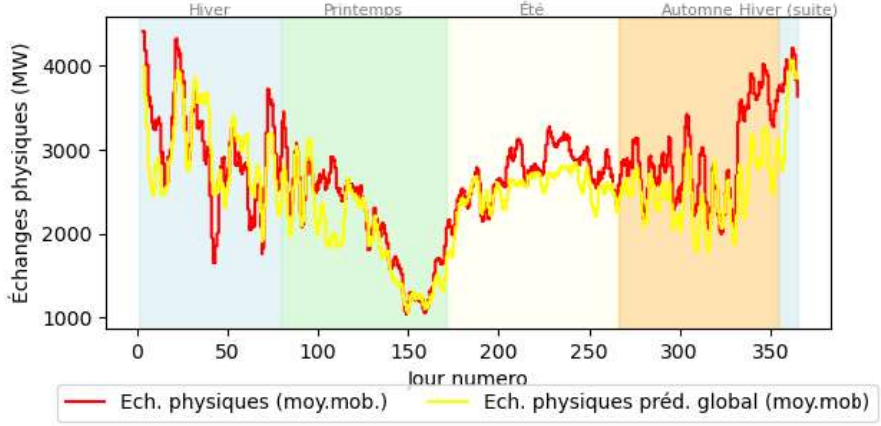
Ech. physiques - prévisions -Modèle global



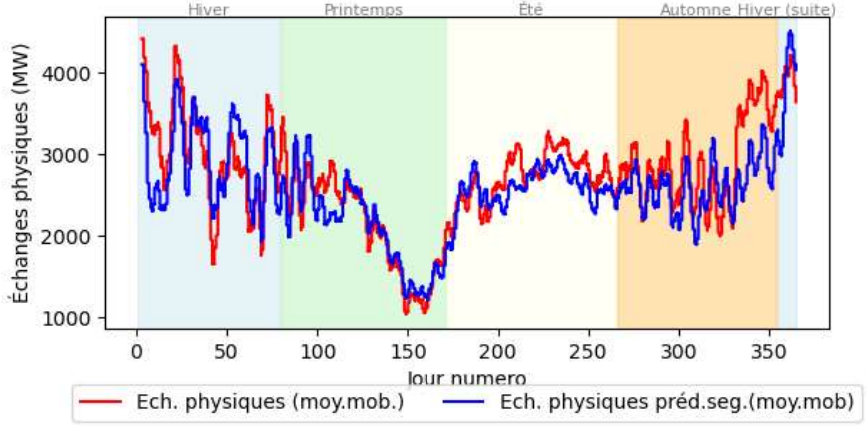
Ech. physiques - prévision - Modèle régional



Moyennes mobiles WS144- Modèle global

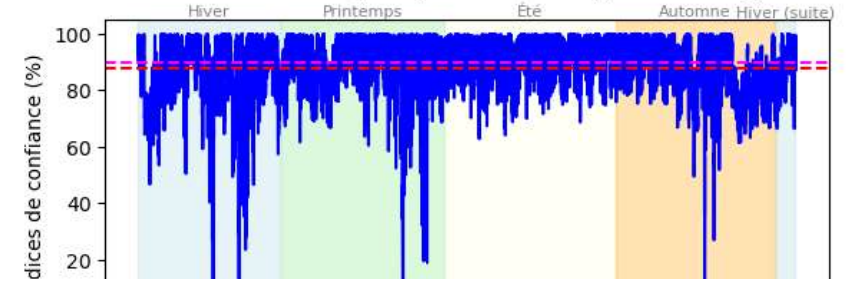


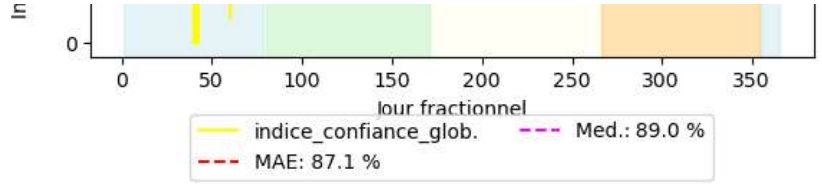
Moyennes mobiles WS144 - Modèle régional

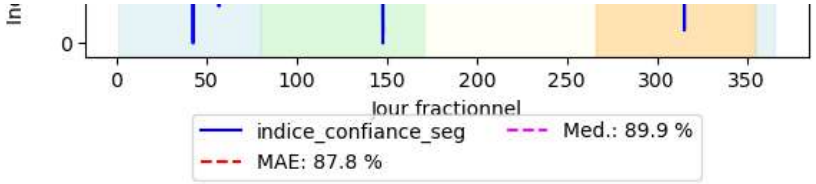


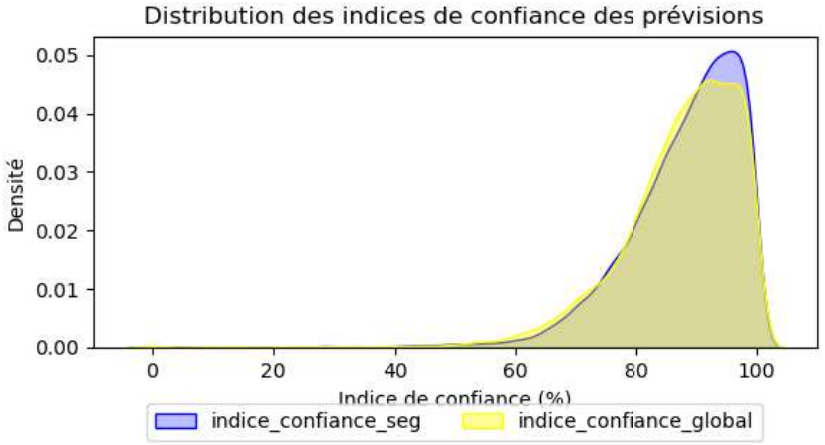
Indices de confiance (100-|erreur relative|) - Modèle global

Indice de confiance (100-|erreur relative|)- Modèle régional







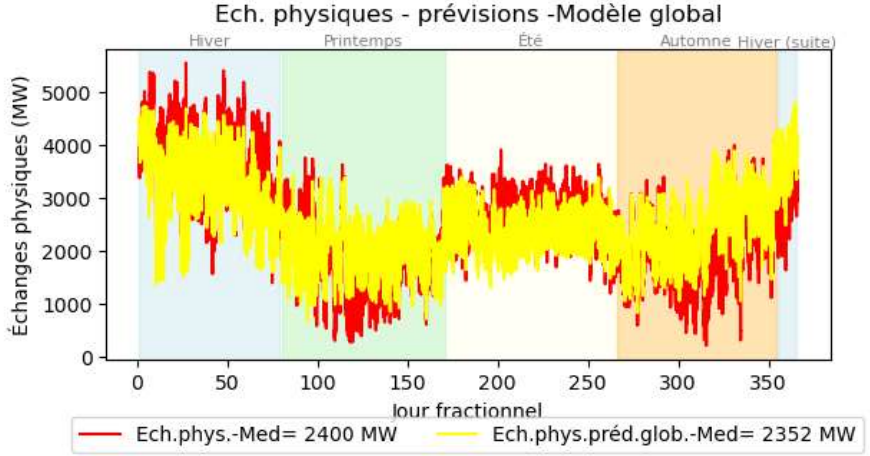


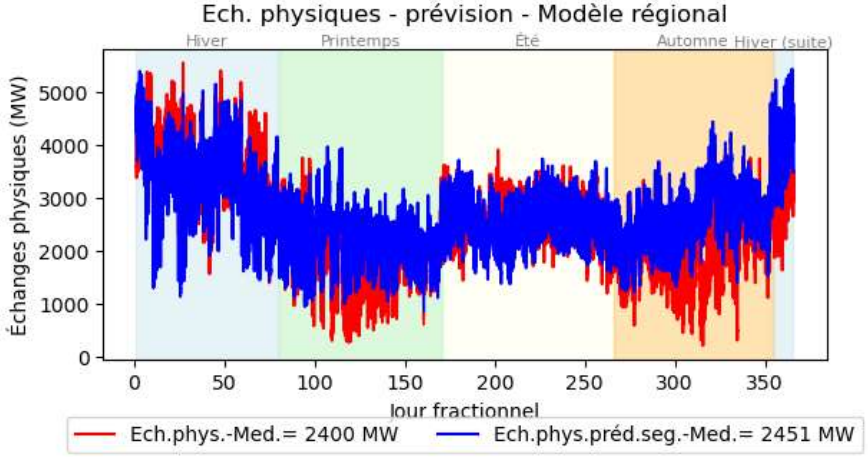
Métriques 2021

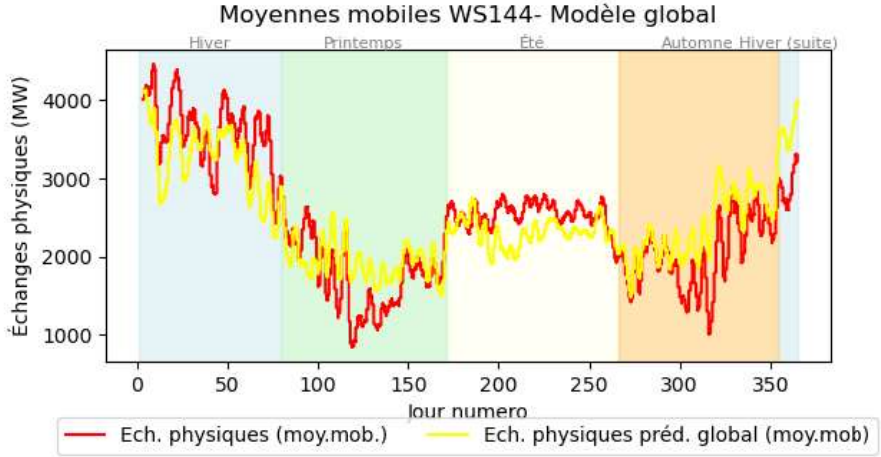
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2718 MW	Médiane: 2518 MW	Médiane: 2565 MW
IQR: 1042 MW	IQR: 885 MW	IQR: 847 MW
	Ind.Conf.Moy.: 87.1 %	Ind.Conf.Moy.: 87.8 %

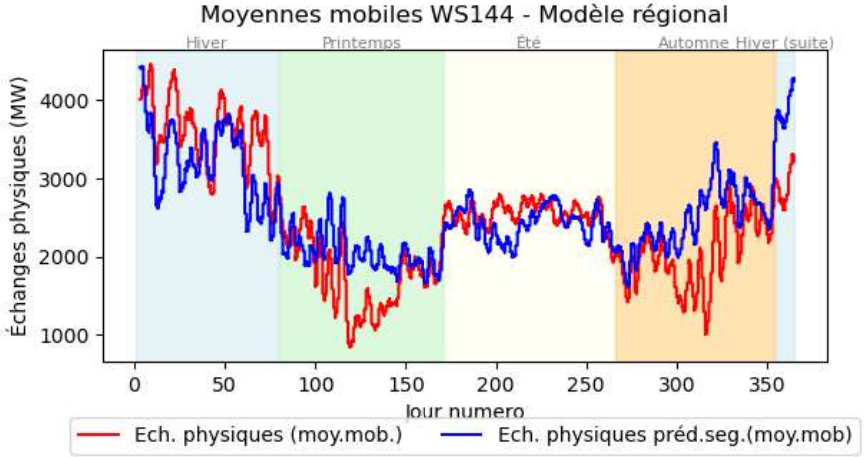
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

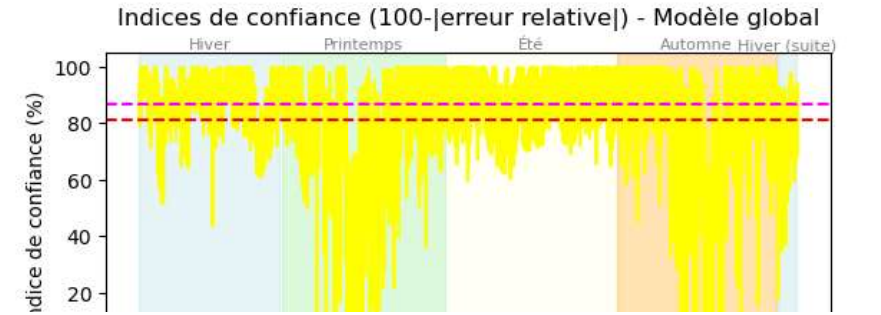
Prévisions des échanges physiques par XGBoost sans transformation cible
PROVENCE ALPES COTE D AZUR, 2022

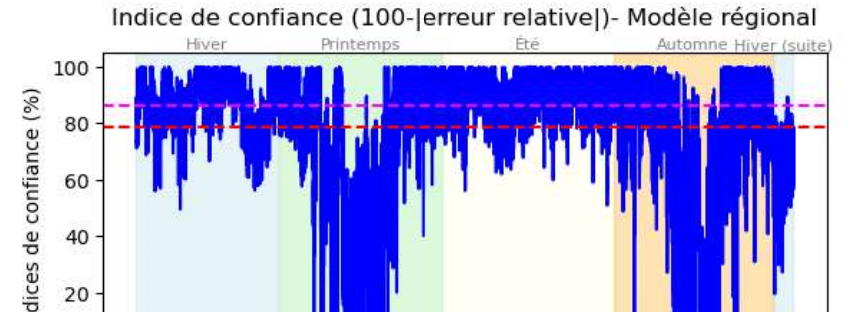


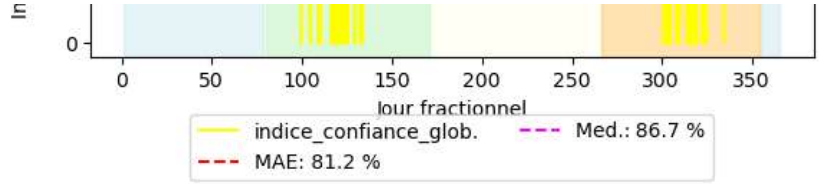


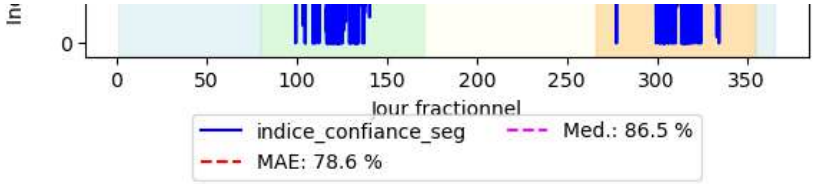


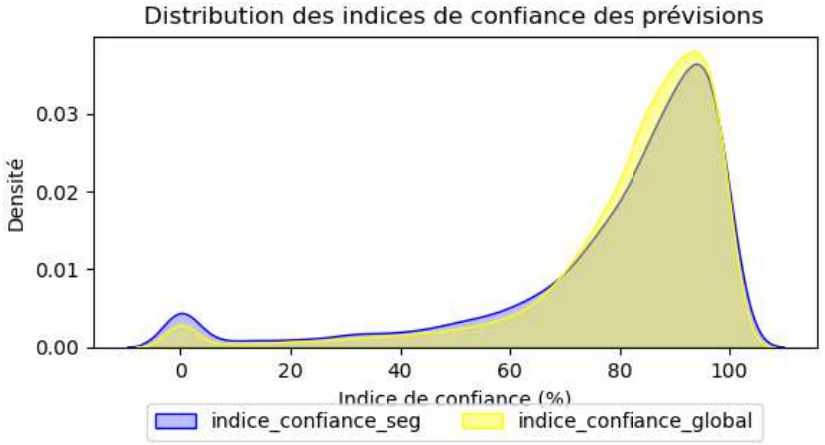










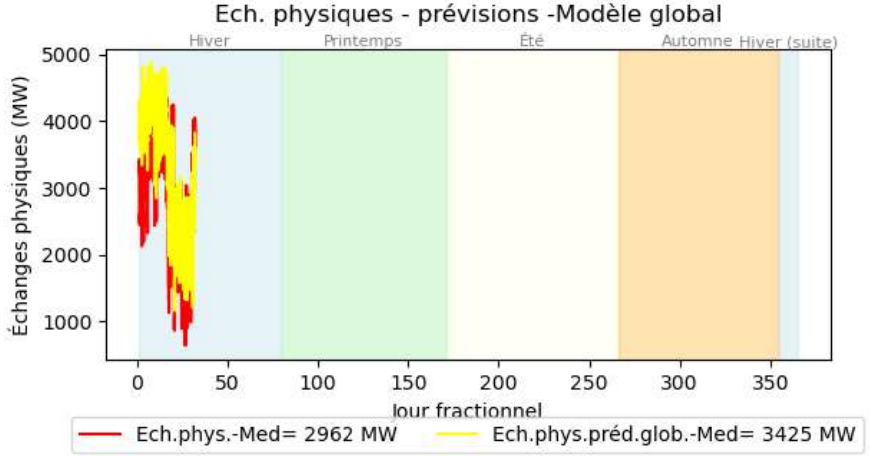


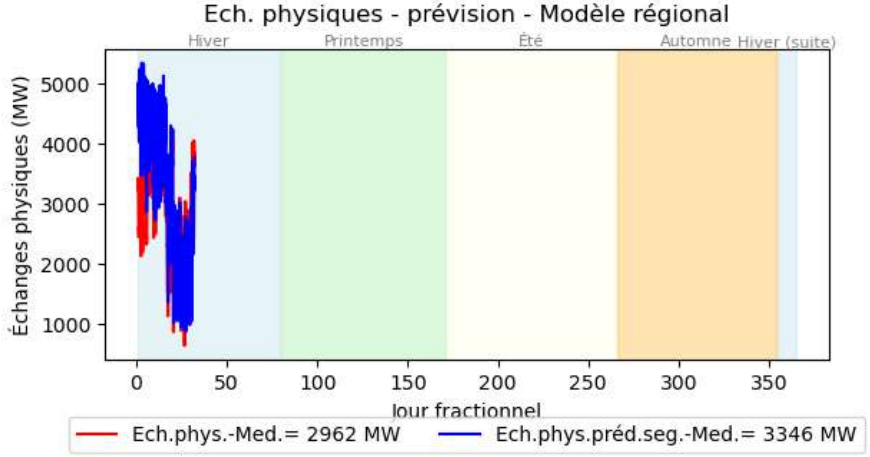
Métriques 2022

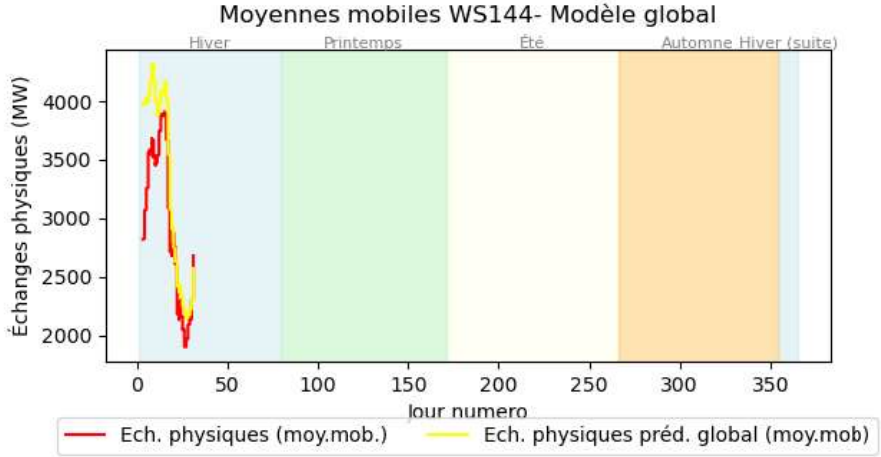
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2400 MW	Médiane: 2352 MW	Médiane: 2451 MW
IQR: 1123 MW	IQR: 910 MW	IQR: 875 MW
	Ind.Conf.Moy.: 81.2 %	Ind.Conf.Moy.: 78.6 %

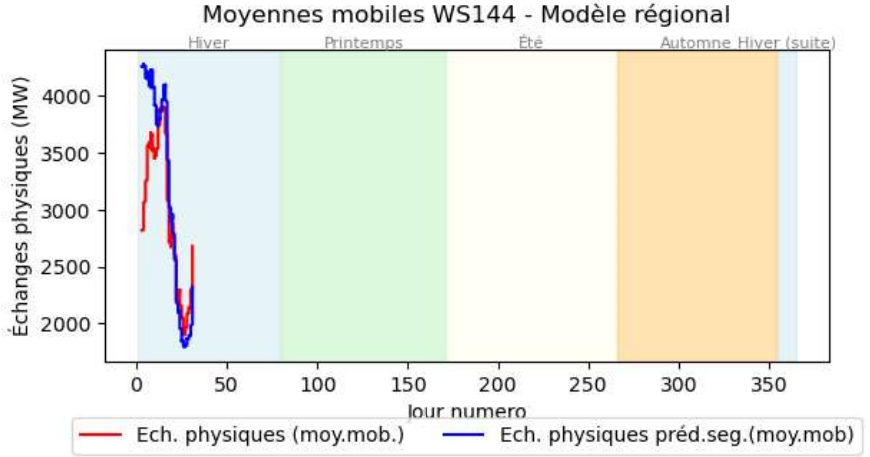
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

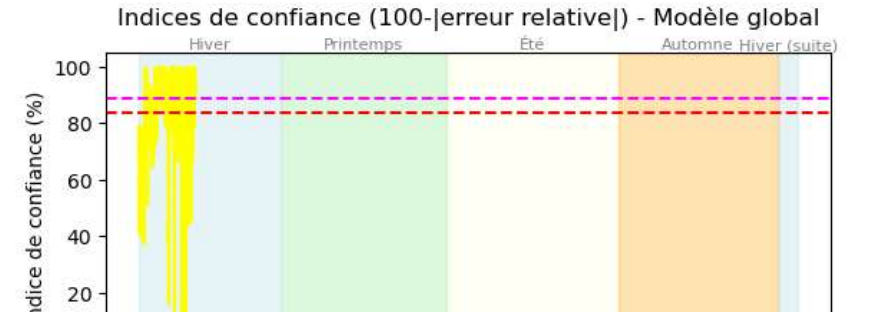
Prévisions des échanges physiques par XGBoost sans transformation cible
PROVENCE ALPES COTE D AZUR, 2023

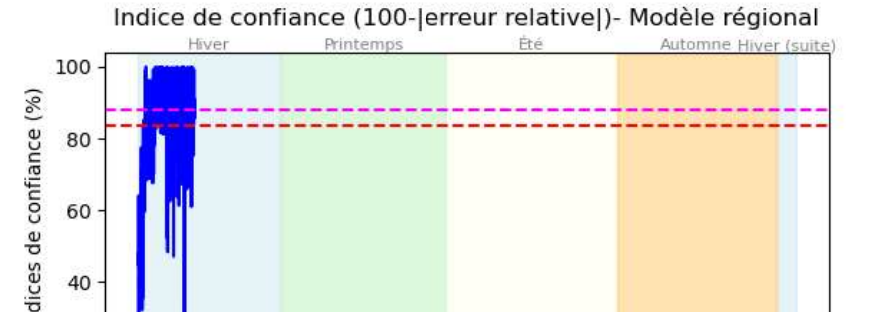


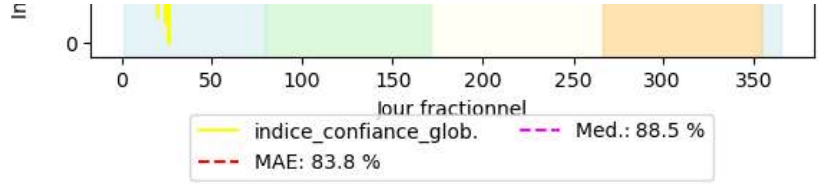


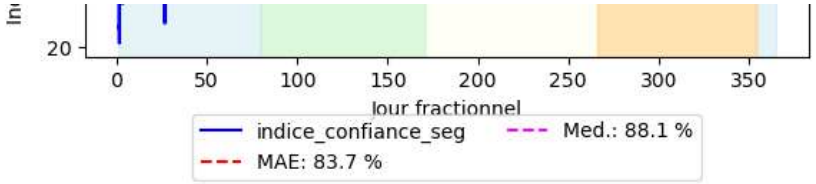


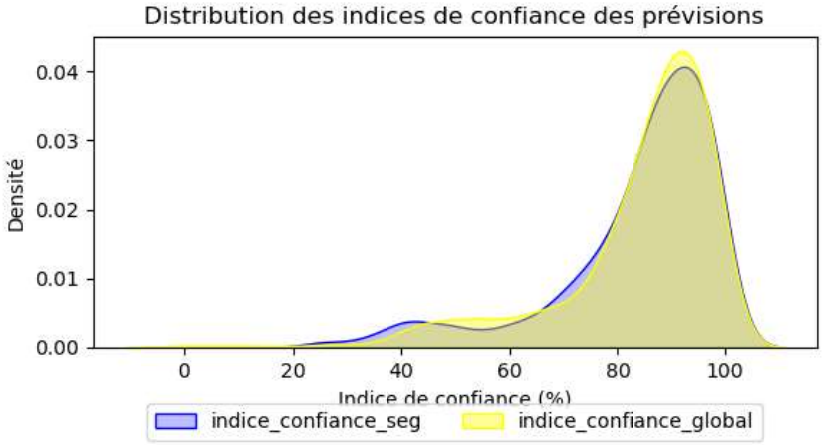










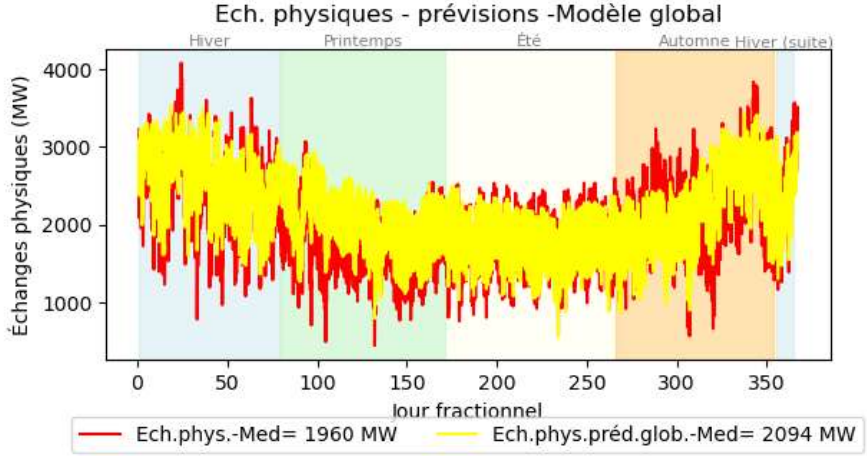


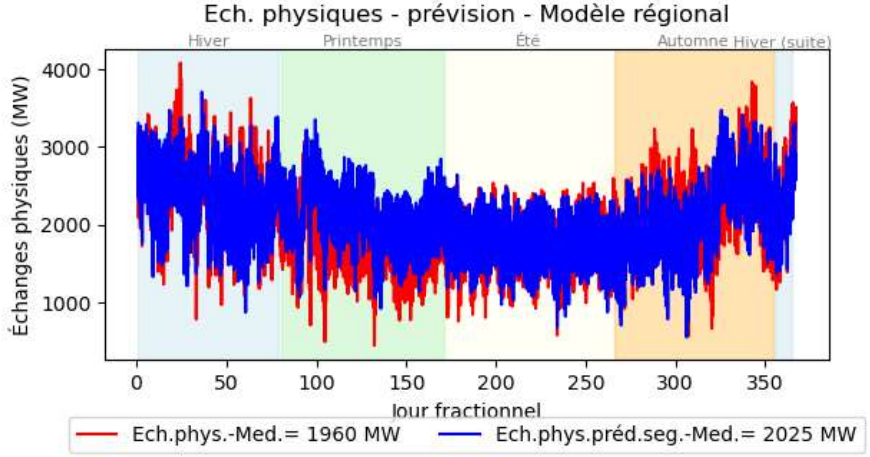
Métriques 2023

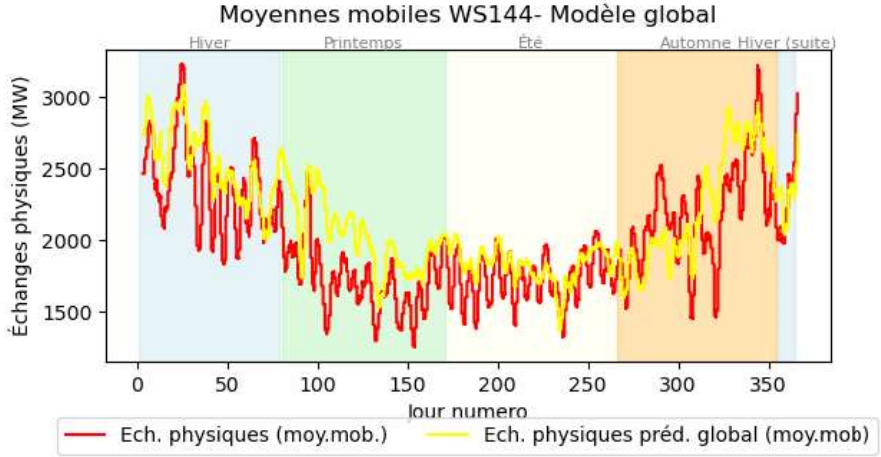
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2962 MW	Médiane: 3425 MW	Médiane: 3346 MW
IQR: 1336 MW	IQR: 1624 MW	IQR: 1944 MW
	Ind.Conf.Moy.: 83.8 %	Ind.Conf.Moy.: 83.7 %

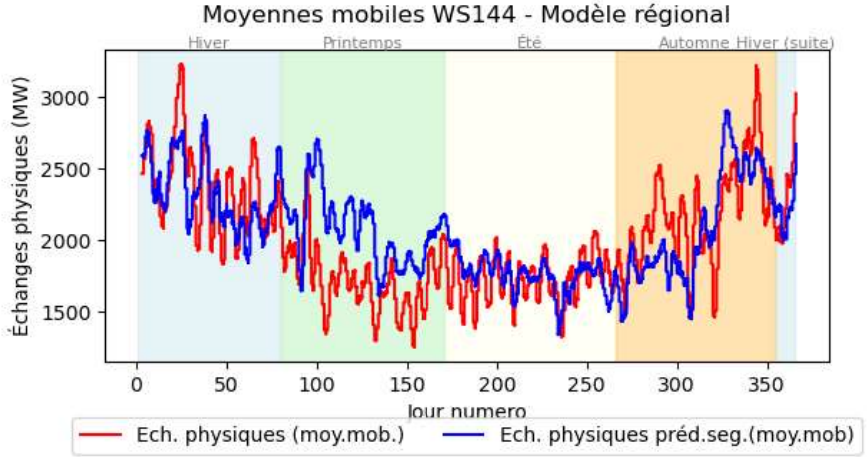
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

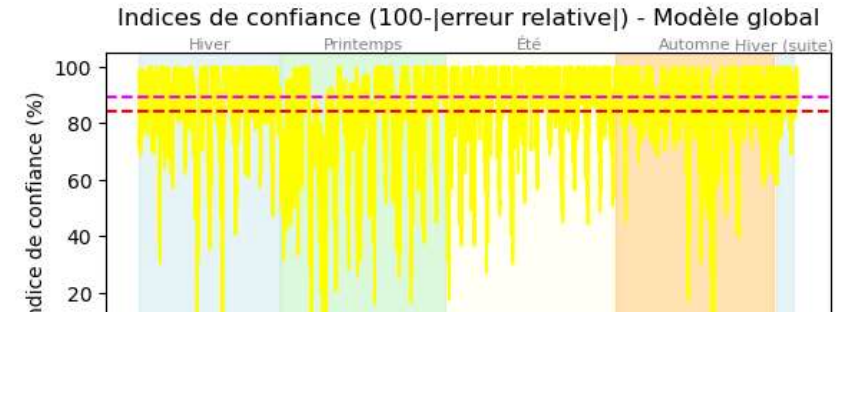
Prévisions des échanges physiques par XGBoost sans transformation cible
BRETAGNE, 2020

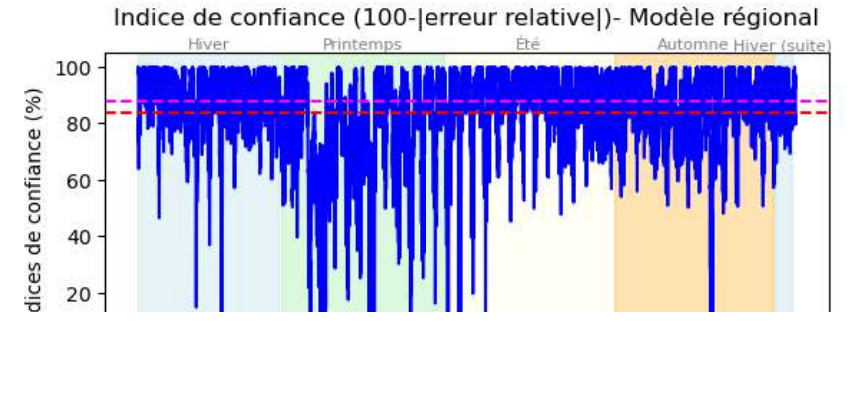


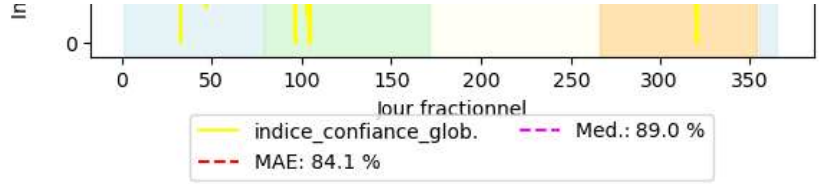


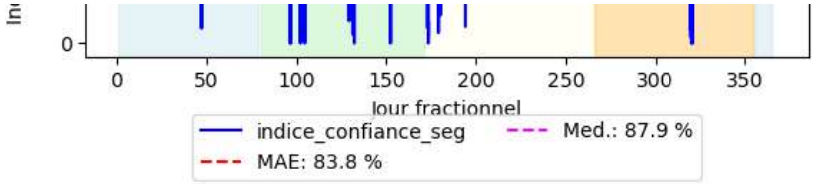


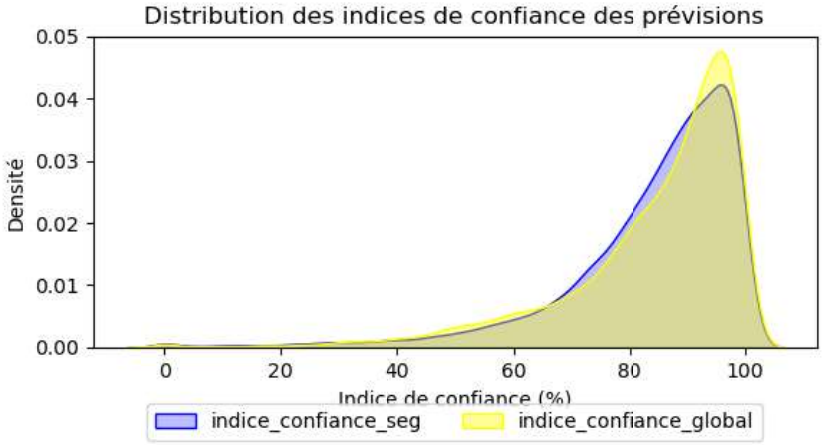










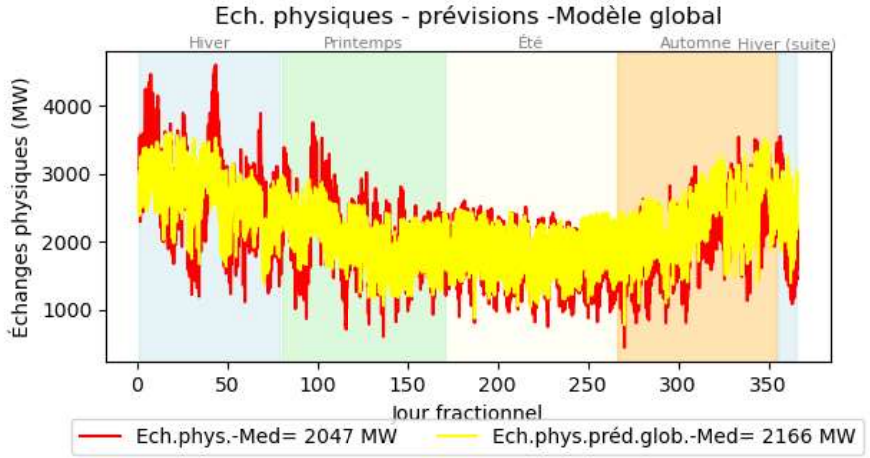


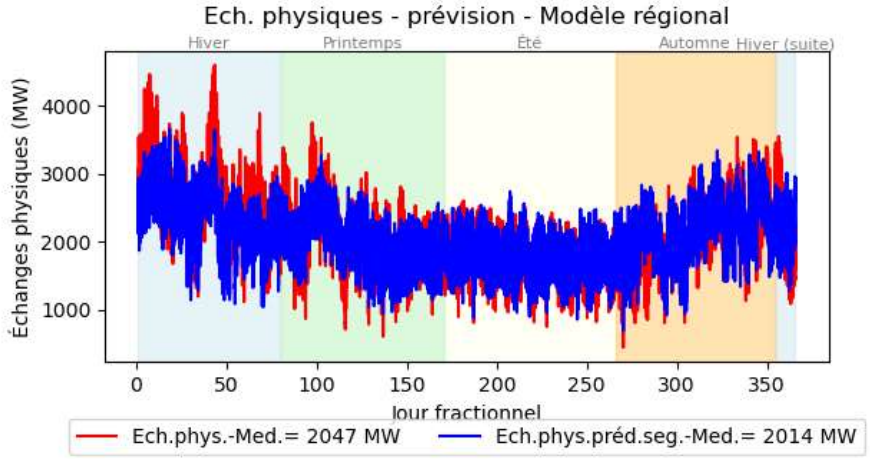
Métriques 2020

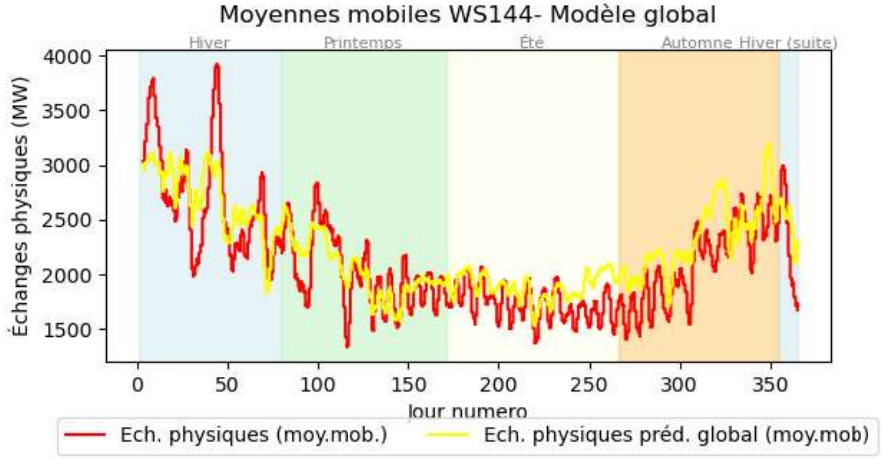
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1960 MW	Médiane: 2094 MW	Médiane: 2025 MW
IQR: 726 MW	IQR: 636 MW	IQR: 614 MW
	Ind.Conf.Moy.: 84.1 %	Ind.Conf.Moy.: 83.8 %

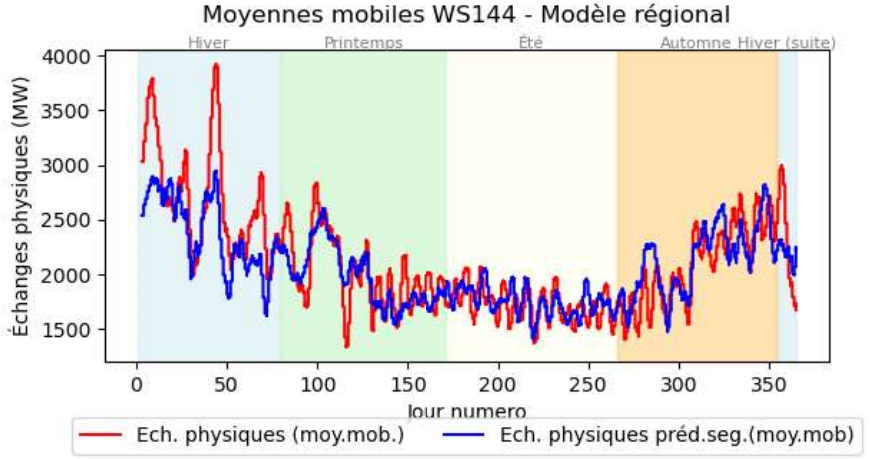
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

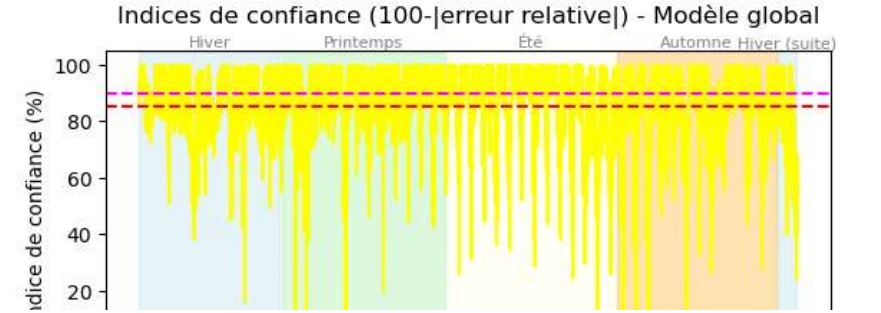
Prévisions des échanges physiques par XGBoost sans transformation cible
BRETAGNE, 2021

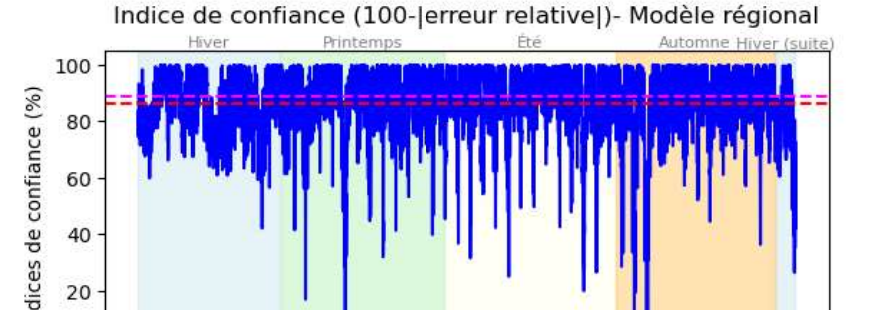


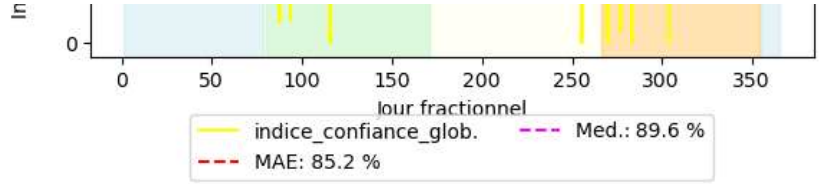


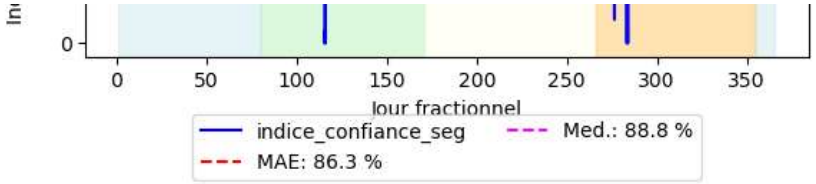


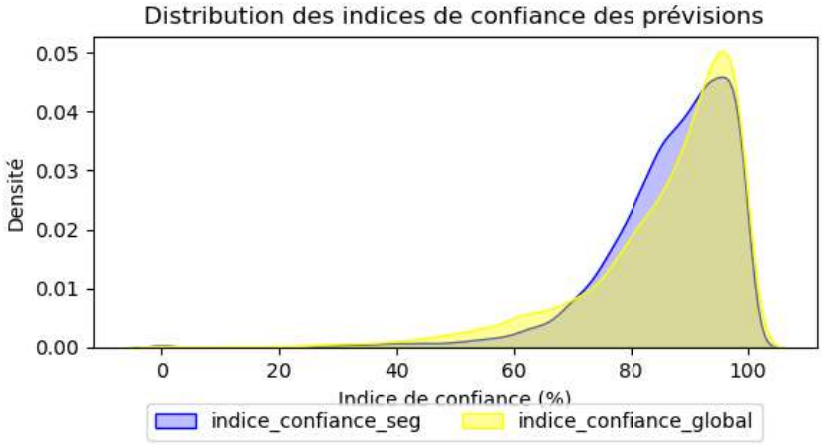










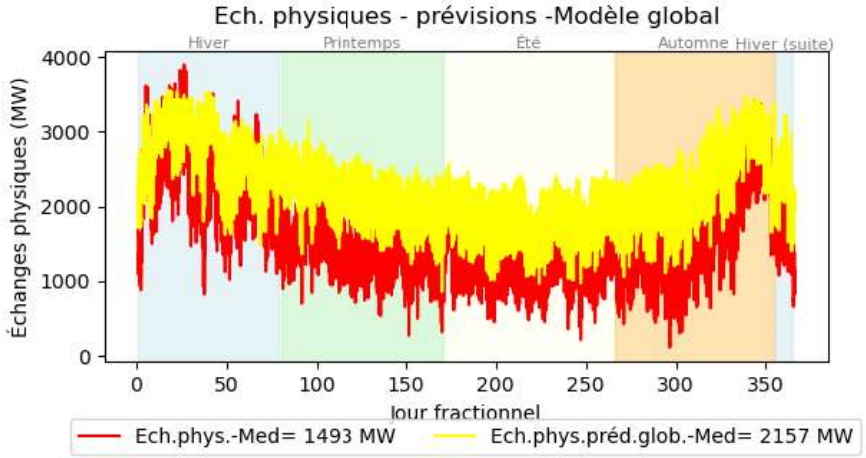


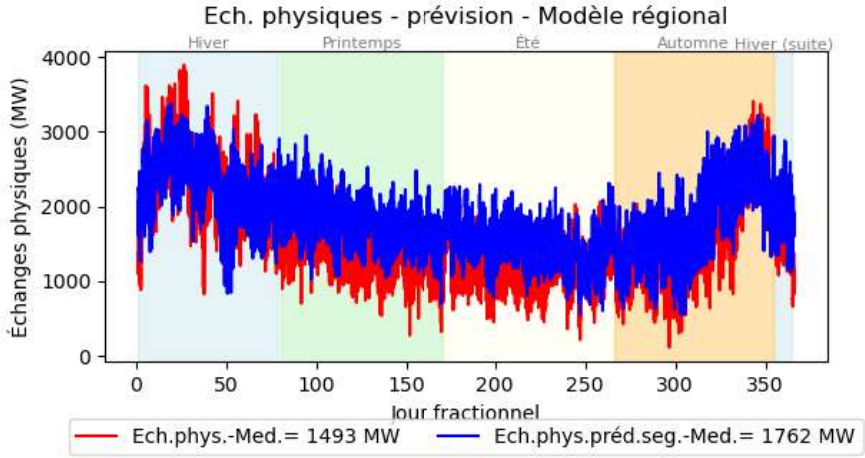
Métriques 2021

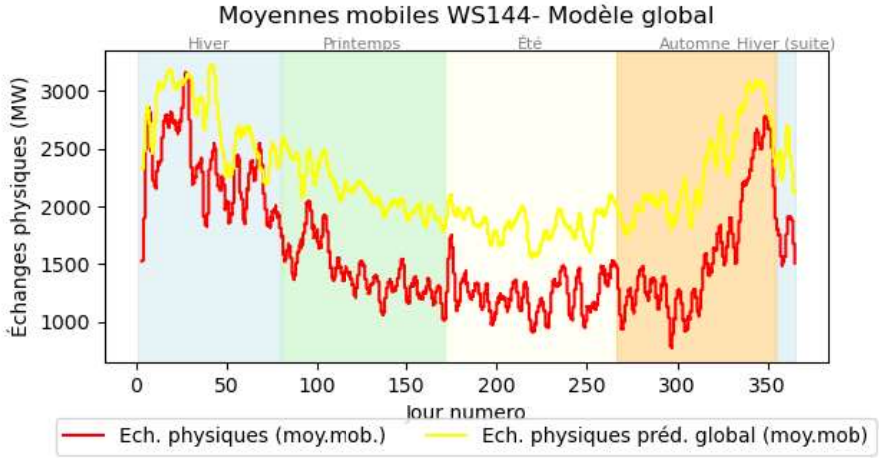
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2047 MW	Médiane: 2166 MW	Médiane: 2014 MW
IQR: 754 MW	IQR: 651 MW	IQR: 643 MW
	Ind.Conf.Moy.: 85.2 %	Ind.Conf.Moy.: 86.3 %

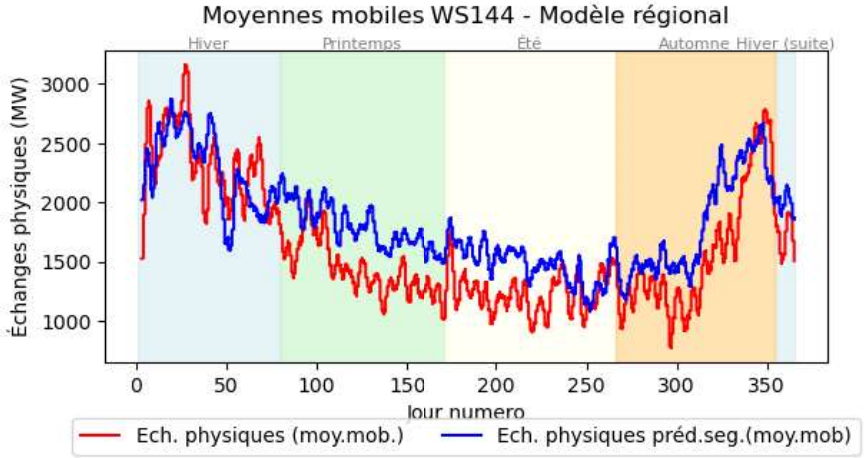
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

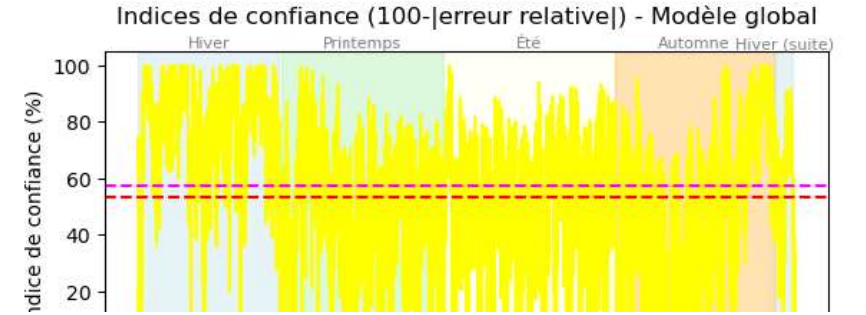
Prévisions des échanges physiques par XGBoost sans transformation cible
BRETAGNE, 2022

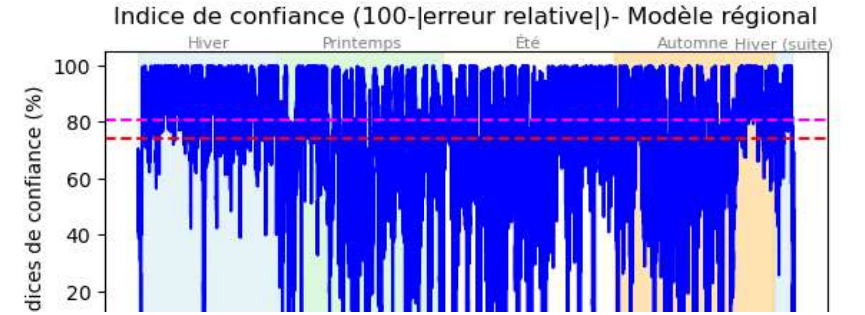


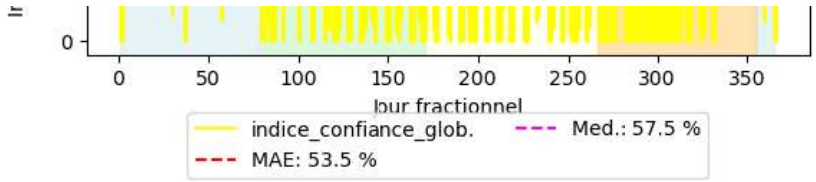


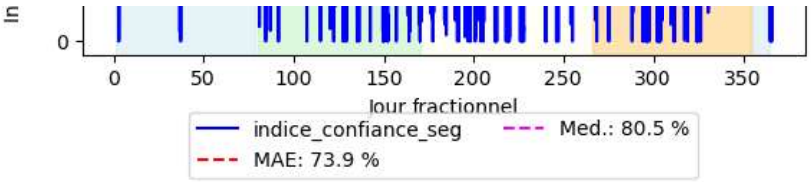


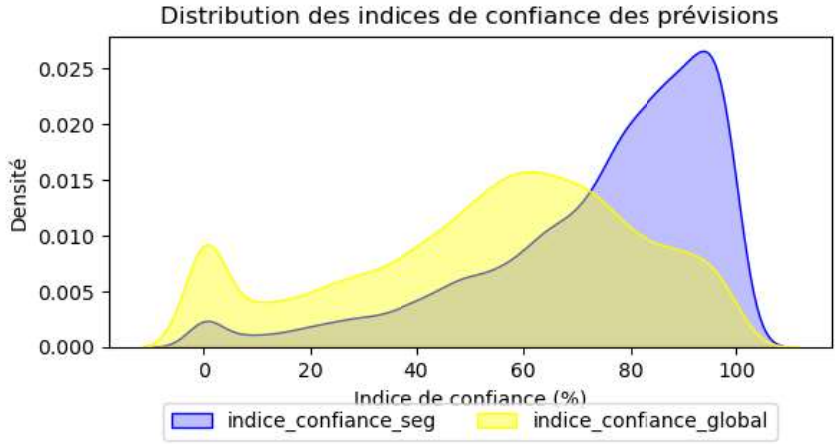










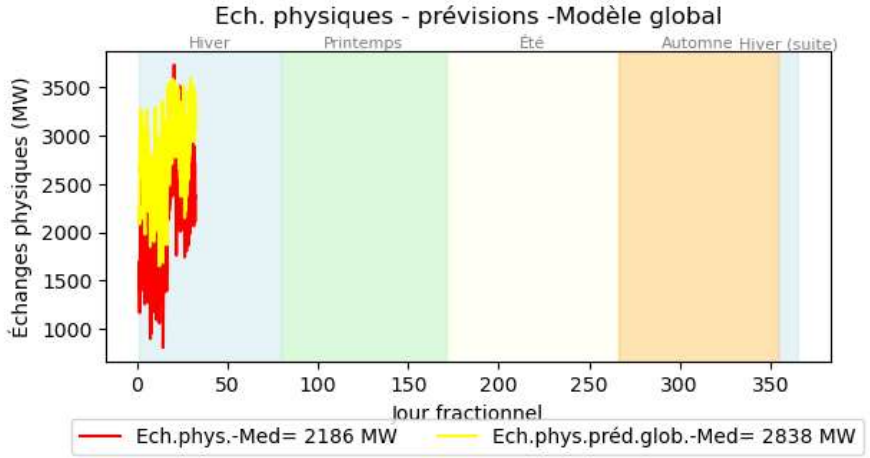


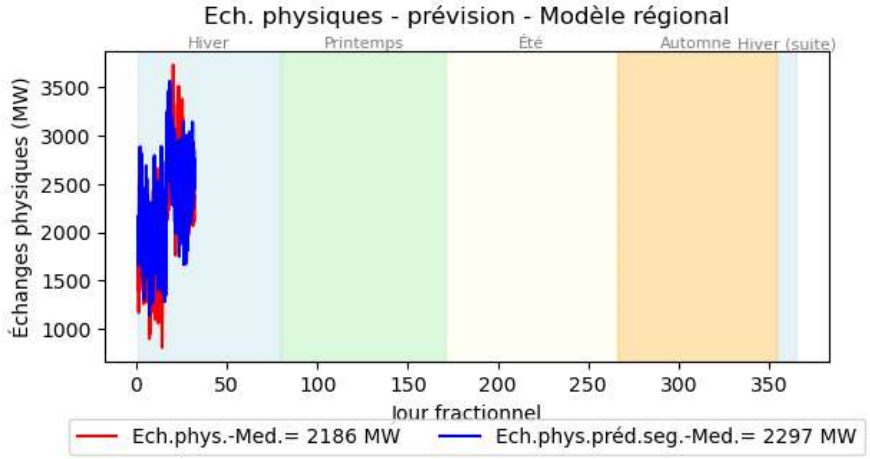
Métriques 2022

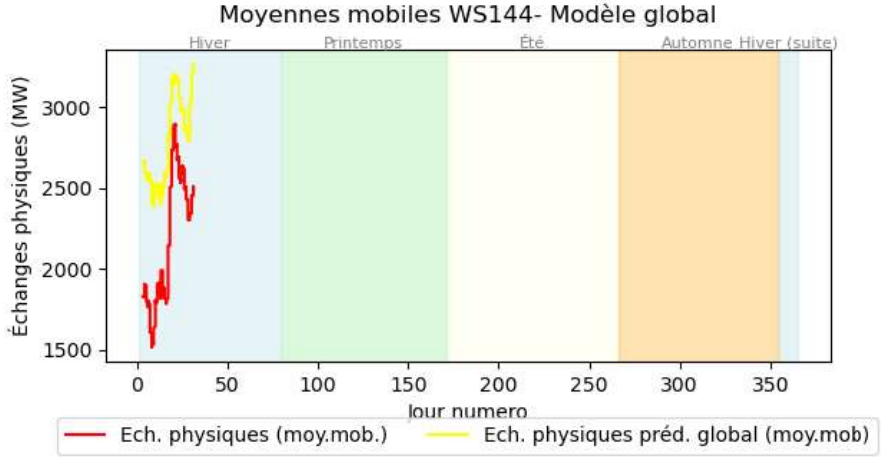
Valeurs réelles	Modèle global	Modèle régional
Médiane: 1493 MW	Médiane: 2157 MW	Médiane: 1762 MW
IQR: 773 MW	IQR: 671 MW	IQR: 651 MW
	Ind.Conf.Moy.: 53.5 %	Ind.Conf.Moy.: 73.9 %

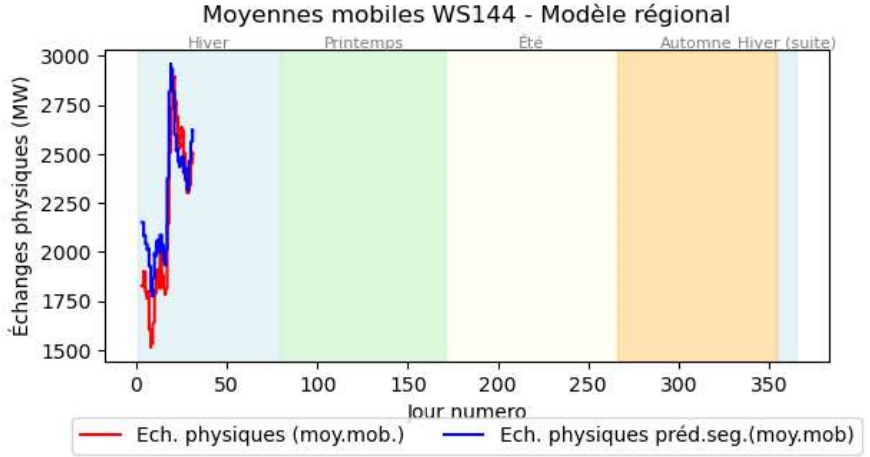
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

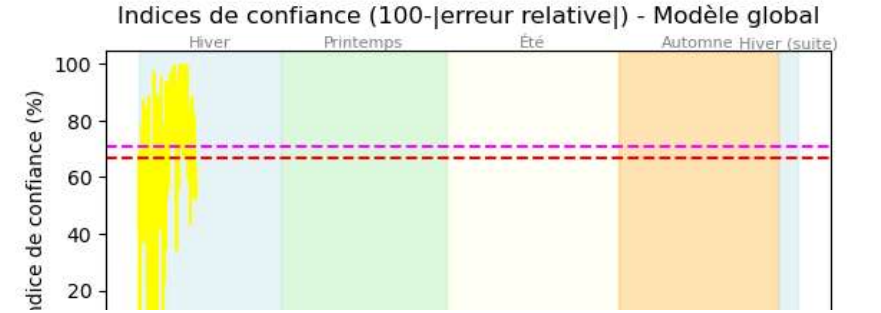
Prévisions des échanges physiques par XGBoost sans transformation cible
BRETAGNE, 2023

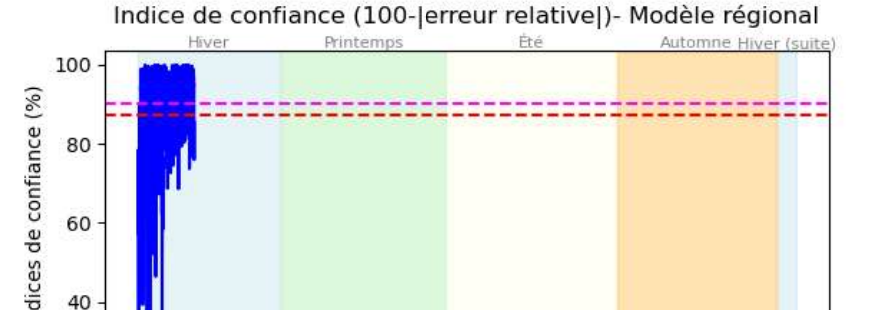


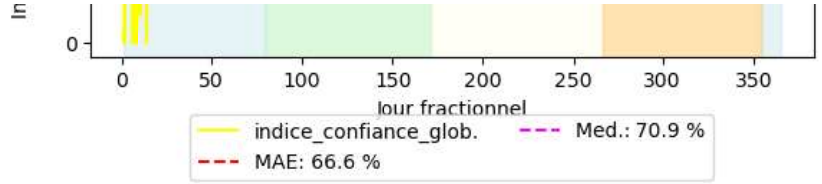


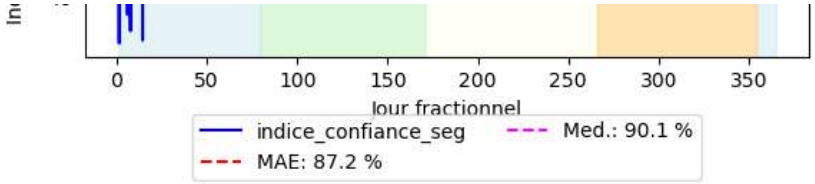


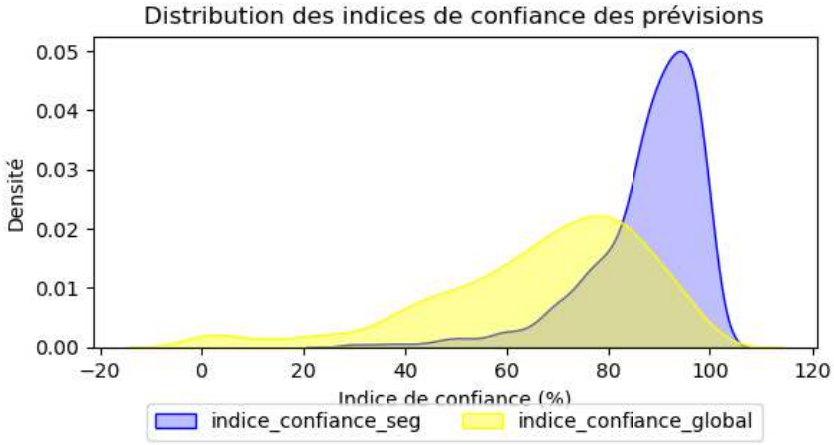










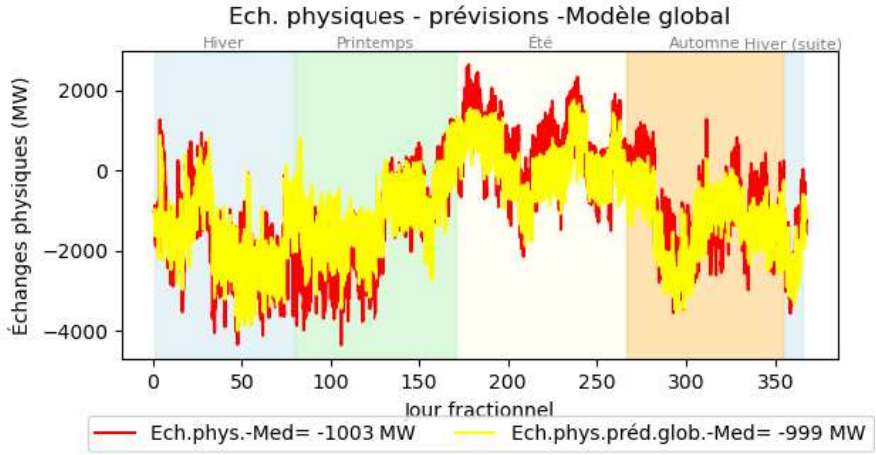


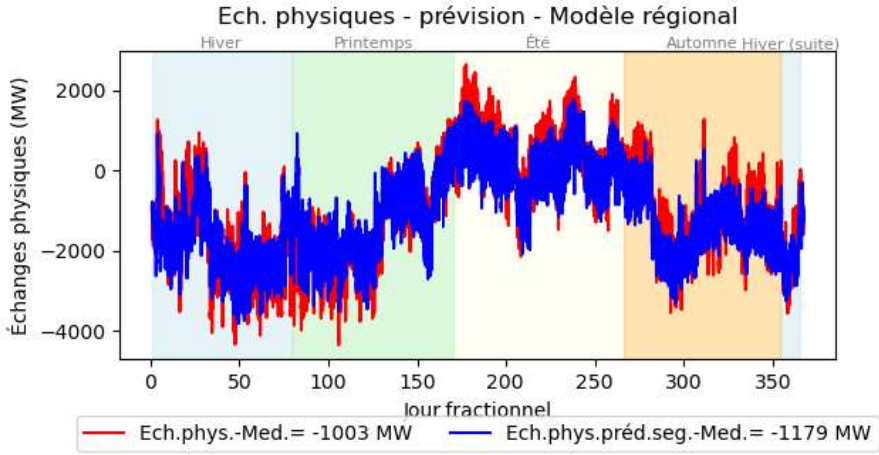
Métriques 2023

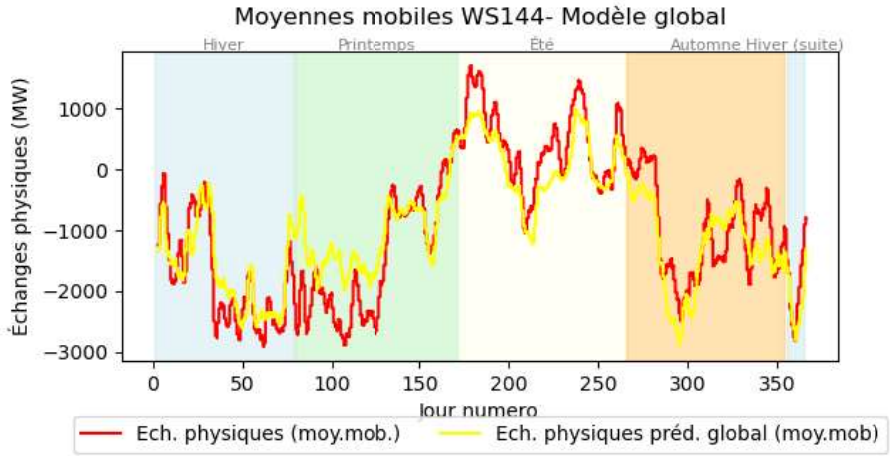
Valeurs réelles	Modèle global	Modèle régional
Médiane: 2186 MW	Médiane: 2838 MW	Médiane: 2297 MW
IQR: 803 MW	IQR: 664 MW	IQR: 673 MW
	Ind.Conf.Moy.: 66.6 %	Ind.Conf.Moy.: 87.2 %

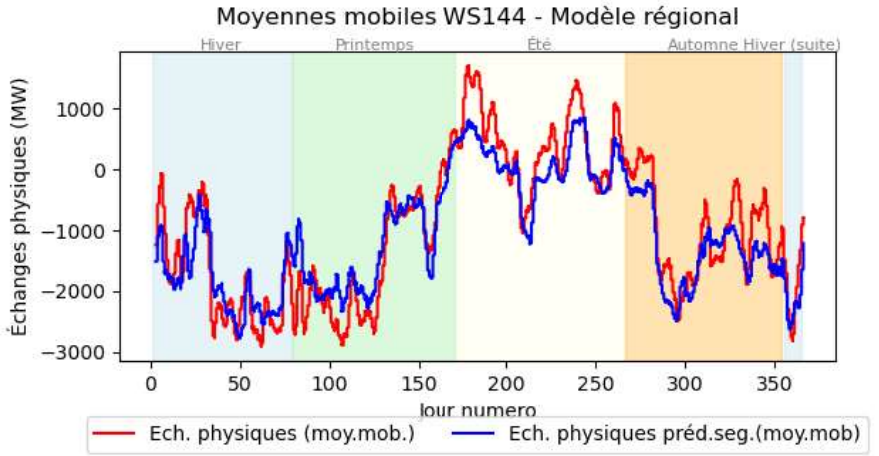
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

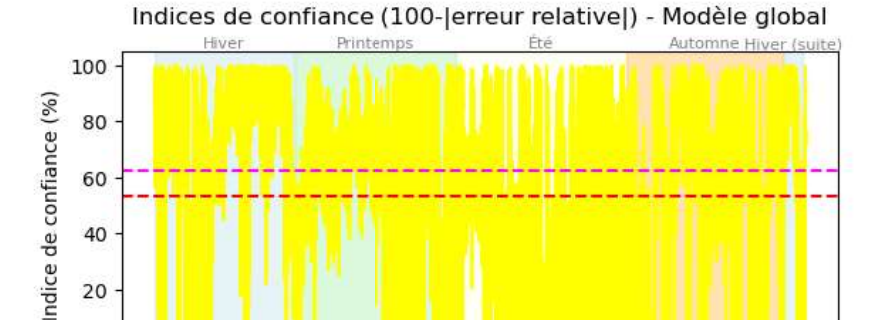
Prévisions des échanges physiques par XGBoost sans transformation cible
NOUVELLE AQUITAINE, 2020

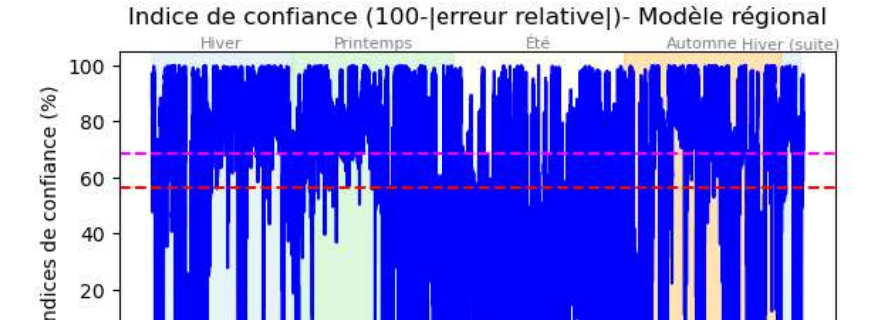


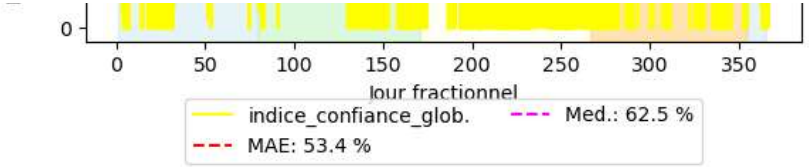


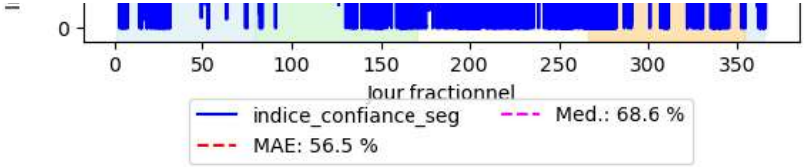


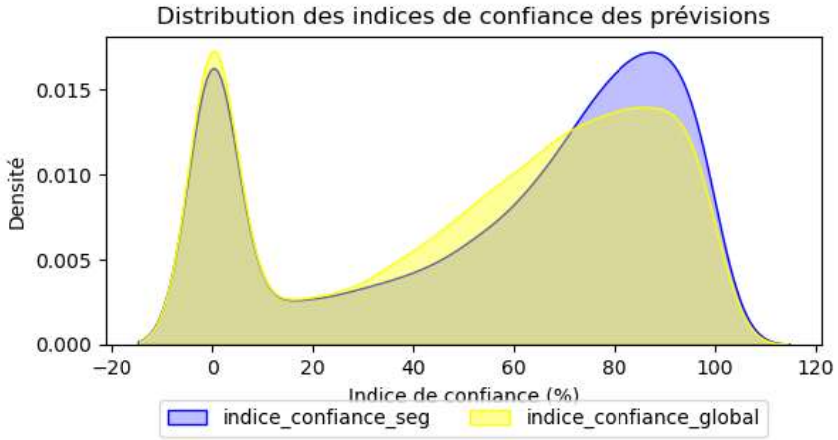










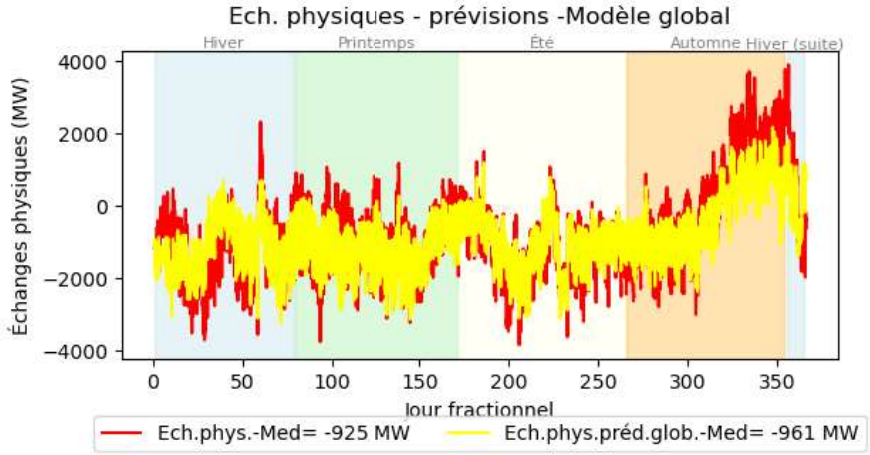


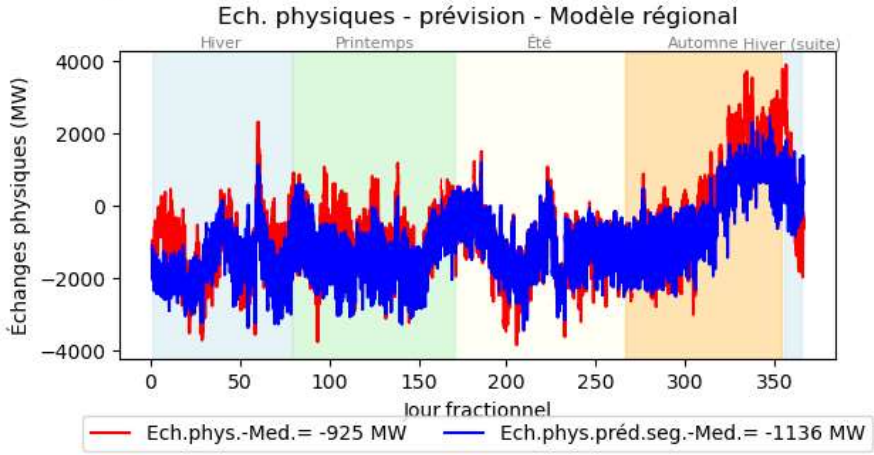
Métriques 2020

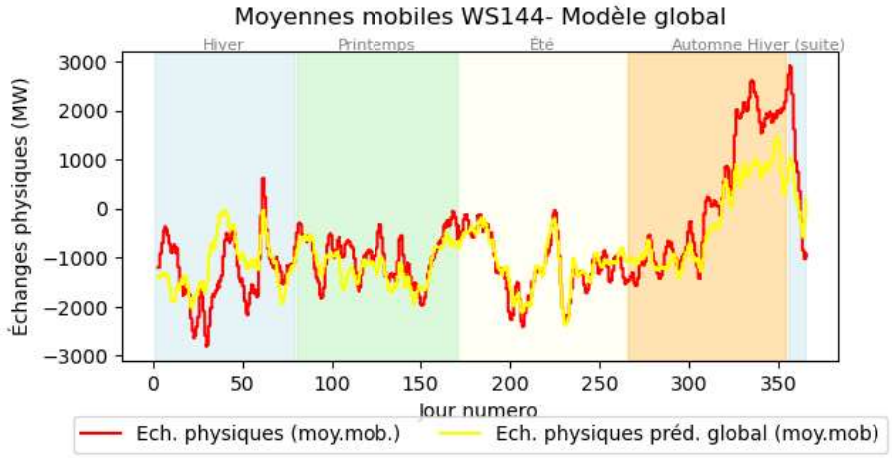
Valeurs réelles	Modèle global	Modèle régional
Médiane: -1003 MW	Médiane: -999 MW	Médiane: -1179 MW
IQR: 1976 MW	IQR: 1495 MW	IQR: 1680 MW
	Ind.Conf.Moy.: 53.4 %	Ind.Conf.Moy.: 56.5 %

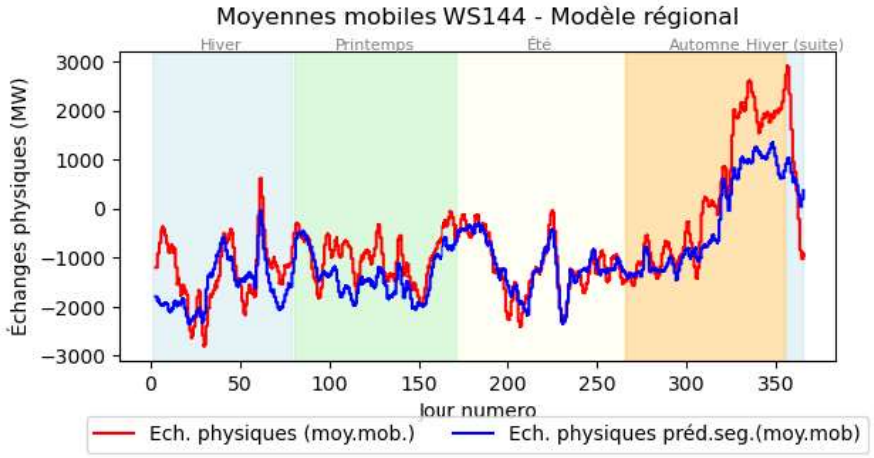
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

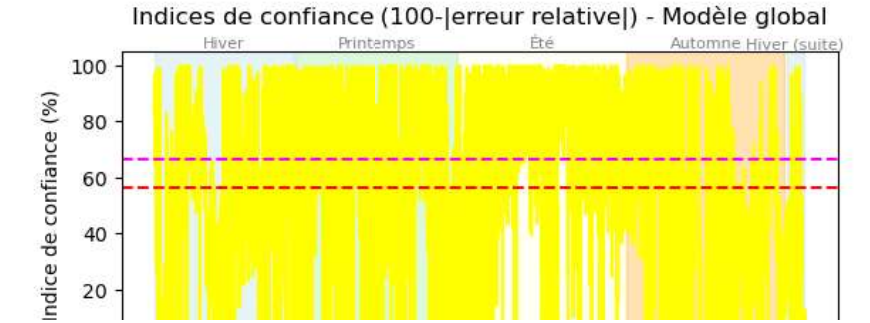
Prévisions des échanges physiques par XGBoost sans transformation cible
NOUVELLE AQUITAINE, 2021

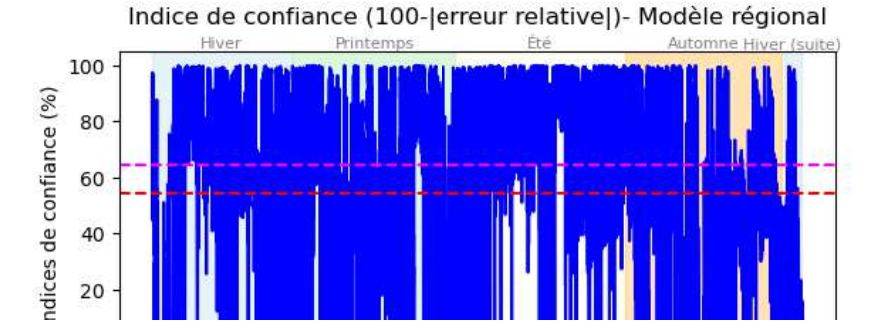


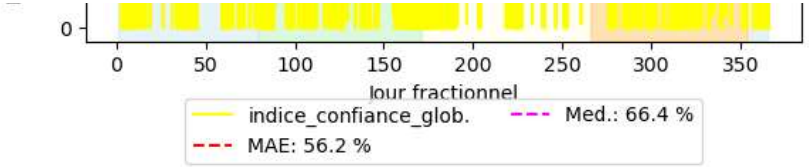


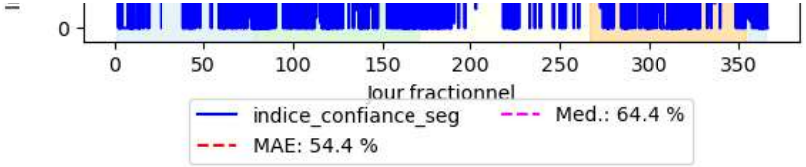


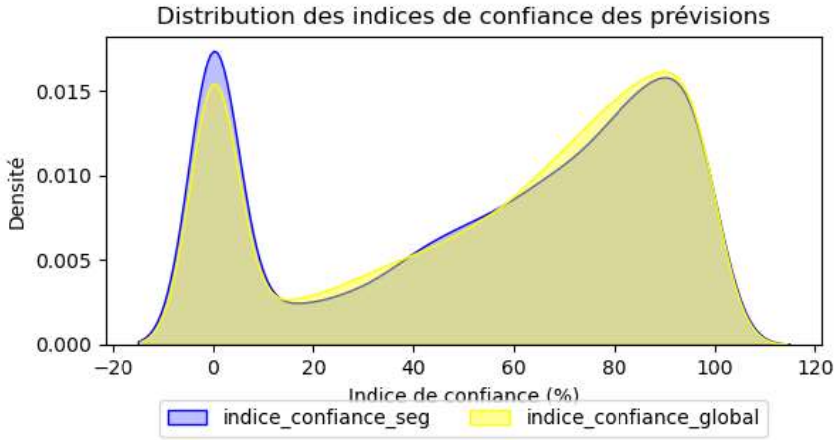










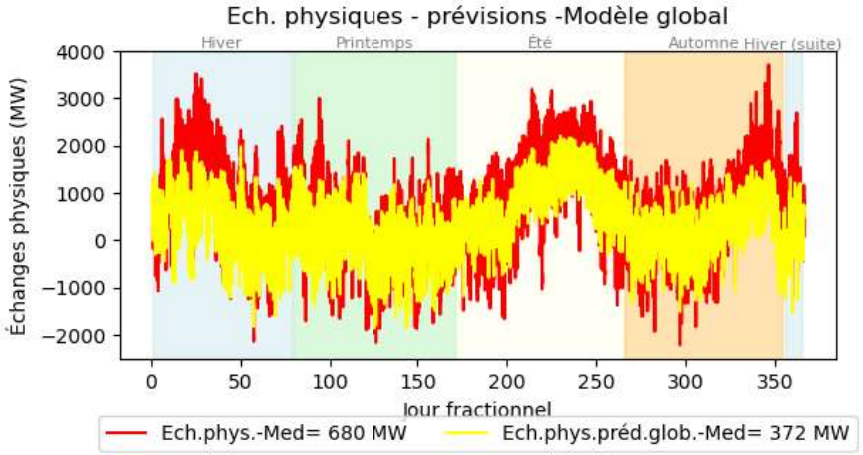


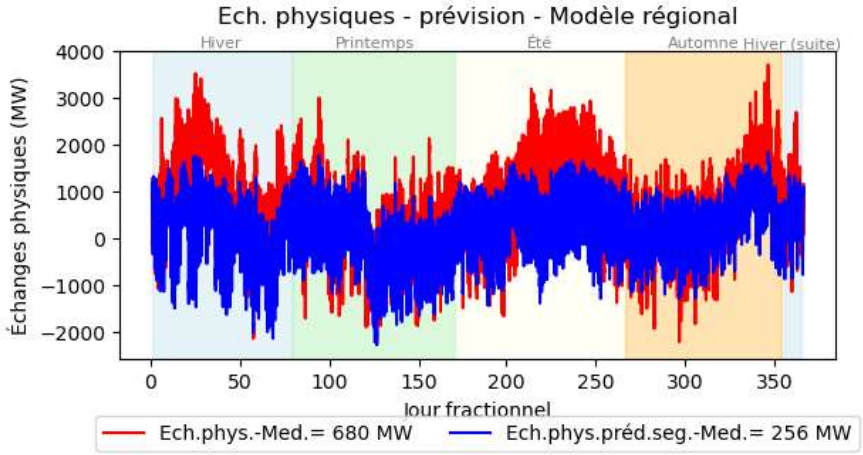
Métriques 2021

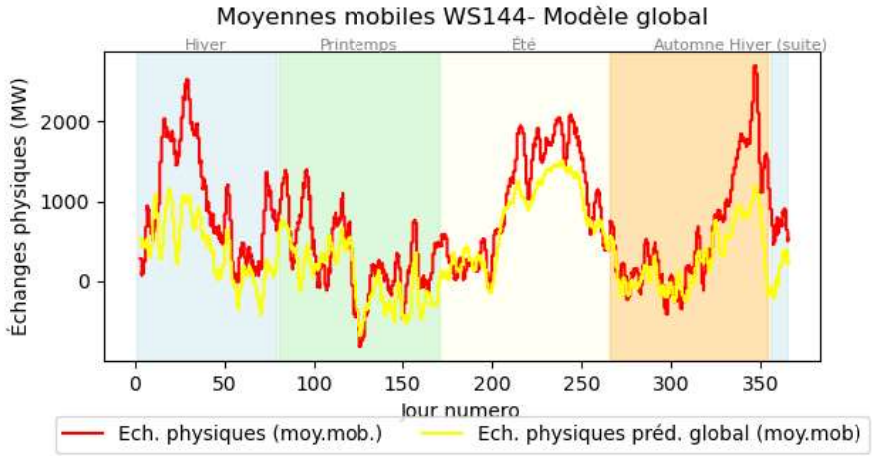
Valeurs réelles	Modèle global	Modèle régional
Médiane: -925 MW	Médiane: -961 MW	Médiane: -1136 MW
IQR: 1313 MW	IQR: 1032 MW	IQR: 1183 MW
	Ind.Conf.Moy.: 56.2 %	Ind.Conf.Moy.: 54.4 %

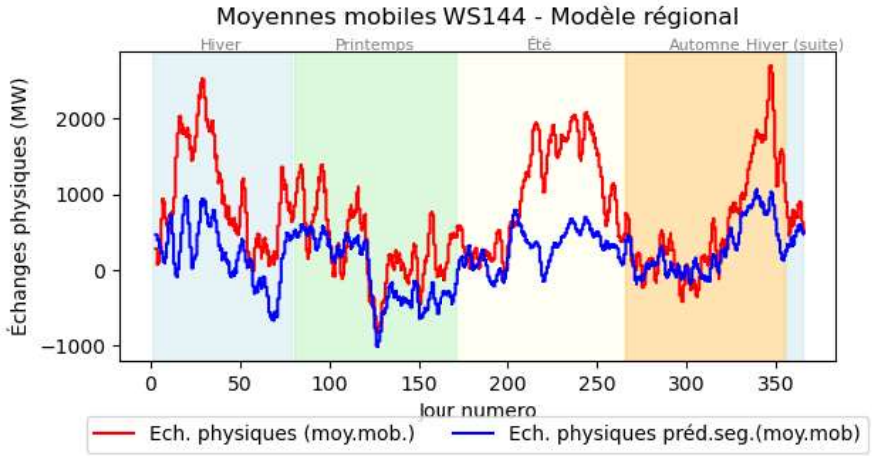
XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

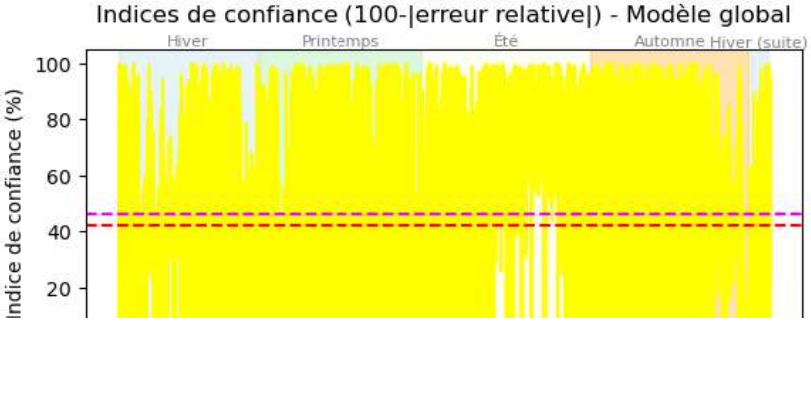
Prévisions des échanges physiques par XGBoost sans transformation cible
NOUVELLE AQUITAINE, 2022

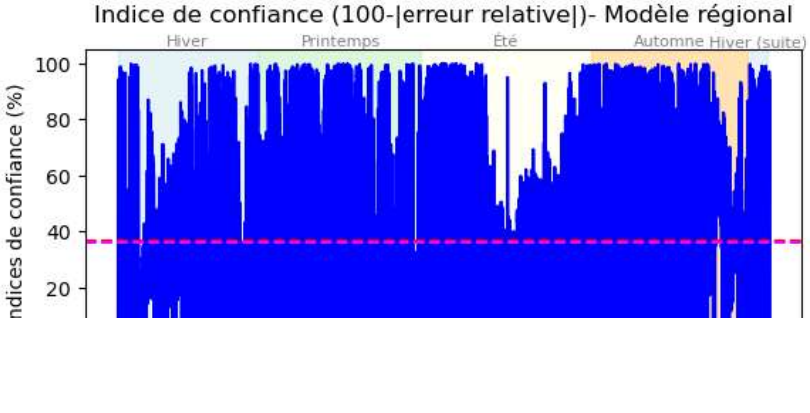


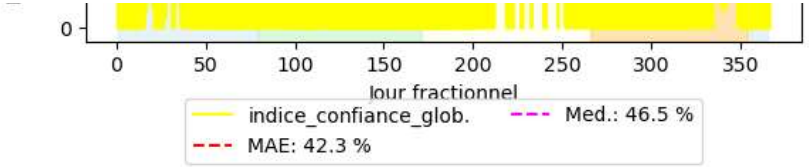


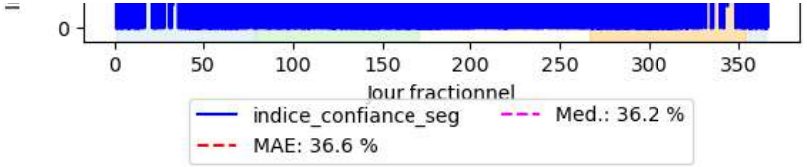


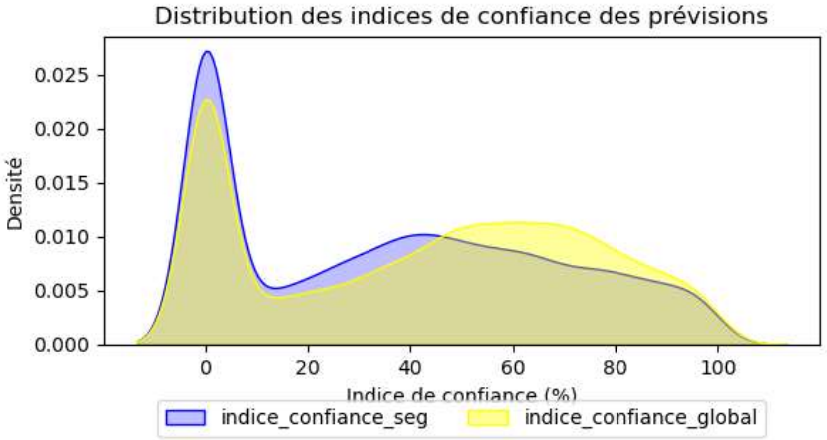












Métriques 2022

Valeurs réelles	Modèle global	Modèle régional
Médiane: 680 MW	Médiane: 372 MW	Médiane: 256 MW
IQR: 1257 MW	IQR: 937 MW	IQR: 898 MW
	Ind.Conf.Moy.: 42.3 %	Ind.Conf.Moy.: 36.6 %

XGBoost *subsample: 0.7, n_estimators: 400, max_depth: 6, learning_rate: 0.1, 'gamma': 0.2, 'colsample_bytree': 0.7

Prévisions des échanges physiques par XGBoost sans transformation cible
NOUVELLE AQUITAINE, 2023