In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
df = pd.read_csv("Electricity.csv")
df.head().style.set_properties(
    **{
        'background-color': 'OliveDrab',
        'color': 'white',
        'border-color': 'darkblack'
    })
```

Code + Data :https://t.me/AIMLDeepThaught/555

Out[3]:

	DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar	Biomass
0	2019-01-01 00:00:00	6352	6527	1395	79	1383	1896	1744	0	30
1	2019-01-01 01:00:00	6116	5701	1393	96	1112	1429	1641	0	30
2	2019-01-01 02:00:00	5873	5676	1393	142	1030	1465	1616	0	30
3	2019-01-01 03:00:00	5682	5603	1397	191	972	1455	1558	0	30
4	2019-01-01 04:00:00	5557	5454	1393	159	960	1454	1458	0	30

In [4]:
```
df['DateTime'] = pd.to_datetime(df['DateTime'])
```

In [5]:
```
df.describe().style.background_gradient(cmap='rainbow')
```

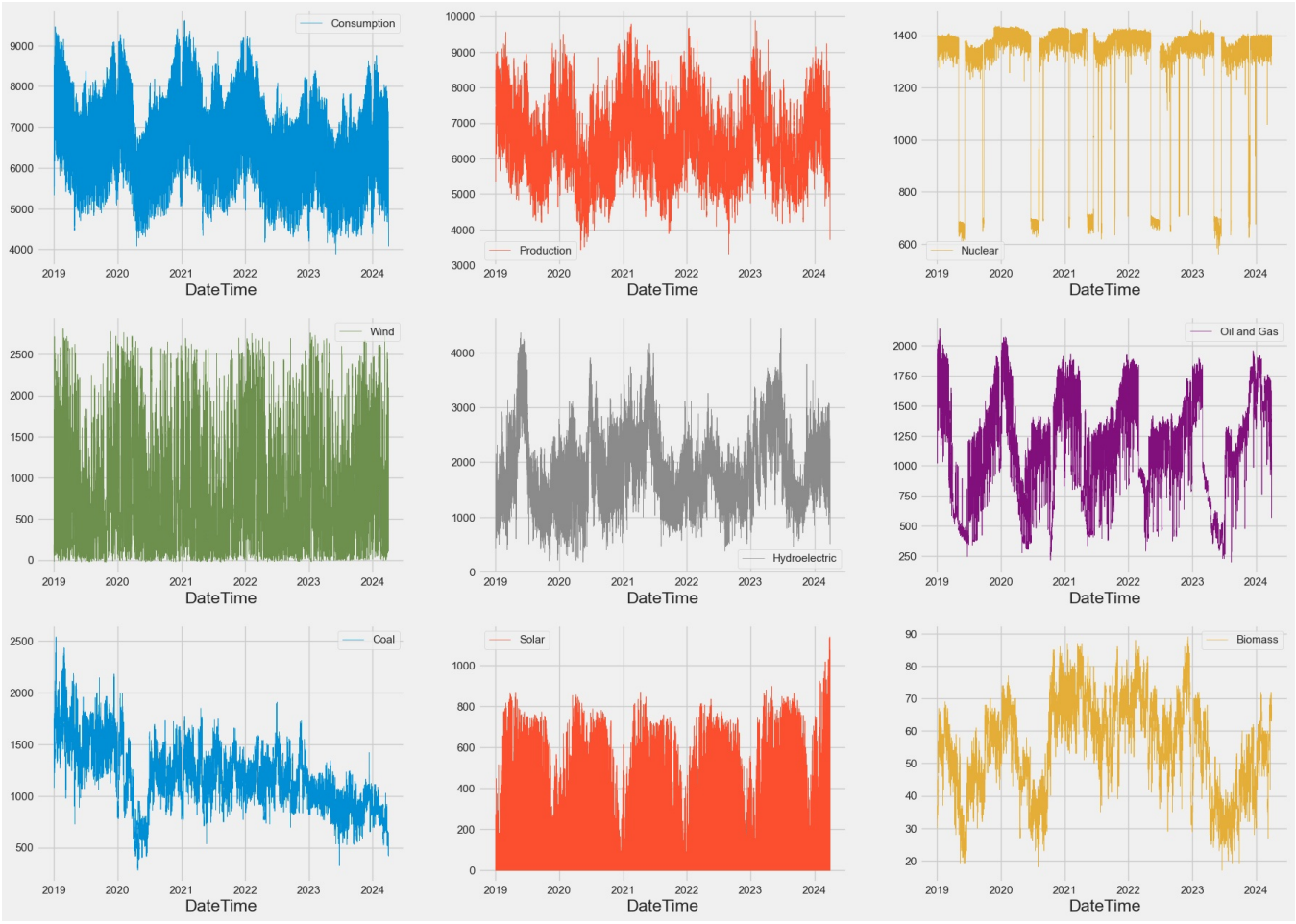
Out[5]:

	DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar
count	46011	46011.000000	46011.000000	46011.000000	46011.000000	46011.000000	46011.000000	46011.000000	46011.000000
mean	2021-08-16 11:19:47.715981056	6587.616440	6518.645628	1291.177501	792.310882	1857.052444	1171.890418	1193.157332	156.688031
min	2019-01-01 00:00:00	3889.000000	3315.000000	562.000000	-26.000000	175.000000	198.000000	279.000000	0.000000
25%	2020-04-24 06:30:00	5773.000000	5814.000000	1347.000000	236.000000	1347.000000	858.000000	962.000000	0.000000
50%	2021-08-16 12:00:00	6552.000000	6462.000000	1383.000000	592.000000	1747.000000	1211.000000	1172.000000	2.000000
75%	2022-12-08 15:30:00	7321.000000	7176.000000	1405.000000	1205.000000	2265.000000	1511.000000	1406.000000	280.000000
max	2024-03-31 23:00:00	9615.000000	9886.000000	1457.000000	2811.000000	4434.000000	2141.000000	2537.000000	1137.000000
std	nan	1043.654923	986.805018	236.549637	675.812712	692.592157	434.748917	320.449368	229.502650

In [6]:
```
print("Starting Date: ", df['DateTime'].min())
print("End Date     : ", df['DateTime'].max())
```

```
Starting Date:  2019-01-01 00:00:00
End Date     :  2024-03-31 23:00:00
```

In [100…
```
plt.style.use('fivethirtyeight')

df2 = df.copy('Deep')
df2 = df2.set_index('DateTime')

# Facet plots
df2.plot(subplots=True,
        linewidth=0.5,
        layout=(3, 3),
        figsize=(20, 15),
        sharex=False,
        sharey=False)
plt.show()
```

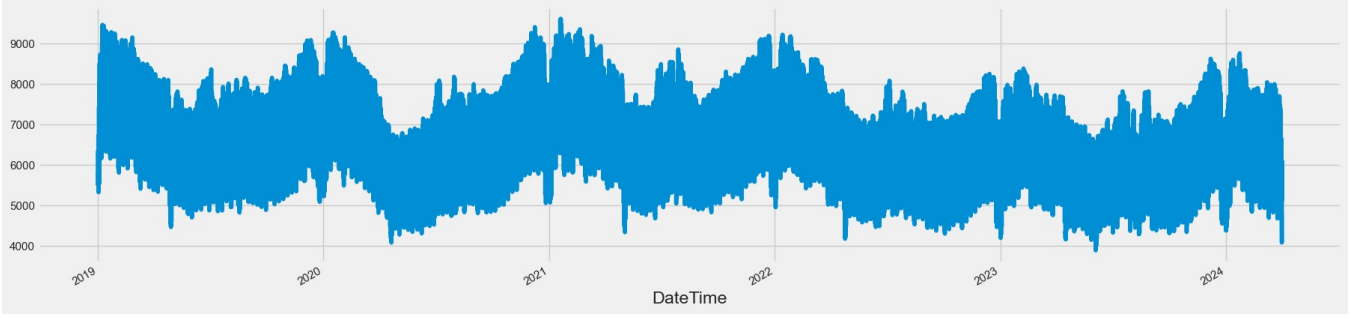


In [102…
```
df_consumption = df[['DateTime','Consumption']]
df_consumption.head()
```

Out[102]:

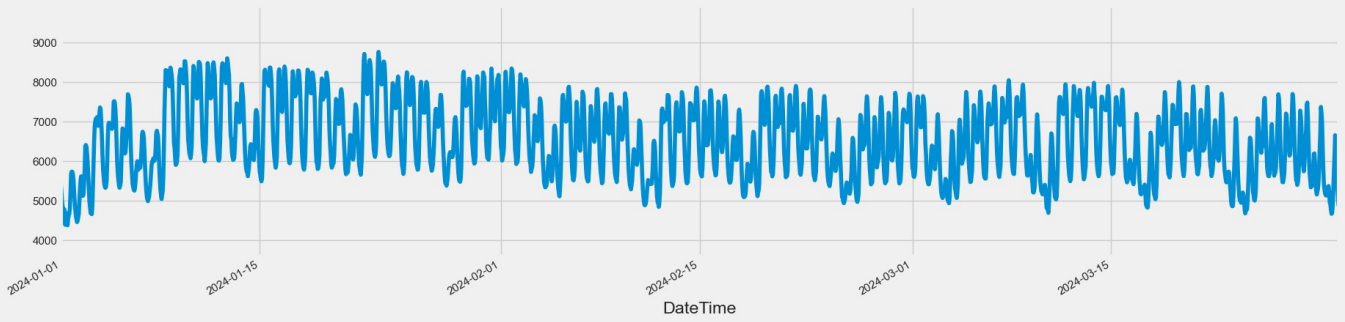
	DateTime	Consumption
0	2019-01-01 00:00:00	6352
1	2019-01-01 01:00:00	6116
2	2019-01-01 02:00:00	5873
3	2019-01-01 03:00:00	5682
4	2019-01-01 04:00:00	5557

In [103…
```
df5 = df_consumption.copy('Deep')
df5 = df5.set_index('DateTime')
df5['Consumption'].plot(figsize=(20,5))
plt.show()
```

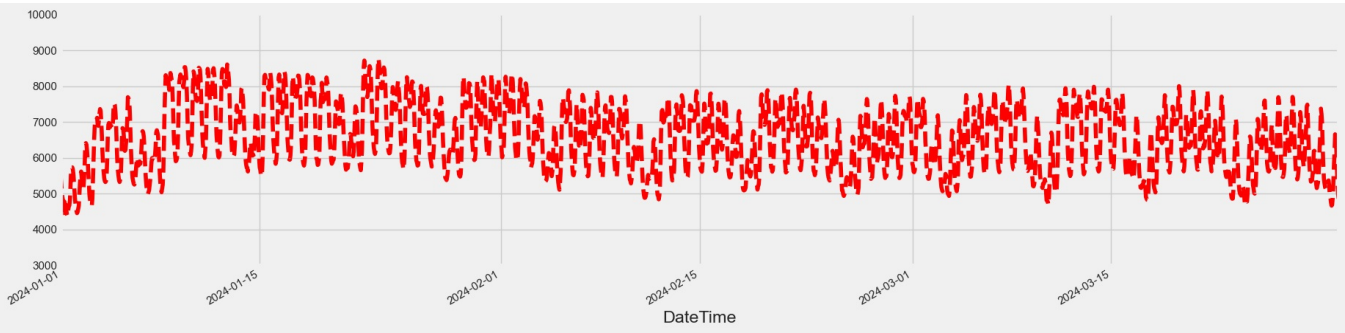


In [104…
```
## xlimit and y limit
df5['Consumption'].plot(xlim=['2024-01-01','2024-03-31'],figsize=(20,5))
plt.show()
```

Code + Data :https://t.me/AIMLDeepThaught/555



In [105…
```
## xlimit and y limit
df5['Consumption'].plot(xlim=['2024-01-01','2024-03-31'],figsize=(20,5),ylim=[3000,10000],ls='--',c='Red')
plt.show()
```



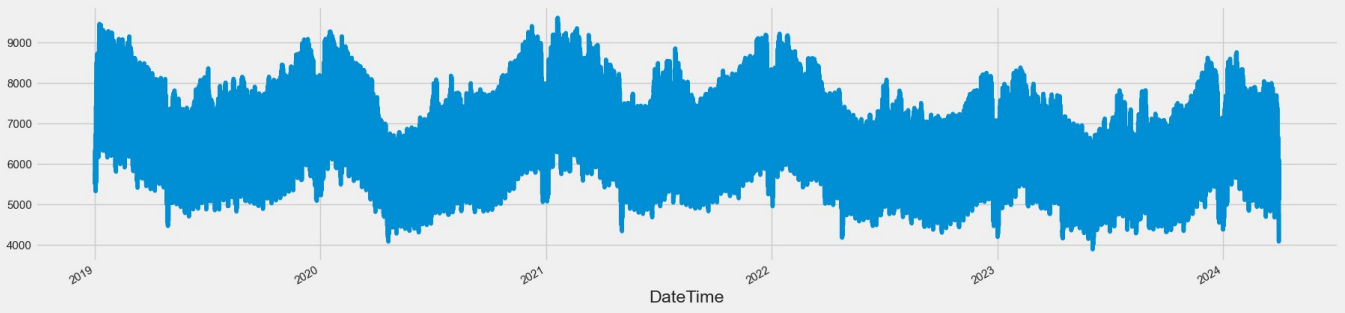
In [106…
```
index=df5.loc['2023-01-01':'2023-09-01'].index
Consumption=df5.loc['2023-01-01':'2023-09-01']['Consumption']
Consumption
```

Out[106]:
```
DateTime
2023-01-01 00:00:00    4996
2023-01-01 01:00:00    4995
2023-01-01 02:00:00    4816
2023-01-01 03:00:00    4627
2023-01-01 04:00:00    4581
                       ...
2023-09-01 19:00:00    6704
2023-09-01 20:00:00    6932
2023-09-01 21:00:00    6712
2023-09-01 22:00:00    6090
2023-09-01 23:00:00    5582
Name: Consumption, Length: 5855, dtype: int64
```

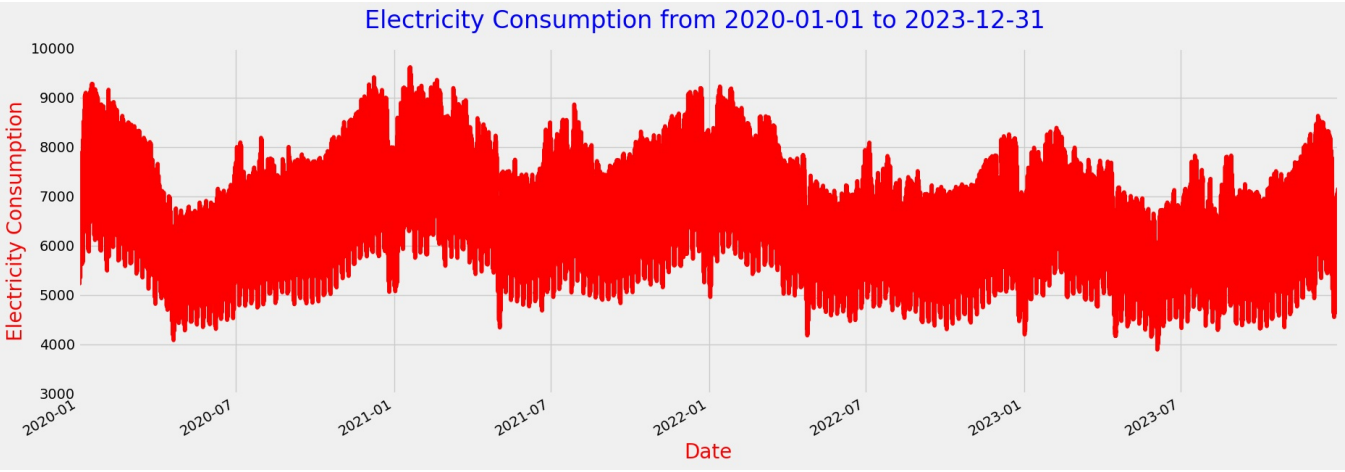
In [107…
```
print(plt.style.available)
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid', 'bmh', 'classic', 'dark_backg
round', 'fast', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn-v0_8', 'seaborn-v0_8-bright', 'seaborn-v0_8-
colorblind', 'seaborn-v0_8-dark', 'seaborn-v0_8-dark-palette', 'seaborn-v0_8-darkgrid', 'seaborn-v0_8-deep', 's
eaborn-v0_8-muted', 'seaborn-v0_8-notebook', 'seaborn-v0_8-paper', 'seaborn-v0_8-pastel', 'seaborn-v0_8-poster'
, 'seaborn-v0_8-talk', 'seaborn-v0_8-ticks', 'seaborn-v0_8-white', 'seaborn-v0_8-whitegrid', 'tableau-colorblin
d10']
```

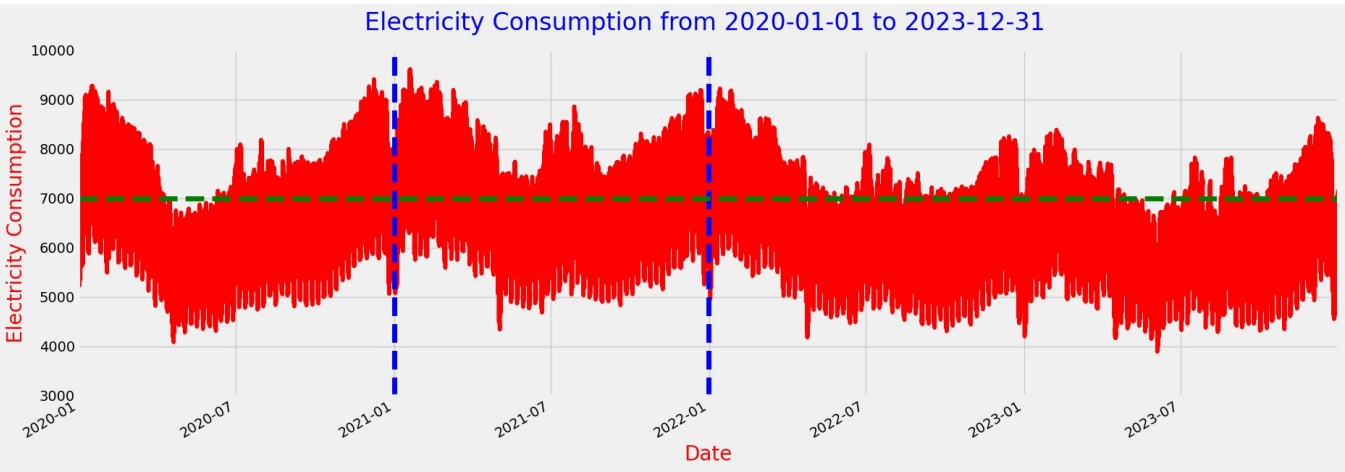
In [108…
```
plt.style.use('fivethirtyeight')
df5 = df_consumption.copy('Deep')
df5 = df5.set_index('DateTime')
df5['Consumption'].plot(figsize=(20,5))
plt.show()
```



In [16]:
```
ax = df5['Consumption'].plot(xlim=['2020-01-01','2023-12-31'], ylim=[3000,10000] ,color ="Red", figsize=(20,7))
ax.set_xlabel('Date', color = "Red" ,fontsize= 20)
ax.set_ylabel('Electricity Consumption', color = "Red", fontsize=20)
ax.set_title('Electricity Consumption from 2020-01-01 to 2023-12-31 ', color = "Blue",  fontsize=24 ,pad=20)
plt.show()
```

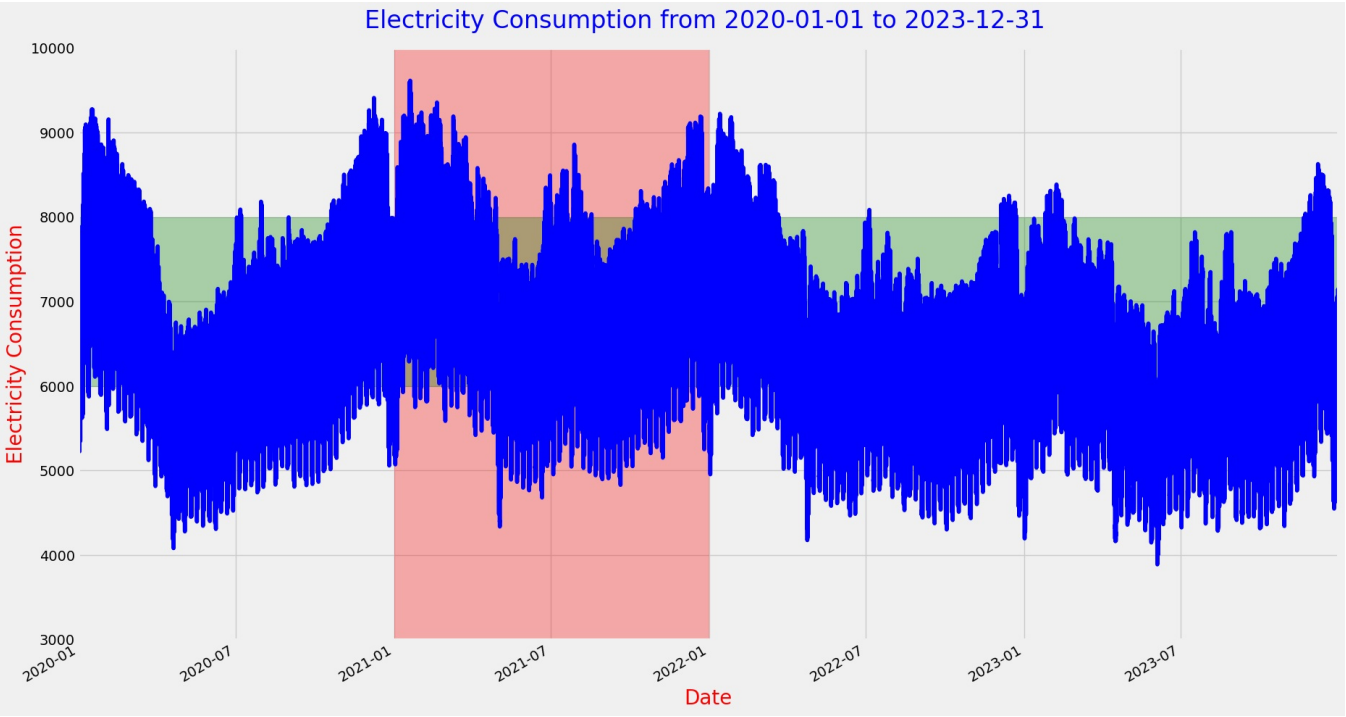


In [17]:
```
# adding markers
ax = df5['Consumption'].plot(xlim=['2020-01-01','2023-12-31'], ylim=[3000,10000] ,color ="Red", figsize=(20,7))
ax.set_xlabel('Date', color = "Red" ,fontsize= 20)
ax.set_ylabel('Electricity Consumption', color = "Red", fontsize=20)
ax.set_title('Electricity Consumption from 2020-01-01 to 2023-12-31 ', color = "Blue",  fontsize=24 ,pad=20)

ax.axvline('2021-01-01', color='Blue', linestyle='--', lw = 5)
ax.axvline('2021-12-31', color='Blue', linestyle='--', lw = 5)
ax.axhline(7000, color='green', linestyle='--', lw = 5)
plt.show()
```

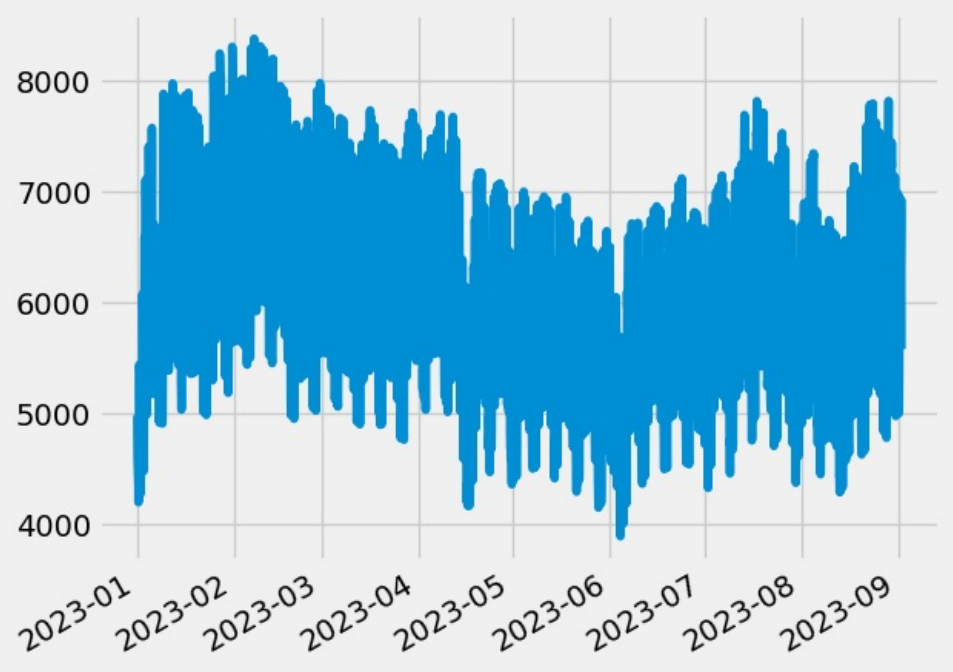


In [18]:
```
# Highlighting regions of interest
ax = df5['Consumption'].plot(xlim=['2020-01-01','2023-12-31'], ylim=[3000,10000] ,color ="Blue", figsize=(20,12
ax.set_xlabel('Date', color = "Red" ,fontsize= 20)
ax.set_ylabel('Electricity Consumption', color = "Red", fontsize=20)
ax.set_title('Electricity Consumption from 2020-01-01 to 2023-12-31 ', color = "Blue",  fontsize=24 ,pad=20)

ax.axvspan('2021-01-01', '2021-12-31', color='Red', alpha=0.3)
ax.axhspan(8000, 6000, color='green', alpha=0.3)
plt.show()
```

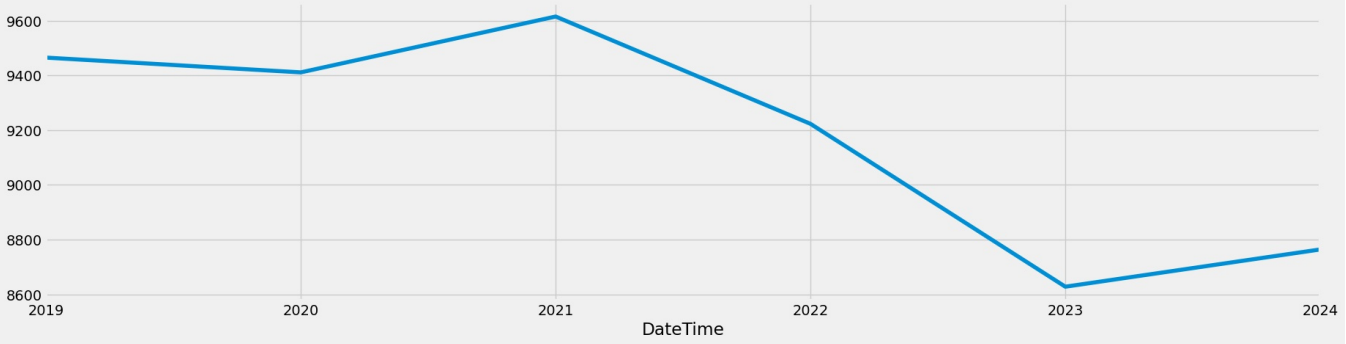
Code + Data :https://t.me/AIMLDeepThaught/555



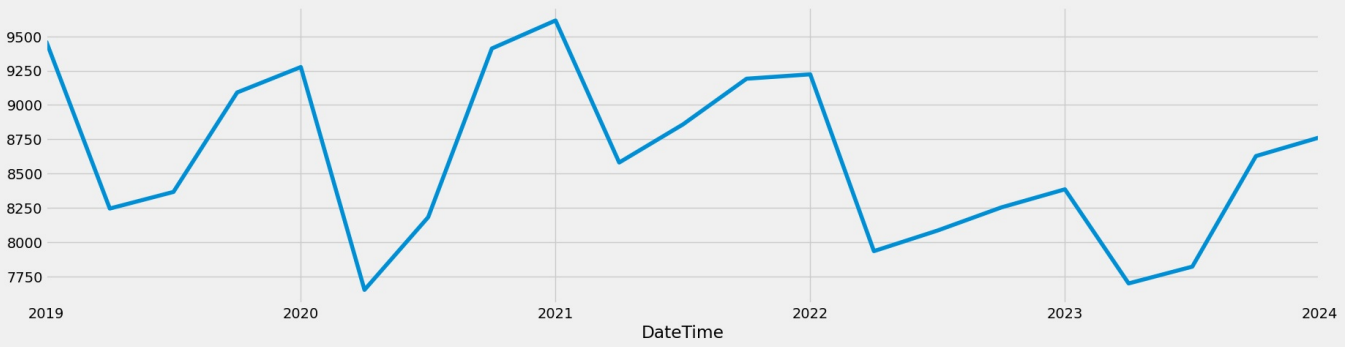
In [19]:
```
figure,axis=plt.subplots()
plt.tight_layout()
## Preventing overlapping
figure.autofmt_xdate()
axis.plot(index,Consumption);
```



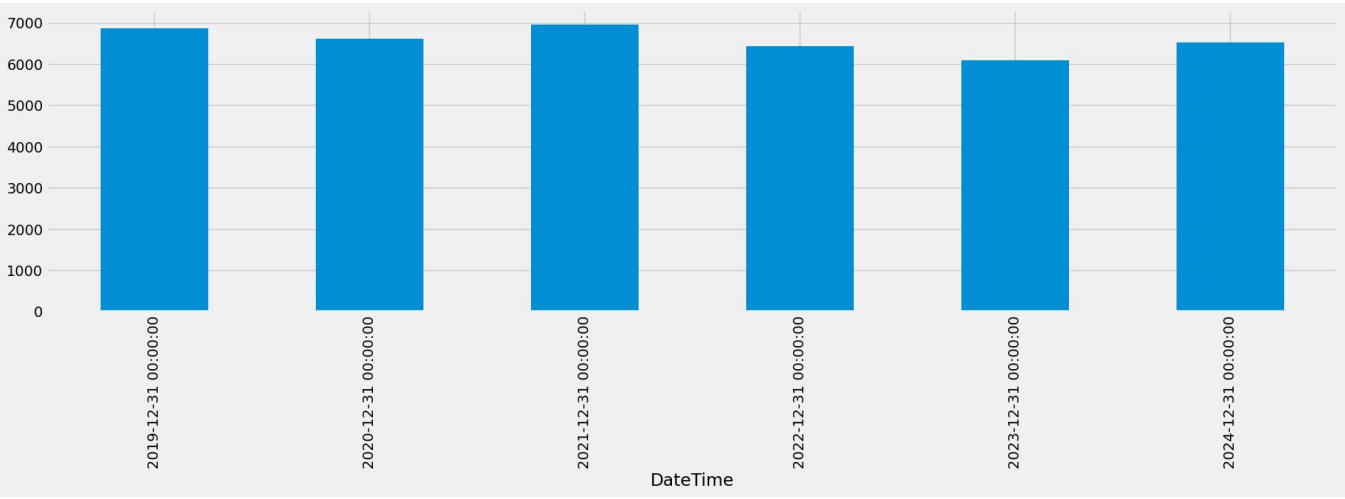
In [20]:
```
##year end frequency
df5.resample(rule='A').max()['Consumption'].plot(figsize=(20,5));
```



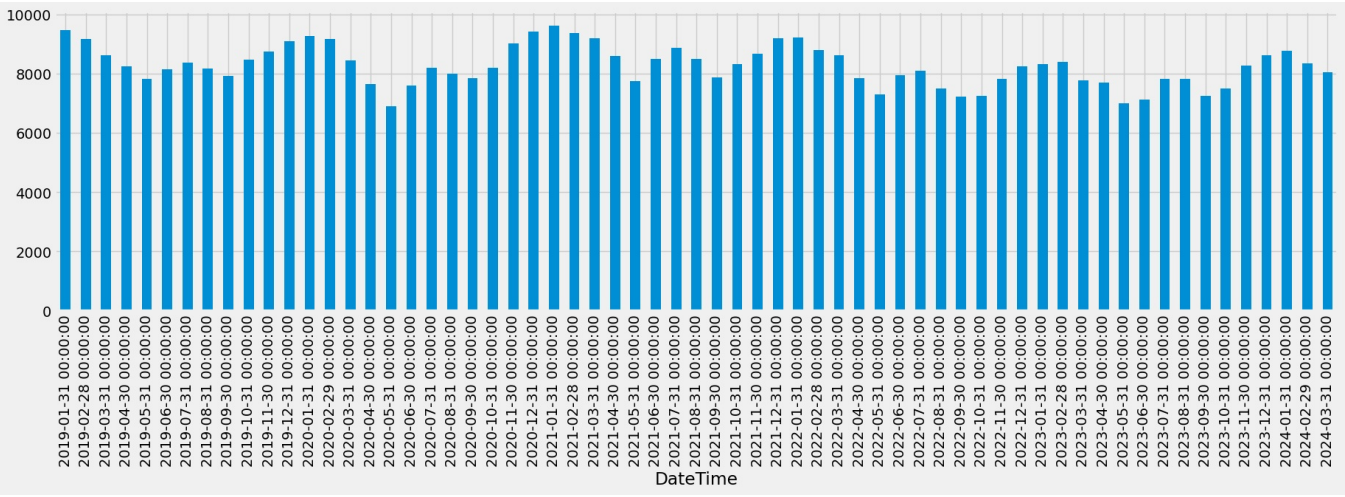
In [21]:
```
df5.resample(rule='QS').max()['Consumption'].plot(figsize=(20,5));
```



In [22]:
```
##plotting
df5['Consumption'].resample(rule='A').mean().plot(kind='bar',figsize=(20,5));
```



In [23]:
```
df5['Consumption'].resample(rule='M').max().plot(kind='bar',figsize=(20,5));
```



In [24]:
```
df5['Consumption'].rolling(5).max().head(8)
```

Out[24]:
```
DateTime
2019-01-01 00:00:00       NaN
2019-01-01 01:00:00       NaN
2019-01-01 02:00:00       NaN
2019-01-01 03:00:00       NaN
2019-01-01 04:00:00    6352.0
2019-01-01 05:00:00    6116.0
2019-01-01 06:00:00    5873.0
2019-01-01 07:00:00    5682.0
Name: Consumption, dtype: float64
```

In [25]:
```
count_date = df5.groupby(df5.index.date)['Consumption'].sum()

pw_clean = pd.DataFrame(count_date)
pw_clean['DateTime'] = pd.to_datetime(pw_clean.index)
pw_clean = pw_clean.set_index('DateTime')
pw_clean.head()
```

Out[25]:

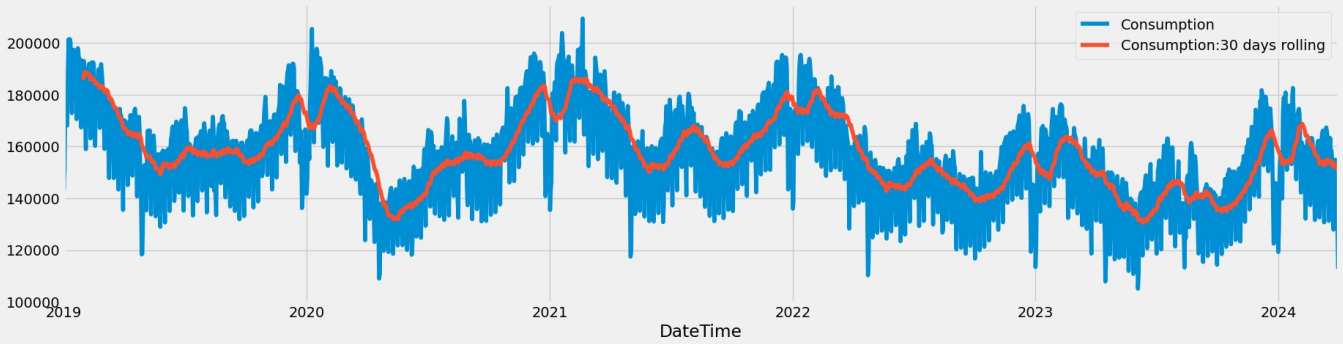
DateTime	Consumption
2019-01-01	142984
2019-01-02	151729
2019-01-03	174098
2019-01-04	183242
2019-01-05	177114

In [26]:
```
pw_clean['Consumption:30 days rolling']=pw_clean['Consumption'].rolling(30).mean()
pw_clean.head(3)
```

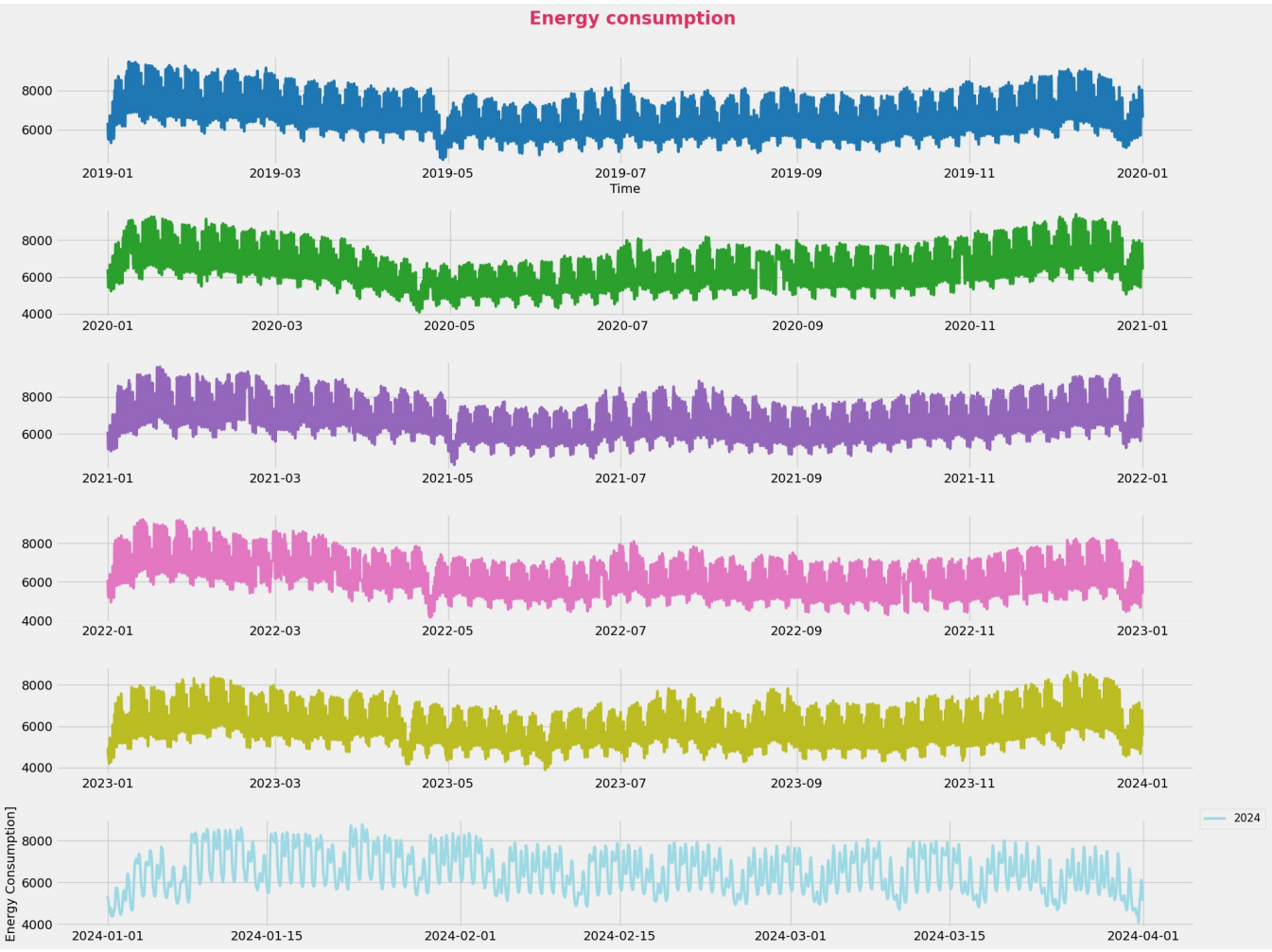
Out[26]:

DateTime	Consumption	Consumption:30 days rolling
2019-01-01	142984	NaN
2019-01-02	151729	NaN
2019-01-03	174098	NaN

In [27]:
```
pw_clean[['Consumption','Consumption:30 days rolling']].plot(figsize=(20,5));
```



In [28]:
```
import matplotlib.cm as cm  # Import colormap library

df1 = df[['DateTime','Consumption']].copy('Deep')
df1 = df1.set_index('DateTime')

years = [2019, 2020, 2021, 2022, 2023, 2024]

cmap = cm.get_cmap('tab20')  # Choose a colormap with bright colors

fig, axs = plt.subplots(len(years), 1, figsize=(20, 15))  # Adjust figsize for layout
for i, year in enumerate(years):
    df_year = df1[(df1.index >= f"{year}-01-01") & (df1.index < f"{year+1}-01-01")]
    color = cmap(i / (len(years) - 1))  # Get color from colormap based on index
    axs[i].plot(df_year, lw=3, color=color, label=f"{year}")  # Include year as label

# Set common labels and title
axs[0].set_xlabel('Time', fontsize=14)  # Set on first subplot for all
axs[-1].set_ylabel('Energy Consumption]', fontsize=14)  # Set on last subplot for all
plt.suptitle('Energy consumption \n', weight='bold', fontsize=20, color='#DE3163')

# Add legend
handles, labels = axs[-1].get_legend_handles_labels()  # Get labels from last subplot
plt.legend(handles, labels, loc='upper left', bbox_to_anchor=(1, 1.15), fontsize=12)  # Add legend outside plot

plt.tight_layout()
plt.show()
```

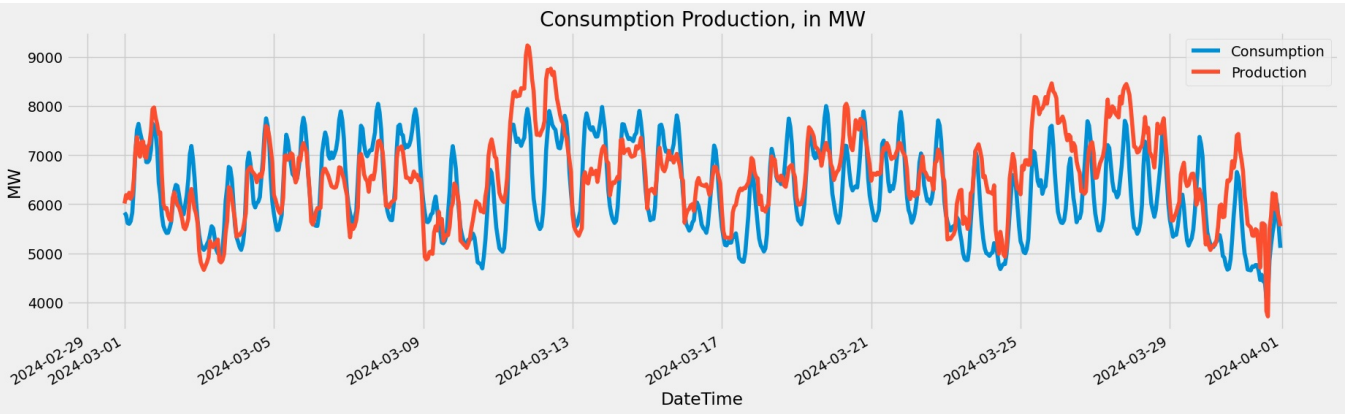


In [29]:
```
df.head(2)
```

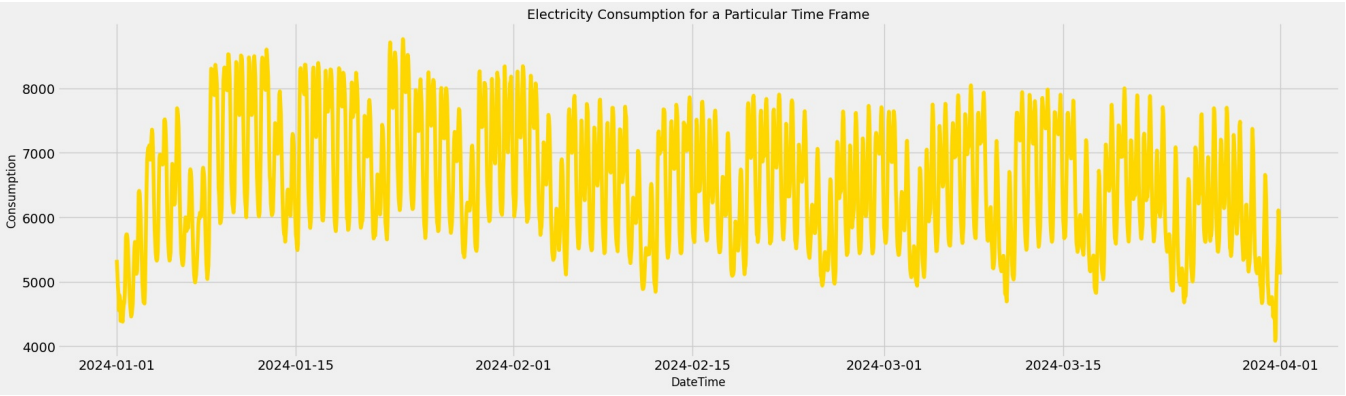
Out[29]:

	DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar	Biomass
0	2019-01-01 00:00:00	6352	6527	1395	79	1383	1896	1744	0	30
1	2019-01-01 01:00:00	6116	5701	1393	96	1112	1429	1641	0	30

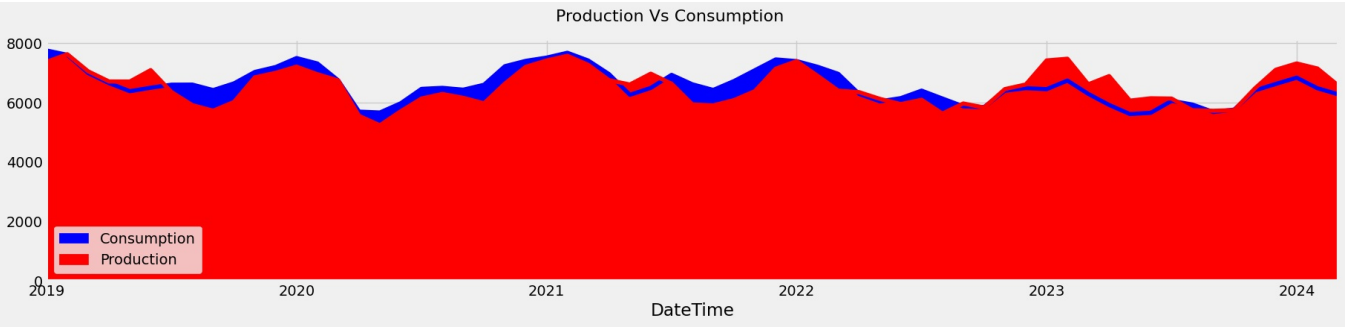
In [30]:
```
df2 = df.copy('Deep')
df2 = df2.set_index('DateTime')

dfSummer = df2[["Consumption", "Production"]]["2024-03-01 00:00:00" : "2024-04-01 23:59:59"]
dfSummer.plot(style="-", figsize=(20, 6), title=f"Consumption Production, in MW")
plt.ylabel('MW')
plt.show()
```



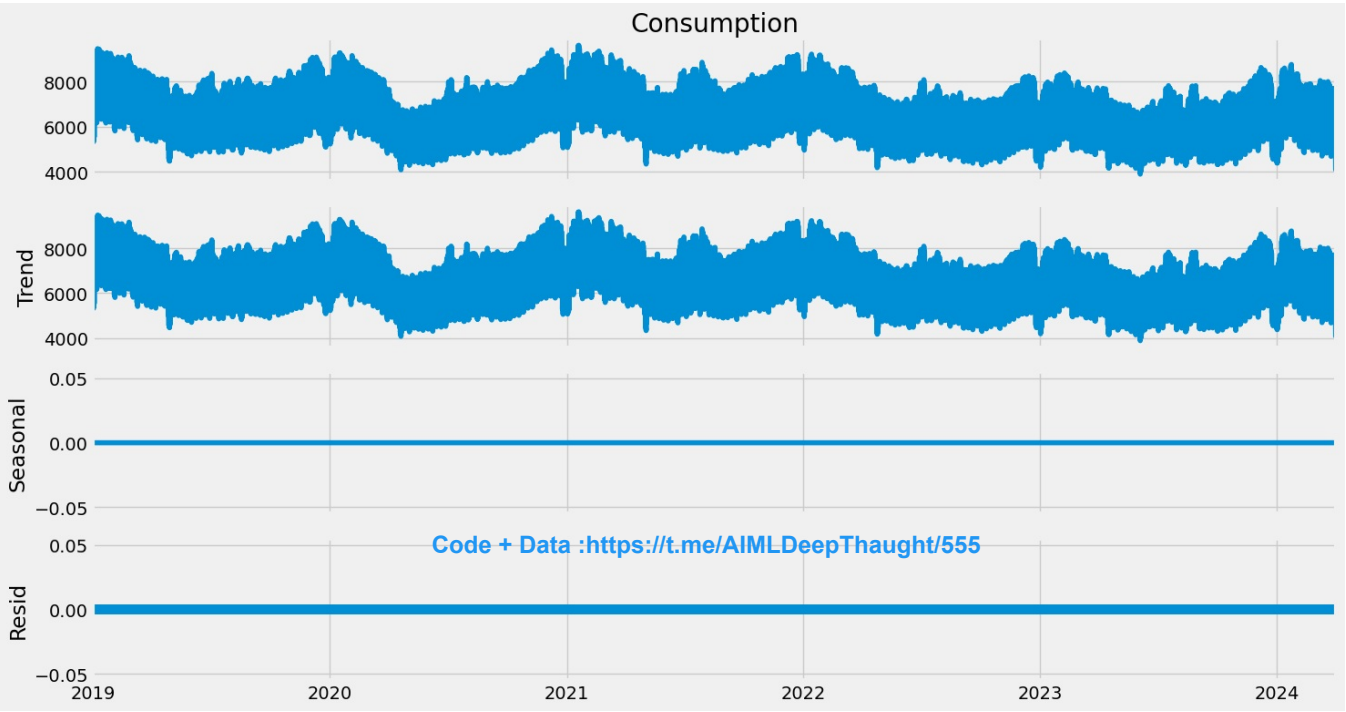
In [31]:
```
data1 = df[(df['DateTime'] >= '2024-01-01') & (df['DateTime'] < '2024-04-01')]

plt.figure(figsize=(20,6))
plt.plot(data1['DateTime'], data1['Consumption'], color='Gold')
plt.ylabel('Consumption', fontsize=12)
plt.xlabel('DateTime', fontsize=12)
plt.title('Electricity Consumption for a Particular Time Frame', fontsize=14)
plt.tight_layout()
plt.grid(True)
sns.despine(bottom=True, left=True)
plt.show()
```



In [32]:
```
df1 = df.copy('Deep')
df1= df1.set_index('DateTime')

fig, ax = plt.subplots(figsize=(20,5)) # Create the figure and axes object

fig.suptitle('Production Vs Consumption', fontsize=16)
# Plot the first x and y axes:
df1.resample('M').mean().plot.area(use_index=True, y = 'Consumption', ax = ax,color='Blue')
df1.resample('M').mean().plot.area(use_index=True, y = 'Production', ax = ax, secondary_y = False,color='Red')
```



In [33]:
```
plt.rcParams["figure.figsize"] = (15,8)
from statsmodels.tsa.seasonal import seasonal_decompose
decomp=seasonal_decompose(df1['Consumption'], model='additive', period=1)
decomp.plot()
plt.show()
```



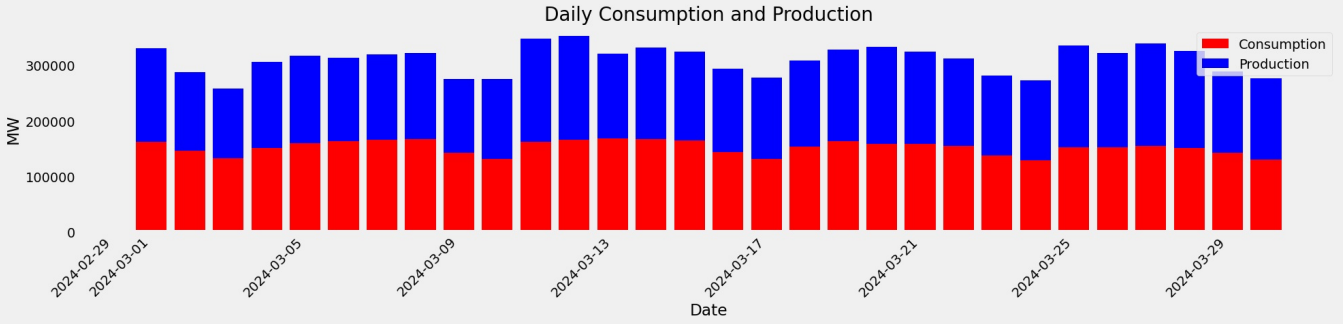
In [34]:
```
df_con = df.copy('deep')
df_con["DATE"] = pd.to_datetime(df_con["DateTime"]).dt.date
df_con["TIME"] = pd.to_datetime(df_con["DateTime"]).dt.time
df_con = df_con.set_index('DateTime')
df_con = df_con[["Consumption", "Production", "Solar","DATE" , "TIME"]]["2024-03-01 00:00:00" : "2024-03-30 23:
df_con.head()
```

Out[34]:

DateTime	Consumption	Production	Solar	DATE	TIME
2024-03-01 00:00:00	5830	6014	0	2024-03-01	00:00:00
2024-03-01 01:00:00	5780	6186	0	2024-03-01	01:00:00
2024-03-01 02:00:00	5617	6127	0	2024-03-01	02:00:00
2024-03-01 03:00:00	5600	6234	0	2024-03-01	03:00:00
2024-03-01 04:00:00	5656	6112	0	2024-03-01	04:00:00

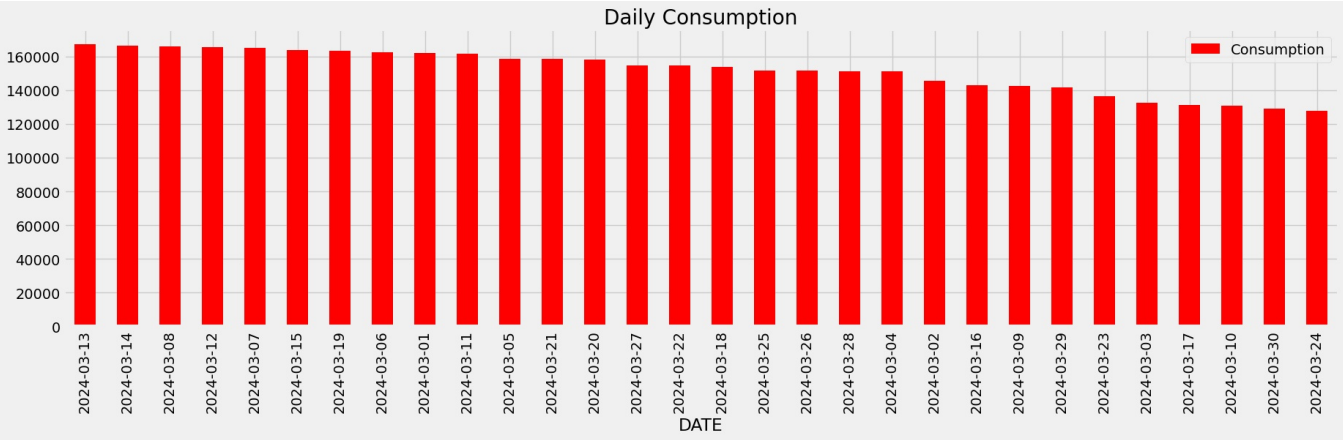
In [35]:

```
# Calculate daily consumption and production sums
daily_consumption = df_con.groupby('DATE')['Consumption'].agg('sum')
daily_production = df_con.groupby('DATE')['Production'].agg('sum')

# Create the combined plot
fig, ax = plt.subplots(figsize=(20, 5))  # Create figure and axis

# Plot consumption (red) and production (blue) on the same axis
ax.bar(daily_consumption.index, daily_consumption, color='red', label='Consumption')
ax.bar(daily_production.index, daily_production, color='blue', label='Production', bottom=daily_consumption.val

# Set labels, title, and legend
ax.set_xlabel('Date')
ax.set_ylabel('MW')
plt.title('Daily Consumption and Production')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better readability (optional)
plt.legend()
plt.grid(False)  # Add grid lines for better readability (optional)
plt.tight_layout()  # Adjust spacing to prevent overlapping elements (optional)

plt.show()
```



In [36]:

```
daily_Consumption = df_con.groupby('DATE')['Consumption'].agg('sum')

ax = daily_Consumption.sort_values(ascending=False).plot.bar(figsize=(20,5), legend=True,color='red')
plt.title('Daily Consumption')
plt.show()
```



In [37]:

```
df_solar =  df.copy('deep')

df_solar["DATE"] = pd.to_datetime(df_solar["DateTime"]).dt.date
df_solar["TIME"] = pd.to_datetime(df_solar["DateTime"]).dt.time
df_solar["DATE"] = pd.to_datetime(df_solar["DateTime"]).dt.date
df_solar["DATE_STRING"] = df_solar["DATE"].astype(str) # add column with date as string

df_solar.head()
```

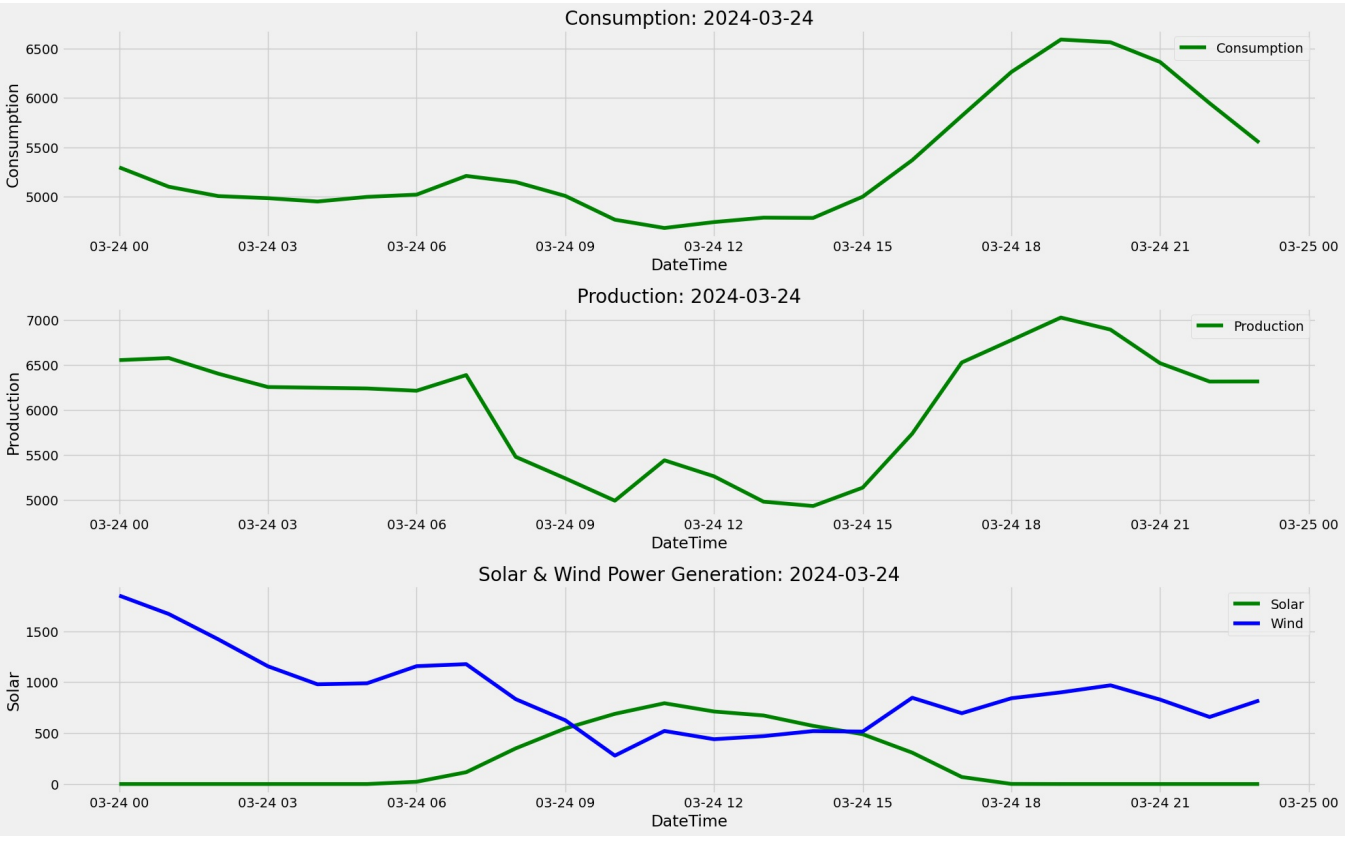
Code + Data :https://t.me/AIMLDeepThaught/555

Out[37]:

	DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar	Biomass	DATE	TIME	DATE_STRING
0	2019-01-01 00:00:00	6352	6527	1395	79	1383	1896	1744	0	30	2019-01-01	00:00:00	2019-01-01
1	2019-01-01 01:00:00	6116	5701	1393	96	1112	1429	1641	0	30	2019-01-01	01:00:00	2019-01-01
2	2019-01-01 02:00:00	5873	5676	1393	142	1030	1465	1616	0	30	2019-01-01	02:00:00	2019-01-01
3	2019-01-01 03:00:00	5682	5603	1397	191	972	1455	1558	0	30	2019-01-01	03:00:00	2019-01-01
4	2019-01-01 04:00:00	5557	5454	1393	159	960	1454	1458	0	30	2019-01-01	04:00:00	2019-01-01

In [38]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming 'df_solar' has columns 'DateTime', 'Consumption', 'Production', 'Solar', and 'Wind'

date = ["2024-03-24"]  # List of dates to filter

# Filter data for the specified date(s)
filtered_data = df_solar[df_solar["DATE_STRING"].isin(date)]

# Create the figure with desired size
plt.figure(figsize=(20, 16))

# Subplot 1: Consumption
plt.subplot(411)
sns.lineplot(data=filtered_data, x="DateTime", y="Consumption", label="Consumption", color='green')
plt.title("Consumption: {}".format(date[0]))

# Subplot 2: Production
plt.subplot(412)
sns.lineplot(data=filtered_data, x="DateTime", y="Production", label="Production", color='green')
plt.title("Production: {}".format(date[0]))

# Subplot 3: Solar & Wind
plt.subplot(413)
sns.lineplot(data=filtered_data, x="DateTime", y="Solar", label="Solar", color='green')
sns.lineplot(data=filtered_data, x="DateTime", y="Wind", label="Wind", color='blue')
plt.title("Solar & Wind Power Generation: {}".format(date[0]))

plt.tight_layout()
plt.show()
```



In [39]:

```
df_con_pro = df_con.pivot_table(values=['Consumption', 'Production'], index='TIME', columns='DATE')
df_con_pro.head()
```

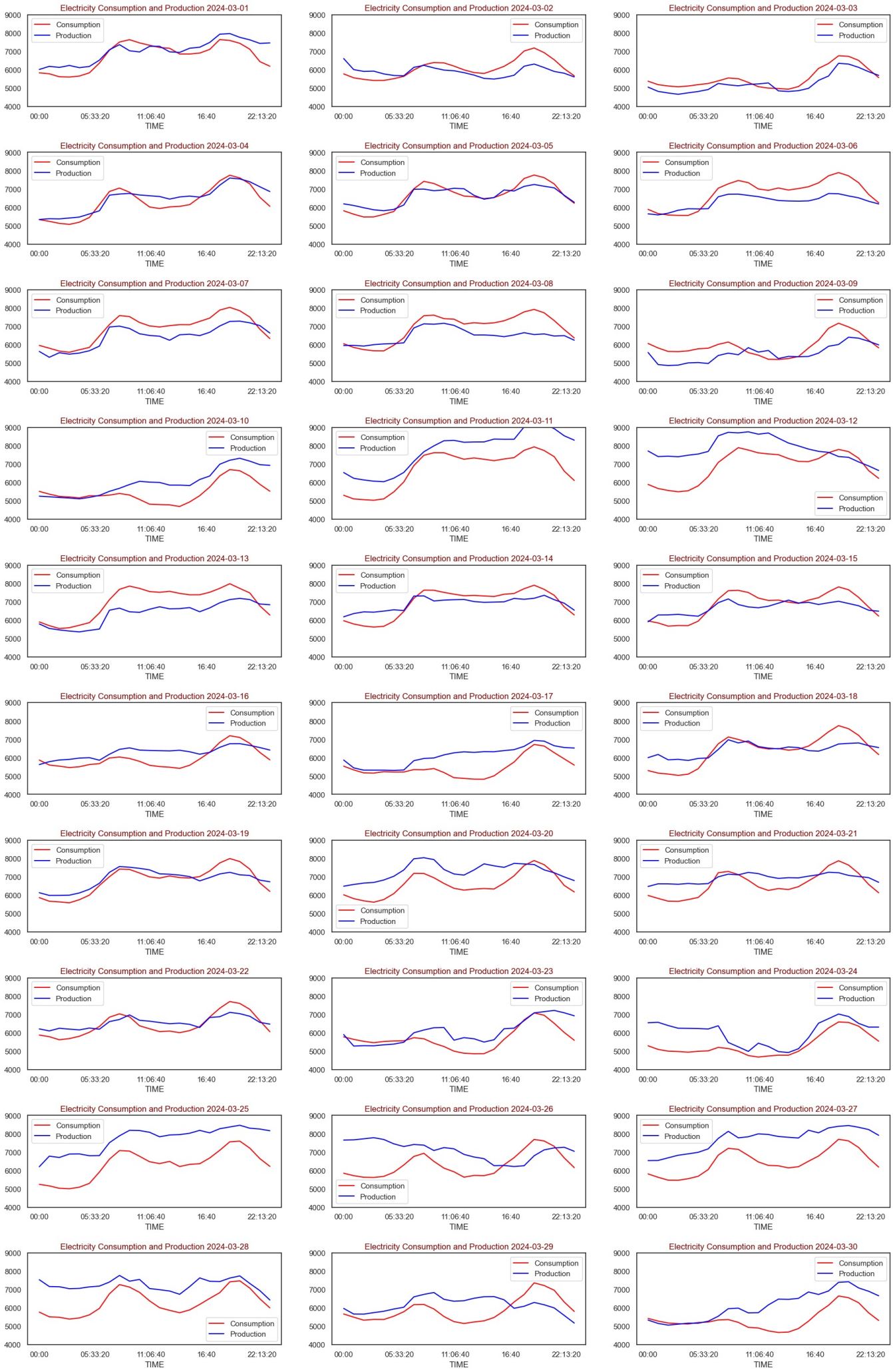
Out[39]:

	Consumption										...							
DATE	2024-03-01	2024-03-02	2024-03-03	2024-03-04	2024-03-05	2024-03-06	2024-03-07	2024-03-08	2024-03-09	2024-03-10	...	2024-03-21	2024-03-22	2024-03-23	2024-03-24	2024-03-25	2024-03-26	2
TIME																		
00:00:00	5830.0	5774.0	5375.0	5331.0	5813.0	5889.0	5973.0	6064.0	6079.0	5516.0	...	6479.0	6215.0	5907.0	6551.0	6202.0	7654.0	6
01:00:00	5780.0	5560.0	5186.0	5236.0	5625.0	5659.0	5821.0	5863.0	5834.0	5366.0	...	6624.0	6106.0	5281.0	6574.0	6780.0	7670.0	6
02:00:00	5617.0	5475.0	5115.0	5126.0	5473.0	5582.0	5664.0	5743.0	5646.0	5244.0	...	6622.0	6250.0	5301.0	6400.0	6706.0	7724.0	6
03:00:00	5600.0	5415.0	5069.0	5070.0	5478.0	5561.0	5600.0	5680.0	5634.0	5211.0	...	6599.0	6202.0	5295.0	6252.0	6893.0	7786.0	6
04:00:00	5656.0	5418.0	5113.0	5189.0	5615.0	5559.0	5736.0	5675.0	5677.0	5161.0	...	6644.0	6162.0	5348.0	6244.0	6900.0	7688.0	6

5 rows × 60 columns

In [40]:

```
sns.set_theme(style="white")
df_con_pro = df_con.pivot_table(values=['Consumption', 'Production'], index='TIME', columns='DATE')

def Daywise_plot(data=None, row=None, col=None, title='Electricity Consumption and Production', ylim_top=8000):
    """
    Plots timeseries data for each column in a grid layout.

    Args:
        data: A pandas DataFrame containing the timeseries data.
        row: Number of rows in the grid layout (optional).
        col: Number of columns in the grid layout (optional).
        title: Title for the overall plot (optional).
        ylim_top: Upper limit for the y-axis (optional, default: 8000).
    """
    cols = data.columns.levels[1]  # Get all column names

    # Create the figure with desired size
    gp = plt.figure(figsize=(20, 40))

    # Adjust spacing between subplots
    gp.subplots_adjust(wspace=0.2, hspace=0.5)

    for i in range(1, len(cols) + 1):
        ax = gp.add_subplot(row, col, i)
        data['Consumption', cols[i - 1]].plot(ax=ax, color='red', label='Consumption')
        data['Production', cols[i - 1]].plot(ax=ax, color='blue', label='Production')

        # Set title and y-axis limit for each subplot
        ax.set_title('{} {}'.format(title, cols[i - 1]), color='#800000')
        ax.set_ylim(4000, 9000)  # Update y-axis limit to 4000-8000
        ax.legend()  # Show legend

    # Display the plot
    plt.show()

# Call the function with desired parameters and new y-axis limit
Daywise_plot(data=df_con_pro, row=12, col=3, ylim_top=8000)
plt.tight_layout()
plt.show()
```



<Figure size 1500x800 with 0 Axes>

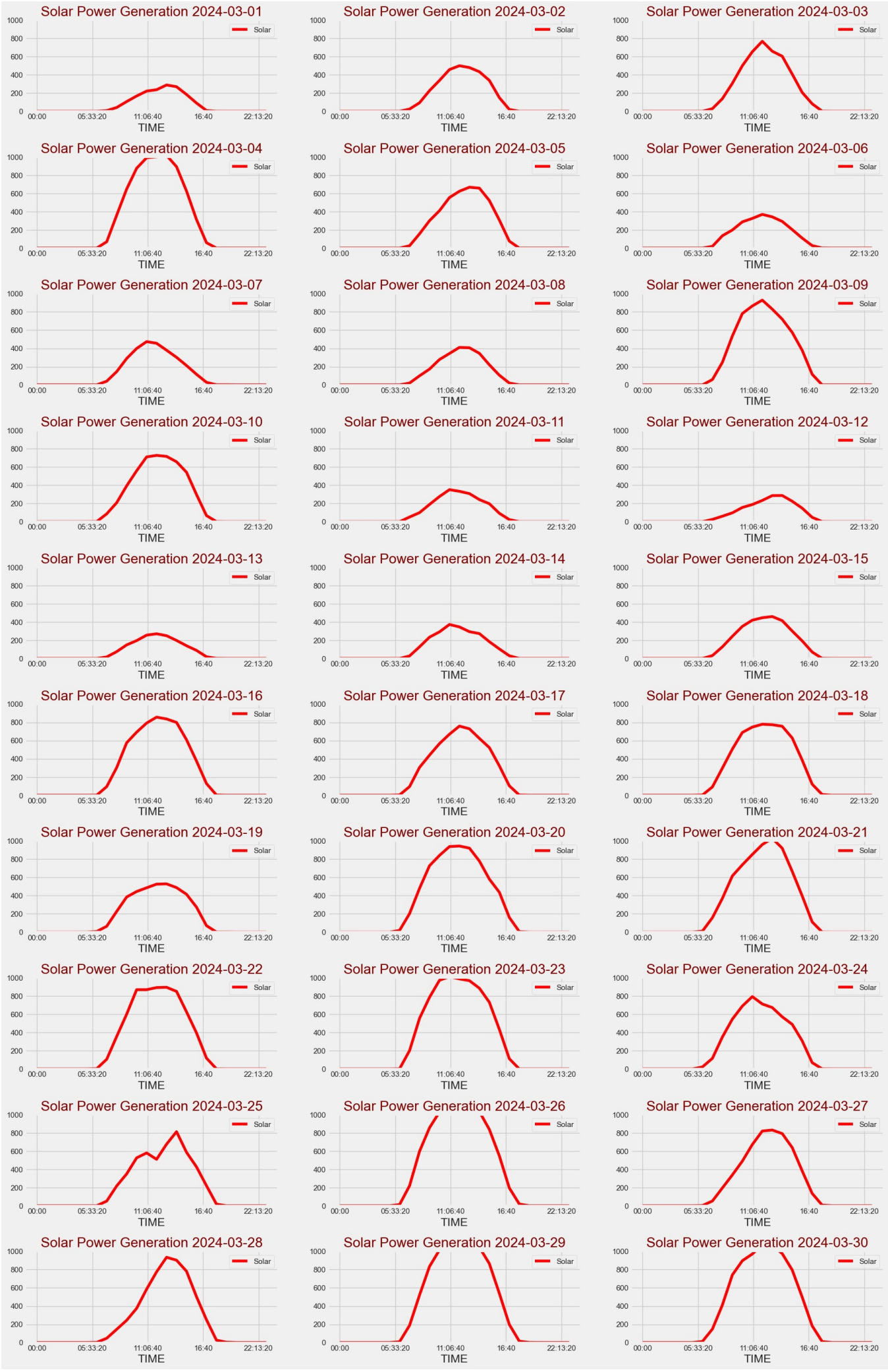
Timeseries visualization of electricity consumption and generation for the entire month of March

2024, with the units on the y-axis labeled as MW (Megawatts).

1. Red Line: This line represents the electricity consumption trend over the month. It appears to fluctuate, potentially indicating higher consumption during daytime hours and lower consumption at night.

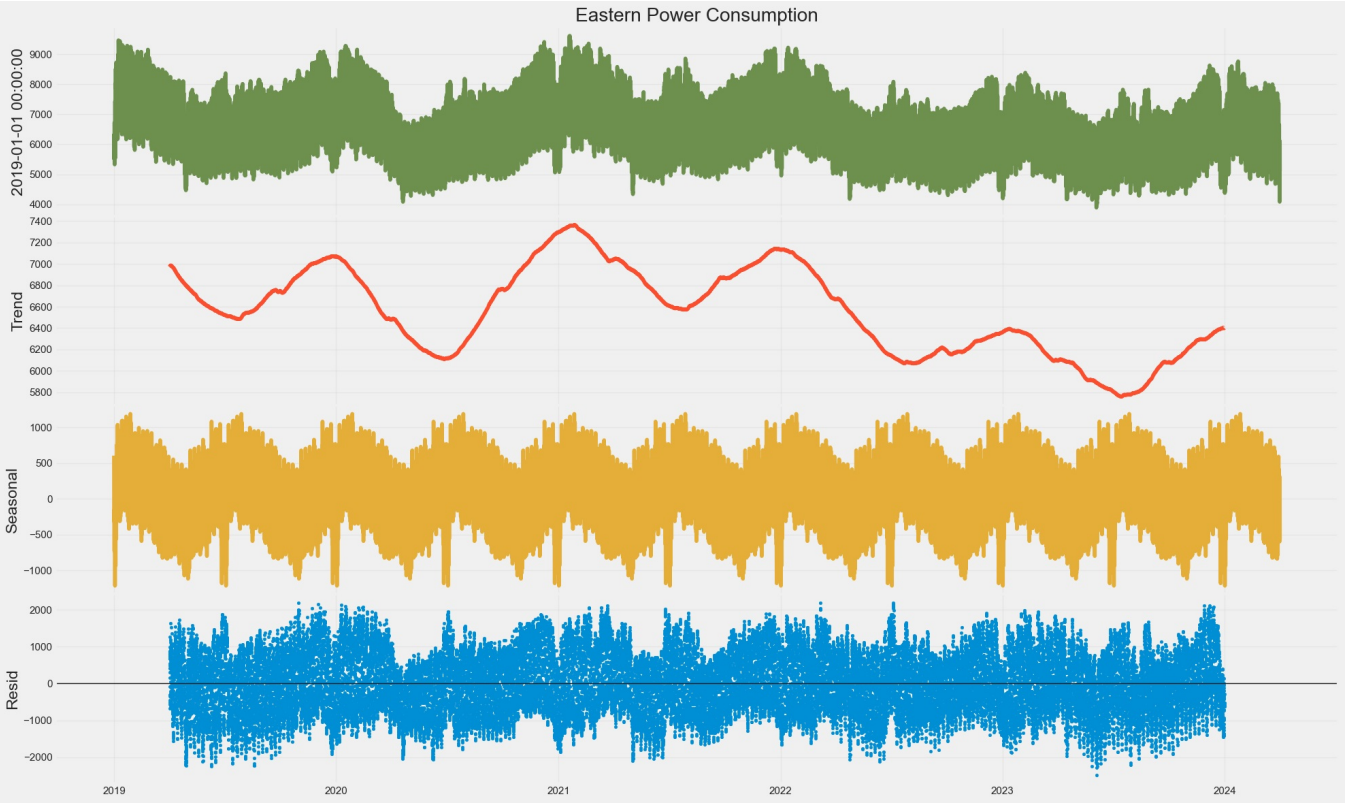
2. Blue Line: This line represents the electricity generation trend over the month. It also seems to fluctuate, and it's possible that the generation may not always keep up with consumption (indicated by the red line going above the blue line in some areas).

In [41]:
```
plt.style.use('fivethirtyeight')
df_con_pro = df_con.pivot_table(values=['Solar'], index='TIME', columns='DATE')

def Daywise_plot(data=None, row=None, col=None, title='Solar Power Generation', ylim_top=1000):
    """
    Plots timeseries data for each column in a grid layout.

    Args:
        data: A pandas DataFrame containing the timeseries data.
        row: Number of rows in the grid layout (optional).
        col: Number of columns in the grid layout (optional).
        title: Title for the overall plot (optional).
        ylim_top: Upper limit for the y-axis (optional, default: 8000).
    """
    cols = data.columns.levels[1]  # Get all column names

    # Create the figure with desired size
    gp = plt.figure(figsize=(20, 40))

    # Adjust spacing between subplots
    gp.subplots_adjust(wspace=0.2, hspace=0.5)

    for i in range(1, len(cols) + 1):
        ax = gp.add_subplot(row, col, i)
        data['Solar', cols[i - 1]].plot(ax=ax, color='red', label='Solar')

        # Set title and y-axis limit for each subplot
        ax.set_title('{} {}'.format(title, cols[i - 1]), color='#800000')
        ax.set_ylim(0, 1000)  # Update y-axis limit to 4000-8000
        ax.legend()  # Show legend

    # Display the plot
    plt.show()

# Call the function with desired parameters and new y-axis limit
Daywise_plot(data=df_con_pro, row=12, col=3, ylim_top=1000)
```



In [42]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

def seasonal_decompose_plotter(df: pd.DataFrame, period=12, title='', figsize=(20, 12)):
```

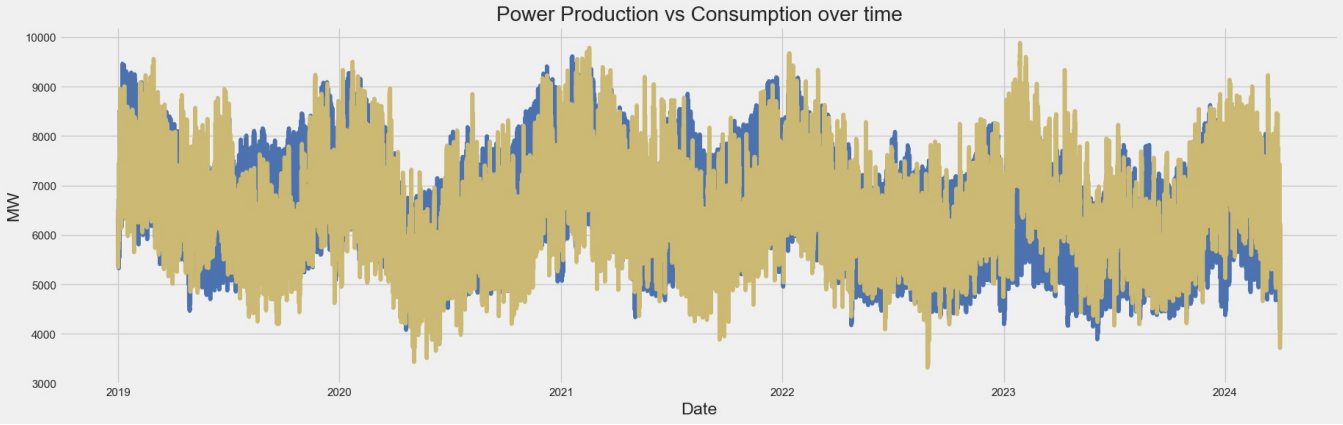
```
    """
    Perform and plot seasonal decomposition of a time series.

    Parameters:
        df: DataFrame with time series data.
        col: Column name for data to decompose. Default is 'sqrt(O3 AQI)'.
        date_col: Column name for datetime values. Default is 'Date'.
        period: Seasonality period. Default is 12.

    Returns:
        A DecomposeResult object with seasonal, trend, and residual components.
    """
    # Decompostion
    decomposition = seasonal_decompose(df.values, period=period)
    de_season = decomposition.seasonal
    de_resid = decomposition.resid
    de_trend = decomposition.trend

    fig, ax = plt.subplots(4, sharex=True, figsize=figsize)

    ax[0].set_title(title)
    ax[0].plot(df.index, df.values, color='C3')
    ax[0].set_ylabel(df.keys()[0])
    ax[0].grid(alpha=0.25)

    ax[1].plot(df.index, de_trend, color='C1')
    ax[1].set_ylabel('Trend')
    ax[1].grid(alpha=0.25)

    ax[2].plot(df.index, de_season, color='C2')
    ax[2].set_ylabel('Seasonal')
    ax[2].grid(alpha=0.25)

    ax[3].axhline(y=0, color='k', linewidth=1)
    ax[3].scatter(df.index, de_resid, color='C0', s=10)
    ax[3].set_ylabel('Resid')
    ax[3].grid(alpha=0.25)

    plt.tight_layout(h_pad=0)
    plt.show()

    return decomposition

data1 = df[['DateTime','Consumption']].copy("deep")
data1 = data1.set_index('DateTime')

_ = seasonal_decompose_plotter(data1['Consumption'], period=365*12, title='Eastern Power Consumption', figsize=
```



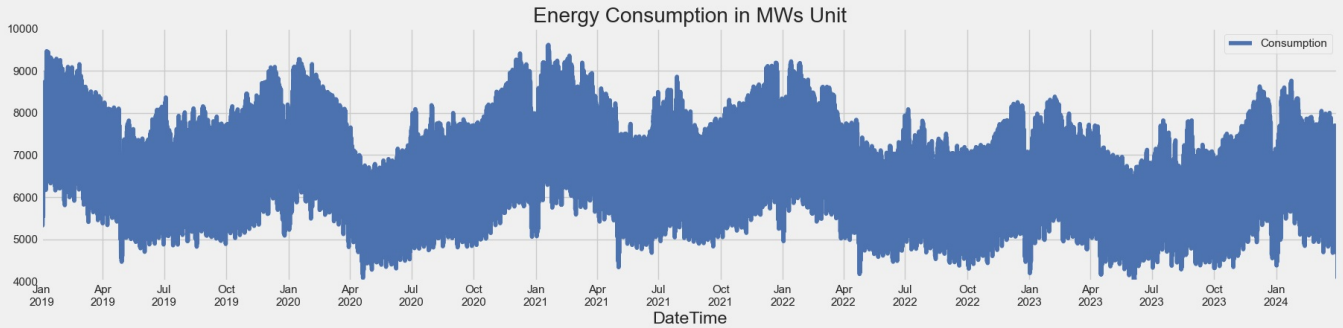
In [43]:
```
data = df.copy("deep")
data = data.set_index('DateTime')
```

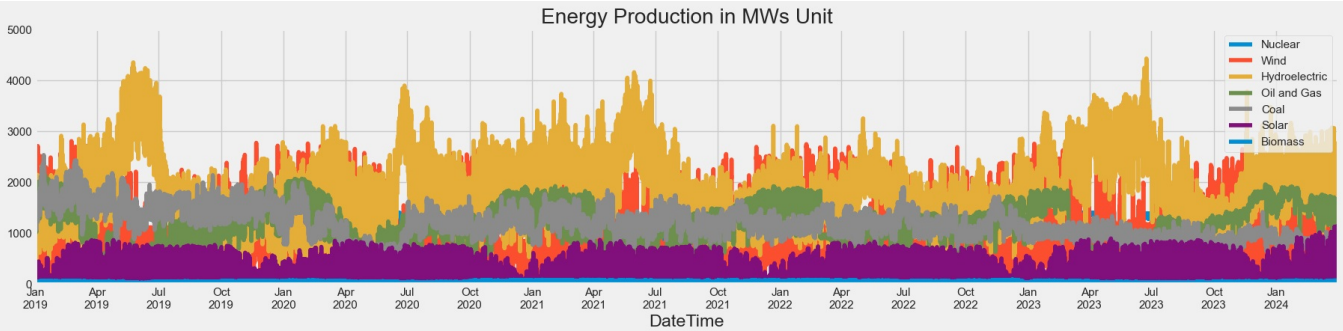
In [44]:
```
plt.figure(figsize=(20,6))
plt.plot(data.index,data['Consumption'], 'b')
plt.plot(data.index,data['Production'], 'y')
plt.title('Power Production vs Consumption over time')
```

```
plt.xlabel('Date')
plt.ylabel('MW')
plt.show()
```



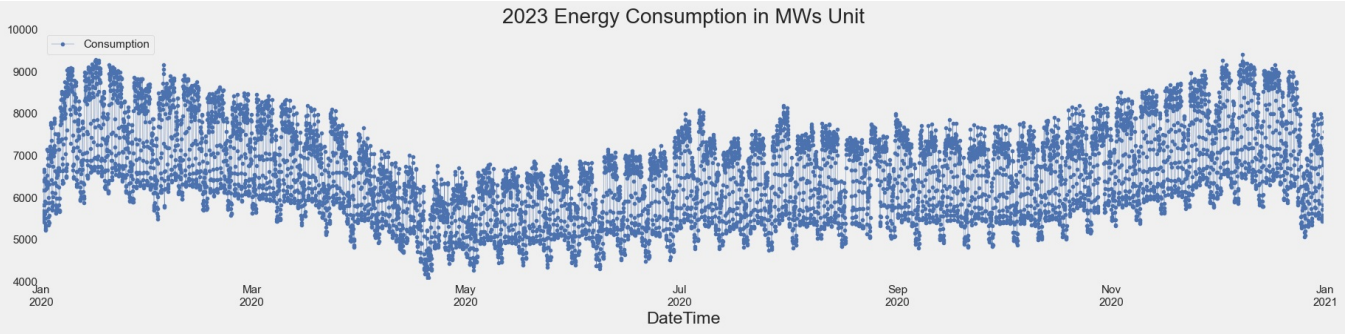
In [45]:
```
import matplotlib.pyplot as plt
from matplotlib.dates import MonthLocator, DateFormatter

# Assuming your data is in a pandas DataFrame named 'data'

# Plot for Consumption
ax = data.plot(figsize=(20, 5), use_index=True, grid=True,
               y='Consumption',
               title='Energy Consumption in MWs Unit',
               ylim=([4000, 10000]),
               xlim=([data.index[0], data.index[-1]]),
               style='b-')

# Set x-axis labels with monthly formatting
ax.set_xticklabels(data.index, rotation=0, ha='center')
ax.xaxis.set_major_locator(MonthLocator(bymonth=(1, 4, 7, 10)))
ax.xaxis.set_major_formatter(DateFormatter('%b\n%Y'))

plt.show()

# Plot for Production (assuming 'Nuclear' etc. are columns in data)
ay = data.plot(figsize=(20, 5), use_index=True, grid=True,
               y=['Nuclear', 'Wind', 'Hydroelectric', 'Oil and Gas', 'Coal', 'Solar', 'Biomass'],
               title='Energy Production in MWs Unit',
               ylim=([0, 5000]),
               xlim=([data.index[0], data.index[-1]]))

# Set x-axis labels with monthly formatting
ay.set_xticklabels(data.index, rotation=0, ha='center')
ay.xaxis.set_major_locator(MonthLocator(bymonth=(1, 4, 7, 10)))
ay.xaxis.set_major_formatter(DateFormatter('%b\n%Y'))

plt.show()
```





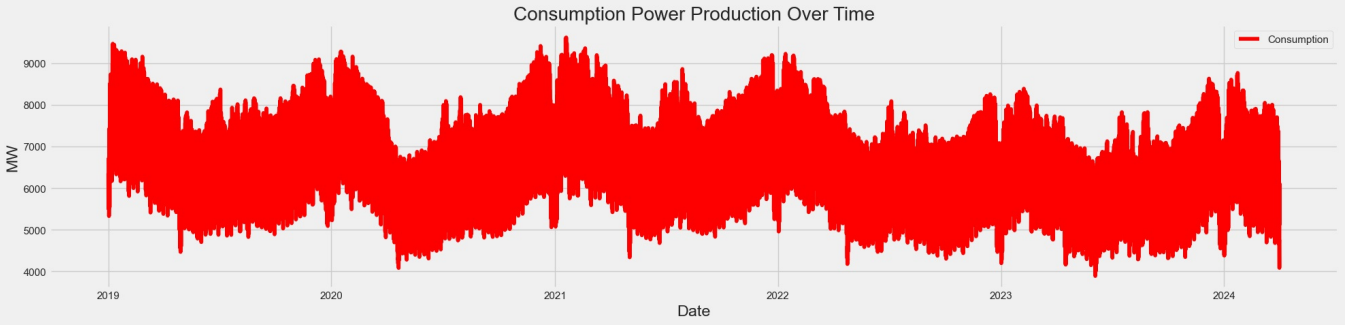
In [46]:
```
ax = data.plot(figsize=(20,5),use_index=True,grid=False,
               y='Consumption',
               title='2023 Energy Consumption in MWs Unit',
               ylim=([4000,10000]),
```

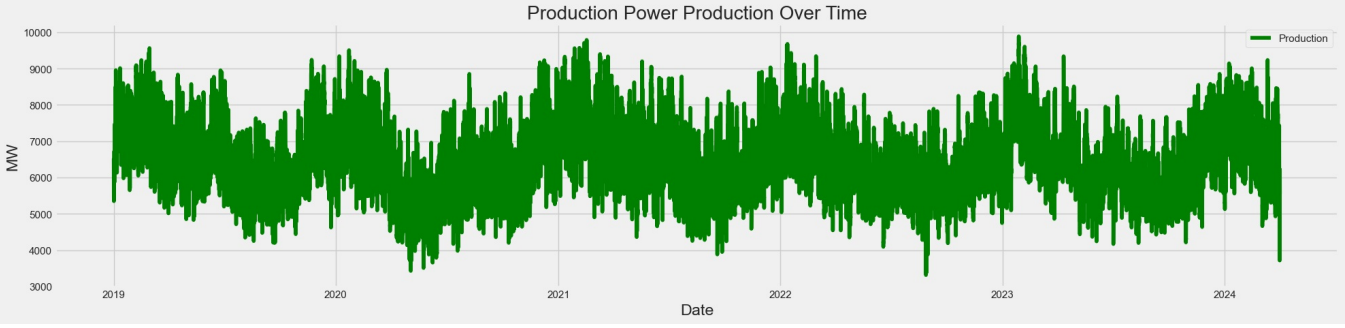
```
                xlim=([pd.Timestamp('2020-01-01'),pd.Timestamp('2021-01-01')]),
                style='b.-',lw=0.3)

ax.set_xticklabels(data.index,rotation=0,ha='center')
ax.xaxis.set_major_locator(MonthLocator(interval=2))
ax.xaxis.set_major_formatter(DateFormatter('%b\n%Y'))

plt.show()
```

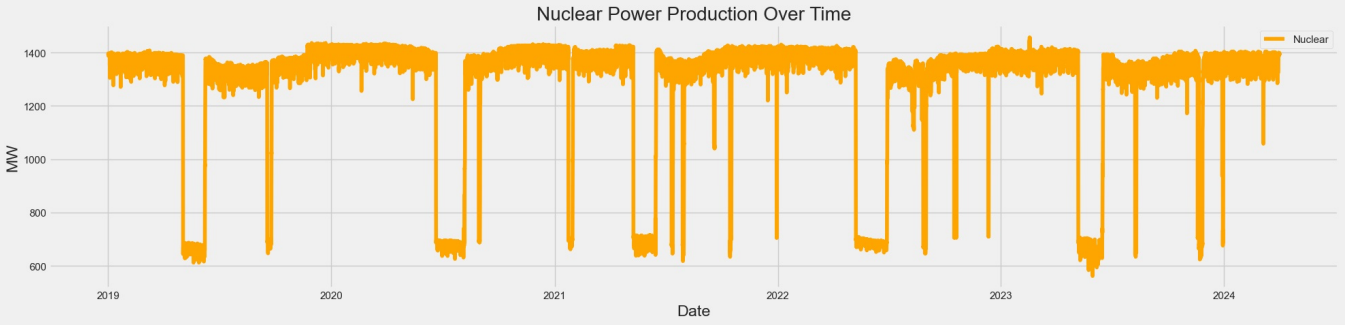


In [47]:

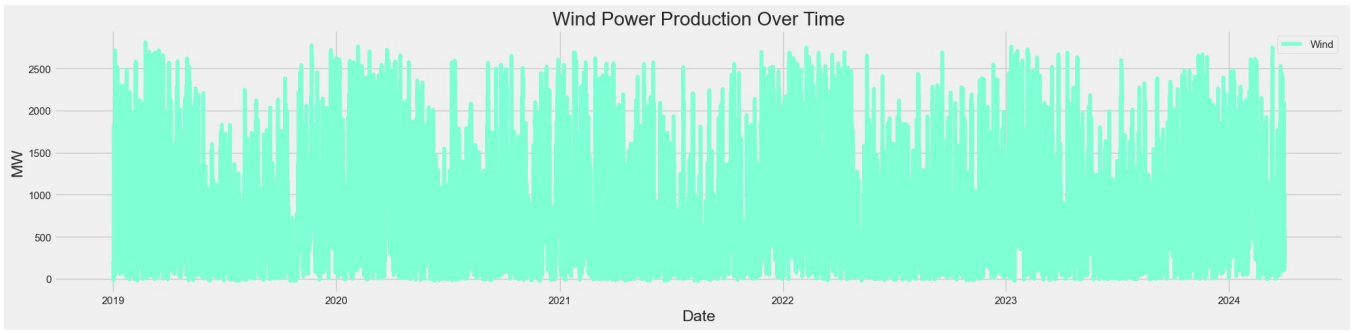
```
production_types = list(data.columns)  # Get all columns from index 2 onwards (skipping the first two)

# Dictionary of production type and color mapping
colors = {'Consumption' : 'Red', 'Production' : 'Green' , 'Nuclear': 'orange', 'Wind': 'aquamarine', 'Hydroelec
          'Oil and Gas': 'saddlebrown', 'Coal': 'black', 'Solar': 'y', 'Biomass': 'crimson'}

# Loop through production types and create separate plots
for prType in production_types:
    plt.figure(figsize=(20, 5))  # Adjust figure size as desired
    plt.plot(data.index, data[prType], color=colors[prType], label=prType)  # Add label
    plt.title(f"{prType} Power Production Over Time")
    plt.xlabel("Date")
    plt.ylabel("MW")
    plt.legend()  # Add legend to identify each line
    plt.grid(True)  # Add grid lines for better readability (optional)
    plt.tight_layout()  # Adjust spacing to prevent overlapping elements (optional)
    plt.show()
```

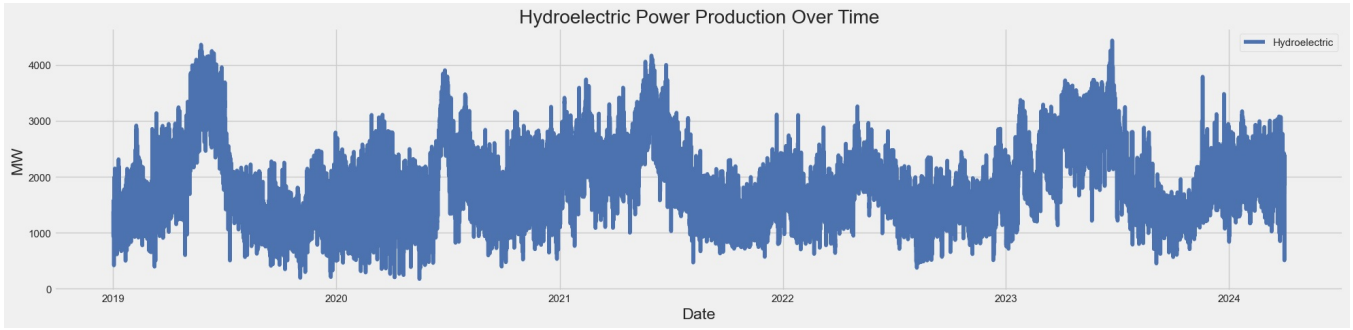


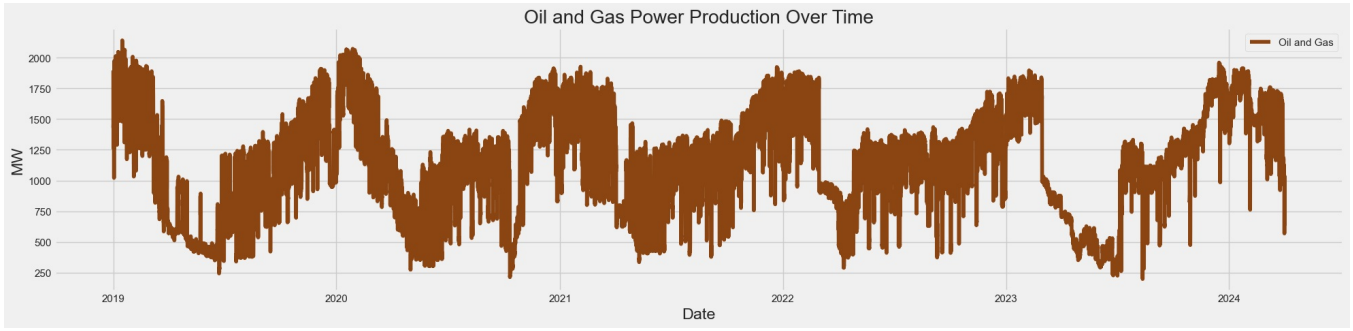


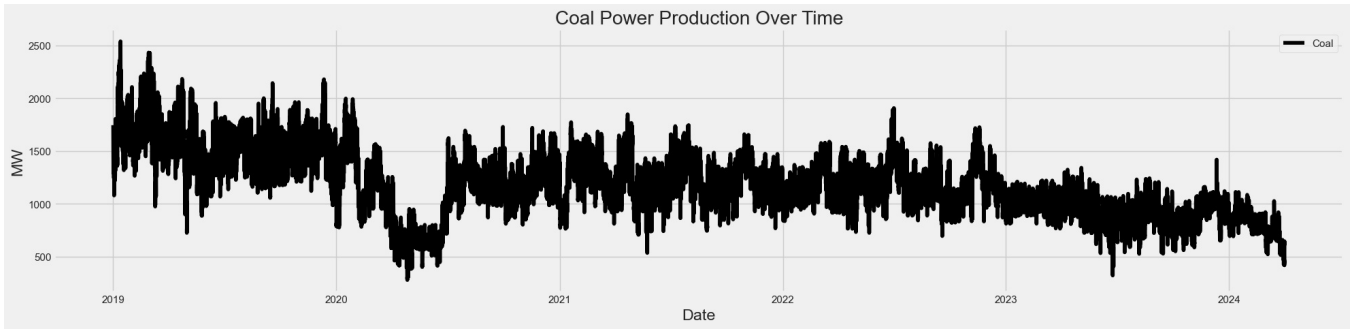


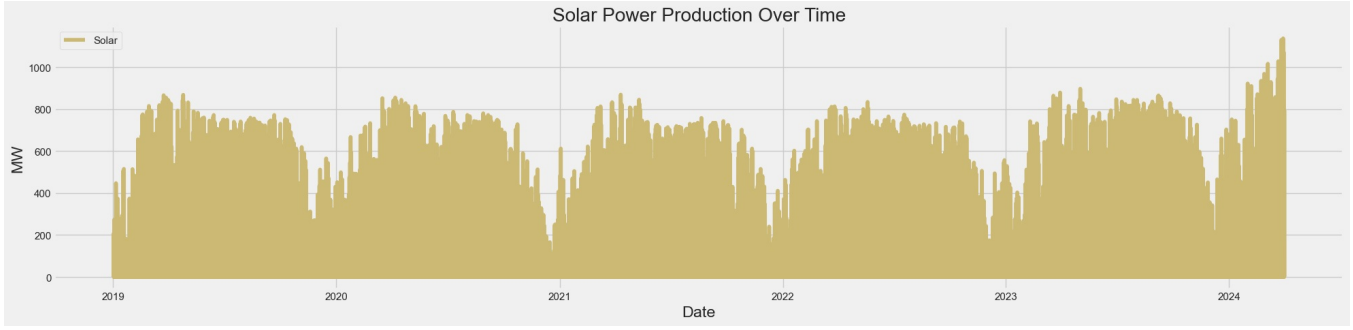
Code + Data :https://t.me/AIMLDeepThaught/555

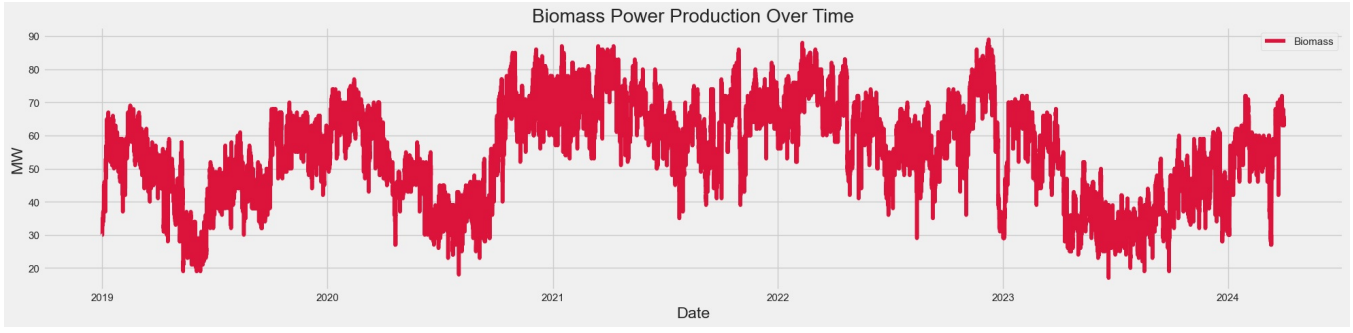

Wind Power Production Over Time
Wind
MW
Date
2019
2020
2021
2022
2023
2024


Hydroelectric Power Production Over Time
Hydroelectric
MW
Date
2019
2020
2021
2022
2023
2024


Oil and Gas Power Production Over Time
Oil and Gas
MW
Date
2019
2020
2021
2022
2023
2024


Coal Power Production Over Time
Coal
MW
Date
2019
2020
2021
2022
2023
2024

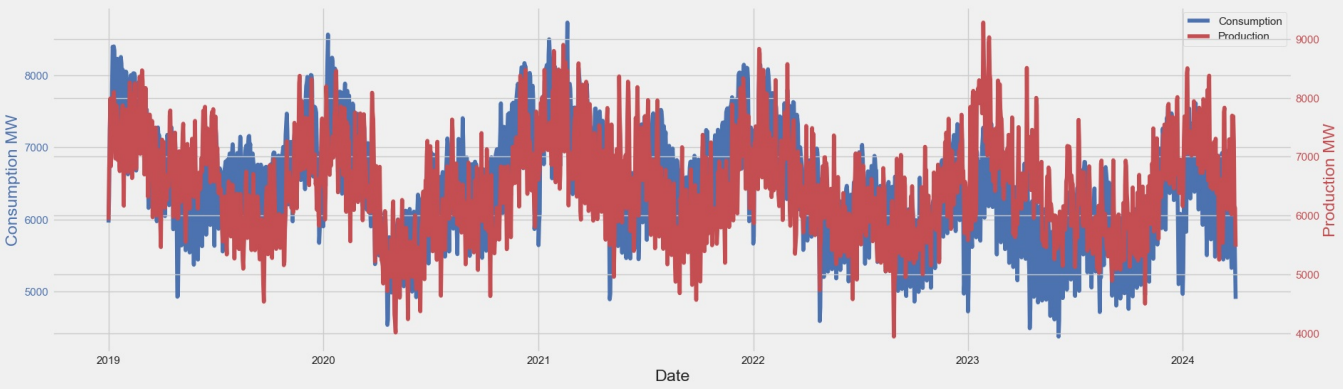

Solar Power Production Over Time
Solar
MW
Date
2019
2020
2021
2022
2023
2024


Biomass Power Production Over Time
Biomass
MW
Date
2019
2020
2021
2022
2023
2024

In [48]:
```
df3 = df_solar[['DateTime','Consumption','Production']]

df3 = df3.set_index('DateTime')
daily_data = df3.resample('24h').mean()
display(daily_data.head(2))
```

DateTime	Consumption	Production
2019-01-01	5957.666667	5924.416667
2019-01-02	6322.041667	6795.708333

In [49]:
```
fig, ax1 = plt.subplots(figsize=(20,6))
ax1.plot(daily_data.index, daily_data['Consumption'], 'b', label='Consumption')
ax1.set_xlabel('Date')
ax1.set_ylabel('Consumption MW', color='b')
ax1.tick_params('y', colors='b')

ax2 = ax1.twinx()

ax2.plot(daily_data.index, daily_data['Production'], 'r', label='Production')
ax2.set_ylabel('Production MW', color='r')
ax2.tick_params('y', colors='r')

lines1, labels1 = ax1.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
lines = lines1 + lines2
labels = labels1 + labels2
ax1.legend(lines, labels, loc='upper right')
plt.show()
```



In [50]:
```
#group data by week
groups = df_con['Consumption'].groupby(pd.Grouper(freq='W'))

#set figure and axis
fig, axs = plt.subplots(len(groups), 1, figsize=(20,30))
for ax, (name, group) in zip(axs, groups):

    #plot the data
    ax.plot(pd.Series(group.values))

    ax.set_xlabel('Hour of Year')
    ax.set_ylabel('Consumption')
    ax.set_title(name.week)
    plt.subplots_adjust(hspace=0.5)
```

Power Consumption by Day of the Week

In [51]:
```
df6 = df[['DateTime','Consumption','Production']]
df6 = df6.set_index('DateTime')
df6.head()
```

Code + Data :https://t.me/AIMLDeepThaught/555

Out[51]:

DateTime	Consumption	Production
2019-01-01 00:00:00	6352	6527
2019-01-01 01:00:00	6116	5701
2019-01-01 02:00:00	5873	5676
2019-01-01 03:00:00	5682	5603
2019-01-01 04:00:00	5557	5454

In [52]:
```
df6['Day'] = df6.index.day
df6['Year'] = df6.index.year
df6['Month'] = df6.index.month_name()
df6['WeekDay'] = df6.index.day_name()
df6.head()
```

Out[52]:

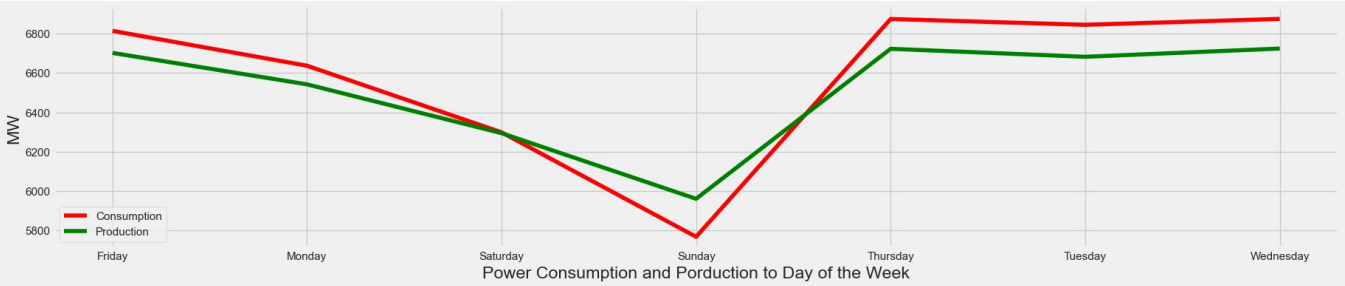
DateTime	Consumption	Production	Day	Year	Month	WeekDay
2019-01-01 00:00:00	6352	6527	1	2019	January	Tuesday
2019-01-01 01:00:00	6116	5701	1	2019	January	Tuesday
2019-01-01 02:00:00	5873	5676	1	2019	January	Tuesday
2019-01-01 03:00:00	5682	5603	1	2019	January	Tuesday
2019-01-01 04:00:00	5557	5454	1	2019	January	Tuesday

In [53]:
```
dfbyDay = df6.drop('Month',axis=1).groupby('WeekDay').mean()
dfbyDay.head()
```

Out[53]:

WeekDay	Consumption	Production	Day	Year
Friday	6814.832725	6702.620894	15.580292	2021.142336
Monday	6637.362332	6542.623474	15.739927	2021.142857
Saturday	6298.403437	6294.190389	15.686131	2021.145985
Sunday	5766.934793	5960.282110	15.804682	2021.148807
Thursday	6875.098844	6723.519009	15.791971	2021.138686

In [54]:
```
plt.figure(figsize=(20,4))
plt.plot(dfbyDay.index, dfbyDay['Consumption'], 'Red')
plt.plot(dfbyDay.index, dfbyDay['Production'], 'Green')
plt.xlabel('Power Consumption and Porduction to Day of the Week')
plt.ylabel('MW')
plt.legend(['Consumption','Production'])
plt.show()
```



Power Consumption by Month

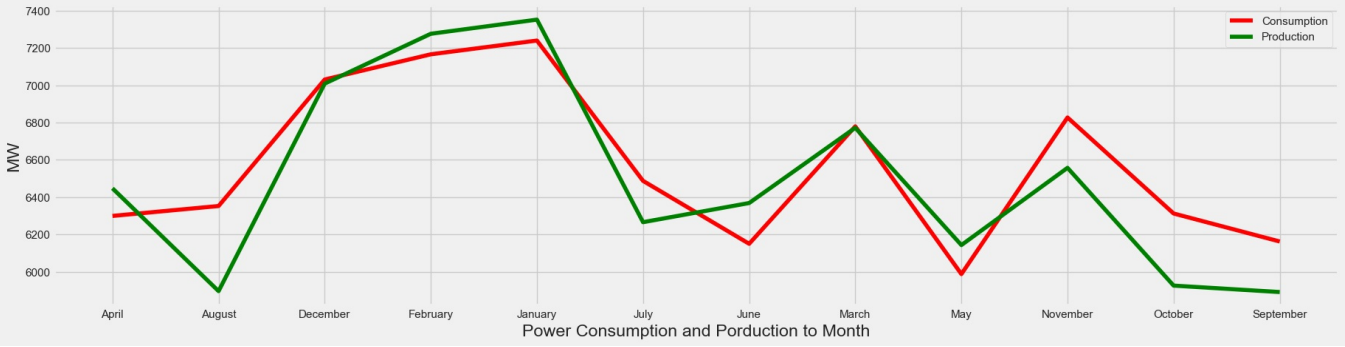
In [55]:
```
dfbyMonth = df6.drop('WeekDay',axis=1).groupby('Month').mean()
dfbyMonth.head()
```

Out[55]:

Month	Consumption	Production	Day	Year
April	6300.157500	6447.891389	15.500000	2021.000000
August	6353.122581	5897.455376	16.000000	2021.000000
December	7030.345161	7008.483065	16.000000	2021.000000
February	7165.422794	7275.392402	14.670588	2021.505882
January	7239.078629	7351.026434	16.000000	2021.500000

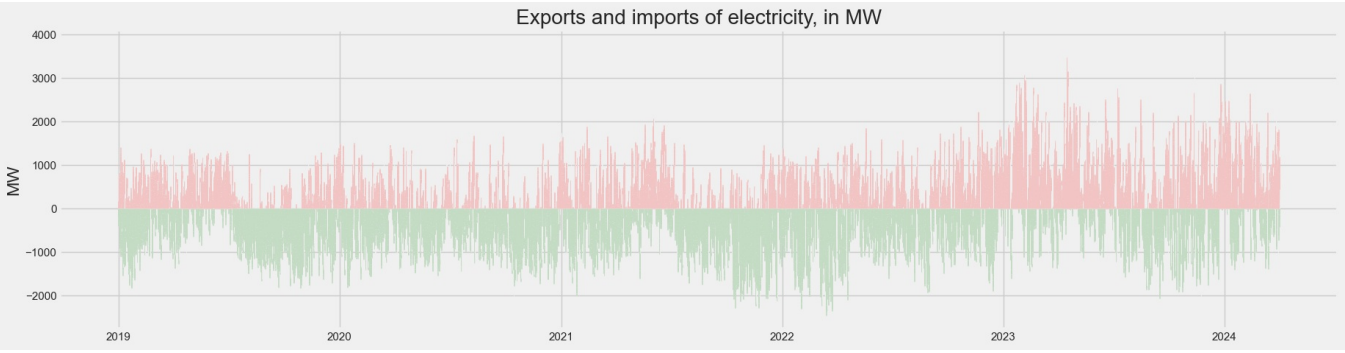
In [56]:
```
plt.figure(figsize=(20,5))
```

In [56]:
```
plt.figure(figsize=(20,5))
plt.plot(dfbyMonth.index, dfbyMonth['Consumption'], 'Red')
plt.plot(dfbyMonth.index, dfbyMonth['Production'], 'Green')
plt.xlabel('Power Consumption and Porduction to Month')
plt.ylabel('MW')
plt.legend(['Consumption','Production'])
plt.show()
```



Electricity Consumption and Production

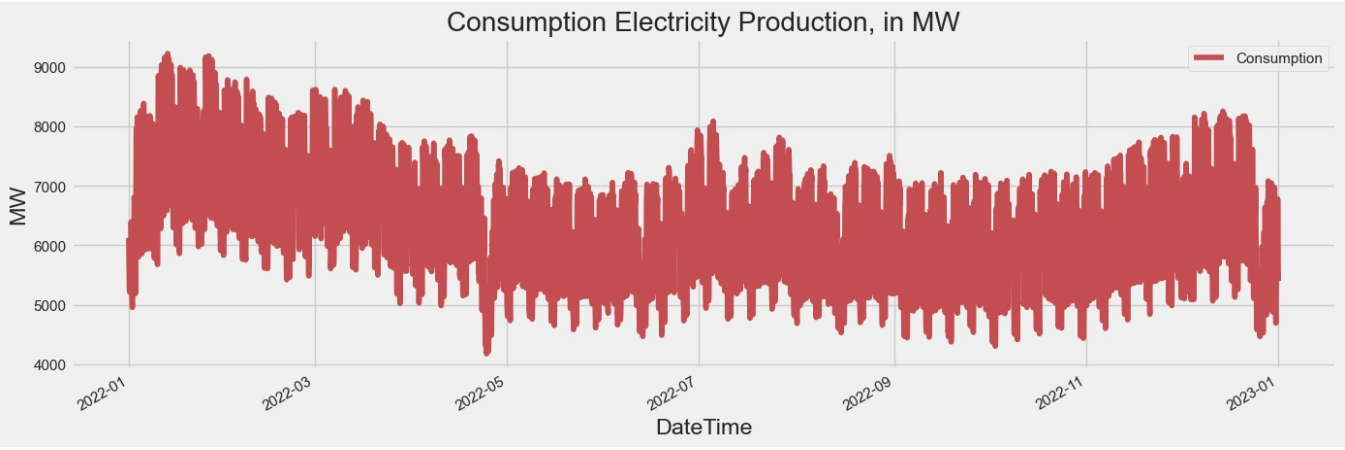
In [57]:
```
%%time
# add a new column for the delta
df6["delta"] = df6["Production"] - df6["Consumption"]

plt.rcParams["figure.figsize"] = (20,5)

plt.bar(
    df6.index, df6['delta'],
    color=np.where(df6['delta'] > 0, 'Red', 'Green')
)

plt.title("Exports and imports of electricity, in MW")
plt.ylabel('MW')
plt.show()

# drop the column we have used for the delta
df6.drop(["delta"], axis=1, inplace=True)
```

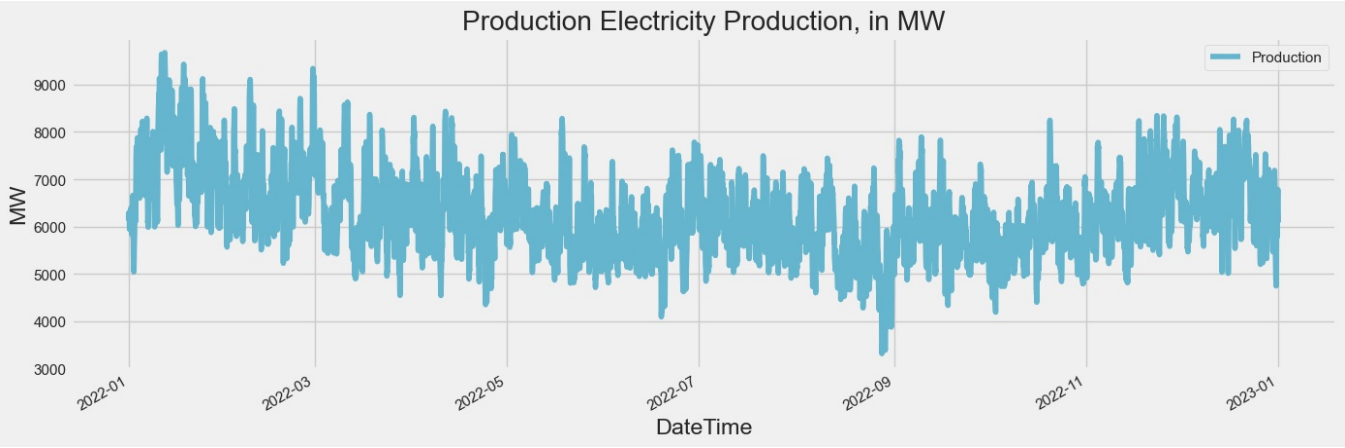



```
CPU times: total: 1min 28s
Wall time: 1min 33s
```

Specific time Electricity Production and Consumption

In [58]:
```
dfYear = df6["2022-01-01 00:00:00" : "2022-12-31 23:59:59"]
productionTypes = ['Consumption', 'Production']

colorMap = {"Consumption":"r", "Production":"c"}

for productionType in productionTypes:
    dfYear[[productionType]].plot(style="-", figsize=(15, 5), title=f"{productionType} Electricity Production,
    plt.ylabel('MW')
    plt.show()
```





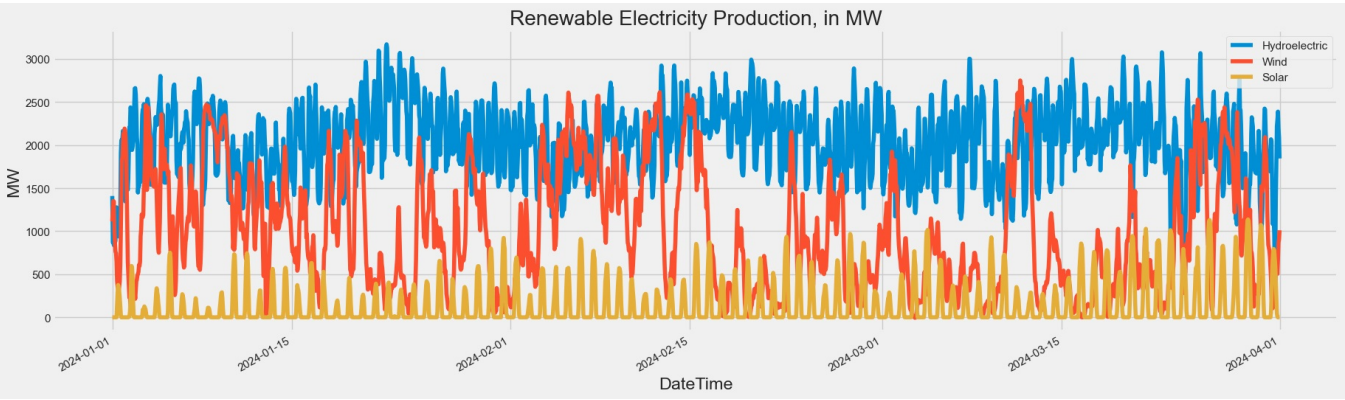
Specific features and Specific date plot

In [59]:
```
df7 = df[['DateTime','Consumption','Production',"Hydroelectric", "Wind", "Solar"]]
df7 = df7.set_index('DateTime')
df7.head()
```

Out[59]:

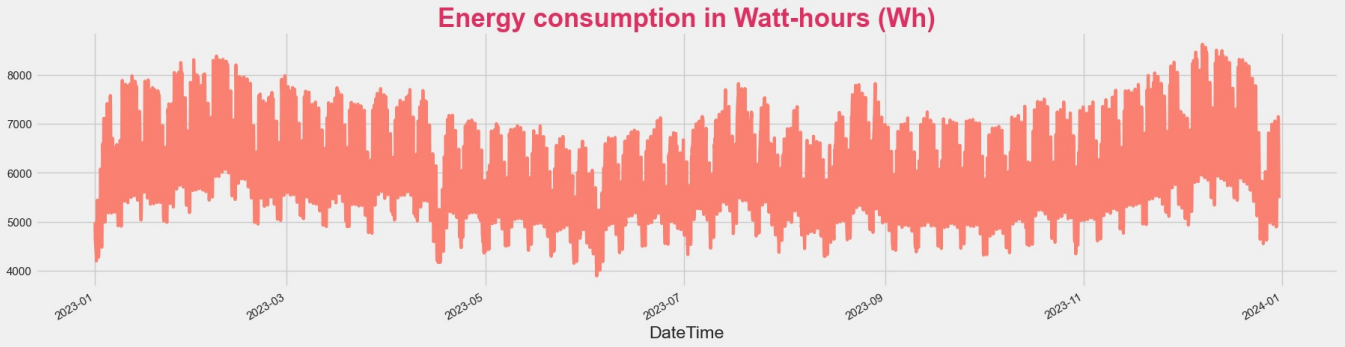
DateTime	Consumption	Production	Hydroelectric	Wind	Solar
2019-01-01 00:00:00	6352	6527	1383	79	0
2019-01-01 01:00:00	6116	5701	1112	96	0
2019-01-01 02:00:00	5873	5676	1030	142	0
2019-01-01 03:00:00	5682	5603	972	191	0
2019-01-01 04:00:00	5557	5454	960	159	0

In [60]:
```
df_winter = df7[["Hydroelectric", "Wind", "Solar"]]["2024-01-01" : "2024-03-31"]
df_winter.plot(style="-", figsize=(20, 6), title=f"Renewable Electricity Production, in MW")
plt.ylabel('MW')
plt.show()
```



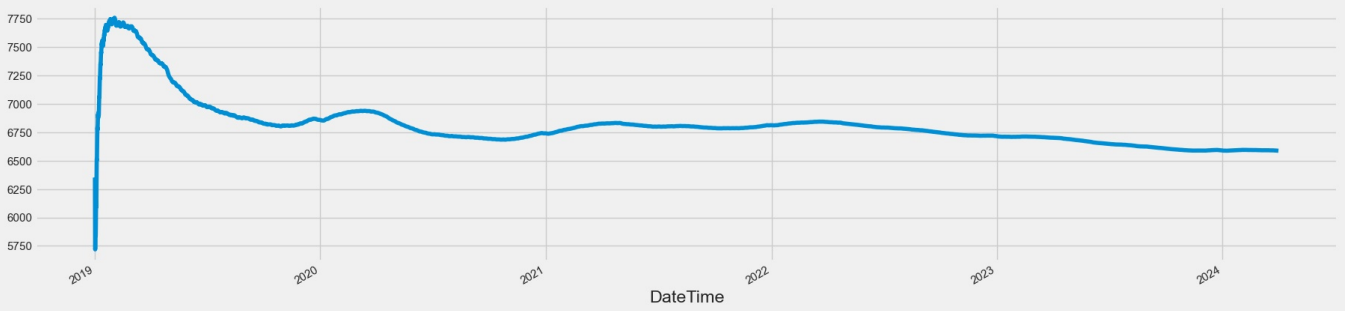
Specific Date Plot

In [61]:
```
df_2023 = df7["Consumption"][(df7["Consumption"].index >= '2023-01-01') & (df7["Consumption"].index < '2023-12-
df_2023.plot(figsize=(20,5), lw=3,color = '#FA8072')
plt.title('Energy consumption in Watt-hours (Wh)', weight='bold', fontsize=25,color = '#DE3163');
```

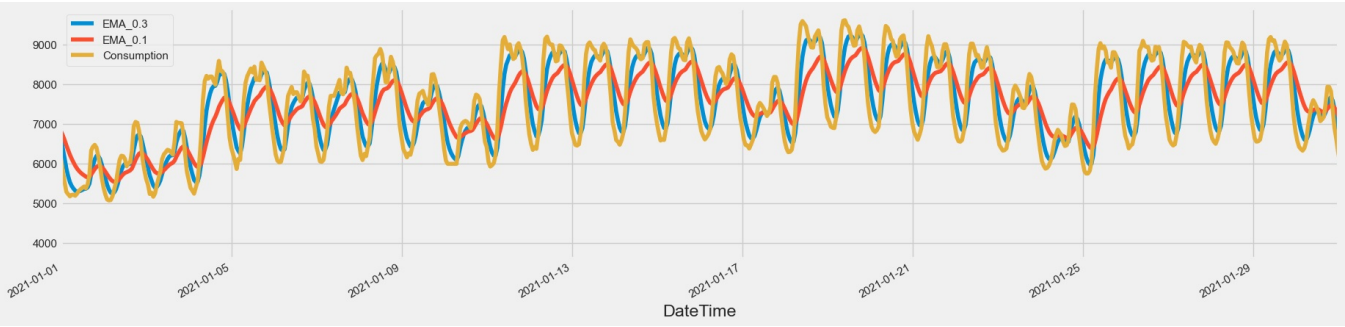


Moving Average

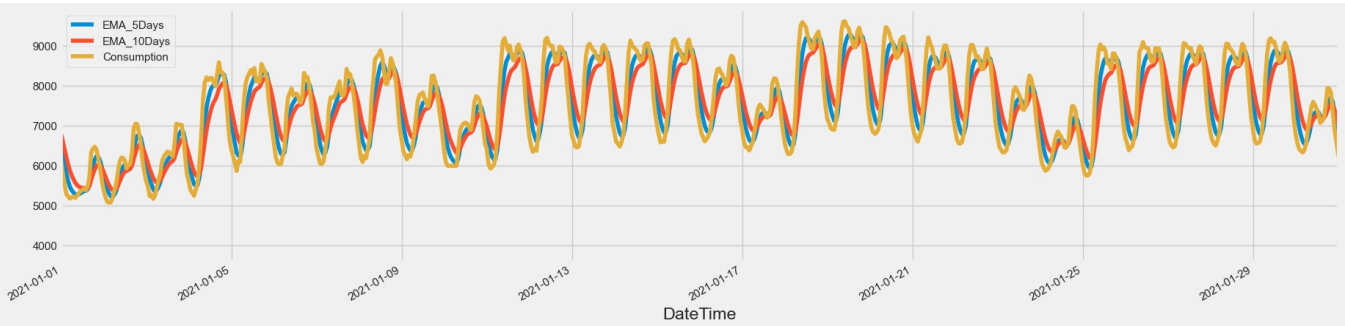
In [62]:
```
# Simple Moving Average
df7["Consumption"].expanding().mean().plot(figsize=(20,5));
```



In [63]:
```
# Moving Average (Smoothening Factor 0.1)
df7['EMA_0.1'] = df7['Consumption'].ewm(alpha=0.1,adjust=False).mean()
df7['EMA_0.3'] = df7['Consumption'].ewm(alpha=0.3,adjust=False).mean()
df7[['EMA_0.3','EMA_0.1','Consumption']].plot(figsize=(20,5),xlim=['2021-01-01','2021-01-31']);
```



In [64]:
```
# Span
df7['EMA_5Days'] = df7['Consumption'].ewm(span=5,adjust=False).mean()
df7['EMA_10Days'] = df7['Consumption'].ewm(span=10,adjust=False).mean()
df7[['EMA_5Days','EMA_10Days','Consumption']].plot(figsize=(20,5),xlim=['2021-01-01','2021-01-31']);
```



adfuller Test

In [65]:
```
from statsmodels.tsa.stattools import adfuller

def adf_test(series):
    result=adfuller(series)
    print('ADF Statistics: {}'.format(result[0]))
    print('p- value: {}'.format(result[1]))
    if result[1] <= 0.05:
        print("strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root a
    else:
        print("weak evidence against null hypothesis, time series has a unit root, indicating it is non-station
```

In [66]:
```
adf_test(df7['Consumption'])
```

```
ADF Statistics: -13.926470911140704
p- value: 5.18213926141328e-26
strong evidence against the null hypothesis, reject the null hypothesis. Data has no unit root and is stationar
y
```

In [67]:
```
df2.head(2)
```

Out[67]:

DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar	Biomass
2019-01-01 00:00:00	6352	6527	1395	79	1383	1896	1744	0	30
2019-01-01 01:00:00	6116	5701	1393	96	1112	1429	1641	0	30

Correlation

In [68]:
```
# Computing Correlation Matrices
from scipy.stats.stats import pearsonr
from scipy.stats.stats import spearmanr
from scipy.stats.stats import kendalltau

corr_p = df2[['Consumption', 'Nuclear','Coal', 'Solar']].corr(method='pearson')
print('Pearson correlation matrix')
print(corr_p)
print("\n")
corr_s = df2[['Consumption', 'Nuclear','Coal', 'Solar']].corr(method='spearman')
print('Spearman correlation matrix')
print(corr_s)
```

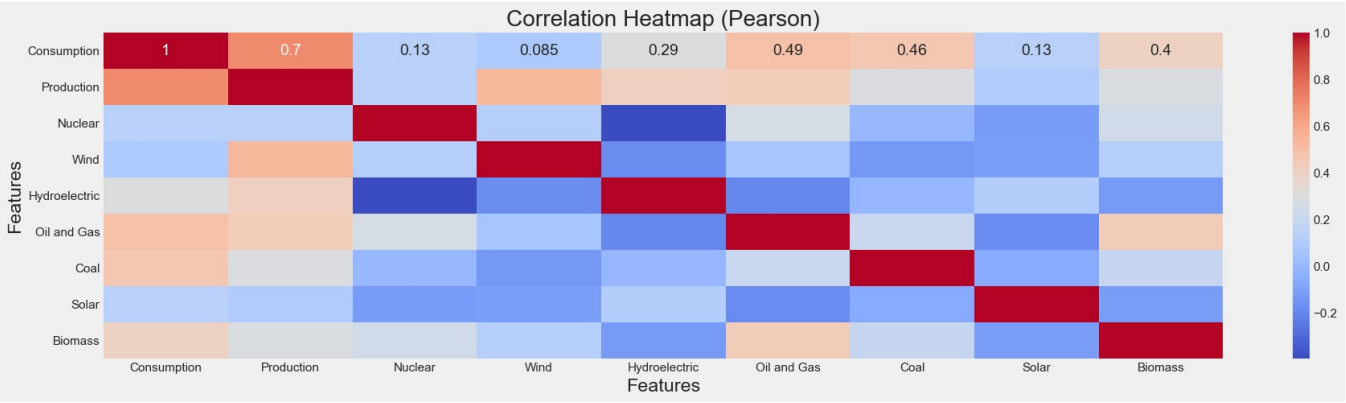
```
Pearson correlation matrix
             Consumption   Nuclear      Coal     Solar
Consumption     1.000000  0.127617  0.461859  0.126887
Nuclear         0.127617  1.000000 -0.008732 -0.128614
Coal            0.461859 -0.008732  1.000000 -0.066005
Solar           0.126887 -0.128614 -0.066005  1.000000


Spearman correlation matrix
             Consumption   Nuclear      Coal     Solar
Consumption     1.000000  0.010702  0.451529  0.254557
Nuclear         0.010702  1.000000 -0.084438 -0.316097
Coal            0.451529 -0.084438  1.000000 -0.025992
Solar           0.254557 -0.316097 -0.025992  1.000000
```

In [114…
```
df2.head()
```

Out[114]:

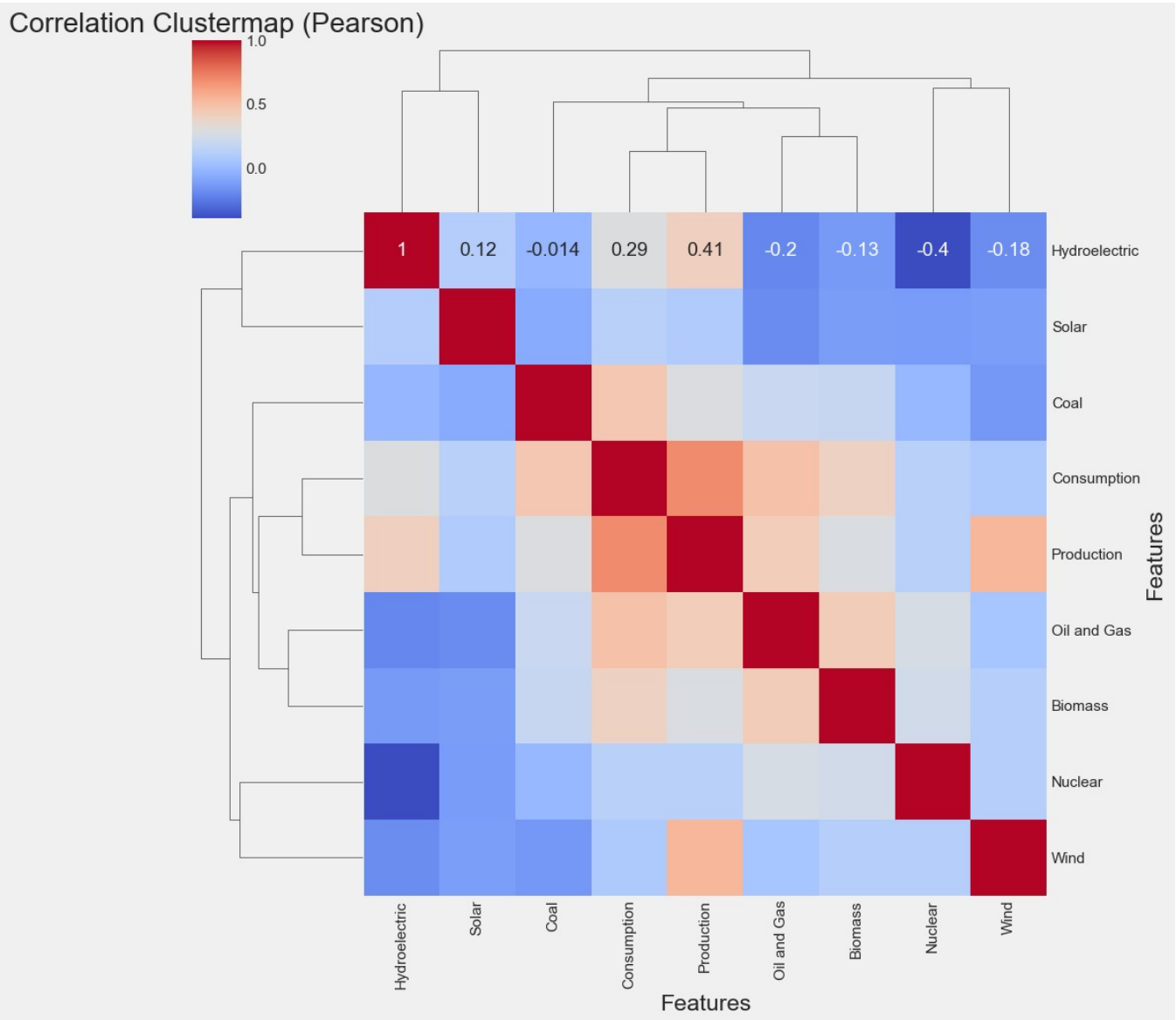
DateTime	Consumption	Production	Nuclear	Wind	Hydroelectric	Oil and Gas	Coal	Solar	Biomass
2019-01-01 00:00:00	6352	6527	1395	79	1383	1896	1744	0	30
2019-01-01 01:00:00	6116	5701	1393	96	1112	1429	1641	0	30
2019-01-01 02:00:00	5873	5676	1393	142	1030	1465	1616	0	30
2019-01-01 03:00:00	5682	5603	1397	191	972	1455	1558	0	30
2019-01-01 04:00:00	5557	5454	1393	159	960	1454	1458	0	30

In [115…
```
import seaborn as sns
import matplotlib.pyplot as plt

corr_mat = df2.corr(method='pearson')

# Add annotation for correlation values
sns.heatmap(corr_mat, annot=True, cmap='coolwarm')

# Additional customizations (optional)
plt.title("Correlation Heatmap (Pearson)")
plt.xlabel("Features")
plt.ylabel("Features")

plt.show()
```



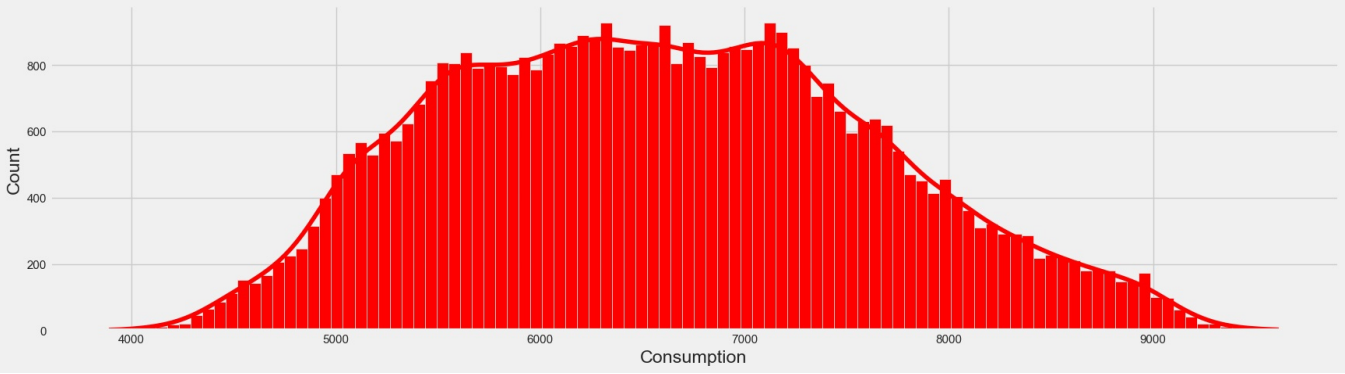
In [116…

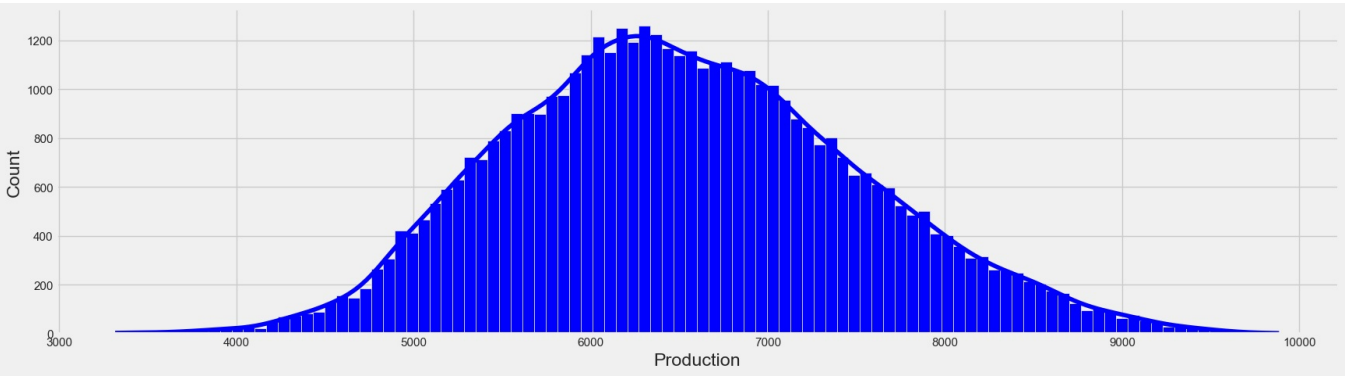
```
import seaborn as sns
import matplotlib.pyplot as plt

corr_mat = df2.corr(method='pearson')

# Create a clustermap with annotations
g = sns.clustermap(corr_mat, annot=True, cmap='coolwarm')

# Add title and labels
plt.title("Correlation Clustermap (Pearson)")
g.ax_heatmap.set_xlabel("Features")
g.ax_heatmap.set_ylabel("Features")

plt.show()
```



In [109…

```
# Create the first subplot with red color
ax1 = sns.displot(data=df, x="Consumption", kde=True, bins=100, color="red",
            facecolor="#FF0000", height=5, aspect=3.5)

# Create the second subplot on the same figure with blue color
ax2 = sns.displot(data=df, x="Production", kde=True, bins=100, color="blue",
            facecolor="#0000FF", height=5, aspect=3.5)
```





Differencing

In [71]:
```
monthly_data = df7.resample('M')['Consumption'].agg('mean')
monthly_data = monthly_data.reset_index()
df8 = monthly_data.set_index('DateTime')
df8.head()
```

Out[71]:

DateTime	Consumption
2019-01-31	7752.168011
2019-02-28	7605.071429
2019-03-31	6992.792732
2019-04-30	6652.491667
2019-05-31	6379.282258

In [72]:
```
## Use Techniques Differencing
df8['Consumption First Difference']= df8['Consumption'] - df8['Consumption'].shift(1)
df8.head()
```

Out[72]:

DateTime	Consumption	Consumption First Difference
2019-01-31	7752.168011	NaN
2019-02-28	7605.071429	-147.096582
2019-03-31	6992.792732	-612.278696
2019-04-30	6652.491667	-340.301066
2019-05-31	6379.282258	-273.209409

In [73]:
```
adf_test(df8['Consumption First Difference'].dropna())
```

```
ADF Statistics: -2.1379721278691894
p- value: 0.22952237850384044
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

In [74]:
```
### 12 months shift
## Use Techniques Differencing
df8['Consumption 12 Difference']=df8['Consumption']-df8['Consumption'].shift(12)
df8.head()
```

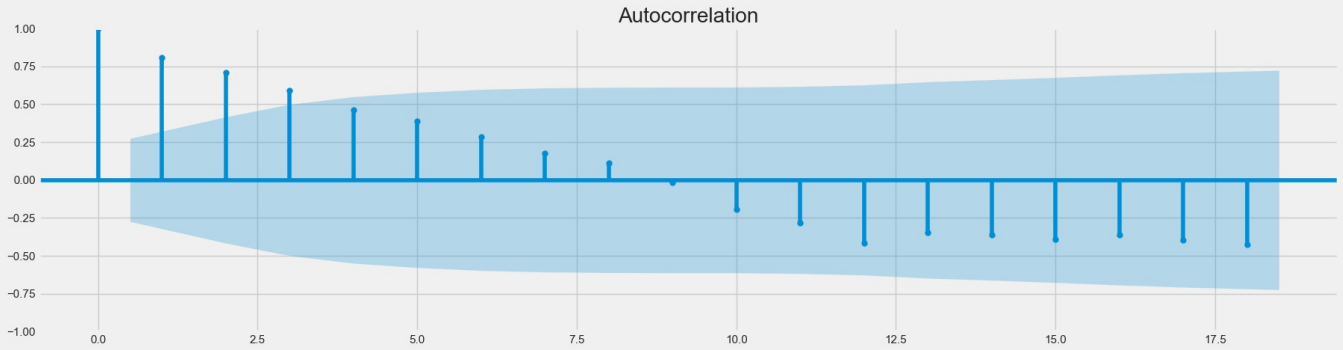
Out[74]:

DateTime	Consumption	Consumption First Difference	Consumption 12 Difference
2019-01-31	7752.168011	NaN	NaN
2019-02-28	7605.071429	-147.096582	NaN
2019-03-31	6992.792732	-612.278696	NaN
2019-04-30	6652.491667	-340.301066	NaN
2019-05-31	6379.282258	-273.209409	NaN

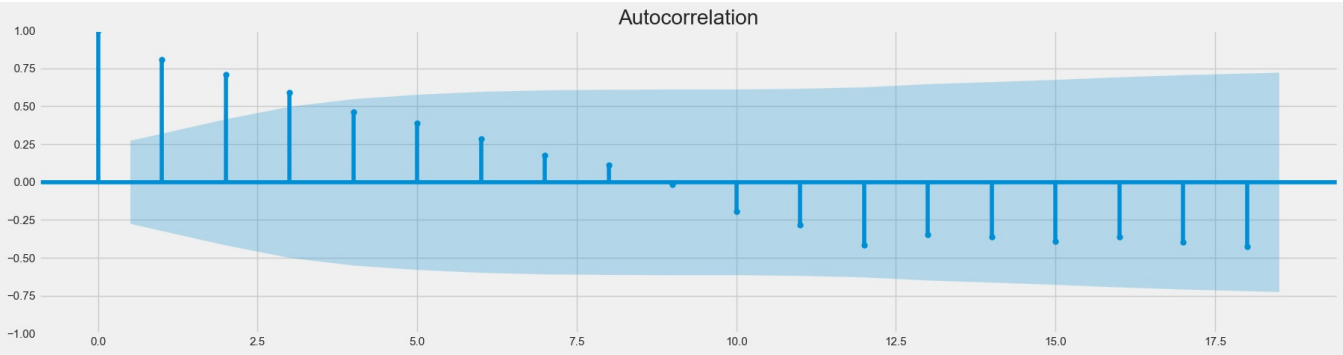
In [75]:
```
adf_test(df8['Consumption 12 Difference'].dropna())
```

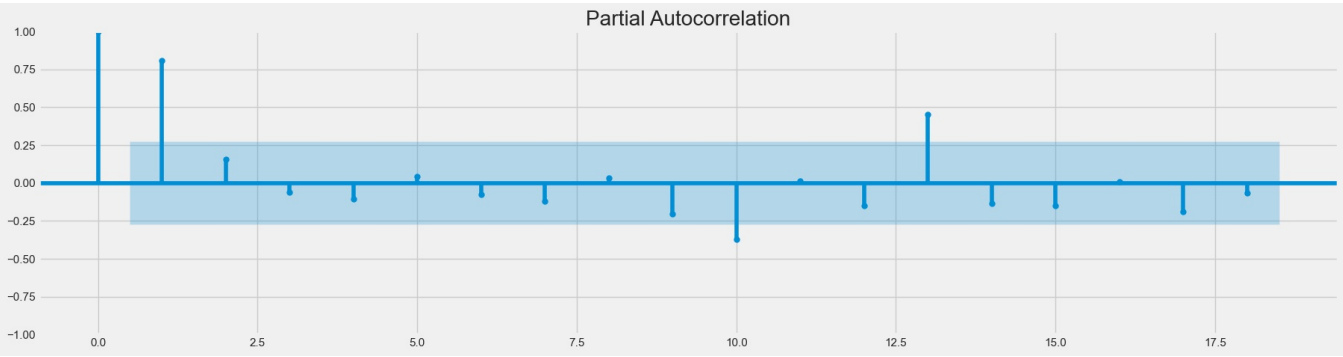
```
ADF Statistics: -2.2278541415816235
p- value: 0.19629175142304744
weak evidence against null hypothesis, time series has a unit root, indicating it is non-stationary
```

In [76]:
```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
acf = plot_acf(df8['Consumption 12 Difference'].dropna())
```



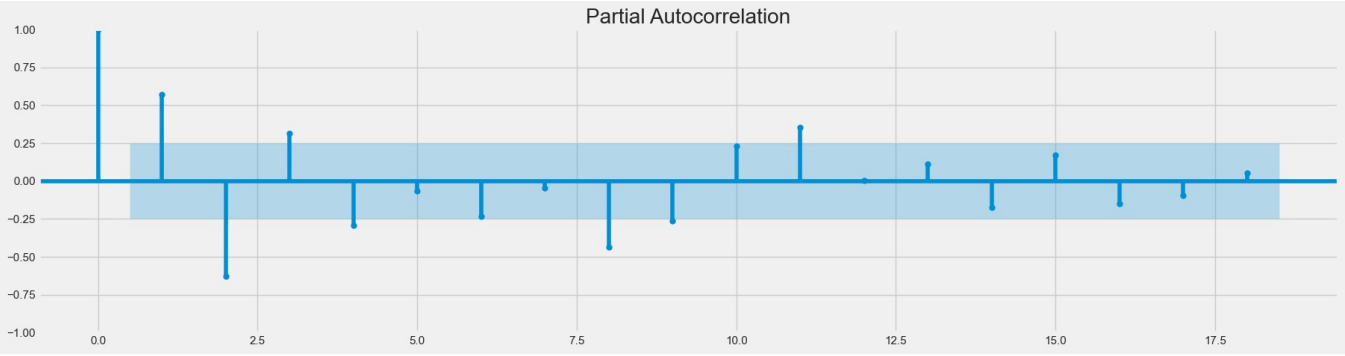
In [77]:
```
acf12 = plot_acf(df8['Consumption 12 Difference'].dropna())
pacf12 = plot_pacf(df8['Consumption 12 Difference'].dropna())
```





In [78]:
```
## Use Techniques Differencing
df8['Consumption 2 Difference']=df8['Consumption']-df8['Consumption'].shift(2)
display(df8.head(3))

result = plot_pacf(df8["Consumption 2 Difference"].dropna())
```

DateTime	Consumption	Consumption First Difference	Consumption 12 Difference	Consumption 2 Difference
2019-01-31	7752.168011	NaN	NaN	NaN
2019-02-28	7605.071429	-147.096582	NaN	NaN
2019-03-31	6992.792732	-612.278696	NaN	-759.375279



In [79]:
```
df9 = df8[['Consumption']]
df9.head()
```

Out[79]:

DateTime	Consumption
2019-01-31	7752.168011
2019-02-28	7605.071429
2019-03-31	6992.792732
2019-04-30	6652.491667
2019-05-31	6379.282258

In [80]:
```
from datetime import datetime,timedelta
train_dataset_end=datetime(2023,6,1)
test_dataset_end=datetime(2024,4,1)
```

In [81]:
```
train_data=df9[:train_dataset_end]
test_data=df9[train_dataset_end+timedelta(days=1):test_dataset_end]
##prediction
pred_start_date=test_data.index[0]
pred_end_date=test_data.index[-1]
```

In [82]:
```
train_data.head()
```

Out[82]:

DateTime	Consumption
2019-01-31	7752.168011
2019-02-28	7605.071429
2019-03-31	6992.792732
2019-04-30	6652.491667
2019-05-31	6379.282258

In [83]:
```
test_data.head()
```

Out[83]:

DateTime	Consumption
2023-06-30	5651.966667
2023-07-31	6053.303763
2023-08-31	5929.065860
2023-09-30	5678.083333
2023-10-31	5758.722148

In [84]:
```
import warnings
warnings.filterwarnings("ignore")

from statsmodels.tsa.arima.model import ARIMA

model_ARIMA=ARIMA(train_data['Consumption'],order=(10,2,0))
```

In [85]:
```
model_Arima_fit=model_ARIMA.fit()
model_Arima_fit.summary()
```

Out[85]:

SARIMAX Results

Dep. Variable:	Consumption	**No. Observations:**	53
Model:	ARIMA(10, 2, 0)	**Log Likelihood**	-354.120
Date:	Thu, 22 Aug 2024	**AIC**	730.241
Time:	16:48:41	**BIC**	751.491
Sample:	01-31-2019	**HQIC**	738.361
	- 05-31-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.4217	0.103	-4.111	0.000	-0.623	-0.221
ar.L2	-0.4829	0.119	-4.045	0.000	-0.717	-0.249
ar.L3	-0.6508	0.110	-5.899	0.000	-0.867	-0.435
ar.L4	-0.5284	0.158	-3.339	0.001	-0.839	-0.218
ar.L5	-0.4235	0.132	-3.205	0.001	-0.683	-0.164
ar.L6	-0.5286	0.154	-3.438	0.001	-0.830	-0.227
ar.L7	-0.5325	0.154	-3.463	0.001	-0.834	-0.231
ar.L8	-0.3378	0.167	-2.026	0.043	-0.665	-0.011
ar.L9	-0.4171	0.111	-3.748	0.000	-0.635	-0.199
ar.L10	-0.6336	0.140	-4.526	0.000	-0.908	-0.359
sigma2	5.081e+04	1.36e+04	3.742	0.000	2.42e+04	7.74e+04

Ljung-Box (L1) (Q):	3.19	**Jarque-Bera (JB):**	0.39
Prob(Q):	0.07	**Prob(JB):**	0.82
Heteroskedasticity (H):	0.47	**Skew:**	-0.15
Prob(H) (two-sided):	0.13	**Kurtosis:**	2.70

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [86]:
```
##prediction
pred_start_date=test_data.index[0]
pred_end_date=test_data.index[-1]
print(pred_start_date)
print(pred_end_date)
```

```
2023-06-30 00:00:00
2024-03-31 00:00:00
```

In [87]:
```
pred=model_Arima_fit.predict(start=pred_start_date,end=pred_end_date)
residuals=test_data['Consumption']-pred
```

In [88]:
```
pred.to_frame()
```

Out[88]:

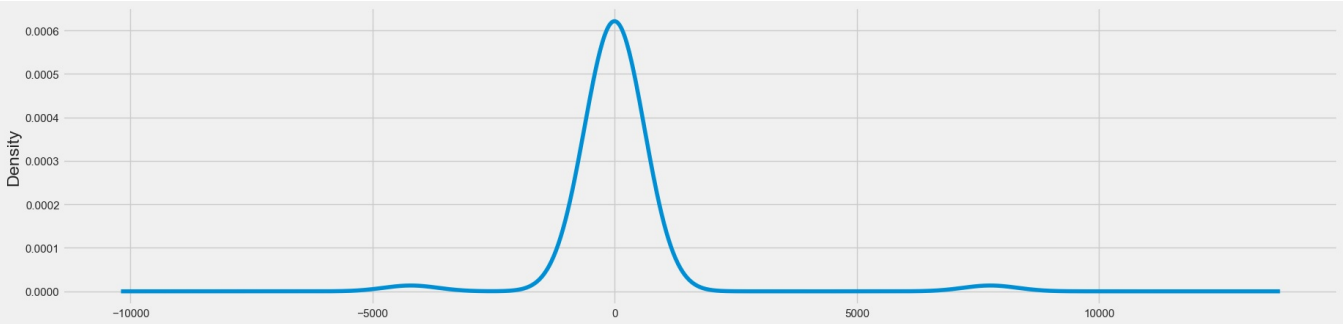
	predicted_mean
2023-06-30	5782.510258
2023-07-31	5941.097195
2023-08-31	5762.945329
2023-09-30	5441.840938
2023-10-31	5659.123037
2023-11-30	5858.474618
2023-12-31	5870.687607
2024-01-31	6003.153652
2024-02-29	5911.563521
2024-03-31	5778.196544

In [89]:
```
residuals.to_frame()
```

Out[89]:

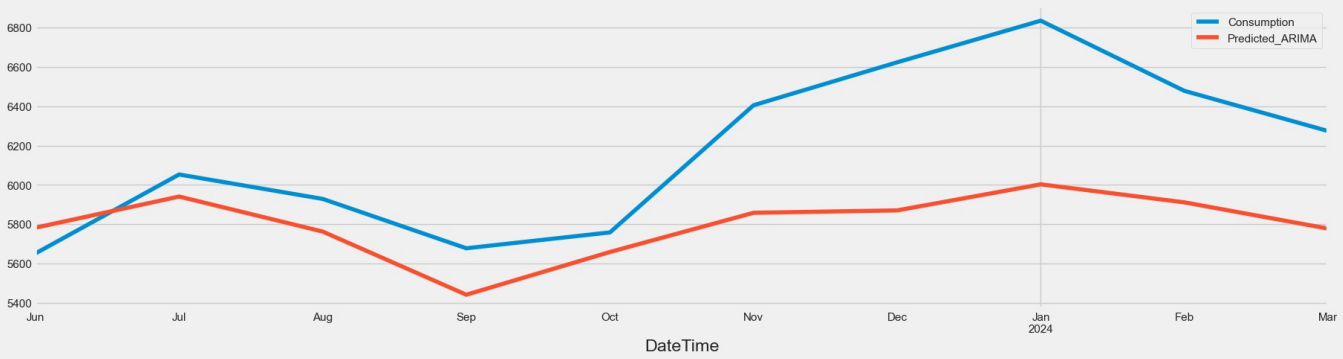
DateTime	0
2023-06-30	-130.543592
2023-07-31	112.206569
2023-08-31	166.120531
2023-09-30	236.242395
2023-10-31	99.599110
2023-11-30	546.747604
2023-12-31	752.983092
2024-01-31	832.097692
2024-02-29	566.848835
2024-03-31	496.099553

In [90]:
```
model_Arima_fit.resid.plot(kind='kde',figsize=(20,5));
```



In [91]:
```
test_data['Predicted_ARIMA']=pred
```

In [92]:
```
test_data[['Consumption','Predicted_ARIMA']].plot(figsize=(20,5));
```



In [93]:
```
## create a SARIMA model
from statsmodels.tsa.statespace.sarimax import SARIMAX
model_SARIMA=SARIMAX(train_data['Consumption'],order=(3,0,5),seasonal_order=(0,1,0,12))
model_SARIMA_fit=model_SARIMA.fit()
model_SARIMA_fit.summary()
```

Out[93]:

SARIMAX Results

Dep. Variable:	Consumption	**No. Observations:**	53
Model:	SARIMAX(3, 0, 5)x(0, 1, [], 12)	**Log Likelihood**	-290.962
Date:	Thu, 22 Aug 2024	**AIC**	599.923
Time:	16:48:43	**BIC**	615.345
Sample:	01-31-2019	**HQIC**	605.539
	- 05-31-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.5045	0.482	1.047	0.295	-0.440	1.449
ar.L2	0.5952	0.577	1.032	0.302	-0.535	1.725
ar.L3	-0.3886	0.225	-1.728	0.084	-0.829	0.052
ma.L1	0.0356	3644.131	9.77e-06	1.000	-7142.331	7142.402
ma.L2	-0.3636	4242.153	-8.57e-05	1.000	-8314.831	8314.103
ma.L3	0.8613	1335.581	0.001	0.999	-2616.830	2618.553
ma.L4	-0.2701	1933.450	-0.000	1.000	-3789.763	3789.223
ma.L5	-0.5306	0.533	-0.995	0.320	-1.575	0.514
sigma2	5.707e+04	0.130	4.38e+05	0.000	5.71e+04	5.71e+04

Ljung-Box (L1) (Q):	2.06	**Jarque-Bera (JB):**	3.61
Prob(Q):	0.15	**Prob(JB):**	0.16
Heteroskedasticity (H):	1.35	**Skew:**	0.62
Prob(H) (two-sided):	0.58	**Kurtosis:**	3.77

Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).

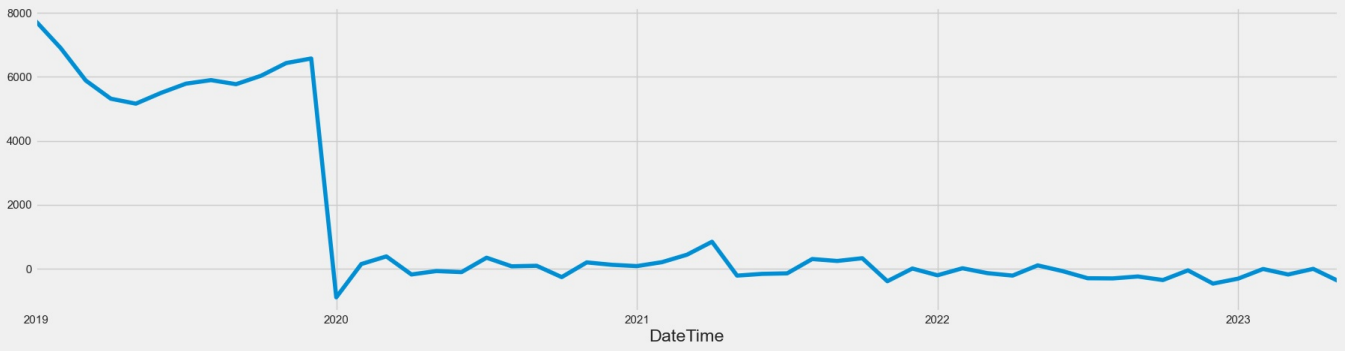
[2] Covariance matrix is singular or near-singular, with condition number 6.26e+25. Standard errors may be unstable.

In [94]:
```
##prediction
pred_start_date=test_data.index[0]
pred_end_date=test_data.index[-1]
print(pred_start_date)
print(pred_end_date)
```

```
2023-06-30 00:00:00
2024-03-31 00:00:00
```

In [95]:
```
pred_Sarima=model_SARIMA_fit.predict(start=datetime(2023,6,1),end=datetime(2024,4,1))
residuals=test_data['Consumption']-pred_Sarima
```

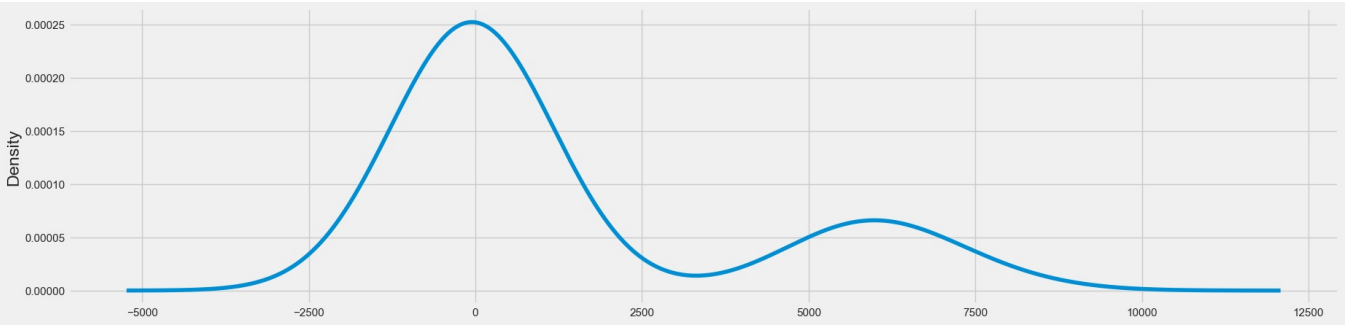
In [96]:
```
model_SARIMA_fit.resid.plot(figsize=(20,5));
```



In [97]:
```
model_SARIMA_fit.resid.plot(kind='kde',figsize=(20,5));
```

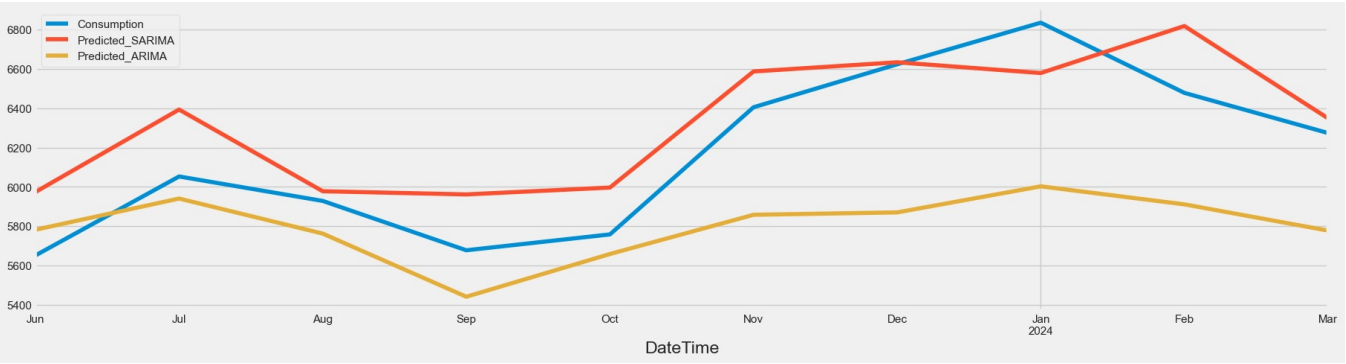
Follow for more :https://lnkd.in/gxcsx77g

Code + Data :https://t.me/AIMLDeepThaught/555



In [98]:
```
test_data['Predicted_SARIMA']=pred_Sarima
```

In [99]:
```
test_data[['Consumption','Predicted_SARIMA','Predicted_ARIMA']].plot(figsize=(20,5));
```



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Code + Data :https://t.me/AIMLDeepThaught/555