LAB-2: Exploratory Data Analysis (EDA) Lab Report – UPC Campus Nord data

TABARE REGULES

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Exploratory Data Analysis (EDA) is the process of **analyzing and investigating datasets** to summarize their main characteristics through **statistical graphics** and **data visualization techniques**.

It is a critical first step in any data science project to:

- Understand the structure and content of the data
- Identify patterns, trends, and relationships
- Spot anomalies or data quality issues
- Prepare the data for further modeling or hypothesis testing

EDA is not just about numbers, it's about telling the story behind the data.

The following images provides a complete steps of EDA. Not all of them have to be conducted.

EDA steps

Objective of this Lab

Conduct an Exploratory Data Analysis on the dataset `Campus_DiagonalNordUPC_data.xlsx`, which contains information about the **consumption of electricity, water resources, etc** of the **UPC Diagonal Nord Campus**.

The **goal** is to:

- Extract insights from the data
- Identify patterns or anomalies
- Visualize findings in a clear, meaningful way

You are free to choose your **visualization style** and the **story you want to tell** through your analysis.

Tip: Use this Jupyter Notebook to document your process. Combine **text (Markdown)**, **code**, and **visualizations** to build a clear and insightful narrative.

Suggested Steps

1. Data Loading and Initial Exploration

- Load the dataset and display its structure (columns, data types, missing values, etc.)

2. Data Cleaning

- Handle missing, inconsistent, or incorrect data if necessary.
- Create new relevant variables or filters when useful

3. Exploratory Analysis

- Compute summary statistics and explore distributions. (week/weekends, monthly distributions, seasonal, etc).
- Look for correlations or relationships between variables.
- Detect and analyze anomalies or outliers and discuss possible causes

4. Data Visualization

- Use appropriate plots to represent your findings clearly and effectively:

```
- Line plots for time series
- Bar charts for comparisons
- Heatmaps for correlations
- Boxplots for distributions
```

5. Insights and Conclusions

- Summarize your key findings
- Reflect on the main takeaways from your analysis

Lab Assignment 2: Exploratory Data Analysis (EDA)

1. Dataset overview

The dataset contains hourly measurements of **electricity**, **water**, and **gas consumption**, along with **exterior temperature**, recorded at UPC Campus Nord.
Each variable is expressed in consistent engineering units (kWh, m^3, °C).
The dataset covers nearly one full year of operation, allowing observation of both **seasonal** and **weekly** variations.

In [ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


from scipy import stats
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# read the dataset
data = pd.read_excel(r"Campus_DiagonalNordUPC_data.xlsx")
print ("Shape of the dataset", data.shape)
print ("Columns:", data.columns.tolist()) #name of the dataset columns
print (data.dtypes) #type of the dataset columns
```

```
Shape of the dataset (9793, 6)
Columns: ['Date', 'Hour', 'Electricity Campus DN [kWh]', 'Water consumption Campus DN
[m3]', 'Temperature exterior [Celsius]', 'Gas [kwh]']
Date                                    datetime64[ns]
Hour                                    datetime64[ns]
Electricity Campus DN [kWh]                      int64
Water consumption Campus DN [m3]               float64
Temperature exterior [Celsius]                 float64
Gas [kwh]                                      float64
dtype: object
```

2. Descriptive statistics and data quality

A summary of descriptive statistics confirms that all variables are complete and contain no missing values.
Electricity and water consumption exhibit a wide dynamic range, while gas usage remains close to zero except during winter.
Temperature data ranges roughly from **5 °C to 35 °C**, following a smooth annual pattern.

In [3]:
```
data.head() #first rows
```

Out[3]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
0	2024-09-01 00:00:00	2024-09-01 00:00:00	741	0.797139	22.7	0.0
1	2024-09-01 01:00:00	2024-09-01 01:00:00	734	0.793457	22.5	0.0
2	2024-09-01 02:00:00	2024-09-01 02:00:00	735	0.768367	22.4	0.0
3	2024-09-01 03:00:00	2024-09-01 03:00:00	732	0.767533	22.1	0.0
4	2024-09-01 04:00:00	2024-09-01 04:00:00	729	0.784900	21.4	0.0

In [4]:
```
data.tail() #last rows
```

Out[4]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
9788	2025-10-15 19:00:00	2025-10-15 19:00:00	1413	2.195682	18.2	0.0
9789	2025-10-15 20:00:00	2025-10-15 20:00:00	1283	4.113499	18.0	0.0
9790	2025-10-15 21:00:00	2025-10-15 21:00:00	1084	7.020899	17.9	0.0
9791	2025-10-15 22:00:00	2025-10-15 22:00:00	893	2.743192	16.9	0.0
9792	2025-10-15 23:00:00	2025-10-15 23:00:00	746	1.010154	17.2	0.0

In [5]:

```
data.describe() #Summary of the columns, for Date and Hour doesn't makes sense as the
```

Out[5]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas
count	9793	9793	9793.000000	9793.000000	9793.000000	9793.0
mean	2025-03-24 03:46:26.480139008	2025-03-24 03:46:26.480139008	1039.818952	2.711848	17.350985	7.9
min	2024-09-01 00:00:00	2024-09-01 00:00:00	0.000000	0.277742	1.000000	0.0
25%	2024-12-11 23:00:00	2024-12-11 23:00:00	738.000000	1.103867	12.100000	0.0
50%	2025-03-23 23:00:00	2025-03-23 23:00:00	853.000000	1.949100	17.000000	0.0
75%	2025-07-04 00:00:00	2025-07-04 00:00:00	1338.000000	3.913985	22.200000	0.0
max	2025-10-15 23:00:00	2025-10-15 23:00:00	2875.000000	18.637224	37.000000	197.3
std	NaN	NaN	377.519473	2.054874	6.862379	22.6

In [6]:

```
data.isna().sum() # Count of missing values
```

Out[6]:

```
Date                                0
Hour                                0
Electricity Campus DN [kWh]         0
Water consumption Campus DN [m3]    0
Temperature exterior [Celsius]      0
Gas [kwh]                           0
dtype: int64
```

In [7]:
```
#no missing values are found
```

In [8]:
```
data['Month'] = data['Date'].dt.month
data['Weekday'] = data['Date'].dt.day_name()

# Weekday and month are obtained from the Date variable, for potentially useful featu
data[['Month',  'Weekday']].head()
```

Out[8]:

	Month	Weekday
0	9	Sunday
1	9	Sunday
2	9	Sunday
3	9	Sunday
4	9	Sunday

In [9]:
```
data
```

Out[9]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]	Month	Weekday
0	2024-09-01 00:00:00	2024-09-01 00:00:00	741	0.797139	22.7	0.0	9	Sunday
1	2024-09-01 01:00:00	2024-09-01 01:00:00	734	0.793457	22.5	0.0	9	Sunday
2	2024-09-01 02:00:00	2024-09-01 02:00:00	735	0.768367	22.4	0.0	9	Sunday
3	2024-09-01 03:00:00	2024-09-01 03:00:00	732	0.767533	22.1	0.0	9	Sunday
4	2024-09-01 04:00:00	2024-09-01 04:00:00	729	0.784900	21.4	0.0	9	Sunday
...	...	...	...	...	...	...	...	...
9788	2025-10-15 19:00:00	2025-10-15 19:00:00	1413	2.195682	18.2	0.0	10	Wednesday
9789	2025-10-15 20:00:00	2025-10-15 20:00:00	1283	4.113499	18.0	0.0	10	Wednesday
9790	2025-10-15 21:00:00	2025-10-15 21:00:00	1084	7.020899	17.9	0.0	10	Wednesday
9791	2025-10-15 22:00:00	2025-10-15 22:00:00	893	2.743192	16.9	0.0	10	Wednesday
9792	2025-10-15 23:00:00	2025-10-15 23:00:00	746	1.010154	17.2	0.0	10	Wednesday

9793 rows × 8 columns

In [10]:

```
# The column Hour is turn into a number instead of a datetime
data['Hour'] = data['Date'].dt.hour
data
```

Out[10]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]	Month	Weekday
0	2024-09-01 00:00:00	0	741	0.797139	22.7	0.0	9	Sunday
1	2024-09-01 01:00:00	1	734	0.793457	22.5	0.0	9	Sunday
2	2024-09-01 02:00:00	2	735	0.768367	22.4	0.0	9	Sunday
3	2024-09-01 03:00:00	3	732	0.767533	22.1	0.0	9	Sunday
4	2024-09-01 04:00:00	4	729	0.784900	21.4	0.0	9	Sunday
...	...	...	...	...	...	...	...	...
9788	2025-10-15 19:00:00	19	1413	2.195682	18.2	0.0	10	Wednesday
9789	2025-10-15 20:00:00	20	1283	4.113499	18.0	0.0	10	Wednesday
9790	2025-10-15 21:00:00	21	1084	7.020899	17.9	0.0	10	Wednesday
9791	2025-10-15 22:00:00	22	893	2.743192	16.9	0.0	10	Wednesday
9792	2025-10-15 23:00:00	23	746	1.010154	17.2	0.0	10	Wednesday

9793 rows × 8 columns

In [11]:

```
data.describe()
```

Out[11]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
count	9793	9793.000000	9793.000000	9793.000000	9793.000000	9793.000000
mean	2025-03-24 03:46:26.480139008	11.501174	1039.818952	2.711848	17.350985	7.948224
min	2024-09-01 00:00:00	0.000000	0.000000	0.277742	1.000000	0.000000
25%	2024-12-11 23:00:00	6.000000	738.000000	1.103867	12.100000	0.000000
50%	2025-03-23 23:00:00	12.000000	853.000000	1.949100	17.000000	0.000000
75%	2025-07-04 00:00:00	18.000000	1338.000000	3.913985	22.200000	0.000000
max	2025-10-15 23:00:00	23.000000	2875.000000	18.637224	37.000000	197.353000
std	NaN	6.923162	377.519473	2.054874	6.862379	22.615322

3. Visual exploration

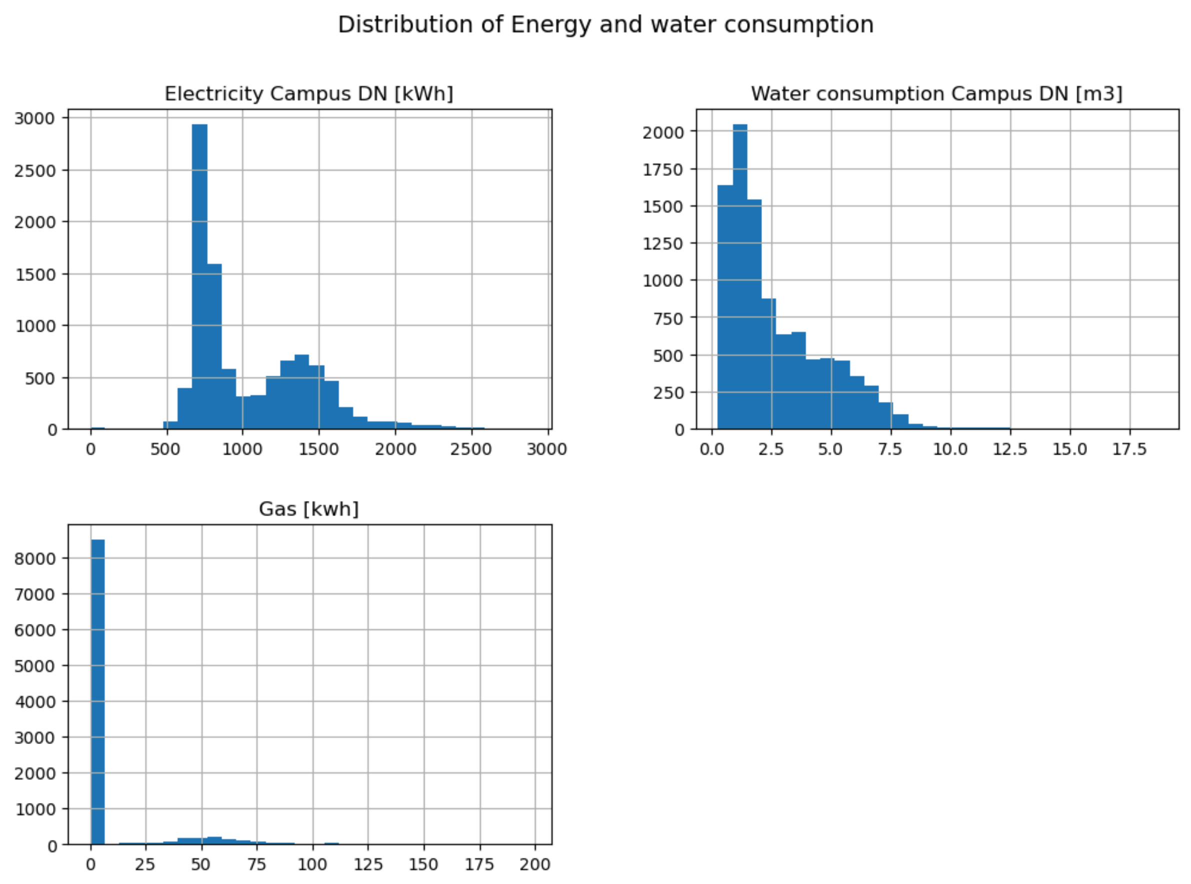
A series of histograms, boxplots, and density plots were used to visualize the distributions. These highlight the right-skewed nature of electricity and gas consumption, confirming the presence of **high-value peaks** likely due to operational intensity.

Boxplots show:

- Electricity and water have **moderate variability** with a few high-end outliers.
- Gas usage shows **many outliers**, corresponding to heating peaks.
- Temperature displays a **balanced distribution** without strong skewness.

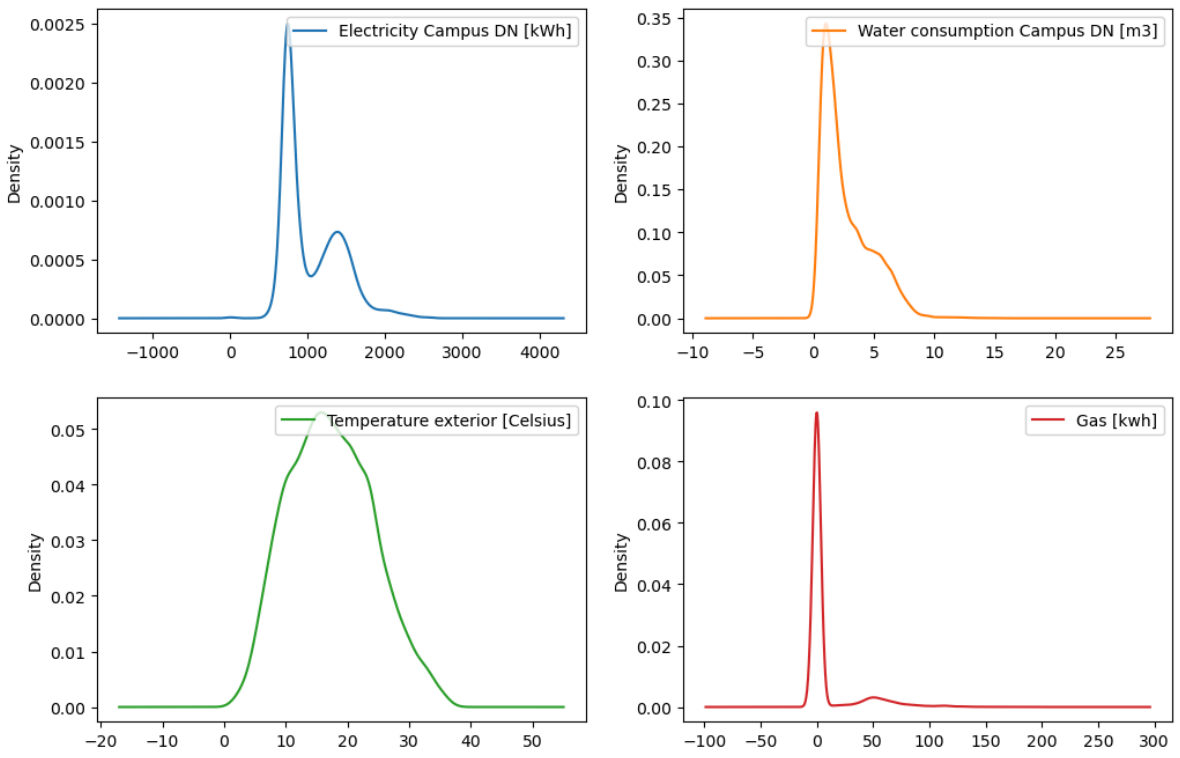
In [12]:
```
# Minimum and maximum values for the energy and water columns
for col in ['Electricity Campus DN [kWh]', 'Water consumption Campus DN [m3]', 'Gas [
    if col in data.columns:
        print(f"{col}: min={data[col].min()}, max={data[col].max()}")

# Histogram for the energy and water columns
data[['Electricity Campus DN [kWh]', 'Water consumption Campus DN [m3]', 'Gas [kwh]']
plt.suptitle('Distribution of Energy and water consumption', fontsize=14)
plt.show()
```

```
Electricity Campus DN [kWh]: min=0, max=2875
Water consumption Campus DN [m3]: min=0.27774240506353554, max=18.6372235242899
Gas [kwh]: min=0.0, max=197.353
```

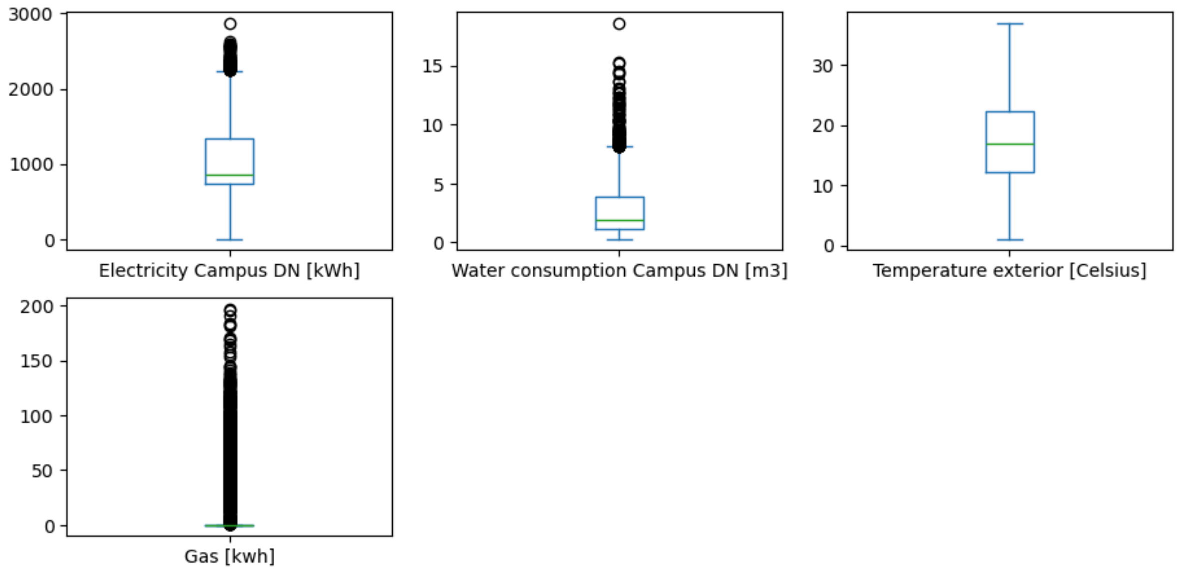


In [13]:
```
#First impressions:
    #Electricity has a maximum higher than 2 times the 50% vaule, check for outlier (
    #Water seems to have a high variability
    #Temperature seems normal
    #Gas is not generally use
```

In [14]:
```
#density plots
cols = ['Electricity Campus DN [kWh]', 'Water consumption Campus DN [m3]', 'Temperatu
axes = data[cols].plot(kind='kde', subplots=True, layout=(2,2),
                       figsize=(12,8), sharex=False, legend=True)
#Modify the position of legend
for ax_row in axes:
    for ax in ax_row:
        if ax is not None:
            ax.legend(loc='upper right')
```

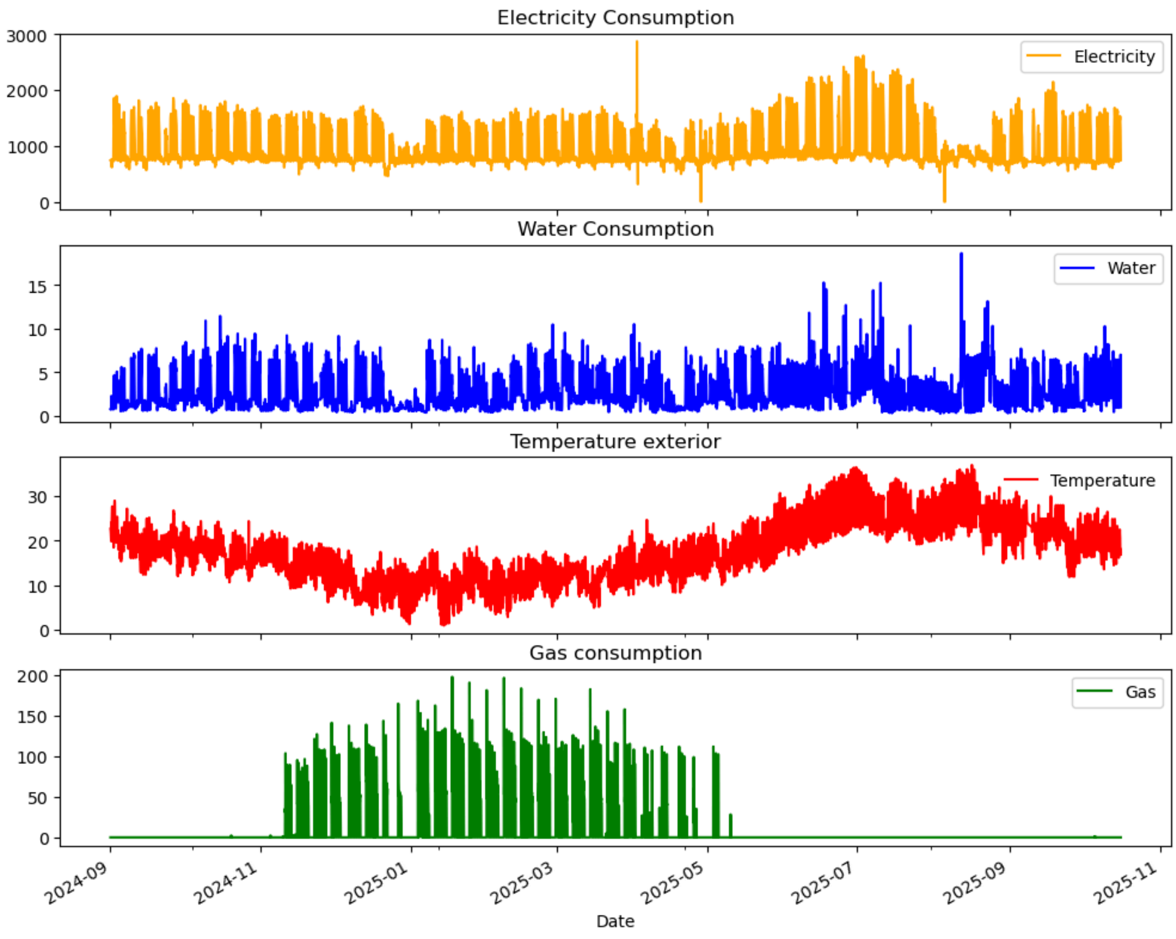


In [15]:
```
#boxplots
atributos_boxplot = data[cols].plot(kind='box', subplots=True, layout=(4, 3), figsize
```



In [16]:
```
#Changes over time
fig, axes = plt.subplots(4, 1, figsize=(12,10), sharex=True)
data.set_index('Date')['Electricity Campus DN [kWh]'].plot(ax=axes[0], color='orange'
axes[0].set_title('Electricity Consumption')
axes[0].legend()
data.set_index('Date')['Water consumption Campus DN [m3]'].plot(ax=axes[1], color='bl
axes[1].set_title('Water Consumption')
axes[1].legend()
data.set_index('Date')['Temperature exterior [Celsius]'].plot(ax=axes[2], color='red'
axes[2].set_title('Temperature exterior')
axes[2].legend(loc='upper right',frameon=False)
data.set_index('Date')['Gas [kwh]'].plot(ax=axes[3], color='green', label='Gas')
axes[3].set_title('Gas consumption')
axes[3].legend()
```

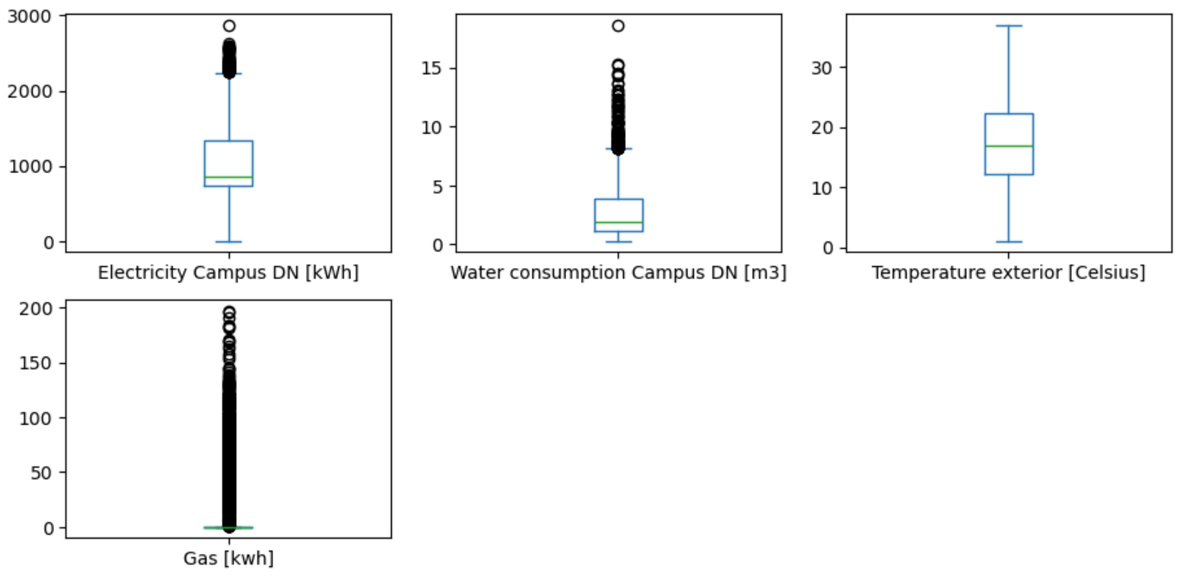
Out[16]:
```
<matplotlib.legend.Legend at 0x2773e017710>
```



Valleys in water and electricity consumption coincide with the winter and summer holiday periods.

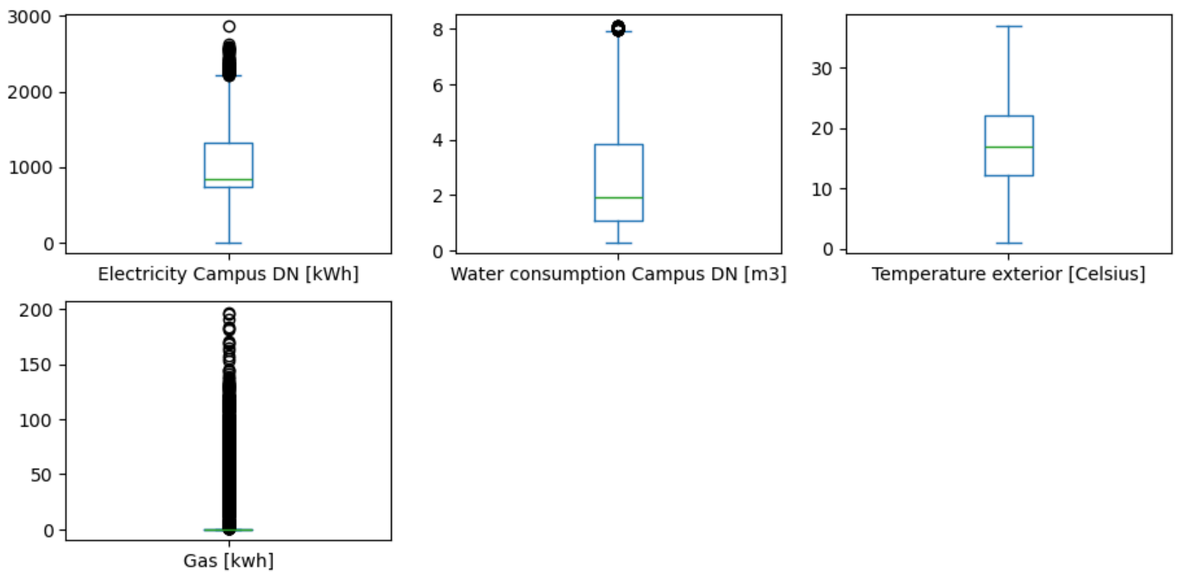
As the temperature increases, there is a noticeable rise in electricity consumption, likely due to air conditioning, and a smaller increase in water usage. As consumption clearly follows the winter, as it is mainly used for heating. The negative peaks correspond to weekends, when no class are taught.

In [17]:
```
#boxplots
boxplot = data[cols].plot(kind='box', subplots=True, layout=(4, 3), figsize=(11, 11),
```



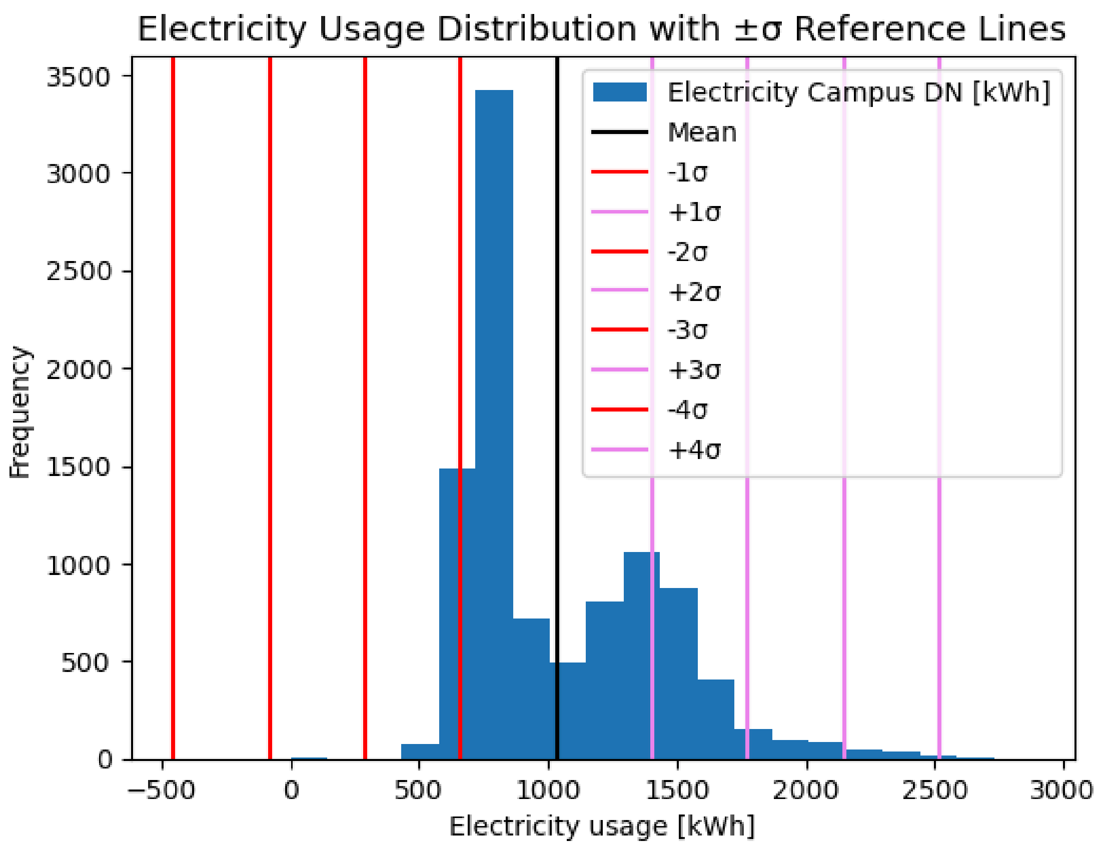
In [18]:
```
#Gas has a lot of ouliers but that is because normally the heating is not turned on.
#Temperature resambles a normal distribution so during the study period there were no
#Lets clean the water consumption as it clearly shows an outlier (could be a leak or

#using the IQR method
def remove_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    return data[(data[column] >= lower_bound) & (data[column] <= upper_bound)]


df_no_outliers_iqr = remove_outliers_iqr(data, 'Water consumption Campus DN [m3]')
```

In [19]:
```
boxplot_clean = df_no_outliers_iqr[cols].plot(kind='box', subplots=True, layout=(4, 3
```



In [20]:
```
#There is still an outlier in electricity use, lets use a broad Z-Score Method
#a broader Z-score because the electricity usage is right skewed so it would cut a lo
#removing 3σ data points seems a bit overcleaning

mean = df_no_outliers_iqr['Electricity Campus DN [kWh]'].mean()
st_dev = df_no_outliers_iqr['Electricity Campus DN [kWh]'].std()
data['Electricity Campus DN [kWh]'].plot.hist(bins=20)
plt.axvline(mean, color = 'Black', label = 'Mean')
plt.axvline(mean - 1*st_dev, color = 'Red', label = '-1σ')
plt.axvline(mean + 1*st_dev, color = 'Violet', label = '+1σ')
plt.axvline(mean - 2*st_dev, color = 'Red', label = '-2σ')
plt.axvline(mean + 2*st_dev, color = 'Violet', label = '+2σ')
plt.axvline(mean - 3*st_dev, color = 'Red', label = '-3σ')
plt.axvline(mean + 3*st_dev, color = 'Violet', label = '+3σ')
plt.axvline(mean - 4*st_dev, color = 'Red', label = '-4σ')
plt.axvline(mean + 4*st_dev, color = 'Violet', label = '+4σ')
plt.xlabel('Electricity usage')
plt.title("Electricity Usage Distribution with ±σ Reference Lines", fontsize=13)
plt.xlabel("Electricity usage [kWh]")
plt.ylabel("Frequency")
plt.legend()
```

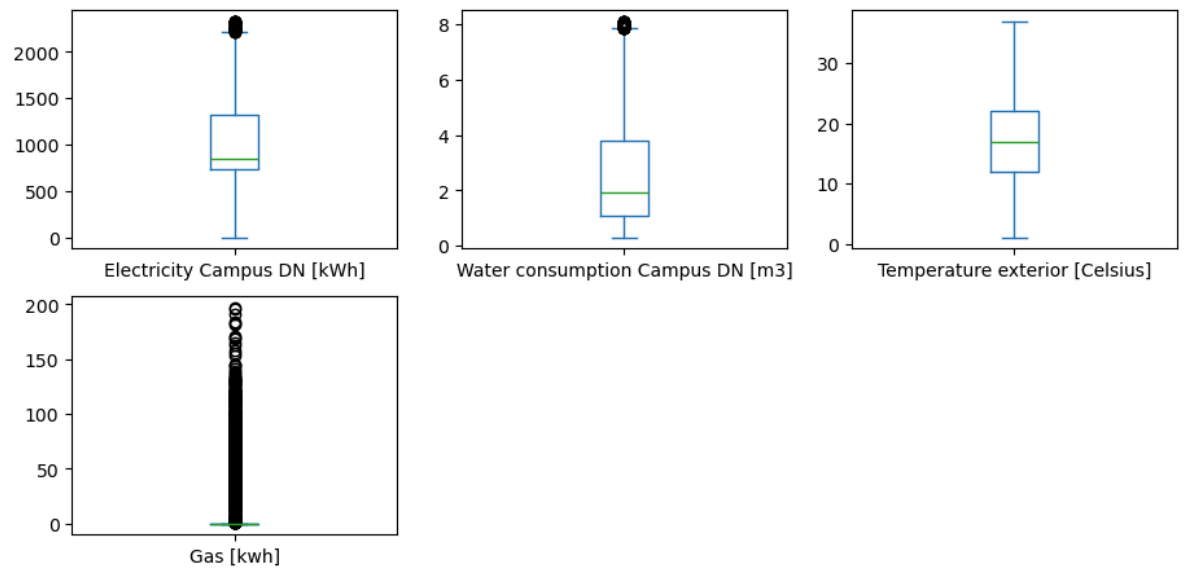
Out[20]:
```
<matplotlib.legend.Legend at 0x277400fe360>
```



```
In [21]: #using a 3.5σ seems fit without overcleaning
         from scipy.stats import zscore


         def remove_outliers_zscore_broad(data, column):
             z_scores = zscore(data[column])
             print(z_scores)
             return data[(z_scores > -3.5) & (z_scores < 3.5)]
         #data already without missing values
         df_no_outliers_zscore_broad = remove_outliers_zscore_broad(df_no_outliers_iqr, 'Elect
```

```
0      -0.786934
1      -0.805782
2      -0.803089
3      -0.811167
4      -0.819245
          ...
9788    1.022442
9789    0.672414
9790    0.136602
9791   -0.377671
9792   -0.773472
Name: Electricity Campus DN [kWh], Length: 9682, dtype: float64
```

```
In [22]: boxplot_clean_2 = df_no_outliers_zscore_broad[cols].plot(kind='box', subplots=True, l
```



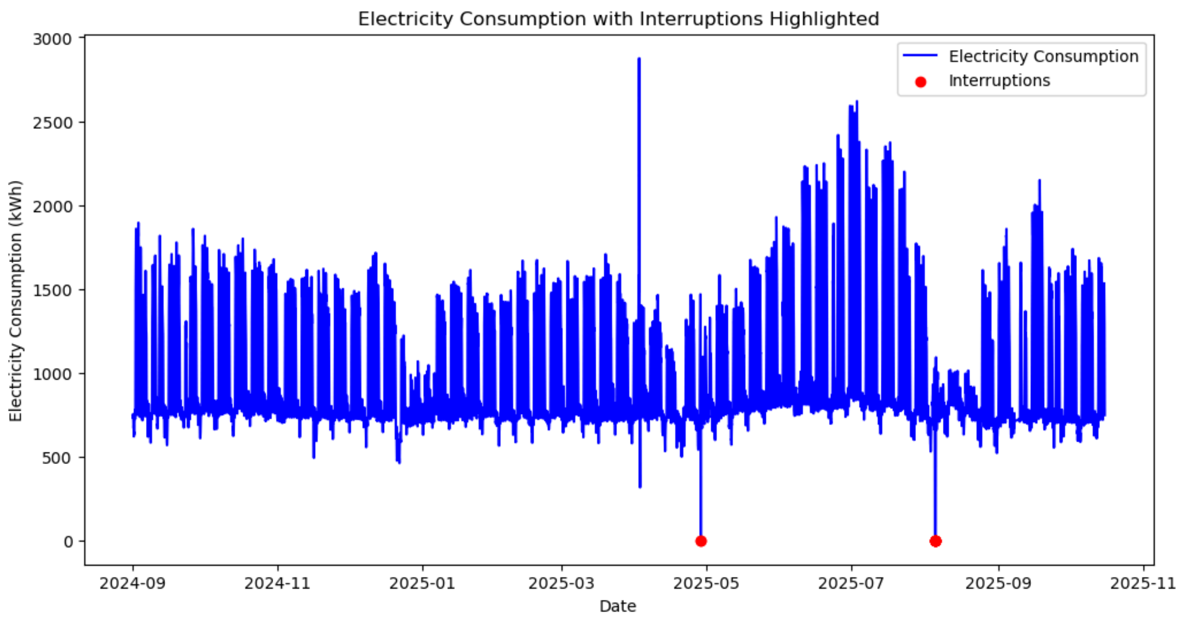
In [23]:
```
# detect anomalies in database

anomalies = data[(data['Water consumption Campus DN [m3]'] > data['Water consumption
                 (data['Electricity Campus DN [kWh]'] > data['Electricity Campus DN [
                 (data['Gas [kwh]'] > data['Gas [kwh]'].quantile(0.99))]
anomalies
```

Out[23]:

	Date	Hour	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]	Month	Weekday
733	2024-10-01 13:00:00	13	1748	8.479750	22.7	0.0	10	Tuesday
926	2024-10-09 14:00:00	14	1593	10.913067	22.3	0.0	10	Wednesday
1068	2024-10-15 12:00:00	12	1714	11.448916	20.5	0.0	10	Tuesday
1069	2024-10-15 13:00:00	13	1759	8.776883	20.9	0.0	10	Tuesday
1072	2024-10-15 16:00:00	16	1613	8.666949	22.2	0.0	10	Tuesday
...	...	...	...	...	...	...	...	...
8589	2025-08-24 21:00:00	21	754	8.348933	25.0	0.0	8	Sunday
8590	2025-08-24 22:00:00	22	743	10.310450	24.0	0.0	8	Sunday
9636	2025-10-09 11:00:00	11	1630	10.277267	24.3	0.0	10	Thursday
9637	2025-10-09 12:00:00	12	1626	8.926365	25.1	0.0	10	Thursday
9646	2025-10-09 21:00:00	21	1067	8.271031	17.8	0.0	10	Thursday

283 rows × 8 columns

In [24]:
```
# check when electricity interruptions happened (hours with very low or zero consumpt
electricity_interruptions = data[data['Electricity Campus DN [kWh]'] < 30]

# create a plot to visualize electricity interruptions over time
plt.figure(figsize=(12, 6))
plt.plot(data['Date'], data['Electricity Campus DN [kWh]'], label='Electricity Consum
plt.scatter(electricity_interruptions['Date'], electricity_interruptions['Electricity
plt.xlabel('Date')
plt.ylabel('Electricity Consumption (kWh)')
plt.title('Electricity Consumption with Interruptions Highlighted')
plt.legend()
plt.show()

# indicate the dates of interruptions
print("Electricity Interruptions Dates:")
print(electricity_interruptions[['Date', 'Electricity Campus DN [kWh]']])
#)
```



```
Electricity Interruptions Dates:
                    Date  Electricity Campus DN [kWh]
5749 2025-04-28 13:00:00                            0
5750 2025-04-28 14:00:00                            0
8120 2025-08-05 08:00:00                            0
8121 2025-08-05 09:00:00                            0
8122 2025-08-05 10:00:00                            0
8123 2025-08-05 11:00:00                            0
8124 2025-08-05 12:00:00                            0
8125 2025-08-05 13:00:00                            0
8126 2025-08-05 14:00:00                            0
8127 2025-08-05 15:00:00                            0
```

what happened in these days?

On April 28th, 2025, a major power outage (Apagón) occurred, causing a drop in electricity, disrupting normal campus operations and highlighting system vulnerability for many hours.

Another drop to 0 kWh appears on August 5th, with no immediate explanation. It could be a data recording issue or a temporary shutdown, requiring further verification.

4. Correlation and interpretation

A correlation heatmap shows:

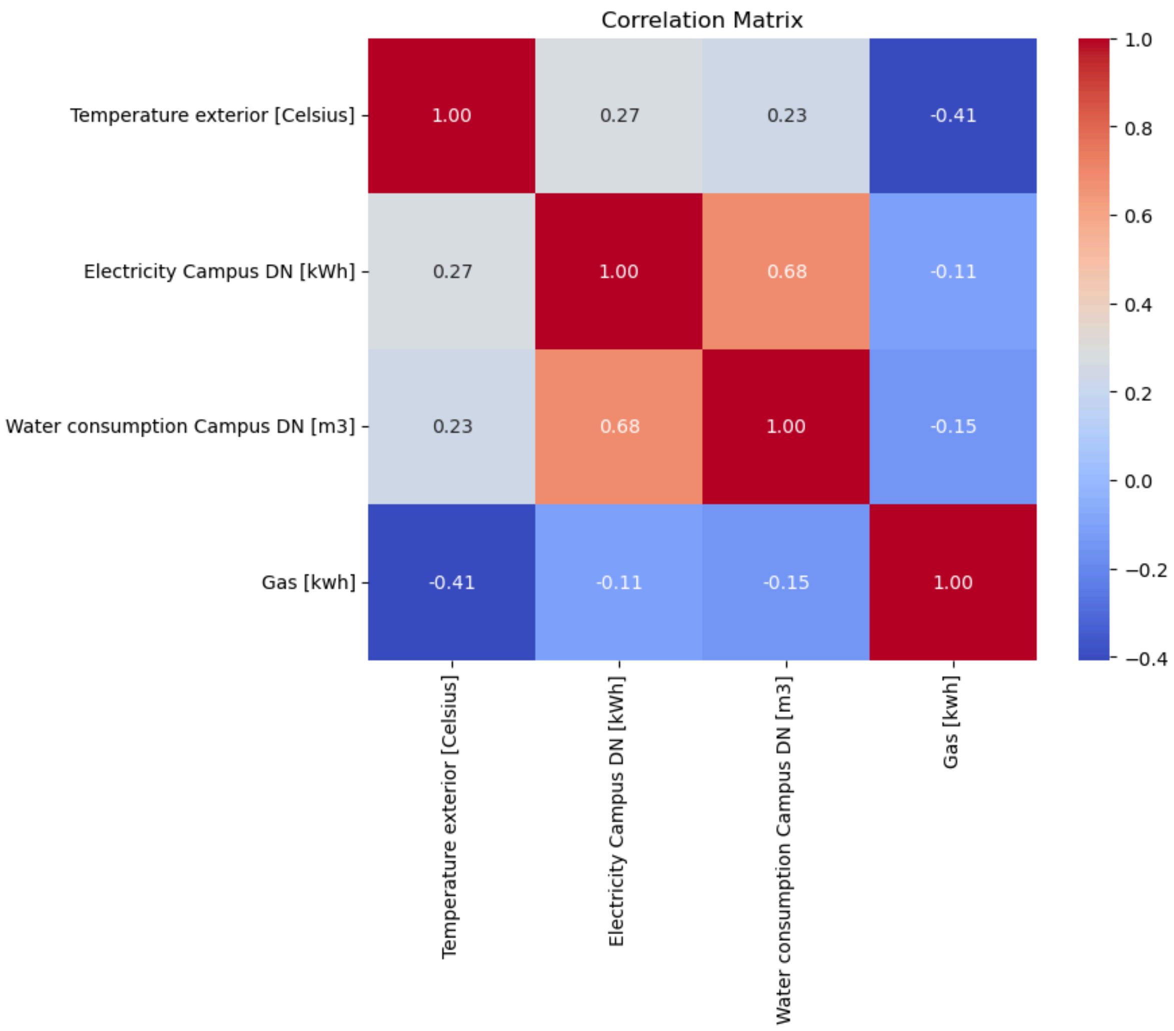
- **Electricity ↔ Water:** strong positive correlation → higher occupancy and activity levels.
- **Temperature ↔ Gas:** strong negative correlation → heating in cold periods, no use in summer.
- **Electricity ↔ Temperature:** mild positive correlation → cooling demand increases with warmer conditions.

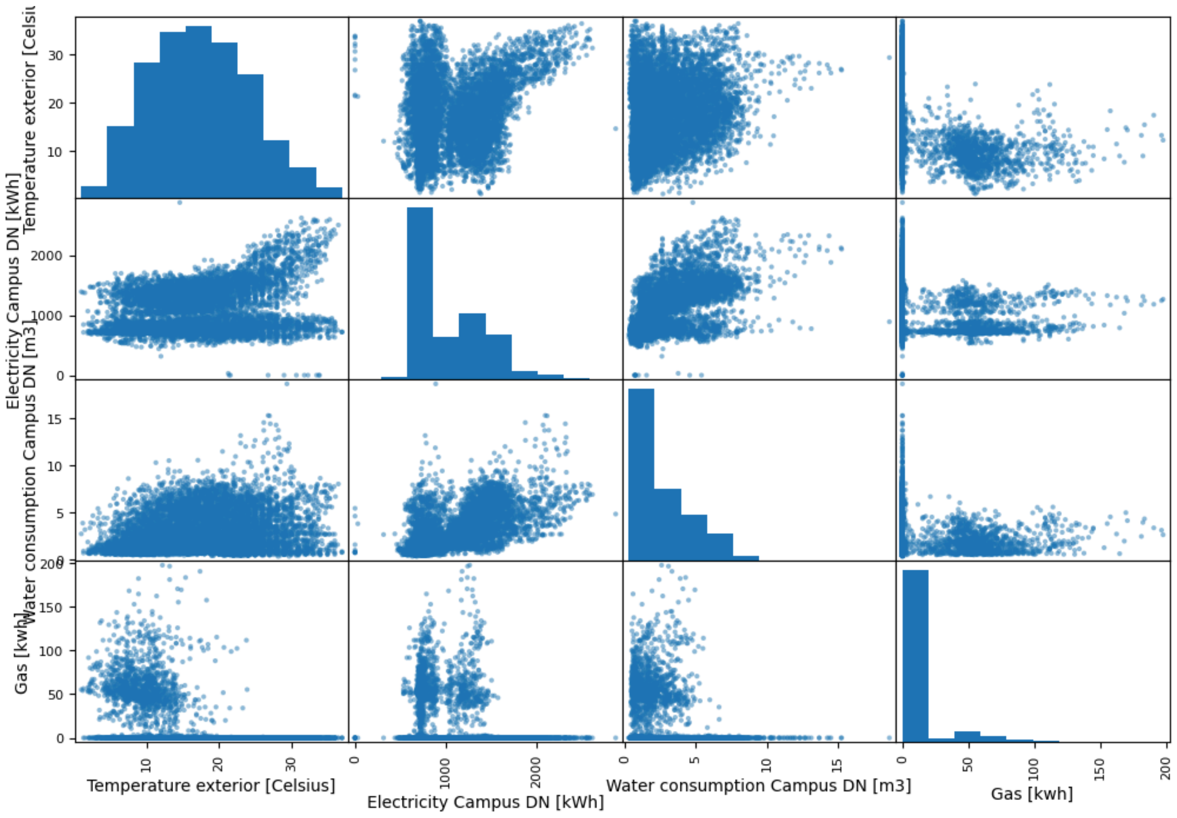
In [25]:
```
#check if there anomalies on 5th august, other than
```

In [26]:
```
# other interesting analysis can be done
# for example, correlation analysis between temperature and energy consumption
correlation_matrix = data[['Temperature exterior [Celsius]', 'Electricity Campus DN [
correlation_matrix

# plot correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')

# pearson correlation coefficients
pearson_corr = data[['Temperature exterior [Celsius]', 'Electricity Campus DN [kWh]',

# check more insights about correlation, with scatter plots
scatter_matrix = pd.plotting.scatter_matrix(data[['Temperature exterior [Celsius]', '

# spearman correlation
spearman_corr = data[['Temperature exterior [Celsius]', 'Electricity Campus DN [kWh]'
spearman_corr
```

Out[26]:

	Temperature exterior [Celsius]	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Gas [kwh]
Temperature exterior [Celsius]	1.000000	0.227189	0.222377	-0.469062
Electricity Campus DN [kWh]	0.227189	1.000000	0.678098	-0.122542
Water consumption Campus DN [m3]	0.222377	0.678098	1.000000	-0.149185
Gas [kwh]	-0.469062	-0.122542	-0.149185	1.000000





From the correlation matrix we can see that:

Electricity and water consumption are positively correlated as they tend to increase and decrease together.

Gas consumption is slightly negatively correlated with temperature — when the outside temperature rises, gas usage likely for heating goes down.

While from the scatter plots, we can notice:

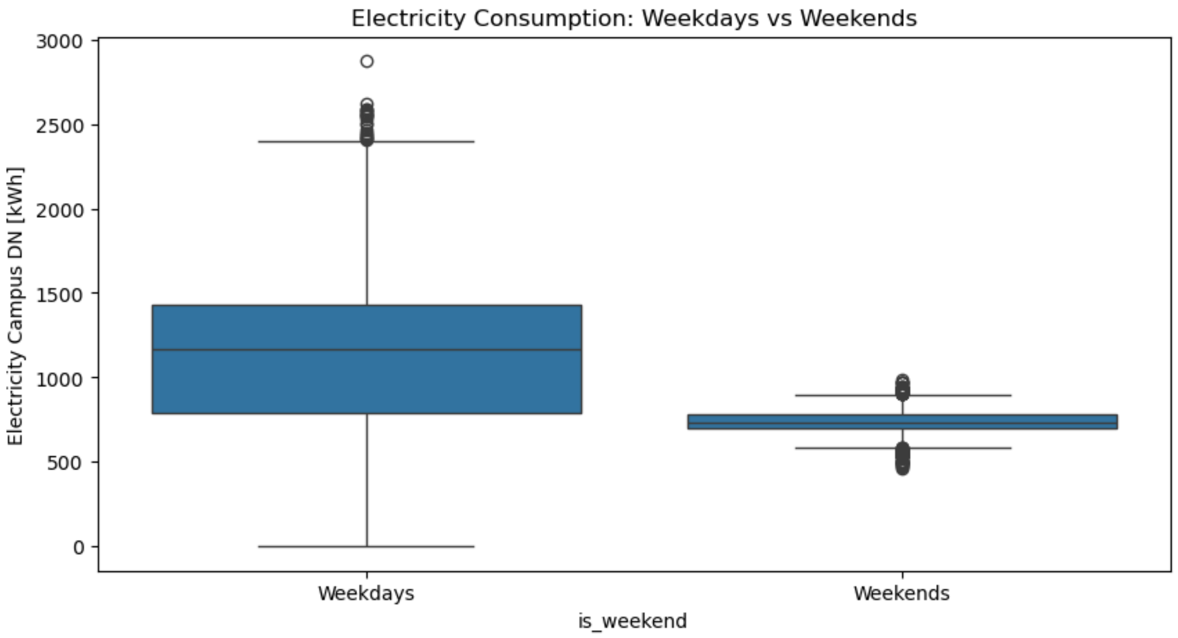
Two distinct patterns in electricity consumption, possibly reflecting different operational modes (e.g., weekdays vs weekends, or academic vs vacation periods).

In the upper range of temperature and electricity, there is a proportional trend — as temperature increases, electricity also rises, probably due to air conditioning use.

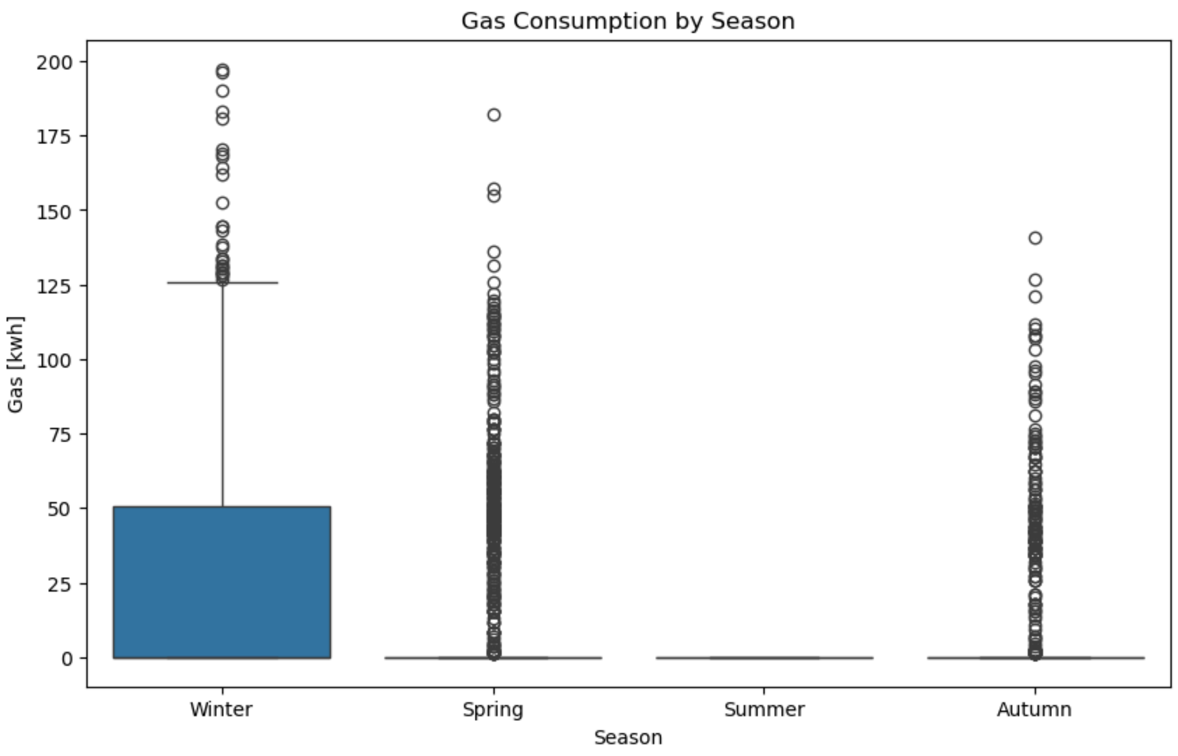
In [27]:
```python
cols = ['Electricity Campus DN [kWh]',
        'Water consumption Campus DN [m3]',
        'Temperature exterior [Celsius]',
        'Gas [kwh]']

# --- 1. Summary statistics ---
summary_stats = data[cols].describe()
display(summary_stats)

# --- 2. Weekday vs Weekend ---
data['is_weekend'] = data['Weekday'].isin(['Saturday', 'Sunday'])

weekend_stats = data.groupby('is_weekend')[cols].mean()
display(weekend_stats)

plt.figure(figsize=(10,5))
sns.boxplot(x='is_weekend', y='Electricity Campus DN [kWh]', data=data)
plt.xticks([0,1], ['Weekdays','Weekends'])
plt.title('Electricity Consumption: Weekdays vs Weekends')
plt.show()


# --- 4. Seasonal analysis ---
# Map months to seasons
season_map = {12: 'Winter', 1: 'Winter', 2: 'Winter',
              3: 'Spring', 4: 'Spring', 5: 'Spring',
              6: 'Summer', 7: 'Summer', 8: 'Summer',
              9: 'Autumn', 10: 'Autumn', 11: 'Autumn'}

data['Season'] = data['Month'].map(season_map)

seasonal_stats = data.groupby('Season')[cols].mean()
display(seasonal_stats)

plt.figure(figsize=(10,6))
sns.boxplot(x='Season', y='Gas [kwh]', data=data,
            order=['Winter','Spring','Summer','Autumn'])
plt.title('Gas Consumption by Season')
plt.xlabel('Season')
plt.show()
```

	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
count	9793.000000	9793.000000	9793.000000	9793.000000
mean	1039.818952	2.711848	17.350985	7.948224
std	377.519473	2.054874	6.862379	22.615322
min	0.000000	0.277742	1.000000	0.000000
25%	738.000000	1.103867	12.100000	0.000000
50%	853.000000	1.949100	17.000000	0.000000
75%	1338.000000	3.913985	22.200000	0.000000
max	2875.000000	18.637224	37.000000	197.353000

	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
is_weekend				
False	1161.742448	3.146707	17.362147	6.441032
True	736.529915	1.630123	17.323219	11.697416



	Electricity Campus DN [kWh]	Water consumption Campus DN [m3]	Temperature exterior [Celsius]	Gas [kwh]
Season				
Autumn	1056.232132	2.772646	18.331697	2.377547
Spring	989.454010	2.814828	15.130856	9.166756
Summer	1111.515851	2.860623	25.744067	0.000000
Winter	993.537037	2.363970	9.578750	23.127304



4. Observations

The dataset represents hourly energy and environmental measurements at **UPC Campus Nord**, including electricity, water, and gas consumption, as well as exterior temperature.

General statistics show that electricity consumption averages around **1,040 kWh/h**, with peaks reaching **2,875 kWh**, indicating substantial variability across time. Water usage remains relatively steady, except for occasional spikes likely related to specific campus activities. Gas consumption, in contrast, is highly intermittent — nearly zero for most of the year but rising sharply during the winter months for heating purposes.

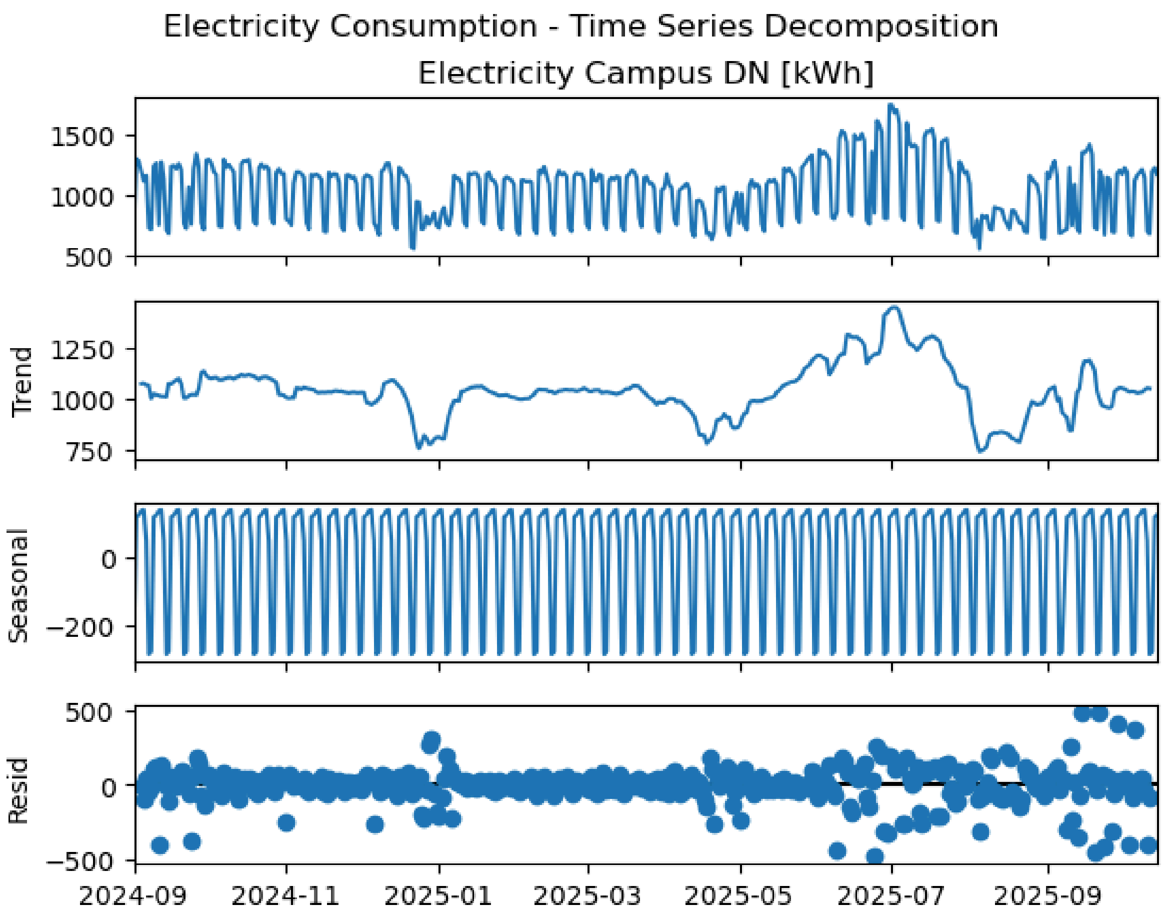
Seasonal and weekly patterns are clearly visible. Electricity and water demand are higher during weekdays and drop significantly on weekends, aligning with typical operational schedules of academic buildings. During summer, electricity use increases, most likely due to cooling loads, whereas gas consumption peaks in colder months to maintain indoor comfort levels.

The **temperature variable** shows a smooth annual cycle ranging roughly from **5 °C in winter to 35 °C in summer**, strongly influencing energy patterns. Electricity and temperature show a **positive relationship**, while temperature and gas usage are **strongly inversely correlated**. Overall, the analysis reveals that electricity and water consumption follow occupancy-driven dynamics, while gas usage reflects seasonal heating demand. These insights provide a clear basis for further forecasting and anomaly detection tasks.

In [28]:
```
print (data.dtypes)
```

```
Date                                     datetime64[ns]
Hour                                              int32
Electricity Campus DN [kWh]                       int64
Water consumption Campus DN [m3]                float64
Temperature exterior [Celsius]                  float64
Gas [kwh]                                       float64
Month                                             int32
Weekday                                          object
is_weekend                                         bool
Season                                           object
dtype: object
```

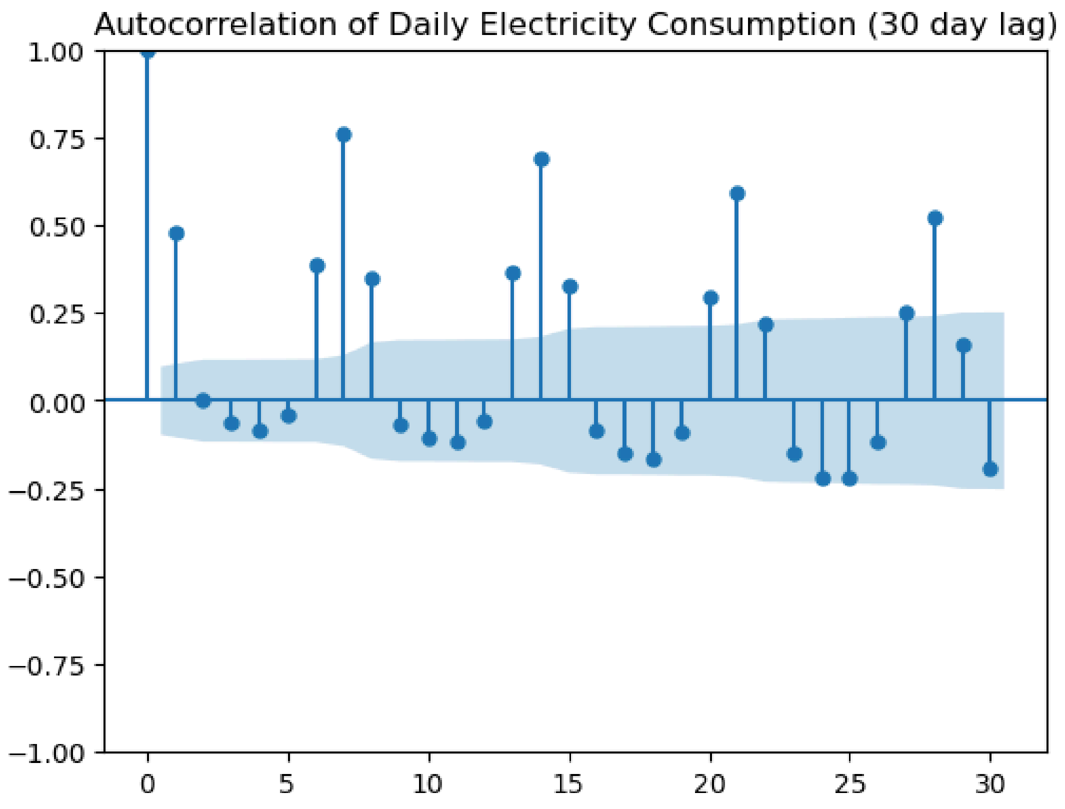
In [29]:
```
# Create a temporary copy to avoid modifying 'data'
df_temp = data.copy()

# Set Date as index (temporarily)
df_temp = df_temp.set_index('Date').sort_index()

# Aggregate to daily mean
daily_elec = df_temp['Electricity Campus DN [kWh]'].resample('D').mean()

# Drop missing days if any
daily_elec = daily_elec.dropna()

# Decompose the time series (trend, seasonality, residual)
decomp = seasonal_decompose(daily_elec, period=7 )  # weekly pattern
decomp.plot()
plt.suptitle('Electricity Consumption - Time Series Decomposition', y=1.02)
plt.show()
```



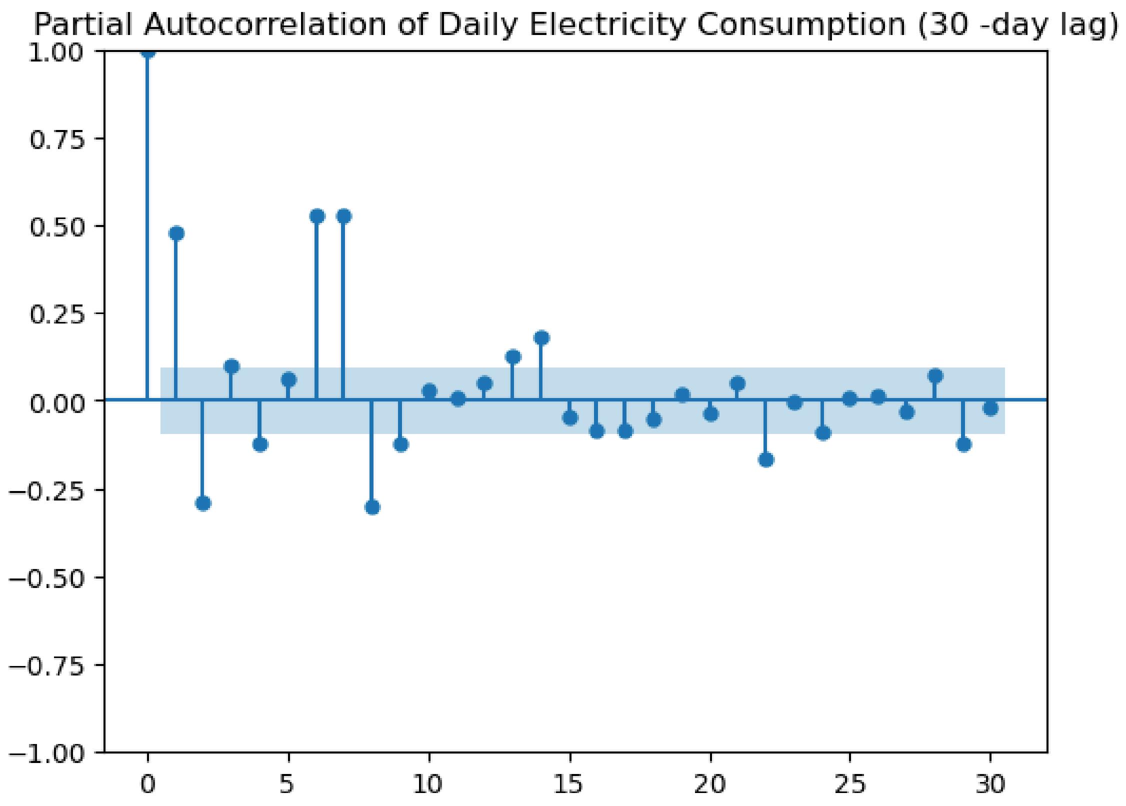
In [30]:
```
# Create temporary copy to avoid index issues
df_temp = data.copy()
```

```python
# Ensure Date is datetime and index
if not pd.api.types.is_datetime64_any_dtype(df_temp['Date']):
    df_temp['Date'] = pd.to_datetime(df_temp['Date'], errors='coerce')
df_temp = df_temp.set_index('Date').sort_index()

# Aggregate to daily mean
daily_elec = df_temp['Electricity Campus DN [kWh]'].resample('D').mean().dropna()

# Plot autocorrelation (ACF)
plt.figure(figsize=(10,5))
plot_acf(daily_elec, lags=30)
plt.title('Autocorrelation of Daily Electricity Consumption (30 day lag)')
plt.show()

# Optional: Partial autocorrelation (PACF)
plt.figure(figsize=(10,5))
plot_pacf(daily_elec, lags=30, method='ywm')
plt.title('Partial Autocorrelation of Daily Electricity Consumption (30 -day lag)')
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



```
<Figure size 1000x500 with 0 Axes>
```



5. Understanding ACF and PACF

The **Autocorrelation Function (ACF)** measures how much a time-series value at time *t* is correlated with its past values at different lags *k*. Mathematically, it is defined as:

$$\rho(k) = \frac{\mathrm{Cov}(Y_t, Y_{t-k})}{\sigma^2}$$

where

- Y_t is the value at time *t*,
- σ^2 is the variance of the series.

The ACF captures both **direct and indirect correlations**.
For example, if electricity consumption on day *t* depends on day *t−1*, and day *t−1* depends on day *t−2*, then ACF at lag 2 (t vs t−2) will still show correlation, even if it is only indirect through day *t−1*.

The **Partial Autocorrelation Function (PACF)** removes these intermediate effects. It measures the correlation between Y_t and Y_{t-k} after controlling for all shorter lags. Mathematically:

$$\phi(k,k) = \mathrm{Corr}(Y_t, Y_{t-k} \mid Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1})$$

PACF therefore shows only the **direct influence** of observations *k* periods apart, without interference from intermediate dependencies.

Summary:

- **ACF** → captures total correlation (direct + indirect)
- **PACF** → captures direct correlation after removing intermediate effects
- A strong spike at **lag 1** indicates day-to-day dependence

- A secondary spike at **lag 7** reveals a **weekly repeating pattern**

6. Time-series analysis

Hourly electricity consumption was aggregated into **daily averages** and decomposed into **trend, seasonal, and residual components** using a 7-day period to capture weekly patterns.

The **STL decomposition** reveals three main insights:

1. **Trend:** Electricity use gradually increases during summer months, driven by **cooling loads** and extended campus activities.
2. **Seasonality:** A consistent **weekly cycle** is observed, with higher consumption on weekdays and lower on weekends, aligning with normal campus operation.
3. **Residuals:** Short-term fluctuations are centered around zero with relatively stable variance, suggesting no major anomalies.

The **ACF** and **PACF** plots confirm strong **weekly periodicity** with significant correlations at **lags 7, 14, and 21**, supporting the suitability of a **seasonal ARIMA model (s = 7)** for forecasting.
These findings highlight distinct operational and climatic influences on campus energy use, forming a robust basis for further predictive modeling and energy optimization.