3_EDA_Ridership

September 3, 2025

1 Temporal analysis of the data

Following the EDA, I will perform a temporal analysis on the ridership data.

[1]:
```
INSTALL_LIB = True
```

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

import requests
```

[3]:
```
file_name = "TPG_meteo_all_df.csv"
TPG_meteo_all_df = pd.read_csv(file_name,sep=",")

TPG_meteo_all_df['date'] = pd.to_datetime(TPG_meteo_all_df['date'])
display(TPG_meteo_all_df.info())
print(f"\n")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4858272 entries, 0 to 4858271
Data columns (total 19 columns):
 #   Column                       Dtype
---  ------                       -----
 0   date                         datetime64[ns]
 1   ligne                        object
 2   ligne_type_act               object
 3   horaire_type                 object
 4   arret_code_long              object
 5   indice_semaine               int64
 6   indice_jour_semaine          int64
 7   nb_de_montees                float64
 8   nb_de_descentes              float64
 9   annee                        int64
 10  mois                         int64
```

```
 11   log_montees                  float64
 12   log_descentes                float64
 13   frequentation_totale         float64
 14   log_frequentation_totale     float64
 15   delta_montees_descentes      float64
 16   log_delta_montees_descentes  float64
 17   type_vehicule                object
 18   weather_code                 int64
dtypes: datetime64[ns](1), float64(8), int64(5), object(5)
memory usage: 704.2+ MB
```

```
None
```

2 1) Stops over time

We will look at the passenger counts at a stop (for one code) over time.
Are some stops present only for a short period?

[4]:
```python
periode_arrets = TPG_meteo_all_df.groupby('arret_code_long')['date'].
 ↪agg(['min', 'max'])
periode_arrets['duree_jours'] = (periode_arrets['max'] - periode_arrets['min']).
 ↪dt.days
periode_arrets_sorted = periode_arrets.sort_values(by='duree_jours')
#display(periode_arrets_sorted[periode_arrets_sorted['duree_jours'] < 10])
display(periode_arrets_sorted.head(10))
display(periode_arrets_sorted.tail(10))
```

arret_code_long	min	max	duree_jours
AUGSST	2024-01-02	2024-01-02	0
CCOL99	2024-05-05	2024-05-05	0
LOUR99	2022-07-17	2022-07-17	0
MEPR03	2025-05-04	2025-05-04	0
MOIL98	2024-10-18	2024-10-18	0
CYTE98	2022-07-17	2022-07-17	0
DEST	2024-12-06	2024-12-06	0
DJST	2025-04-24	2025-04-24	0
PRPI98	2023-05-07	2023-05-07	0
CFOU98	2022-07-17	2022-07-17	0

arret_code_long	min	max	duree_jours
LYIN00	2021-08-01	2025-06-22	1421
CBRI00	2021-08-01	2025-06-22	1421
CBRI01	2021-08-01	2025-06-22	1421
CCAP00	2021-08-01	2025-06-22	1421

```
CCAP01          2021-08-01 2025-06-22        1421
LULY06          2021-08-01 2025-06-22        1421
LULY05          2021-08-01 2025-06-22        1421
LULY04          2021-08-01 2025-06-22        1421
LYON01          2021-08-01 2025-06-22        1421
LAVI01          2021-08-01 2025-06-22        1421
```

[5]:
```
periode_arrets_sorted['duree_jours'].value_counts().sort_index()
```

[5]:
```
0         28
1          3
8          7
9          1
10         1
        …
1417       1
1418      65
1419      43
1420      34
1421    1569
Name: duree_jours, Length: 208, dtype: int64
```

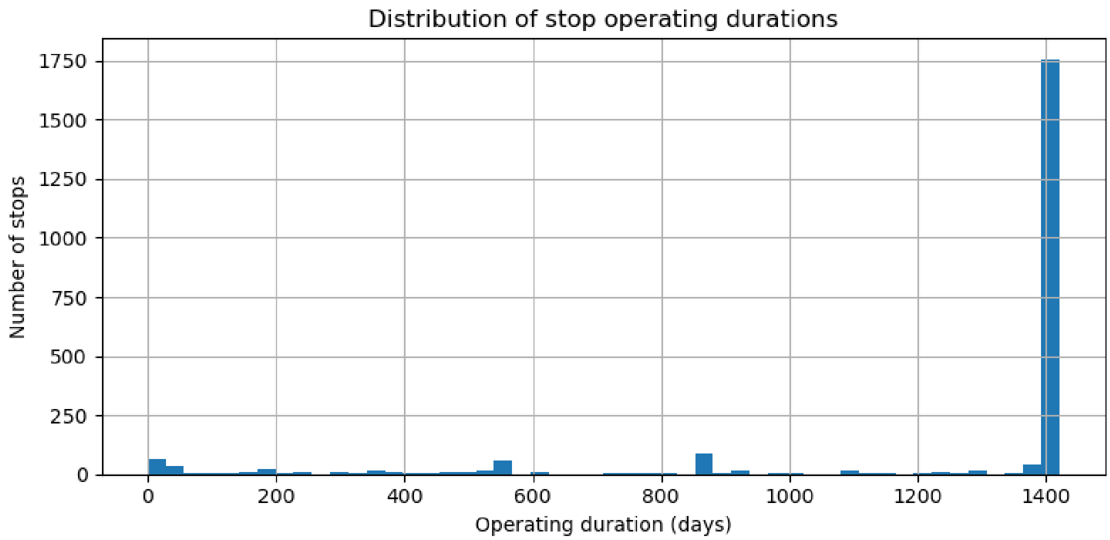
2.0.1 Observation :

The maximum duration of a stop is 1,421 days.
Some stops have a lifetime of 0 days, while others have data for 1,421 days.
Most stops reach this maximum of 1,421 days.

2.0.2 Question :

What is the distribution of the operating duration of stops?

[6]:
```
plt.figure(figsize=(8, 4))
periode_arrets_sorted['duree_jours'].hist(bins=50)
plt.xlabel("Operating duration (days)")
plt.ylabel("Number of stops")
plt.title("Distribution of stop operating durations")
plt.tight_layout()
plt.show()
```



2.0.3 Observation :

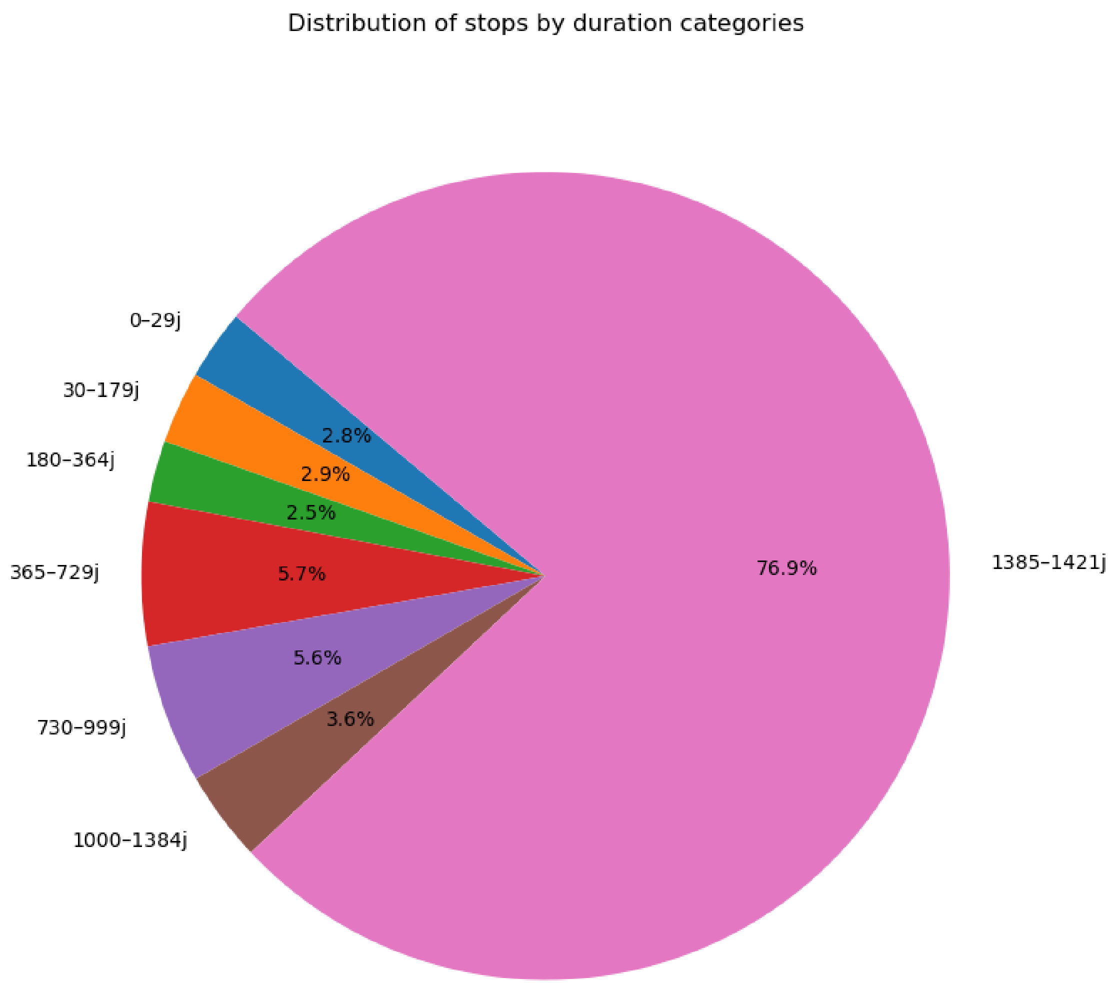
Most stops have a duration around 1,400 days.
There is also a spread of durations across many stops.

2.0.4 Action :

A pie chart will be used for representation.

[7]:
```
#code from chatGPT after debug
# Créer des classes personnalisées
max_duree = periode_arrets_sorted['duree_jours'].max()

bins = [0, 30, 180, 365, 730, 1000, 1385, max_duree + 1]
labels = [f"{bins[i]}-{bins[i+1]-1}j" for i in range(len(bins)-1)]

periode_arrets_sorted['duree_classe'] = pd.
 ↪cut(periode_arrets_sorted['duree_jours'], bins=bins, labels=labels,␣
 ↪include_lowest=True)

# Compter les classes
classe_counts = periode_arrets_sorted['duree_classe'].value_counts().
 ↪sort_index()

# Pie chart
plt.figure(figsize=(8, 8))
plt.pie(
    classe_counts.values,
    labels=classe_counts.index,
```

```
    autopct='%1.1f%%',
    startangle=140
)
plt.title("Distribution of stops by duration categories")
plt.axis('equal')
plt.tight_layout()
plt.show()
```



2.0.5 Observation :

- The majority of stops (77%) have a duration close to the maximum, i.e. **1421 days**.
- The remaining stops are very scattered, with many short durations, mostly **less than one**

year.

- The histogram shows a **clear drop before 365 days**, followed by a few small "peaks" around **600** and **800 days**.

Setting a threshold at **365 days** removes about **8% of stops** (0–30d, 31–180d, 181–365d), and keeps **92% of stops** with a sufficiently long operating duration.

2.0.6 Action :

Remove the stops with less than 365 days of data.

[8]:
```
print(f"Shape before drop arret : {TPG_meteo_all_df.shape}")
seuil_jours = 365
TPG_meteo_all_df = TPG_meteo_all_df[TPG_meteo_all_df['arret_code_long'].isin(
    periode_arrets_sorted[periode_arrets_sorted['duree_jours'] >= seuil_jours].
  ↪index
)]

print(f"Shape after drop arret : {TPG_meteo_all_df.shape}")
```

```
Shape before drop arret : (4858272, 19)
Shape after drop arret : (4837299, 19)
```

3 2) Stops with the highest passenger counts

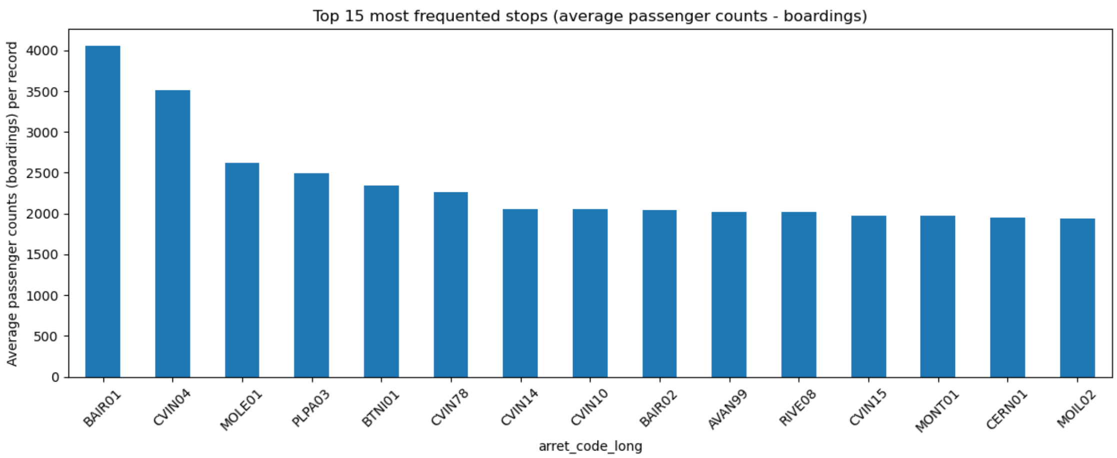
3.0.1 Method :

Group the dataset by 'arret_code_long' and compute the mean of 'nb_de_montees' per stop over the whole period.

[9]:
```
# Moyenne des montées par arrêt
montees_par_arret = TPG_meteo_all_df.
  ↪groupby('arret_code_long')['nb_de_montees'].mean().
  ↪sort_values(ascending=False)

print(montees_par_arret.describe())
```

```
count    2129.000000
mean      139.617559
std       308.645100
min         0.000000
25%         4.534425
50%        24.958146
75%       125.847210
max      4057.307792
Name: nb_de_montees, dtype: float64
```

[10]:
```
# Display the 15 most frequented stops
montees_par_arret.head(15).plot(
    kind='bar',
    figsize=(12,5),
    title="Top 15 most frequented stops (average passenger counts - boardings)"
)
plt.ylabel("Average passenger counts (boardings) per record")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



3.0.2 Leading stops :

- **BAIR01 (Bel-Air)** with more than 4,000 average passenger counts (boardings) per record.
- **CVIN04 (Cornavin train station)** follows closely (~3,500).
- Then there is a gradual decline down to the 15th stop, **CERN01**, around 1,900 boardings.

There is a minority of stops with very high traffic (major hubs).
The majority of other stops have much lower passenger counts.

This type of distribution is typical of a star-shaped or centralized transport system, organized around a few major nodes (e.g., train stations, Bel-Air, Plainpalais).

4 3) Temporal analysis of ridership

4.0.1 Observation :

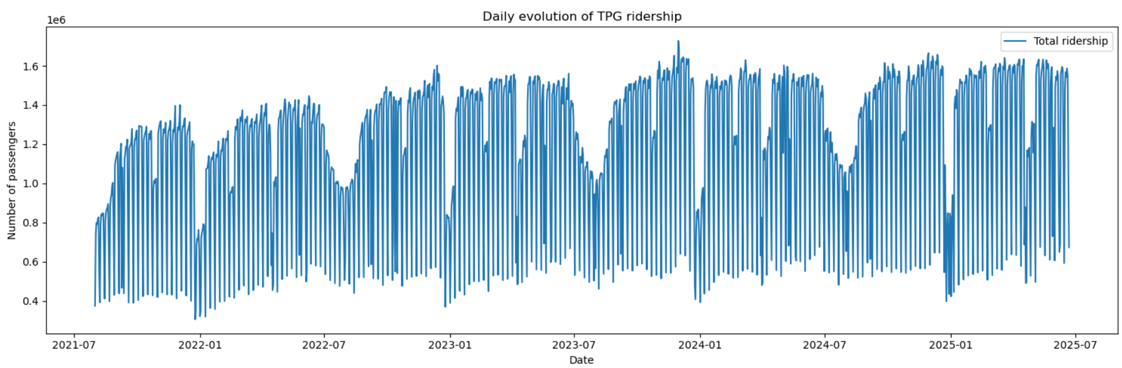
In the study of line 12, we saw recurring patterns:
- a drop during vacation periods,
- an increase in passenger counts (boardings) from September to December.

4.0.2 Question :

Do we observe the same patterns at the global ridership level?

[11]:
```
# agreger les données
global_daily_df = TPG_meteo_all_df.groupby('date')[['nb_de_montees',␣
 ↪'nb_de_descentes']].sum().reset_index()
global_daily_df['frequentation_totale'] = global_daily_df['nb_de_montees'] +␣
 ↪global_daily_df['nb_de_descentes']
```

[12]:
```
plt.figure(figsize=(15, 5))
plt.plot(global_daily_df['date'], global_daily_df['frequentation_totale'],␣
 ↪label='Total ridership')
plt.title("Daily evolution of TPG ridership")
plt.xlabel("Date")
plt.ylabel("Number of passengers")
plt.legend()
plt.tight_layout()
plt.show()
```



4.0.3 Observation :

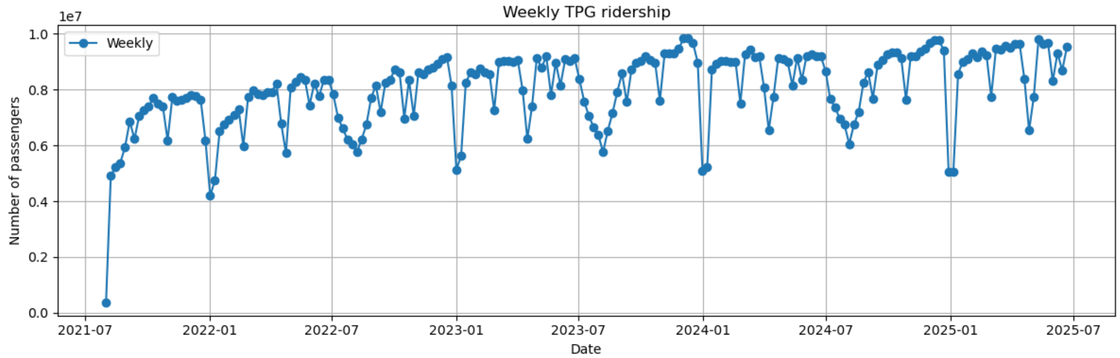
We can see:
- a strong weekly seasonality (sawtooth pattern → weekday/weekend effect),
- recurring drops probably corresponding to vacation periods or public holidays,
- a general upward trend over several years.

These same characteristics were already observed on line 12.

4.1 Resampling

[13]:
```
df = global_daily_df.copy()
df['date'] = pd.to_datetime(df['date'])
df.set_index('date', inplace=True)
```

[14]:
```
df_weekly = df.resample('W').sum()
df_monthly = df.resample('M').sum()

plt.figure(figsize=(12, 4))
plt.plot(df_weekly.index, df_weekly['frequentation_totale'], marker='o',␣
  ↪label='Weekly')
plt.title("Weekly TPG ridership")
plt.xlabel("Date")
plt.ylabel("Number of passengers")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



4.1.1 Observation :

General trend:
A clear increase from 2021 to 2025, with a stabilization effect in the most recent years.

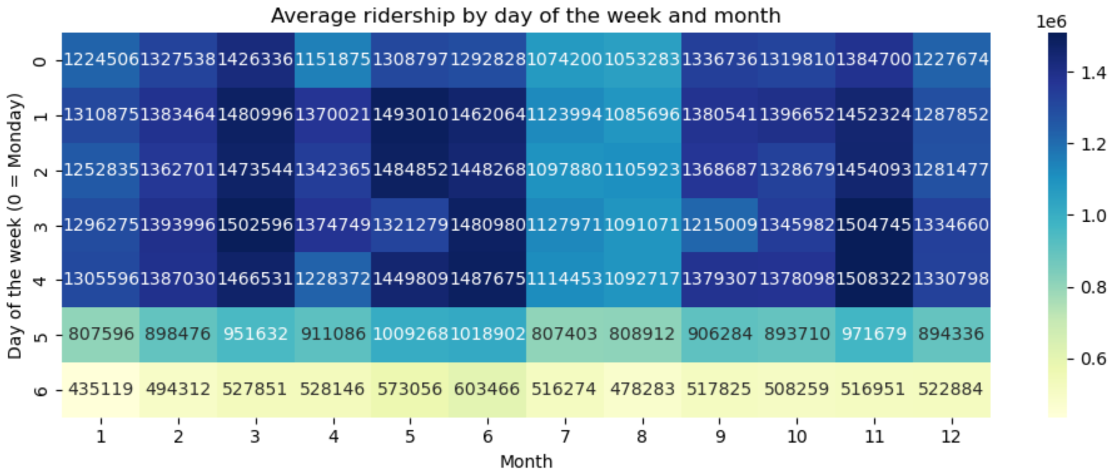
Regular drops:
Sharp declines each year (December–January, July–August), typically linked to vacation periods or end-of-year holidays.

Lower initial values:
The beginning of the series (summer 2021) shows lower values, possibly due to a progressive setup of sensors or post-COVID restrictions.

4.2 Monthly vs day-of-week heatmap

[15]:
```
df['dayofweek'] = df.index.dayofweek  # 0=Monday
df['month'] = df.index.month
pivot = df.pivot_table(index='dayofweek', columns='month',␣
  ↪values='frequentation_totale', aggfunc='mean')

import seaborn as sns
```

```
plt.figure(figsize=(10, 4))
sns.heatmap(pivot, annot=True, fmt=".0f", cmap="YlGnBu")
plt.title("Average ridership by day of the week and month")
plt.xlabel("Month")
plt.ylabel("Day of the week (0 = Monday)")
plt.tight_layout()
plt.show()
```



4.2.1 Reading the heatmap

- **Y-axis (vertical):** 0 = Monday, up to 6 = Sunday
- **X-axis (horizontal):** 1 to 12 → months from January to December
- **Color scale:** the darker the color, the higher the ridership

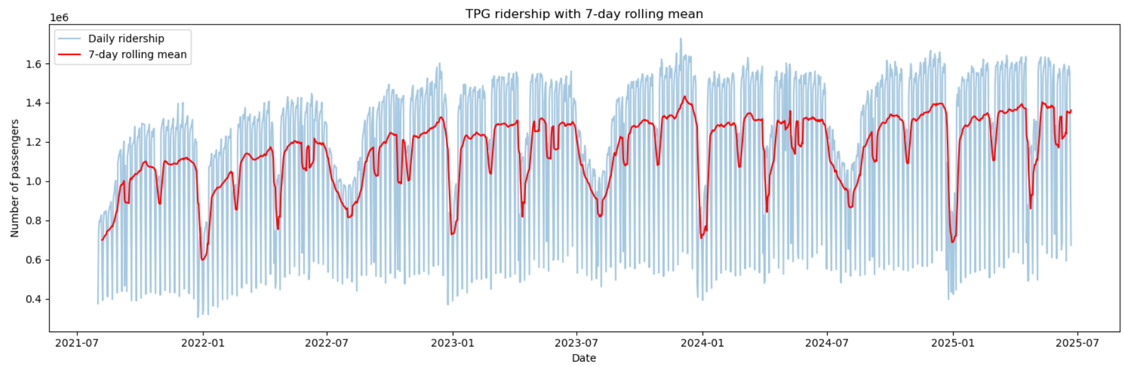
4.2.2 Key observations

- **High ridership on weekdays (Monday to Friday):**
  Days 0 to 4 are much darker compared to day 5 (Saturday) and especially day 6 (Sunday).
  This confirms a predominantly professional and school-related usage.
- **Peaks on Tuesdays and Thursdays between September and November:**
  These days (months 9, 10, 11) show the highest ridership.
  This likely reflects a period of full activity (back-to-school, no vacation periods).

4.3 Rolling mean

[16]:
```
df['rolling_mean_7j'] = df['frequentation_totale'].rolling(window=7).mean()

plt.figure(figsize=(15, 5))
```

```
plt.plot(df.index, df['frequentation_totale'], alpha=0.4, label='Daily␣
    ↪ridership')
plt.plot(df.index, df['rolling_mean_7j'], color='red',  label='7-day rolling␣
    ↪mean')
plt.title("TPG ridership with 7-day rolling mean")
plt.xlabel("Date")
plt.ylabel("Number of passengers")
plt.legend()
plt.tight_layout()
plt.show()
```



4.3.1 Observation :

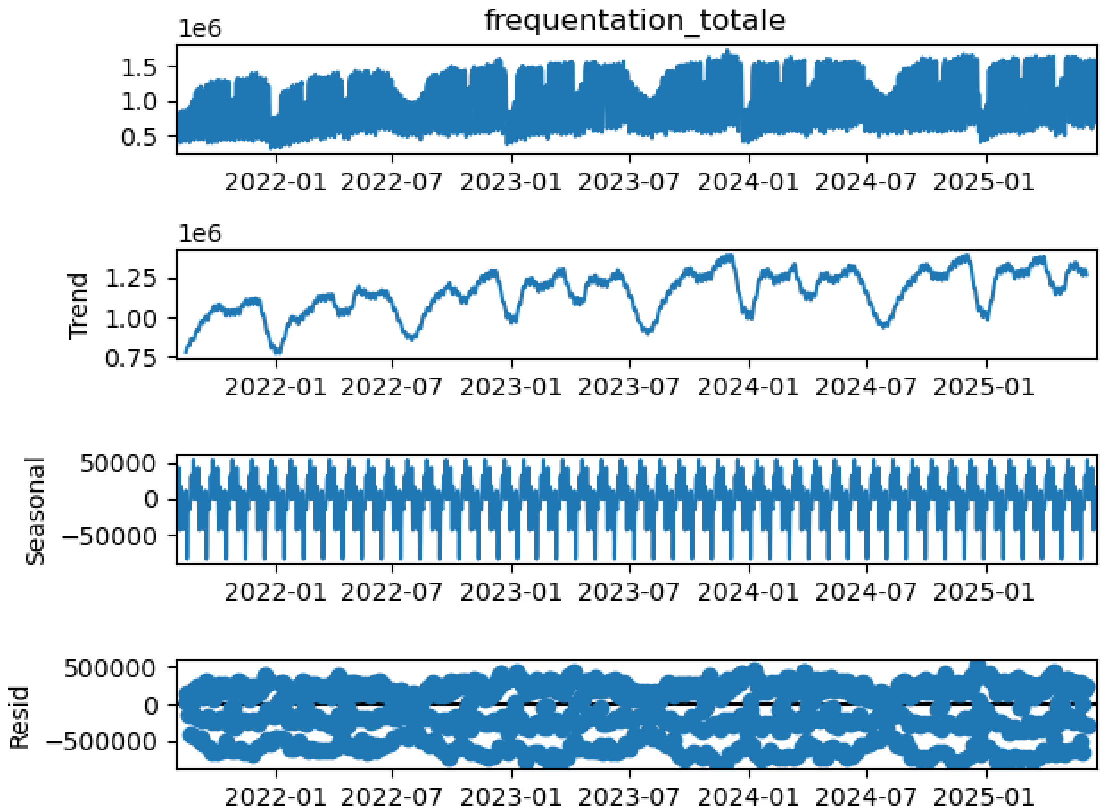
The 7-day rolling mean smooths out the daily variations and highlights the underlying trend. We can clearly see:
- the weekly pattern is reduced,
- the recurring drops during vacation periods remain visible,
- the overall upward trend from 2021 to 2025 is easier to observe.

4.4 Décomposition de la série temporelle (trend / seasonality / residual)

4.4.1 Remark :

I tried the seasonal decomposition, but I did not clearly see strong patterns in the graphs. The following analysis is based on ChatGPT's interpretation of the decomposition results.

[17]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

decomp = seasonal_decompose(df['frequentation_totale'], model='additive',␣
    ↪period=30)
decomp.plot()
plt.tight_layout()
plt.show()
```



4.4.2 Explanation provided by ChatGPT from the graphs :

1. **frequentation_totale (original series)**
   - The original series: the "sawtooth" pattern remains due to the weekly cycle (drop during weekends).

   - Longer seasonal drops are also visible: summer holidays, Christmas/New Year, etc.
2. **Trend**
   - The trend is smooth and consistent.

   - It shows:
     - a progressive increase from late 2021 until mid-2023,

     - drops during summers and holiday periods,

     - relatively stable ridership in 2024–2025, with a slight upward tendency.

   - This provides a good basis for long-term forecasting (e.g., ARIMA or Prophet).
3. **Seasonal**
   - The repetitive pattern is clear: peaks and troughs appear roughly every 30 days.

- This likely reflects a monthly periodicity related to work / weekend / vacation cycles.

- The amplitudes are quite constant (~±50k), which is a good sign.

4. **Residual**
   - These are variations not explained by trend or seasonality.

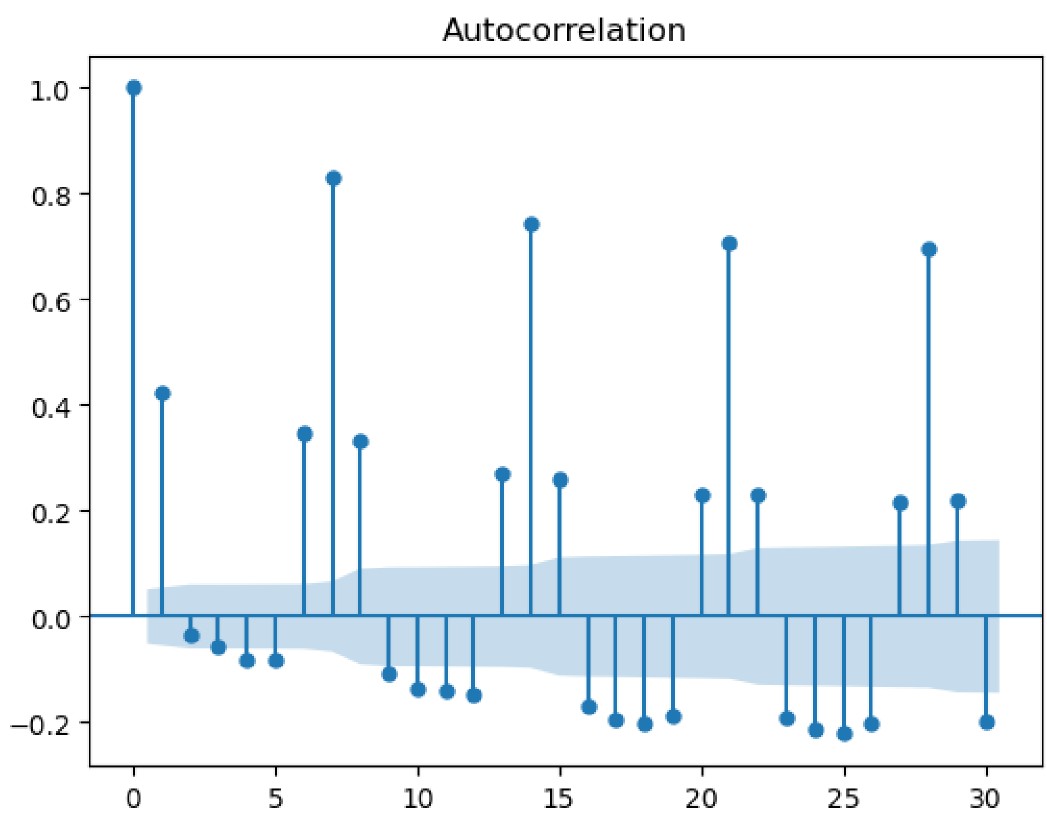
   - Some important spikes can be observed: these correspond to exceptional events.
     - Possible causes: strikes, storms, public events, or measurement anomalies.

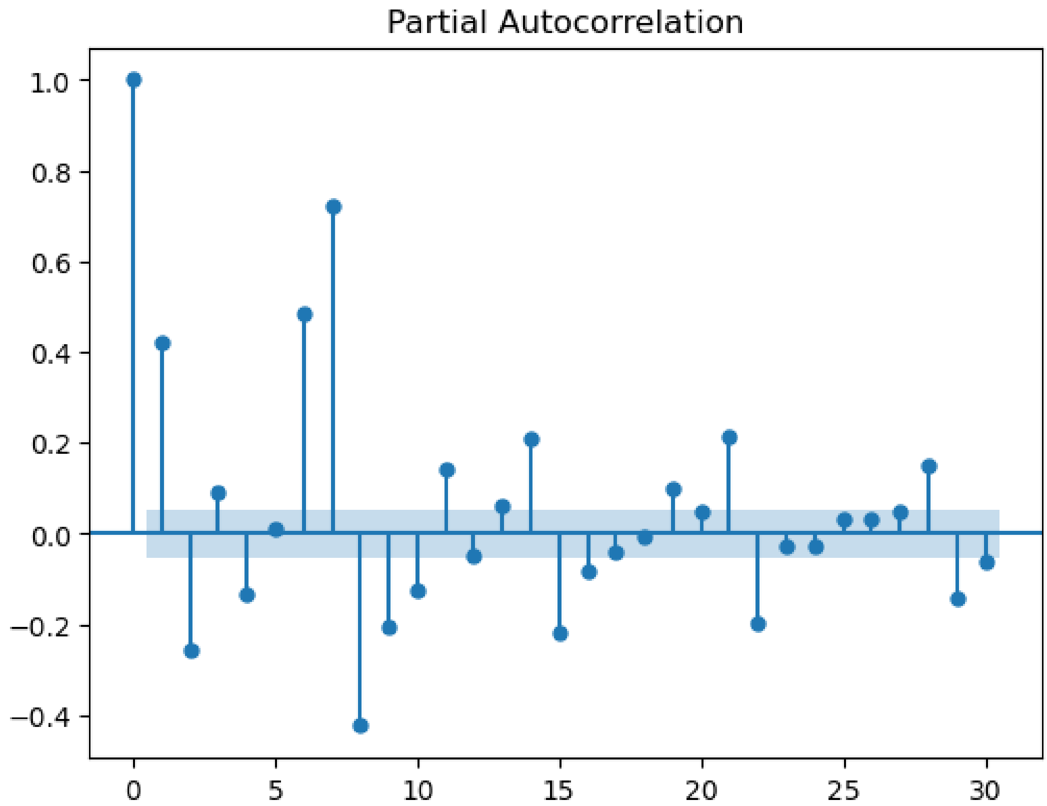
   - To study them further, one could check the dates of these positive or negative peaks.

4.5 Analysis of temporal dependencies

The long-term graph shows repetitive effects.
Do these effects also appear on a smaller scale?
To investigate this, I will study the autocorrelation of the data.

[18]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

plot_acf(df['frequentation_totale'], lags=30)
plot_pacf(df['frequentation_totale'], lags=30)
plt.show()
```





4.6 Autocorrelation Function (ACF)

4.6.1 Observation :

The ACF plot shows the global correlations between daily passenger counts and their lagged values.

- Significant peaks at lags 7, 14, 21, and 28 indicate a clear weekly periodicity.
- This means that passenger counts on a given day are strongly correlated with the same weekday in previous weeks.
- This is typical of human mobility patterns: commuting during weekdays and lower activity on weekends.

There are strong weekly temporal dependencies, which supports: the use of lag features such as `frequentation_lag_7`, `frequentation_lag_14`, etc.,

4.7 Partial Autocorrelation Function (PACF)

4.7.1 Observation :

The PACF plot shows the direct correlation between the series and its lags, after removing the effect of intermediate lags.

- Lags 1, 7, and 8 are significant.

- This means:
  - Lag 1 (the previous day) has a strong direct impact.

  - Lag 7 (the same weekday in the previous week) also plays a major role, consistent with the ACF results.

These results suggest creating additional features to capture direct effects.

4.7.2 Action :

Create lag variables derived from the ACF/PACF analysis.

[19]:
```
global_daily_df['frequentation_totale_lag_1'] =␣
 ↪global_daily_df['frequentation_totale'].shift(1)
global_daily_df['frequentation_totale_lag_7'] =␣
 ↪global_daily_df['frequentation_totale'].shift(7)

# Moyenne glissante sur 7 jours (smoothing)
global_daily_df['rolling_mean_7d'] = global_daily_df['frequentation_totale'].
 ↪rolling(window=7).mean()

# Supprimer les lignes avec des NaN
global_daily_df.dropna(subset=['frequentation_totale_lag_1',␣
 ↪'frequentation_totale_lag_7', 'rolling_mean_7d'], inplace=True)
```

5 4) Preparing the final datasets

5.0.1 Observation :

At the end of the EDA, two datasets were obtained: `TPG_meteo_all_df` and `global_daily_df`.
- `global_daily_df` is designed to address global and daily-level problems.
- `TPG_meteo_all_df` allows for a more detailed analysis of passenger counts.

5.0.2 Action :

To ensure consistency between the two datasets, they will be enriched with cross-features:
- `global_daily_df`: add daily weather, temporal variables, and logarithmic transformations.
- `TPG_meteo_all_df`: add lagged variables.

[20]:
```
# load data from files
meteo_df_daily = pd.read_csv("meteo_daily.csv")
```

```
meteo_df_daily['time'] = pd.to_datetime(meteo_df_daily['time'])
meteo_df_daily = meteo_df_daily.rename(columns={"time": "date"})
```

[21]:
```
# add weather
global_daily_df = global_daily_df.merge(meteo_df_daily[['date',␣
↪'weather_code']], on='date', how='left')

# transformation log
global_daily_df['log_frequentation_totale'] = np.
↪log1p(global_daily_df['frequentation_totale'])
global_daily_df['log_frequentation_totale_lag_1'] = np.
↪log1p(global_daily_df['frequentation_totale_lag_1'])
global_daily_df['log_frequentation_totale_lag_7'] = np.
↪log1p(global_daily_df['frequentation_totale_lag_7'])
global_daily_df['log_rolling_mean_7d'] = np.
↪log1p(global_daily_df['rolling_mean_7d'])

# Temporal variables
global_daily_df['indice_jour_semaine'] = global_daily_df['date'].dt.dayofweek
global_daily_df['indice_semaine'] = global_daily_df['date'].dt.isocalendar().
↪week.astype(int)
global_daily_df['mois'] = global_daily_df['date'].dt.month
global_daily_df['annee'] = global_daily_df['date'].dt.year

global_daily_df['est_weekend'] = global_daily_df['indice_jour_semaine'].
↪isin([5, 6]).astype(int)
```

[22]:
```
if INSTALL_LIB:
    !pip install holidays
```

```
Requirement already satisfied: holidays in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (0.76)
Requirement already satisfied: python-dateutil in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from holidays)
(2.9.0)
Requirement already satisfied: six>=1.5 in
/home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from python-
dateutil->holidays) (1.15.0)
```

Collecting holidays Downloading holidays-0.76-py3-none-any.whl (1.1 MB) | | 1.1 MB 2.1 MB/s
Requirement already satisfied: python-dateutil in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from holidays) (2.9.0) Requirement already satisfied: six>=1.5 in /home/moi/anaconda3/envs/adsml/lib/python3.9/site-packages (from python-dateutil->holidays) (1.15.0) Installing collected packages: holidays Successfully installed holidays-0.76

[23]:
```python
# ajout d'une variable est_ferié
import holidays

# Create a dictionary of Swiss public holidays
ch_holidays = holidays.CH(subdiv='GE')

# Create a column "est_ferie"
global_daily_df['est_ferie'] = global_daily_df['date'].isin(ch_holidays).
    ↪astype(int)
```

[24]:
```python
TPG_meteo_all_df = TPG_meteo_all_df.sort_values(['arret_code_long', 'ligne',␣
    ↪'date'])

# Temporal variables
TPG_meteo_all_df['montees_lag_1'] = TPG_meteo_all_df.
    ↪groupby(['arret_code_long', 'ligne'])['nb_de_montees'].shift(1)
TPG_meteo_all_df["log_montees_lag_1"] = np.
    ↪log1p(TPG_meteo_all_df["montees_lag_1"])

TPG_meteo_all_df['desc_lag_1'] = TPG_meteo_all_df.groupby(['arret_code_long',␣
    ↪'ligne'])['nb_de_descentes'].shift(1)
TPG_meteo_all_df["log_desc_lag_1"] = np.log1p(TPG_meteo_all_df["desc_lag_1"])

TPG_meteo_all_df['montees_lag_7'] = TPG_meteo_all_df.
    ↪groupby(['arret_code_long', 'ligne'])['nb_de_montees'].shift(7)
TPG_meteo_all_df["log_montees_lag_7"] = np.
    ↪log1p(TPG_meteo_all_df["montees_lag_7"])

TPG_meteo_all_df['desc_lag_7'] = TPG_meteo_all_df.groupby(['arret_code_long',␣
    ↪'ligne'])['nb_de_descentes'].shift(7)
TPG_meteo_all_df["log_desc_lag_7"] = np.log1p(TPG_meteo_all_df["desc_lag_7"])

TPG_meteo_all_df['rolling_montees_7d'] = TPG_meteo_all_df.
    ↪groupby(['arret_code_long', 'ligne'])['nb_de_montees'].transform(lambda x: x.
    ↪rolling(7).mean())
TPG_meteo_all_df["log_rolling_montees_7d"] = np.
    ↪log1p(TPG_meteo_all_df["rolling_montees_7d"])

TPG_meteo_all_df['rolling_desc_7d'] = TPG_meteo_all_df.
    ↪groupby(['arret_code_long', 'ligne'])['nb_de_descentes'].transform(lambda x:␣
    ↪x.rolling(7).mean())
TPG_meteo_all_df["log_rolling_desc_7d"] = np.
    ↪log1p(TPG_meteo_all_df["rolling_desc_7d"])

TPG_meteo_all_df['est_weekend'] = TPG_meteo_all_df['indice_jour_semaine'].
    ↪isin([5, 6]).astype(int)
```

```
TPG_meteo_all_df = TPG_meteo_all_df.dropna().reset_index(drop=True)
```

[25]:
```
# Create a column "est_ferie"
TPG_meteo_all_df['est_ferie'] = TPG_meteo_all_df['date'].isin(ch_holidays).
 ↪astype(int)
TPG_meteo_all_df["est_ferie"] = TPG_meteo_all_df["est_ferie"].astype(int)
```

[26]:
```
display(TPG_meteo_all_df.info())
TPG_meteo_all_df.isna().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4794267 entries, 0 to 4794266
Data columns (total 33 columns):
 #   Column                       Dtype
---  ------                       -----
 0   date                         datetime64[ns]
 1   ligne                        object
 2   ligne_type_act               object
 3   horaire_type                 object
 4   arret_code_long              object
 5   indice_semaine               int64
 6   indice_jour_semaine          int64
 7   nb_de_montees                float64
 8   nb_de_descentes              float64
 9   annee                        int64
 10  mois                         int64
 11  log_montees                  float64
 12  log_descentes                float64
 13  frequentation_totale         float64
 14  log_frequentation_totale     float64
 15  delta_montees_descentes      float64
 16  log_delta_montees_descentes  float64
 17  type_vehicule                object
 18  weather_code                 int64
 19  montees_lag_1                float64
 20  log_montees_lag_1            float64
 21  desc_lag_1                   float64
 22  log_desc_lag_1               float64
 23  montees_lag_7                float64
 24  log_montees_lag_7            float64
 25  desc_lag_7                   float64
 26  log_desc_lag_7               float64
 27  rolling_montees_7d           float64
 28  log_rolling_montees_7d       float64
 29  rolling_desc_7d              float64
 30  log_rolling_desc_7d          float64
```

```
 31   est_weekend                   int64
 32   est_ferie                     int64
dtypes: datetime64[ns](1), float64(20), int64(7), object(5)
memory usage: 1.2+ GB
```

```
None
```

[26]:
```
date                          0
ligne                         0
ligne_type_act                0
horaire_type                  0
arret_code_long               0
indice_semaine                0
indice_jour_semaine           0
nb_de_montees                 0
nb_de_descentes               0
annee                         0
mois                          0
log_montees                   0
log_descentes                 0
frequentation_totale          0
log_frequentation_totale      0
delta_montees_descentes       0
log_delta_montees_descentes   0
type_vehicule                 0
weather_code                  0
montees_lag_1                 0
log_montees_lag_1             0
desc_lag_1                    0
log_desc_lag_1                0
montees_lag_7                 0
log_montees_lag_7             0
desc_lag_7                    0
log_desc_lag_7                0
rolling_montees_7d            0
log_rolling_montees_7d        0
rolling_desc_7d               0
log_rolling_desc_7d           0
est_weekend                   0
est_ferie                     0
dtype: int64
```

[27]:
```
display(global_daily_df.info())
global_daily_df.isna().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1415 entries, 0 to 1414
Data columns (total 18 columns):
```

```
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   date                          1415 non-null   datetime64[ns]
 1   nb_de_montees                 1415 non-null   float64
 2   nb_de_descentes               1415 non-null   float64
 3   frequentation_totale          1415 non-null   float64
 4   frequentation_totale_lag_1    1415 non-null   float64
 5   frequentation_totale_lag_7    1415 non-null   float64
 6   rolling_mean_7d               1415 non-null   float64
 7   weather_code                  1415 non-null   int64
 8   log_frequentation_totale      1415 non-null   float64
 9   log_frequentation_totale_lag_1 1415 non-null  float64
 10  log_frequentation_totale_lag_7 1415 non-null  float64
 11  log_rolling_mean_7d           1415 non-null   float64
 12  indice_jour_semaine           1415 non-null   int64
 13  indice_semaine                1415 non-null   int64
 14  mois                          1415 non-null   int64
 15  annee                         1415 non-null   int64
 16  est_weekend                   1415 non-null   int64
 17  est_ferie                     1415 non-null   int64
dtypes: datetime64[ns](1), float64(10), int64(7)
memory usage: 210.0 KB
```

```
None
```

[27]:

```
date                              0
nb_de_montees                     0
nb_de_descentes                   0
frequentation_totale              0
frequentation_totale_lag_1        0
frequentation_totale_lag_7        0
rolling_mean_7d                   0
weather_code                      0
log_frequentation_totale          0
log_frequentation_totale_lag_1    0
log_frequentation_totale_lag_7    0
log_rolling_mean_7d               0
indice_jour_semaine               0
indice_semaine                    0
mois                              0
annee                             0
est_weekend                       0
est_ferie                         0
dtype: int64
```

5.1 Exporting the datasets

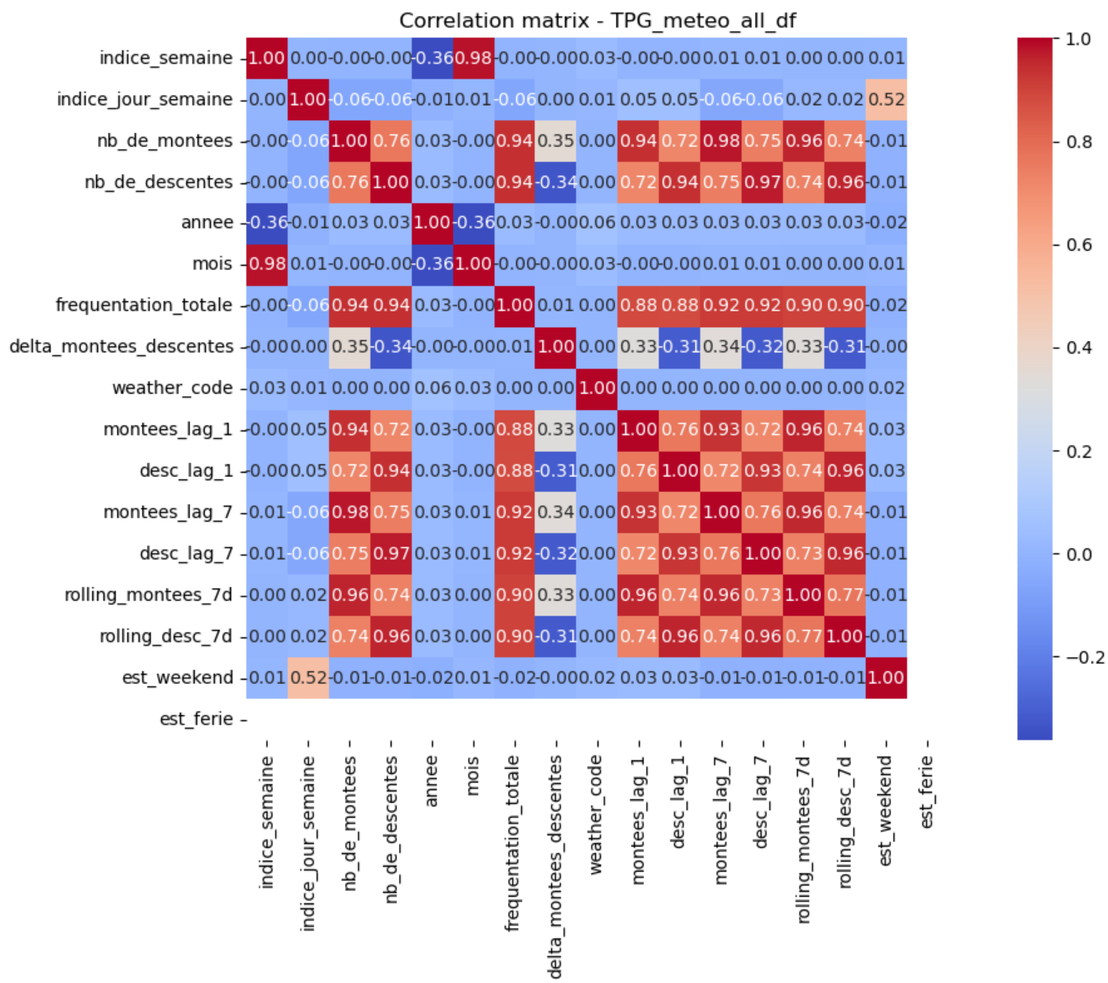
[28]:
```
# Save data to file
file_name = "TPG_daily_df.csv"
TPG_meteo_all_df.to_csv(file_name, index=False)
```

[29]:
```
# Save data to file
file_name = "global_daily_df.csv"
global_daily_df.to_csv(file_name, index=False)
```

6 5) Weather impact analysis

Is there a correlation between ridership and weather?

[30]:
```
# Select only numerical columns (excluding datetime)
df_corr = (TPG_meteo_all_df
           .select_dtypes(include=['float64', 'int64'])
           .drop(columns=[col for col in TPG_meteo_all_df.columns if col.
 ↪startswith("log_")])
           .corr(method='pearson'))

# Display the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df_corr, annot=True, cmap='coolwarm', fmt=".2f", square=True)
plt.title("Correlation matrix - TPG_meteo_all_df")
plt.tight_layout()
plt.show()
```



6.0.1 Observation :

There is a strong correlation (0.97–0.98) between `nb_de_montees` / `nb_de_descentes` and their lagged or rolling mean versions.

The `weather_code` variable remains very weakly correlated with the others (<0.1).
This is expected: weather effects are often non-linear or context-dependent, and not necessarily well captured by Pearson correlation.

6.0.2 Conclusion :

The potential impact of weather on the models will be examined in the next chapter.

[31]:
```
#end
```