In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import json
import plotly.express as px

from prettytable import PrettyTable

import geopandas as gpd
from geopy.geocoders import Nominatim
import folium
from folium import Marker, Choropleth

sns.set(style='darkgrid', palette = 'pastel')
pd.set_option('display.float_format', lambda x: '%.2f' % x)
pd.set_option('display.max_columns', 50)
pd.set_option('display.max_colwidth', None)

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

```
C:\Users\guym\anaconda3\lib\site-packages\pandas\core\computation\expressions.py:21: UserWarning: Pandas requires version '2.8.4' or newer of 'numexpr' (version '2.7.3' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
C:\Users\guym\anaconda3\lib\site-packages\pandas\core\arrays\masked.py:60: UserWarning: Pandas requires version '1.3.6' or newer of 'bottleneck' (version '1.3.2' currently installed).
  from pandas.core import (
C:\Users\guym\AppData\Local\Temp/ipykernel_24632/3921357982.py:1: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
C:\Users\guym\anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version 1.26.3
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [2]:

```
import matplotlib
print(sns.__version__)
print(pd.__version__)
print(matplotlib.__version__)
print(np.__version__)
```

```
0.13.2
2.2.0
3.7.0
1.26.3
```

## Load Data

In [3]:

```
df = pd.read_table('idb5yr.txt', sep='|')
```

In [4]:

```
df.shape
```

Out[4]: (34237, 115)

In [5]:
```
df.head()
```

Out[5]:

| | #YR | GEO_ID | AREA_KM2 | ASFR15_19 | ASFR20_24 | ASFR25_29 | ASFR30_34 | ASFR35_39 | ASFR40_44 | ASFR45_49 | CBR | CDR | E0 | E0_F | E0_M | FMR0_4 | FMR1_4 | FPOP | FPOP0_4 | FPOP10_14 | FPOP100_ | FPOP15_19 | FPOP20_24 | F |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1950 | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **1** | 1951 | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **2** | 1952 | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **3** | 1953 | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **4** | 1954 | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |

5 rows × 115 columns

## variable definitions

In [6]:
```
print('Dataframe contains a total of ' + str(len(df.GEO_ID.unique())) + ' countries.')
print('Dataframe contains data from Year ' + str(df['#YR'].min()) + ' to Year ' + str(df['#YR'].max()) )
```

```
Dataframe contains a total of 227 countries.
Dataframe contains data from Year 1950 to Year 2100
```

### Extract data from year 1950 to year 2050

In [7]:
```
data = df[df['#YR']<2051].copy()
```

In [8]:
```
print('Row number decreased to', data.shape[0], 'rows')
```

```
Row number decreased to 22927 rows
```

### Combine `GEO_ID` with country names

`geoid.csv` is generated from `geoid_etl.py`

In [9]:
```
df_geoid = pd.read_csv('geoid.csv', encoding='iso-8859-1' )
```

In [10]:
```
df_geoid.head()
```

Out[10]:

| | NAME | GEO_ID | POP | YR | AGE | SEX |
|---|---|---|---|---|---|---|
| **0** | Andorra | W140000WOAD | 432 | 2023 | 15 | 2 |
| **1** | United Arab Emirates | W140000WOAE | 52476 | 2023 | 15 | 2 |
| **2** | Afghanistan | W140000WOAF | 422527 | 2023 | 15 | 2 |
| **3** | Antigua and Barbuda | W140000WOAG | 724 | 2023 | 15 | 2 |

| | NAME | GEO_ID | POP | YR | AGE | SEX |
|---|---|---|---|---|---|---|
| **4** | Anguilla | W140000WOAI | 127 | 2023 | 15 | 2 |

In [11]:
```
# take the first two columns
df_geoid = df_geoid.iloc[:,[0,1]]

df_geoid.rename(columns={'NAME':'COUNTRY'}, inplace=True)
```

In [12]:
```
# merge df_geoid with data

data = data.merge(df_geoid, how='left', on='GEO_ID')
```

In [13]:
```
# move country name to the front

country = data.iloc[:,-1]
data.drop(columns=['COUNTRY'], inplace=True)
data.insert(loc=1, column='COUNTRY', value=country)
```

In [14]:
```
data.head(5)
```

Out[14]:

| | #YR | COUNTRY | GEO_ID | AREA_KM2 | ASFR15_19 | ASFR20_24 | ASFR25_29 | ASFR30_34 | ASFR35_39 | ASFR40_44 | ASFR45_49 | CBR | CDR | E0 | E0_F | E0_M | FMR0_4 | FMR1_4 | FPOP | FPOP0_4 | FPOP10_14 | FPOP100_ | FPOP15_19 | FF |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1950 | Andorra | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **1** | 1951 | Andorra | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **2** | 1952 | Andorra | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **3** | 1953 | Andorra | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| **4** | 1954 | Andorra | W140000WOAD | 468.00 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |

5 rows × 116 columns

In [15]:
```
print('There are ', len(data.COUNTRY.unique()), 'countries/territories in data')
```

```
There are  227 countries/territories in data
```

In [16]:
```
data_name = data.COUNTRY.unique().tolist()
```

### World Administrative Boundaries

`world-administrative-boundaries.geojson` is from opendatasoft

In [17]:
```
df_boundaries = gpd.read_file('world-administrative-boundaries.geojson')
```

In [18]:

```
df_boundaries_name = df_boundaries.name.unique().tolist()
```

In [19]:

```
print('There are in total', df_boundaries.shape[0], 'administrative boundaries in the geojson file.')
```

```
There are in total 256 administrative boundaries in the geojson file.
```

In [20]:

```
[name for name in data_name if name not in df_boundaries_name]
```

Out[20]:

```
['Antigua and Barbuda',
 'Bosnia and Herzegovina',
 'Saint Barthelemy',
 'Brunei',
 'Bahamas, The',
 'Congo (Kinshasa)',
 'Congo (Brazzaville)',
 'Cabo Verde',
 'Curaçao',
 'Czechia',
 'Micronesia, Federated States of',
 'United Kingdom',
 'Gambia, The',
 'Iran',
 'Korea, North',
 'Korea, South',
 'Laos',
 'Libya',
 'Moldova',
 'Saint Martin',
 'North Macedonia',
 'Burma',
 'Macau',
 'Saint Pierre and Miquelon',
 'Russia',
 'Saint Helena, Ascension, and Tristan da Cunha',
 'Sint Maarten',
 'Syria',
 'Eswatini',
 'Tanzania',
 'United States',
 'Virgin Islands, British',
 'Virgin Islands, U.S.',
 'Wallis and Futuna',
 'Kosovo']
```

In [21]:

```
# change country names in df_boundaries to match names in data
name_dict = {'Antigua & Barbuda':'Antigua and Barbuda',
                 'Bosnia & Herzegovina': 'Bosnia and Herzegovina',
                 'Brunei Darussalam': 'Brunei',
                 'Bahamas':'Bahamas, The',
                 'Democratic Republic of the Congo':'Congo (Kinshasa)',
                 'Congo': 'Congo (Brazzaville)',
                 'Cape Verde':'Cabo Verde',
                 'Netherlands Antilles': 'Curaçao',
                 'Czech Republic': 'Czechia',
                 'Micronesia (Federated States of)': 'Micronesia, Federated States of',
                 'U.K. of Great Britain and Northern Ireland': 'United Kingdom',
```

```
                   'Gambia': 'Gambia, The',
                   'Iran (Islamic Republic of)': 'Iran',
                   "Democratic People's Republic of Korea": 'Korea, North',
                   'Republic of Korea': 'Korea, South',
                   "Lao People's Democratic Republic": 'Laos',
                   'Libyan Arab Jamahiriya': 'Libya',
                   'Moldova, Republic of': 'Moldova',
                   'The former Yugoslav Republic of Macedonia': 'North Macedonia',
                   'Myanmar': 'Burma',
                   'Russian Federation': 'Russia',
                   'Syrian Arab Republic': 'Syria',
                   'Swaziland': 'Eswatini',
                   'United Republic of Tanzania': 'Tanzania',
                   'United States of America': 'United States',
                   'British Virgin Islands': 'Virgin Islands, British',
                   'United States Virgin Islands': 'Virgin Islands, U.S.'}
```

### Update df_boundaries with name_dict, Non-Exhaustive Mapping

In [22]:

```
df_boundaries['name'] = df_boundaries['name'].map(name_dict).fillna(df_boundaries['name'])
```

In [23]:

```
# double check
df_boundaries_name = df_boundaries.name.unique().tolist()
[name for name in data_name if name not in df_boundaries_name]
```

Out[23]:

```
['Saint Barthelemy',
 'Saint Martin',
 'Macau',
 'Saint Pierre and Miquelon',
 'Saint Helena, Ascension, and Tristan da Cunha',
 'Sint Maarten',
 'Wallis and Futuna',
 'Kosovo']
```

df_boundaries is missing `Saint Martin`, `Saint Barthelemy`, `Macau`, `Saint Pierre and Miquelon`, `Saint Helena, Ascension, and Tristan da Cunha`, `Sint Maarten`, `Wallis and Futuna`, `Kosovo`

### Get coordinates from geojson.io

In [24]:

```
additional_geo = {"type":"FeatureCollection",
 "features":[{"type":"Feature",
              "geometry":{
            "coordinates": [[[-62.91132219738526,17.96343155866785], [-62.907476690909206, 17.950424674152387], [ -62.86303972718257, 17.890662016508315],  [-62.8121935859958, 17.865043283470357], [-62
                  "type": "Polygon"},
            "properties":{"geo_point_2d":{"lon":-62.825598,"lat":17.8967693},
                          "iso3":"BLM",
                          "status":"Overseas Collectivity",
                          "color_code":"BLM",
                          "name":"Saint Barthelemy",
                          "continent":"Americas",
                          "region":"Caribbean",
                          "iso_3166_1_alpha_2_codes":'BL',
                          "french_short":"Saint Barthélemy"}},

             {"type":"Feature",
              "geometry":{
                  "coordinates": [[[-63.16606182461187,18.066994117122547],[-63.11536957085629,18.03719964865043],[-63.07596786452797,18.051440281943258],[-63.07297241317005,18.05691714150373],[-63.066
```

```
        "type":"Polygon"},
    "properties":{"geo_point_2d":{"lon":-63.08380212192628,"lat":18.066775058581598},
                "iso3":'MAF',
                "status":'French Republic',
                "color_code":"MAF",
                "name":"Saint Martin",
                "continent":"Americas",
                "region":"Caribbean",
                "iso_3166_1_alpha_2_codes":'MF',
                "french_short":"Saint Martin"}},

   {"type":"Feature",
    "geometry":{
        "coordinates": [[[113.54412109659705,22.216468895070577],[113.53488535516442,22.20294715848827],[113.52801224526104,22.18345765868783],[113.53982540290883,22.15839575803186],[113.5499
        "type":"Polygon"},
    "properties":{"geo_point_2d":{"lon":113.5406845416461,"lat":22.190020751444877},
                "iso3":'MAC',
                "status":'CN Special Administrative Region',
                "color_code":"CHN",
                "name":"Macau",
                "continent":"Asia",
                "region":"Eastern Asia",
                "iso_3166_1_alpha_2_codes":'MO',
                "french_short":"Macau"}},

   {"type":"Feature",
    "geometry":{
        "coordinates": [[[-56.36097272057373,47.14882610748785],[-56.423344443486585,47.10727482074435],[-56.37006859683218,46.97888011389537],[-56.36227213146806,46.89103998607763],[-56.4207
        "type":"Polygon"},
    "properties":{"geo_point_2d":{"lon":-56.17854216659805,"lat":46.77725962397696},
                "iso3":'SPM',
                "status":'French archipelago',
                "color_code":"SPM",
                "name":"Saint Pierre and Miquelon",
                "continent":"Americas",
                "region":"Northern America",
                "iso_3166_1_alpha_2_codes":'PM',
                "french_short":"Saint Pierre and Miquelon"}},

   {"type":"Feature",
    "geometry":{
        "coordinates": [[[-5.704634894341467,-15.90296453512316],[-5.754876246669795,-15.942378369744631],[-5.793548866554687,-15.993541227517525],[-5.748265542415652,-16.029442745995965],[-5
        "type":"Polygon"},
    "properties":{"geo_point_2d":{"lon":-5.692074556259314,"lat":-15.94873471510013},
                "iso3":'SHN',
                "status":'British Overseas Territory',
                "color_code":"SHN",
                "name":"Saint Helena, Ascension, and Tristan da Cunha",
                "continent":"Africa",
                "region":"Western Africa",
                "iso_3166_1_alpha_2_codes":'SH',
                "french_short":"Saint Helena, Ascension, and Tristan da Cunha"}},

   {"type":"Feature",
    "geometry":{
        "coordinates": [[[-63.0135527824156,18.053619679889835],[-63.02333308922579,18.05723583961033],[-63.0303966441448,18.054480677047763],[-63.03727908227043,18.057924623501805],[-63.0398
        "type":"Polygon"},
    "properties":{"geo_point_2d":{"lon":-63.042712586053455,"lat":18.045353892620525},
                "iso3":'SXM',
                "status":'Constituent country in the Kingdom of the Netherlands',
```

```
                    "color_code":"SXM",
                    "name":"Sint Maarten",
                    "continent":"Americas",
                    "region":"Caribbean",
                    "iso_3166_1_alpha_2_codes":'SX',
                    "french_short":"Sint Maarten"}},

       {"type":"Feature",
        "geometry":{
            "coordinates": [[[[-176.20631916144734,-13.218566032523611],[-176.2248694765352,-13.233012662024095],[-176.23043457106155,-13.267921812149822],[-176.22919788338902,-13.280560096158837
            "type":"MultiPolygon"},
        "properties":{"geo_point_2d":{"lon":-176.1859138148507,"lat":-13.276347407901156},
                    "iso3":'WLF',
                    "status":'Overseas collectivity of France',
                    "color_code":"WLF",
                    "name":"Wallis and Futuna",
                    "continent":"Oceania",
                    "region":"Melanesia",
                    "iso_3166_1_alpha_2_codes":'WF',
                    "french_short":"Wallis-et-Futuna"}},

       {"type":"Feature",
        "geometry":{
            "coordinates": [[[20.81501184605702,43.26992240967351],[20.59053394284237,43.20450741746396],[20.695290297675427,43.11171597794174],[20.654136015419198,43.078932416498986],[20.6728425
            "type":"MultiPolygon"},
        "properties":{"geo_point_2d":{"lon":20.946610412739773,"lat":42.69993248951508},
                    "iso3":'XKK',
                    "status":'autonomous province of Serbia with significant autonomy',
                    "color_code":"XKK",
                    "name":"Kosovo",
                    "continent":"Europe",
                    "region":"Southern Europe",
                    "iso_3166_1_alpha_2_codes":'XK',
                    "french_short":"Kosovo"}}
      ]
}
```

In [25]:

```
# save dict as geojson file

with open('additional_boundaries.geojson','w') as f:
    json.dump(additional_geo, f)
```

In [26]:

```
additional_boundaries = gpd.read_file('additional_boundaries.geojson')
```

In [27]:

```
#update df_boundaries

df_boundaries = pd.concat([df_boundaries, additional_boundaries])
```

In [28]:

```
# set country name as index
df_boundaries.set_index('name', inplace=True)
```

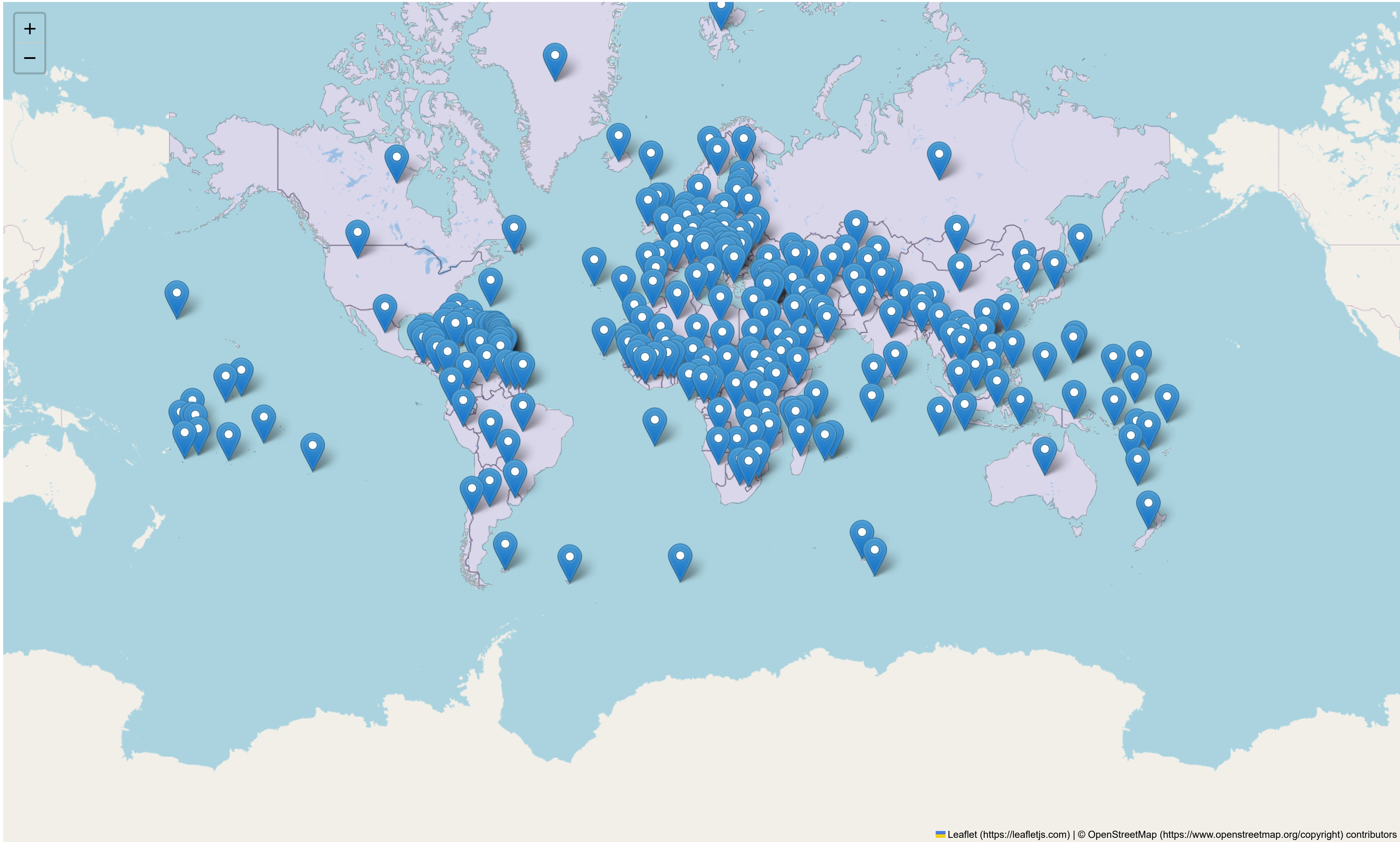
### Plot boundaries on the folium map

Double check that the additional boundaries we added were successfully drawn.

In [29]:

```
m = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

folium.Choropleth(geo_data=df_boundaries,
                   fill_opacity=0.1,
                  line_opacity=0.2
                 ).add_to(m)
for idx, row in df_boundaries.iterrows():
     Marker([row['geo_point_2d']['lat'], row['geo_point_2d']['lon']], popup=row.index).add_to(m)


m
```

Out[29]:




### Tops of interest

Population & Aging: DEPN, POP, MEDAGE, DEPND0*14, DEPND65*

Fertility: ASFR, BIRTH, GRR, TFR, RNI

Immigration:NIM, NMR

In [30]:
```
# extract year 2023 data

df_2023 = data[data['#YR']==2023][['#YR', 'COUNTRY', 'POP','MEDAGE','DEPND0_14', 'DEPND65_','GRR', 'TFR', 'RNI','CBR', 'CDR','NIM', 'NMR']].reset_index(drop=True)
```

In [31]:
```
df_2023
```

Out[31]:

| | #YR | COUNTRY | POP | MEDAGE | DEPND0_14 | DEPND65_ | GRR | TFR | RNI | CBR | CDR | NIM | NMR |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2023 | Andorra | 85468 | 48.10 | 18.10 | 28.60 | 0.70 | 1.46 | -0.11 | 6.87 | 7.98 | 0.00 | 0.00 |
| **1** | 2023 | United Arab Emirates | 9973449 | 35.70 | 19.80 | 2.40 | 0.79 | 1.62 | 0.91 | 10.76 | 1.62 | -33367.00 | -3.35 |
| **2** | 2023 | Afghanistan | 39232003 | 19.90 | 69.40 | 5.00 | 2.21 | 4.53 | 2.27 | 34.79 | 12.08 | -3754.00 | -0.10 |
| **3** | 2023 | Antigua and Barbuda | 101489 | 33.60 | 32.30 | 14.80 | 0.95 | 1.94 | 0.93 | 15.01 | 5.69 | 204.00 | 2.01 |
| **4** | 2023 | Anguilla | 19079 | 36.80 | 30.90 | 16.40 | 0.85 | 1.72 | 0.72 | 11.90 | 4.72 | 200.00 | 10.48 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **222** | 2023 | West Bank | 3176549 | 21.70 | 61.80 | 6.30 | 1.72 | 3.54 | 2.48 | 28.31 | 3.48 | -12271.00 | -3.86 |
| **223** | 2023 | Yemen | 31565602 | 21.60 | 57.10 | 5.40 | 1.42 | 2.91 | 1.85 | 24.05 | 5.54 | -5898.00 | -0.19 |
| **224** | 2023 | South Africa | 59795503 | 30.10 | 42.00 | 11.20 | 1.14 | 2.31 | 1.11 | 18.28 | 7.18 | -17397.00 | -0.29 |
| **225** | 2023 | Zambia | 20216029 | 18.20 | 77.60 | 5.00 | 2.21 | 4.49 | 2.85 | 34.48 | 6.02 | 3144.00 | 0.16 |
| **226** | 2023 | Zimbabwe | 16819805 | 21.00 | 66.80 | 6.70 | 1.73 | 3.51 | 2.27 | 29.41 | 6.68 | -47935.00 | -2.85 |

227 rows × 13 columns

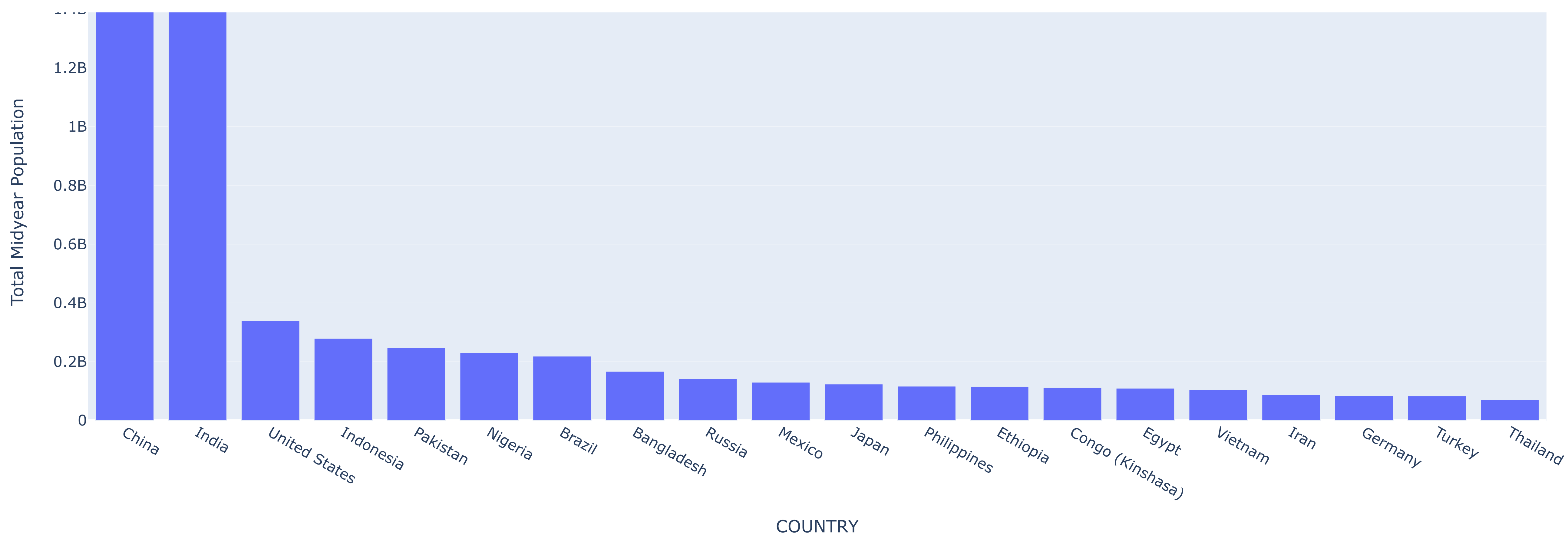
In [32]:
```
# Create a map
# m = folium.Map(location=[54, 15], tiles='openstreetmap', zoom_start=2)
# Marker([location.point.latitude, location.point.longitude]).add_to(m)
```

## 1. 1 Top 20 most populated countries in 2023

- `POP` Total midyear population

In [33]:
```
top_20_pop = df_2023.sort_values('POP', ascending=False)[['COUNTRY', 'POP']].reset_index(drop=True).iloc[:20]
```

In [34]:
```
fig = px.bar(x='COUNTRY', y='POP', data_frame=top_20_pop)
fig.update_layout(title_text="Top 20 most populated countries in 2023", title_x=0.5,
                 yaxis_title="Total Midyear Population")
```




Let's see their locations

In [35]:

```
df_a = pd.merge(top_20_pop, df_boundaries, left_on='COUNTRY', right_on='name', how='left')
```

In [36]:

```
m_1 = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

for idx, row in df_a.iterrows():
    Marker([row['geo_point_2d']['lat'], row['geo_point_2d']['lon']], popup=row['COUNTRY']).add_to(m_1)


m_1
```

Out[36]:


We can see that within TOP 20 list, there are two countries from Europe, one country from South America. Majority of the countries are located in Asia.

### 1.2 How has the population growth changed over time for these top 20 countries?

In [37]:

```
top_20_trend = data[data.COUNTRY.isin(top_20_pop.COUNTRY)][['#YR', 'COUNTRY', 'POP']].reset_index(drop=True)
```

In [38]:

```python
# pivot table
top_20_trend = top_20_trend.pivot_table(index='#YR', values='POP', columns='COUNTRY')
```

In [39]:

```python
top_20_trend.head()
```

Out[39]:

| COUNTRY<br>#YR | Bangladesh | Brazil | China | Congo (Kinshasa) | Egypt | Ethiopia | Germany | India | Indonesia | Iran | Japan | Mexico | Nigeria | Pakistan | Philippines | Russia | Thailand |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1950** | 45645964.00 | 53443075.00 | 562579779.00 | 13568762.00 | 21197691.00 | 20174562.00 | 68374572.00 | 369880000.00 | 82978392.00 | 16357000.00 | 83805000.00 | 28485180.00 | 31796939.00 | 40382206.00 | 21131264.00 | 101936816.00 | 20041628.00 |
| **1951** | 46149840.00 | 54973775.00 | 567159896.00 | 13831813.00 | 21704443.00 | 20511408.00 | 68875884.00 | 376182850.00 | 84113761.00 | 16810772.00 | 85163848.00 | 29296235.00 | 32492088.00 | 41346560.00 | 21736410.00 | 103506916.00 | 20653334.00 |
| **1952** | 46881899.00 | 56557783.00 | 574656098.00 | 14100005.00 | 22223309.00 | 20860941.00 | 69145952.00 | 382791319.00 | 85418340.00 | 17275640.00 | 86459025.00 | 30144317.00 | 33207747.00 | 42342412.00 | 22358886.00 | 105385090.00 | 21289402.00 |
| **1953** | 47652925.00 | 58197231.00 | 584374120.00 | 14373435.00 | 22754580.00 | 21223618.00 | 69550236.00 | 389691318.00 | 86890805.00 | 17747610.00 | 87655163.00 | 31031279.00 | 33944600.00 | 43372063.00 | 22999187.00 | 107302806.00 | 21964158.00 |
| **1954** | 48592988.00 | 59894345.00 | 594972939.00 | 14657484.00 | 23298551.00 | 21599912.00 | 69868115.00 | 396850768.00 | 88521458.00 | 18233684.00 | 88753892.00 | 31959113.00 | 34933877.00 | 44434445.00 | 23657826.00 | 109208917.00 | 22684974.00 |

In [40]:

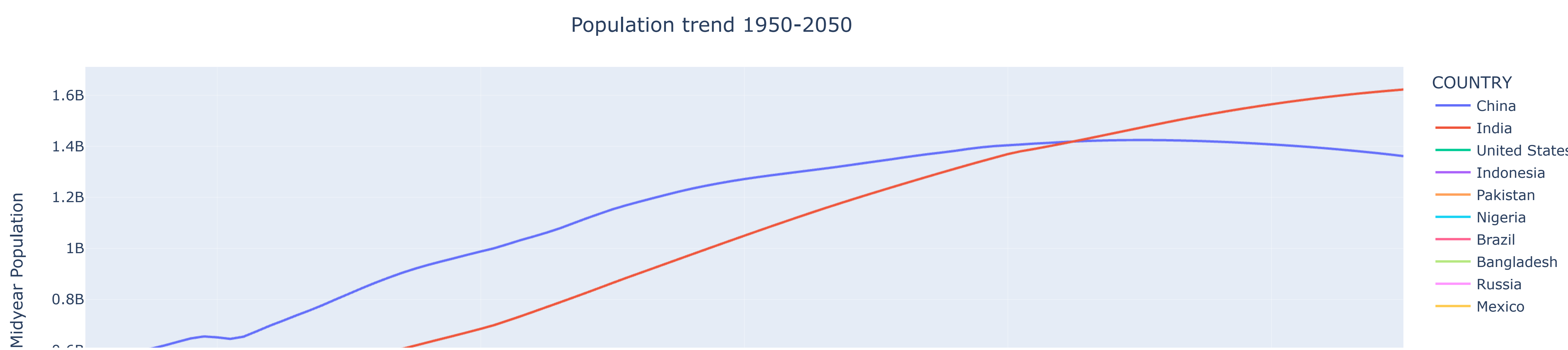
```python
# reorder the columns

col_order = top_20_pop.COUNTRY.tolist()
top_20_trend = top_20_trend.reindex(col_order, axis=1)
```

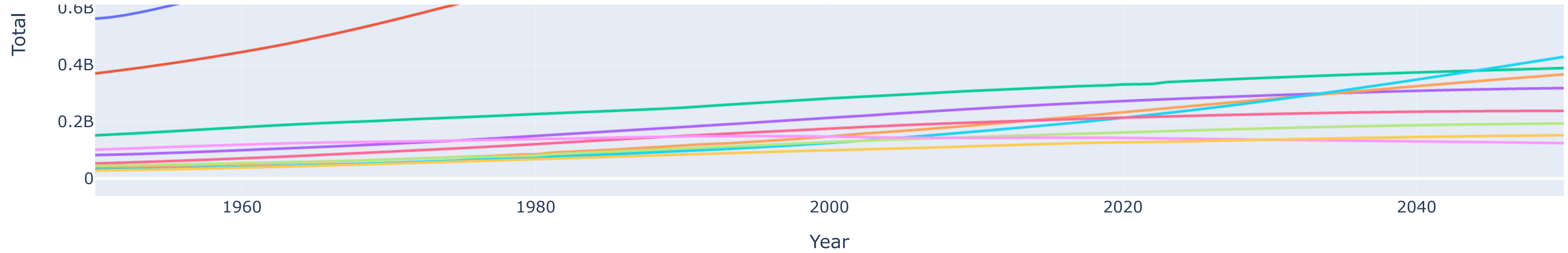
In [41]:

```python
def plot_line(df):
    fig = px.line(df)
    fig.update_layout(xaxis_title="Year", title_x=0.45, title_text="Population trend 1950-2050",
                yaxis_title="Total Midyear Population")
    fig.show()
```

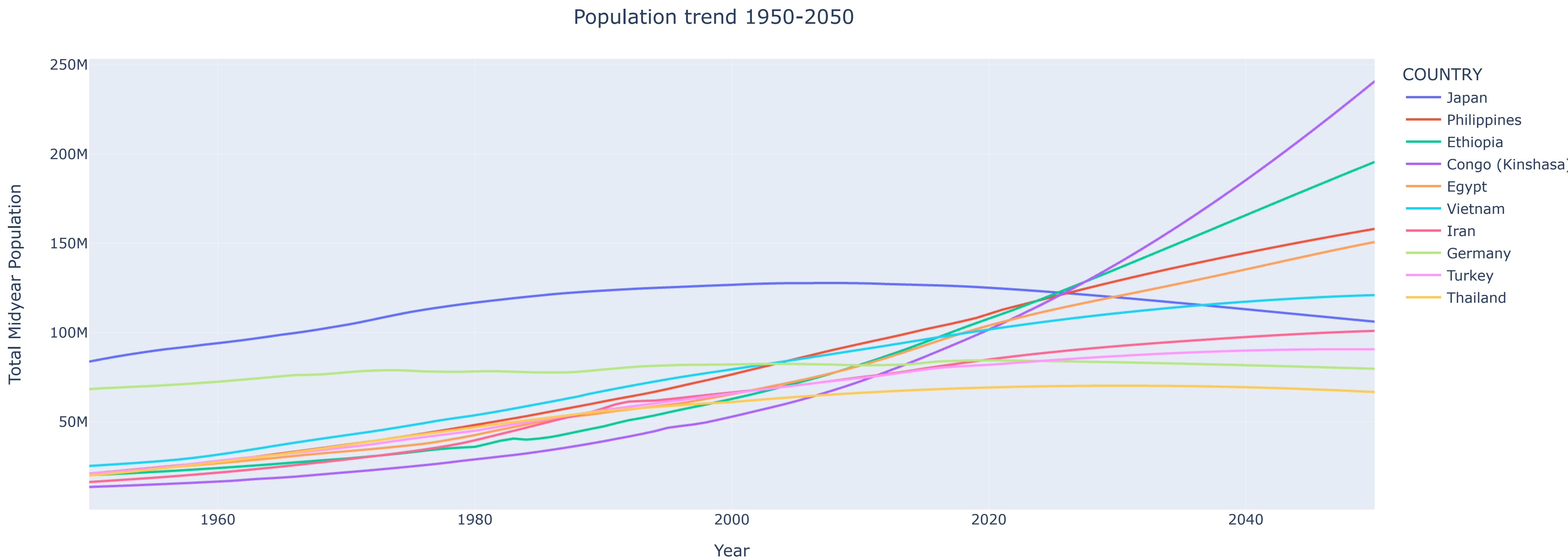
In [42]:

```python
plot_line(top_20_trend.iloc[:,:10])
```






In [43]:
```
plot_line(top_20_trend.iloc[:,10:20])
```




- The population of India will exceed China in year 2024; India will be the country with the most population in the world.
- The population of China and Japan exhibits a noticeable downward trend compared to others.

## 2.Rate of natural increase, crude birth rate, and crude death rate in 2023

The rate of natural increase `RNI` is a measure of how quickly a population is growing or declining.

(Crude Birth Rate/1,000) – (Crude Death Rate/1000) = `CBR - CDR = RNI`

`NATINCR` : Natural increase, both sexes

In [44]:
```
df_RNI = df_2023.sort_values('CBR', ascending=False)[['COUNTRY', 'CBR', 'CDR', 'RNI', 'POP']].reset_index(drop=True )
```

In [45]:
```
print(f'There are {df_RNI[df_RNI.RNI >0].count()[0]} countries with positive RNI, {df_RNI[df_RNI.RNI <=0].count()[0]} with 0 or negative RNI.')
```

```
There are 194 countries with positive RNI, 33 with 0 or negative RNI.
```

### Choropleth map to show RNI around the world

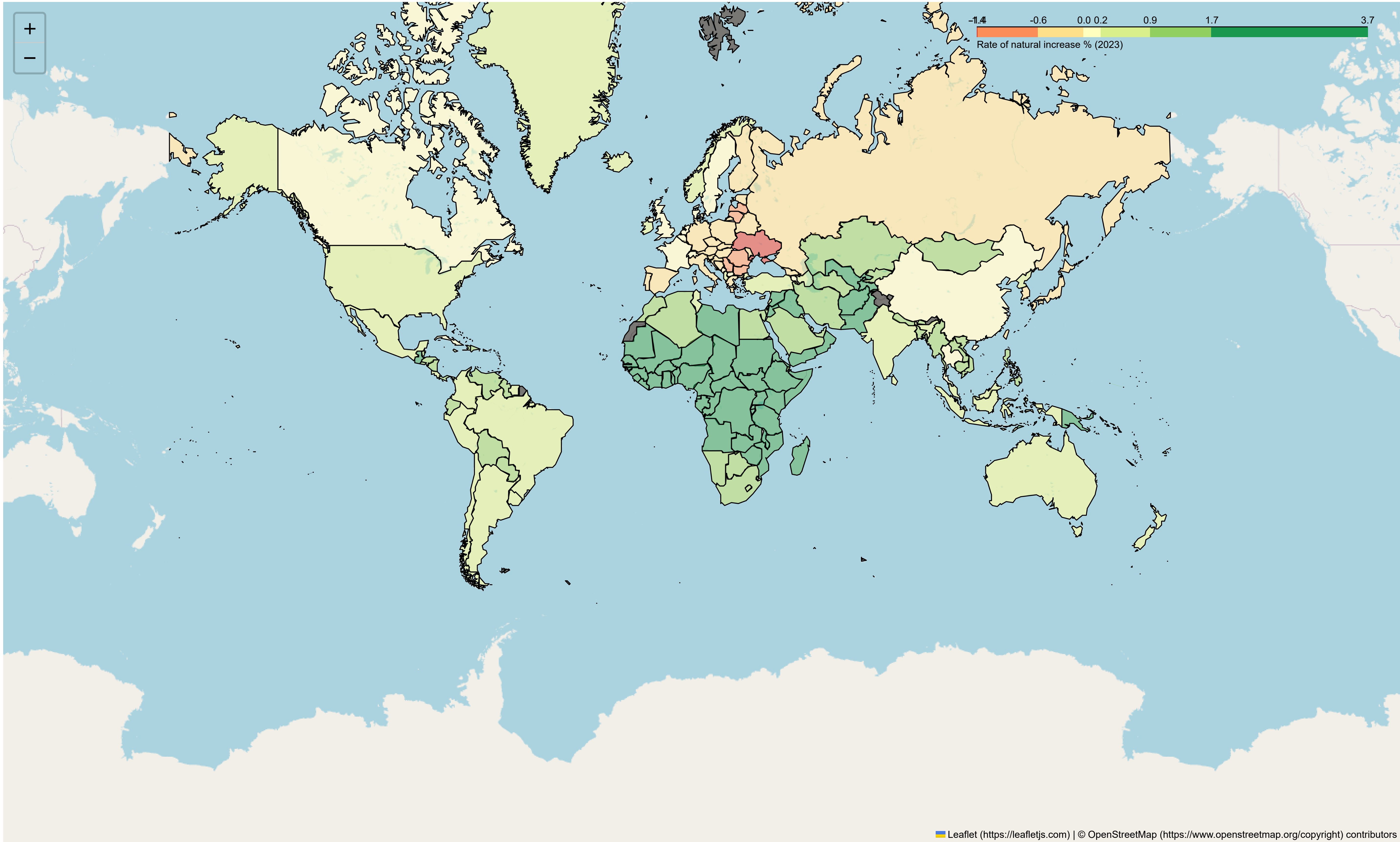
In [46]:
```
# Set COUNTRY as index for df_RNI

df_RNI.set_index('COUNTRY', inplace=True)
```

In [47]:
```
df_RNI['RNI'].describe()
```

Out[47]:
```
count   227.00
mean      1.00
std       1.00
min      -1.40
25%       0.22
50%       0.87
75%       1.68
max       3.72
Name: RNI, dtype: float64
```

In [48]:
```
m_2 = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

choropleth = Choropleth(geo_data=df_boundaries,
           data=df_RNI['RNI'],
           key_on="feature.id",
           fill_color='RdYlGn',
            bins=[-1.41,-1.39, -0.6, 0, 0.22, 0.87, 1.68, 3.73],
           fill_opacity = 0.5,
           highlight=True,
           legend_name='Rate of natural increase % (2023)'
          ).add_to(m_2)

m_2
```

Out[48]:

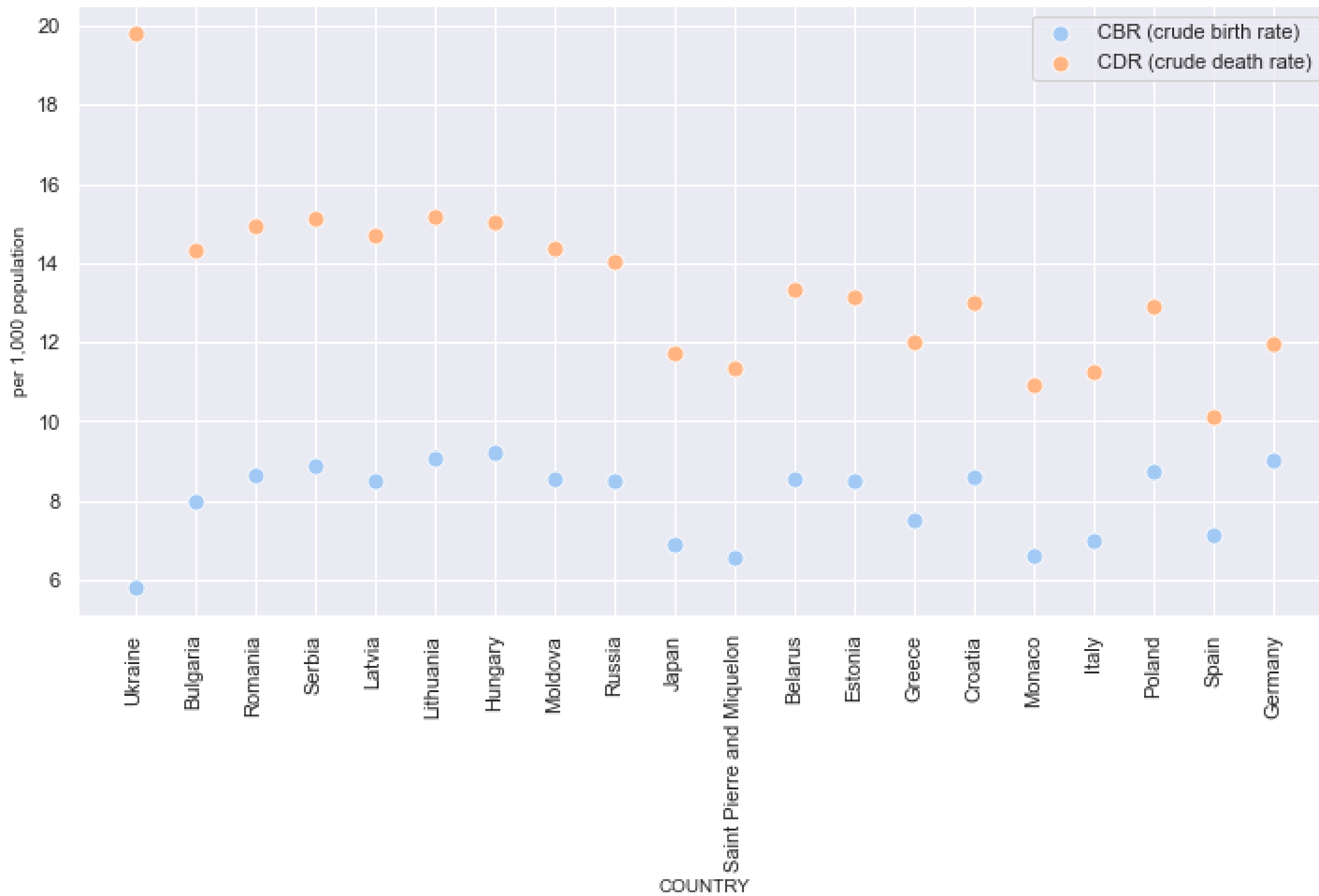



- Ukraine has the lowest RNI due to the ongoing war.
- Africa has the highest average RNI among all continents.
- Europe has the lowest average RNI among all continents.

**Let's check crude birth rates, crude death rate for the 20 countries with least RNI**

In [49]:
```
df_RNI_20 = df_RNI.sort_values('RNI', ascending=True)[:20]
```

In [50]:
```
plt.figure(figsize=(12,6))
ax = sns.scatterplot(data = df_RNI_20, x= df_RNI_20.index, y='CBR', s=80)
ax = sns.scatterplot(data = df_RNI_20, x= df_RNI_20.index, y='CDR', s=80)
_ = plt.xticks(rotation=90)
plt.legend(['CBR (crude birth rate)', 'CDR (crude death rate)'])
_ = plt.ylabel('per 1,000 population')
```




## 3. Population aging in 2023

`MEDAGE` Median age of the population, both sexes

`DEPND0_14` The youth dependency ratio is the ratio of the youth population (ages 0-14) per 100 people of working age (ages 15-64). A high youth dependency ratio indicates that a greater investment needs to be made in schooling and other services for children.

`DEPND65_` The elderly dependency ratio is the ratio of the elderly population (ages 65+) per 100 people of working age (ages 15-64). Increases in the elderly dependency ratio put added pressure on governments to fund pensions and healthcare.

`Working age population` population aged 15 to 64 source: https://www.cia.gov/the-world-factbook/field/dependency-ratios/

In [51]:
```
df_aging = df_2023[['COUNTRY', 'MEDAGE','DEPND0_14', 'DEPND65_', 'POP']].reset_index(drop=True)
```

In [52]:
```
df_aging.set_index('COUNTRY', inplace=True)
```

In [53]:
```
df_aging[df_aging.index=='United States']
```

Out[53]:

| | MEDAGE | DEPND0_14 | DEPND65_ | POP |
|---|---|---|---|---|
| **COUNTRY** | | | | |
| **United States** | NaN | 28.50 | 28.40 | 339665118 |

we don't have MEDAGE data for United States

Let's see how the MEDAGE changes over the years for United States

In [54]:
```
df_medage = data[(data['#YR']<2023) & (data['COUNTRY']=='United States')][['#YR','MEDAGE']]
```

In [55]:
```
df_medage.dropna(subset=['MEDAGE'])
```

Out[55]:

| | #YR | MEDAGE |
|---|---|---|
| **21169** | 2010 | 37.20 |
| **21170** | 2011 | 37.30 |
| **21171** | 2012 | 37.40 |
| **21172** | 2013 | 37.60 |
| **21173** | 2014 | 37.70 |
| **21174** | 2015 | 37.80 |
| **21175** | 2016 | 37.90 |
| **21176** | 2017 | 38.00 |
| **21177** | 2018 | 38.20 |
| **21178** | 2019 | 38.40 |
| **21179** | 2020 | 38.50 |
| **21180** | 2021 | 38.70 |
| **21181** | 2022 | 38.90 |

Let's assume the median age increased by 0.1 years to 39.0 years, in 2023.

In [56]:
```
df_aging.loc['United States', 'MEDAGE'] = 39.0
```

In [57]:
```python
df_aging.describe().T
```

Out[57]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **MEDAGE** | 227.00 | 32.40 | 9.24 | 15.10 | 24.65 | 32.00 | 40.60 | 56.20 |
| **DEPND0_14** | 227.00 | 40.22 | 19.13 | 15.30 | 25.55 | 33.60 | 49.85 | 104.40 |
| **DEPND65_** | 227.00 | 16.68 | 11.07 | 1.70 | 7.30 | 12.70 | 25.80 | 66.50 |
| **POP** | 227.00 | 35163080.17 | 137599206.28 | 5195.00 | 621830.00 | 5953730.00 | 23261072.00 | 1413142846.00 |

In [58]:
```python
df_aging.sort_values(by='MEDAGE', ascending=False)
```

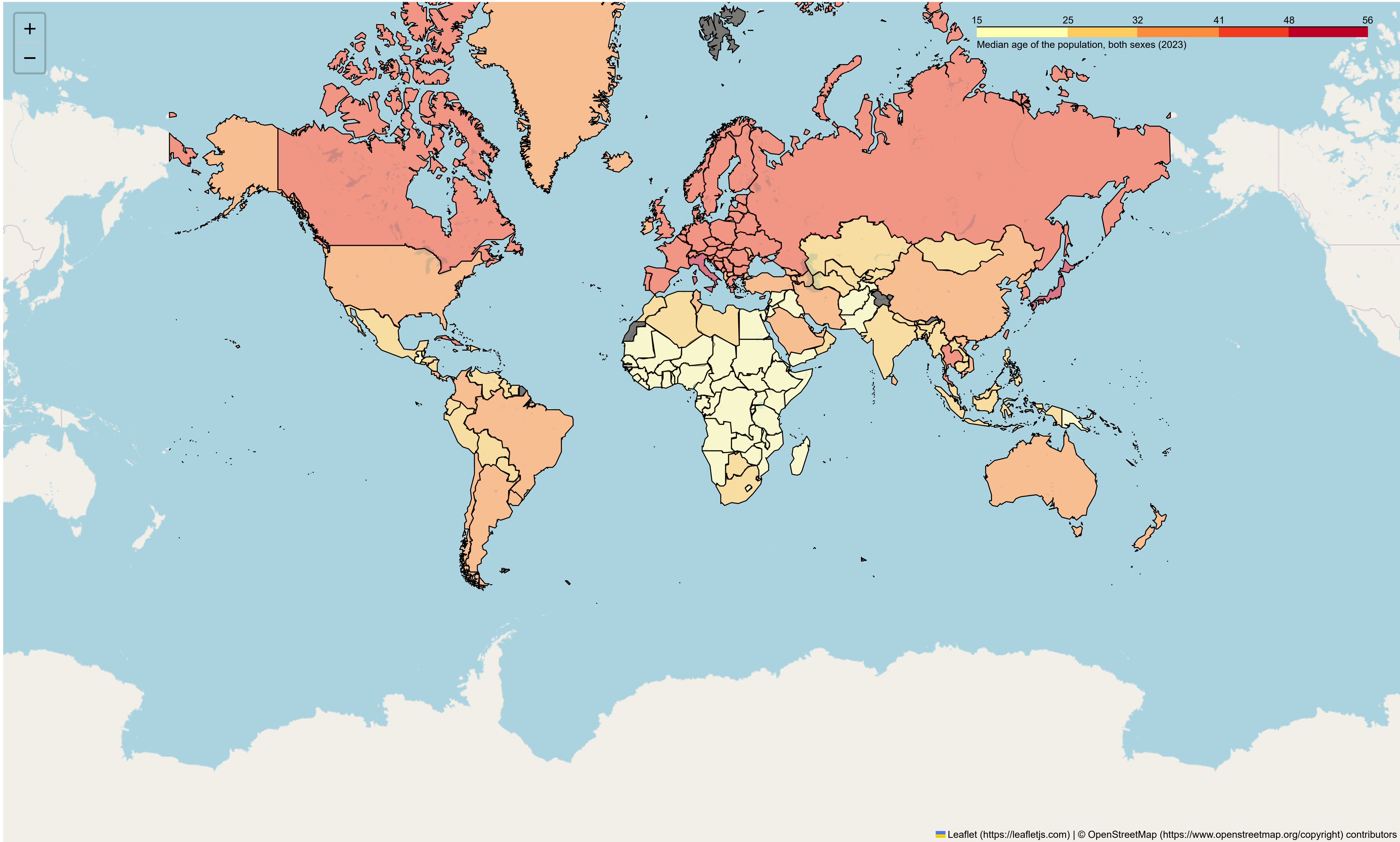
Out[58]:

| | MEDAGE | DEPND0_14 | DEPND65_ | POP |
|---|---|---|---|---|
| **COUNTRY** | | | | |
| **Monaco** | 56.20 | 17.30 | 66.50 | 31597 |
| **Saint Pierre and Miquelon** | 50.60 | 21.60 | 39.70 | 5195 |
| **Japan** | 49.50 | 21.00 | 50.00 | 123719238 |
| **Andorra** | 48.10 | 18.10 | 28.60 | 85468 |
| **Italy** | 48.10 | 18.70 | 36.10 | 61021855 |
| **...** | ... | ... | ... | ... |
| **Chad** | 16.50 | 90.20 | 4.90 | 18523165 |
| **Mali** | 16.30 | 94.30 | 6.20 | 21359722 |
| **Angola** | 16.20 | 93.50 | 4.60 | 35981281 |
| **Uganda** | 16.10 | 94.00 | 4.70 | 47729952 |
| **Niger** | 15.10 | 104.40 | 5.70 | 25396840 |

227 rows × 4 columns

In [59]:
```python
m_3 = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

choropleth = Choropleth(geo_data=df_boundaries,
           data=df_aging['MEDAGE'],
           key_on="feature.id",
           fill_color='YlOrRd',
             bins=[15, 24.65, 32, 40.6, 48, 56.3],
           fill_opacity = 0.5,
           highlight=True,
           legend_name='Median age of the population, both sexes (2023)'
          ).add_to(m_3)

m_3
```

Out[59]:

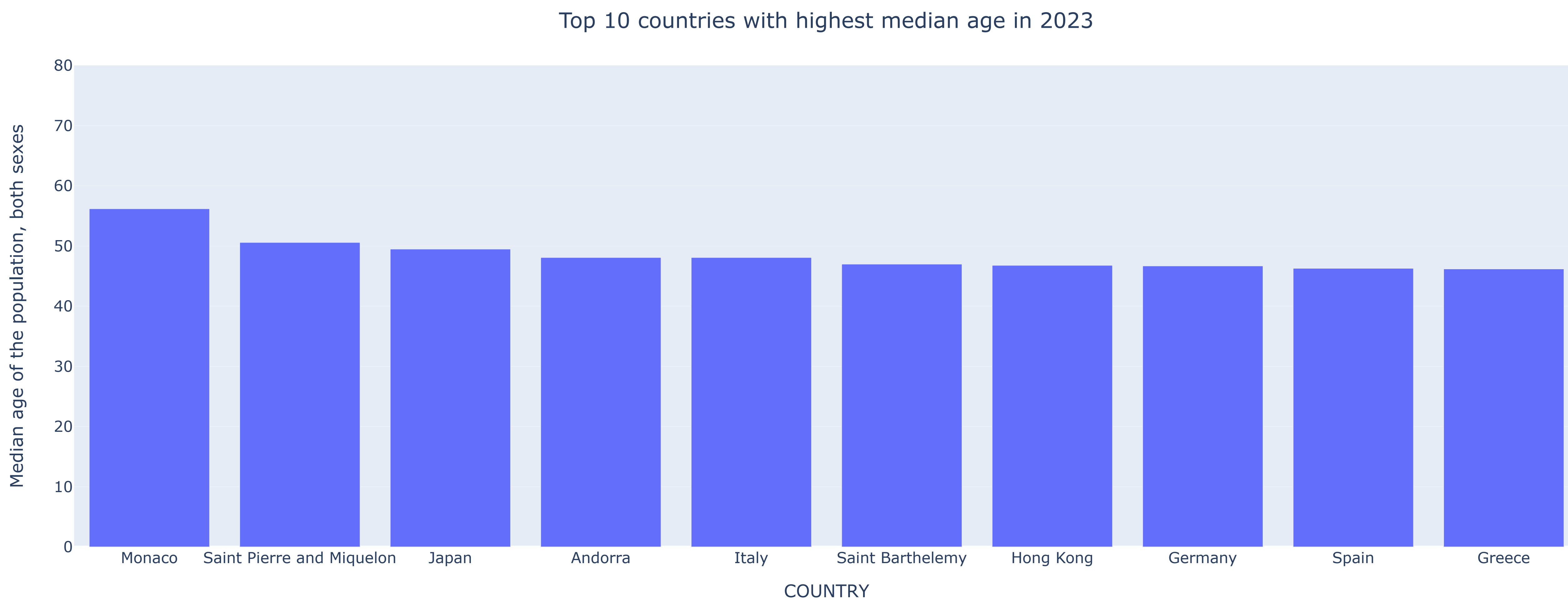



We can see that -

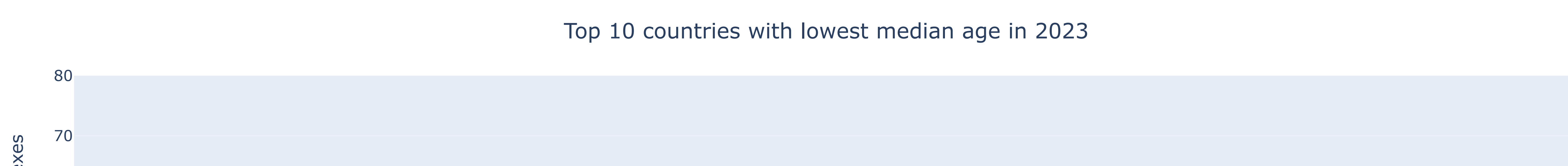
- Africa is the youngest continent in the world
- Almost the whole Europe has median age > 40
- East Asia and Southern Europe has highest median age.

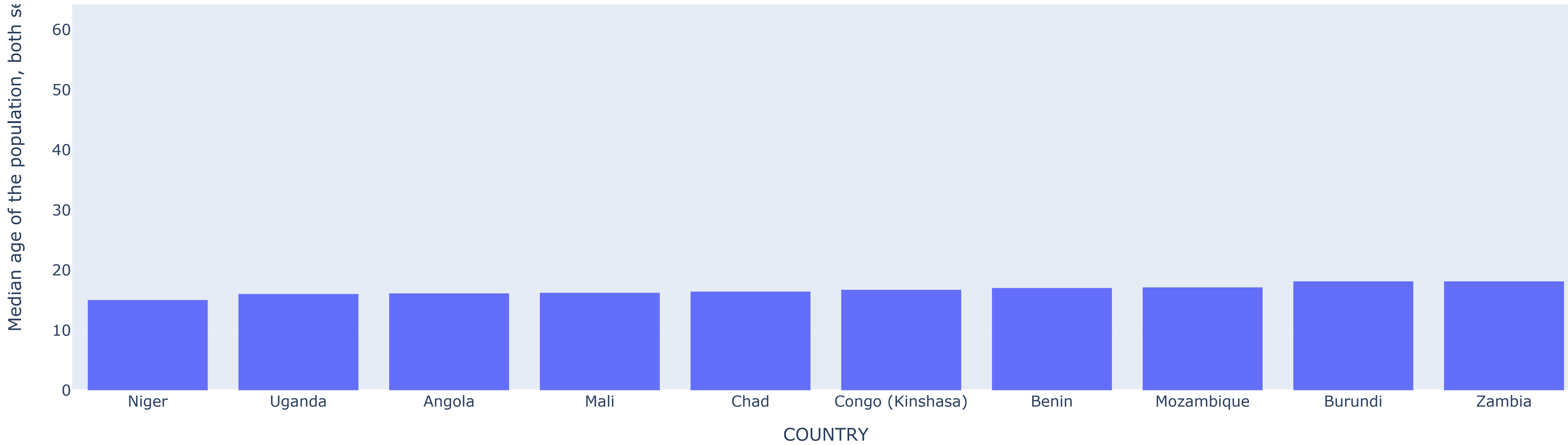
Let's plot 10 countries with highest MEDAGE, and 10 countries with lowest MEDAGE.

In [60]:
```
df_aging_old = df_aging.sort_values(by='MEDAGE', ascending=False).reset_index()[:10]

fig = px.bar(x='COUNTRY', y='MEDAGE', data_frame=df_aging_old)
fig.update_layout(title_text="Top 10 countries with highest median age in 2023", title_x=0.5,
                  yaxis_title="Median age of the population, both sexes",
                  yaxis_range=[0,80])
```




In [61]:
```
df_aging_young = df_aging.sort_values(by='MEDAGE', ascending=True).reset_index()[:10]

fig = px.bar(x='COUNTRY', y='MEDAGE', data_frame=df_aging_young)
fig.update_layout(title_text="Top 10 countries with lowest median age in 2023", title_x=0.5,
                  yaxis_title="Median age of the population, both sexes",
                  yaxis_range=[0,80])
```






Let's take a look at the dependency ratio.
A high total dependency ratio indicates that the working-age population and the overall economy face a greater burden to support and provide social services for youth and elderly persons, who are often economically dependent.

source: https://www.cia.gov/the-world-factbook/field/dependency-ratios/

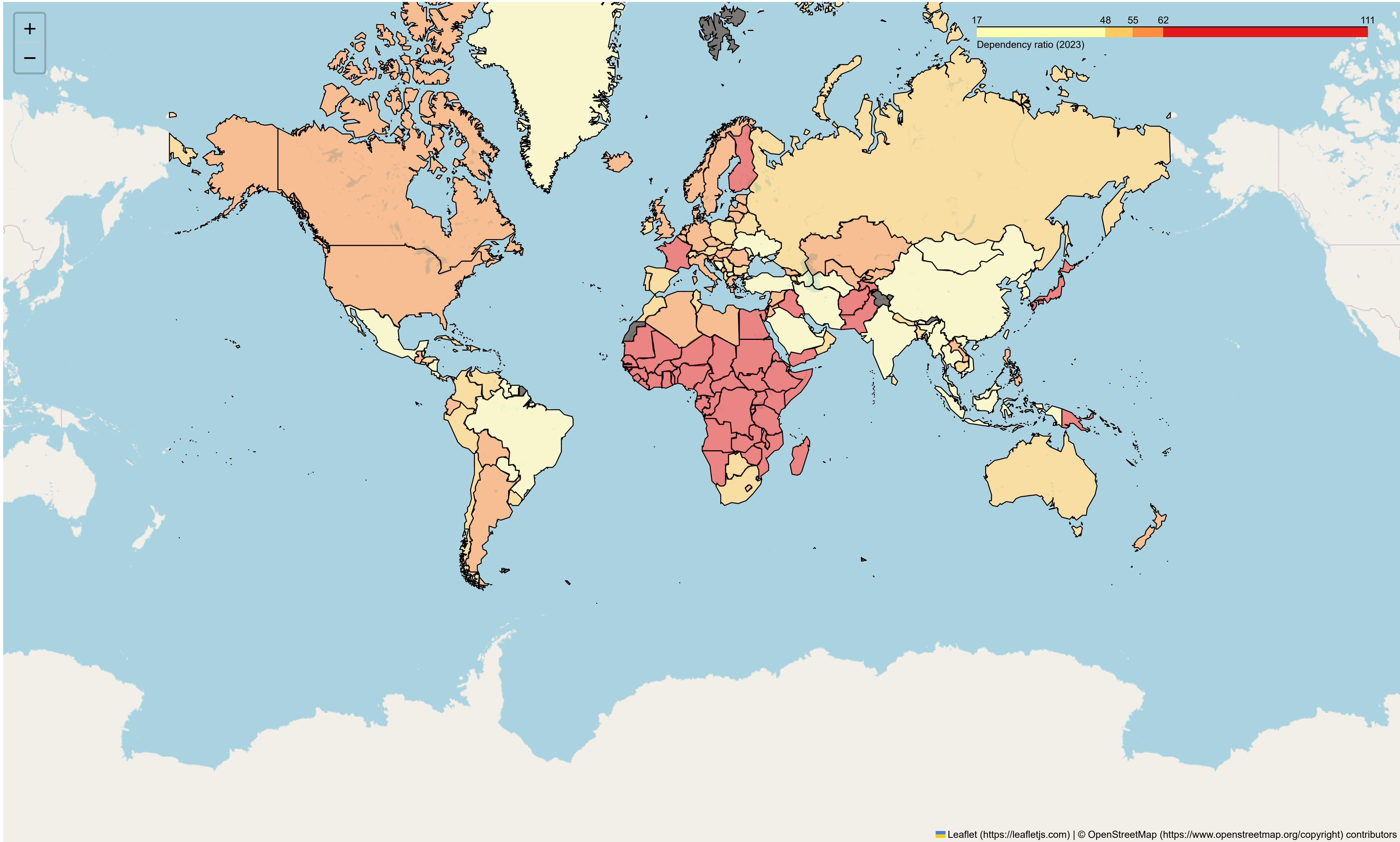
In [62]:
```
df_aging['DEPN'] = df_aging['DEPND0_14'] + df_aging['DEPND65_']
```

In [63]:
```
df_aging['DEPN'].describe()
```

Out[63]:
```
count    227.00
mean      56.90
std       13.92
min       17.00
25%       47.90
50%       54.50
75%       61.80
max      110.10
Name: DEPN, dtype: float64
```

In [64]:
```
m_4 = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

choropleth = Choropleth(geo_data=df_boundaries,
           data=df_aging['DEPN'],
           key_on="feature.id",
           fill_color='YlOrRd',
             bins=[16.9, 47.9,54.5,61.8,111],
           fill_opacity = 0.5,
           highlight=True,
           legend_name='Dependency ratio (2023)'
          ).add_to(m_4)

m_4
```

Out[64]:




In [65]:

```
df_aging['more_young'] = df_aging['DEPND0_14'] - df_aging['DEPND65_']
```

In [66]:

```
df_aging.sort_values(by='more_young', ascending=True)[:20]
```

Out[66]:

| COUNTRY | MEDAGE | DEPND0_14 | DEPND65_ | POP | DEPN | more_young |
|---|---|---|---|---|---|---|
| **Monaco** | 56.20 | 17.30 | 66.50 | 31597 | 83.80 | -49.20 |
| **Japan** | 49.50 | 21.00 | 50.00 | 123719238 | 71.00 | -29.00 |
| **Saint Pierre and Miquelon** | 50.60 | 21.60 | 39.70 | 5195 | 61.30 | -18.10 |
| **Puerto Rico** | 45.60 | 20.40 | 38.40 | 3057311 | 58.80 | -18.00 |
| **Italy** | 48.10 | 18.70 | 36.10 | 61021855 | 54.80 | -17.40 |
| **Germany** | 46.70 | 21.80 | 37.00 | 84220184 | 58.80 | -15.20 |
| **Greece** | 46.20 | 22.40 | 37.20 | 10497595 | 59.60 | -14.80 |
| **Portugal** | 46.00 | 19.70 | 33.70 | 10223150 | 53.40 | -14.00 |
| **Croatia** | 44.80 | 22.00 | 35.70 | 4169239 | 57.70 | -13.70 |
| **Slovenia** | 45.90 | 23.20 | 36.20 | 2099790 | 59.40 | -13.00 |
| **Malta** | 43.20 | 23.10 | 36.00 | 467138 | 59.10 | -12.90 |
| **Saint Barthelemy** | 47.00 | 22.10 | 34.70 | 7093 | 56.80 | -12.60 |
| **Ukraine** | 45.30 | 17.40 | 29.40 | 34831102 | 46.80 | -12.00 |
| **Hong Kong** | 46.80 | 19.80 | 31.70 | 7288167 | 51.50 | -11.90 |
| **Finland** | 43.20 | 26.90 | 38.40 | 5614571 | 65.30 | -11.50 |
| **Spain** | 46.30 | 20.20 | 31.00 | 47222613 | 51.20 | -10.80 |
| **Latvia** | 45.20 | 23.50 | 34.30 | 1821750 | 57.80 | -10.80 |
| **Estonia** | 44.70 | 25.00 | 35.60 | 1202762 | 60.60 | -10.60 |
| **Romania** | 45.10 | 25.20 | 35.80 | 18326327 | 61.00 | -10.60 |
| **Andorra** | 48.10 | 18.10 | 28.60 | 85468 | 46.70 | -10.50 |

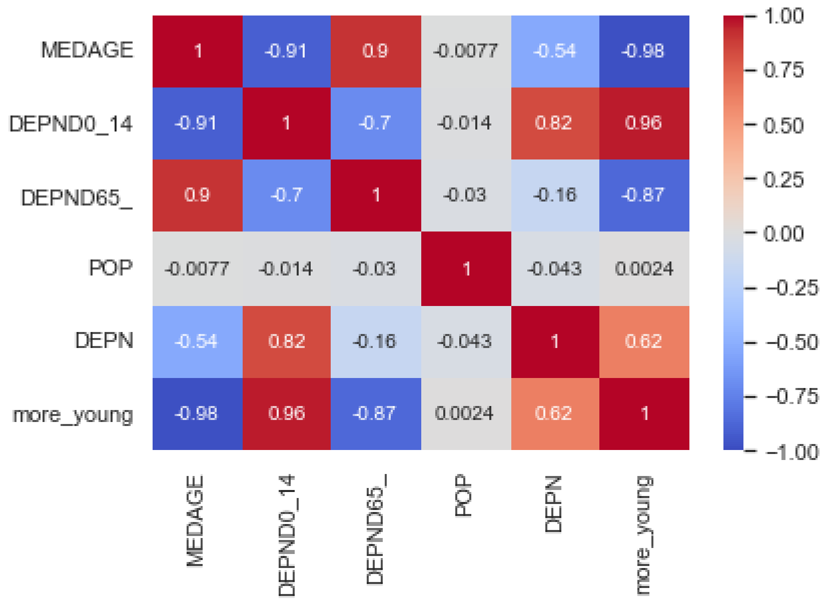
Besides vacation/resort places, Japan and Hong Kong, most of the countries in this top 20 list located in Europe.

In [67]:

```
sns.heatmap(df_aging.corr(), vmin=-1, vmax=1, cmap='coolwarm', annot=True)
```

Out[67]:

```
<Axes: >
```




`MEDAGE` and `DEPN` are highly correlated.

## 4. Fertility rate in 2023

Total fertility rate (TFR) is the total number of children a woman would bear during her lifetime if she were to experience the prevailing age-specific fertility rates of women and survive until the end of her reproductive life.

In [71]:
```
df_fertility = df_2023[['COUNTRY', 'GRR', 'TFR']]
```

In [72]:
```
df_fertility.set_index('COUNTRY', inplace=True)
```

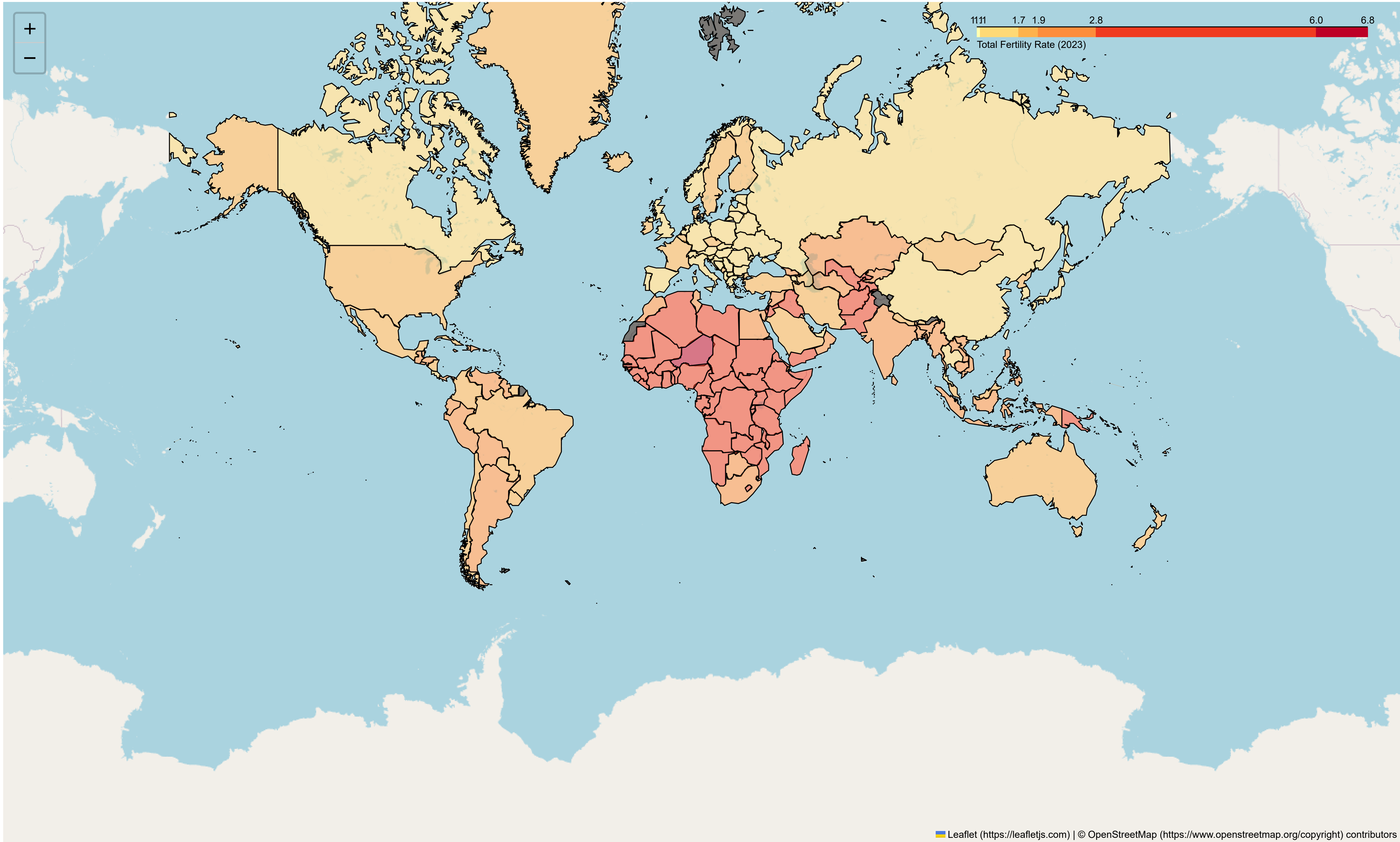
In [73]:
```
df_fertility.describe().T
```

Out[73]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **GRR** | 227.00 | 1.17 | 0.54 | 0.53 | 0.80 | 0.95 | 1.36 | 3.31 |
| **TFR** | 227.00 | 2.39 | 1.08 | 1.09 | 1.66 | 1.95 | 2.79 | 6.73 |

In [76]:
```
m_5 = folium.Map(location=[0,0], tiles="OpenStreetMap", zoom_start=1.5)

choropleth = Choropleth(geo_data=df_boundaries,
           data=df_fertility['TFR'],
           key_on="feature.id",
           fill_color='YlOrRd',
             bins=[1.05, 1.1, 1.66,1.95,2.79,6,6.75],
           fill_opacity = 0.5,
           highlight=True,
           legend_name='Total Fertility Rate (2023)'
          ).add_to(m_5)

m_5
```

Out[76]:




The average TFR of 2023 is 2.3.

- Africa shows much higher TFR than the world average value.
- Mid east and southern Asia have high TFR too.

In [78]:

```
df_fertility.sort_values(by='TFR', ascending=True)[:20]
```

Out[78]:

| COUNTRY | GRR | TFR |
|---|---|---|
| Taiwan | 0.53 | 1.09 |
| Korea, South | 0.54 | 1.11 |
| Singapore | 0.57 | 1.17 |
| Ukraine | 0.59 | 1.22 |
| Hong Kong | 0.60 | 1.23 |
| Macau | 0.60 | 1.23 |
| Italy | 0.60 | 1.24 |
| Moldova | 0.60 | 1.25 |
| Puerto Rico | 0.61 | 1.25 |
| Spain | 0.63 | 1.29 |
| Poland | 0.64 | 1.31 |
| Montserrat | 0.62 | 1.32 |
| Mauritius | 0.65 | 1.35 |
| Virgin Islands, British | 0.67 | 1.37 |
| Bosnia and Herzegovina | 0.66 | 1.37 |
| Japan | 0.68 | 1.39 |
| Costa Rica | 0.68 | 1.40 |
| Greece | 0.68 | 1.40 |
| Portugal | 0.70 | 1.44 |
| Bahamas, The | 0.71 | 1.44 |

Again, Southern Europe and Ease Asia show low TFR.