__🌎 Global Countries || EDA 💹__

link code

🌍 Global Information | 2023

link code

1 | Introduction ✨

Welcome to the Global Country Information Dataset 2023 Notebook! This comprehensive dataset provides a wealth of information about countries worldwide, encompassing a wide range of indicators and attributes. With demographic statistics, economic indicators, environmental factors, healthcare metrics, education statistics, and more, this dataset offers a complete global perspective on various aspects of nations. We will delve into the data to extract insights, perform exploratory data analysis (EDA), and draw meaningful conclusions.

🔴 Import Libraries 📦

In [33]:
```
#Import Library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

🔴 Load Dataset 🗂️

In [4]:
```
#Load Dataset
df = pd.read_csv(r'C:\Users\elcot\Downloads\world-data-2023.csv')
```

🔴 Data Type Conversion 🔄

In [5]:
```
# Data Type Conversion:
# Columns to convert to float
columns_to_convert = ['Density\n(P/Km2)', 'Agricultural Land( %)', 'Land Area
                      'Birth Rate', 'Co2-Emissions', 'Forested Area (%)',
                      'CPI', 'CPI Change (%)', 'Fertility Rate', 'Gasoline Pr
                      'Gross primary education enrollment (%)', 'Armed Forces
                      'Gross tertiary education enrollment (%)', 'Infant mort
                      'Life expectancy', 'Maternal mortality ratio', 'Minimum
                      'Out of pocket health expenditure', 'Physicians per tho
                      'Population', 'Population: Labor force participation (%
                      'Tax revenue (%)', 'Total tax rate', 'Unemployment rate

# Convert columns using a lambda function
df[columns_to_convert] = df[columns_to_convert].applymap(lambda x: float(str
```

🔴 Handling missing values 🧮

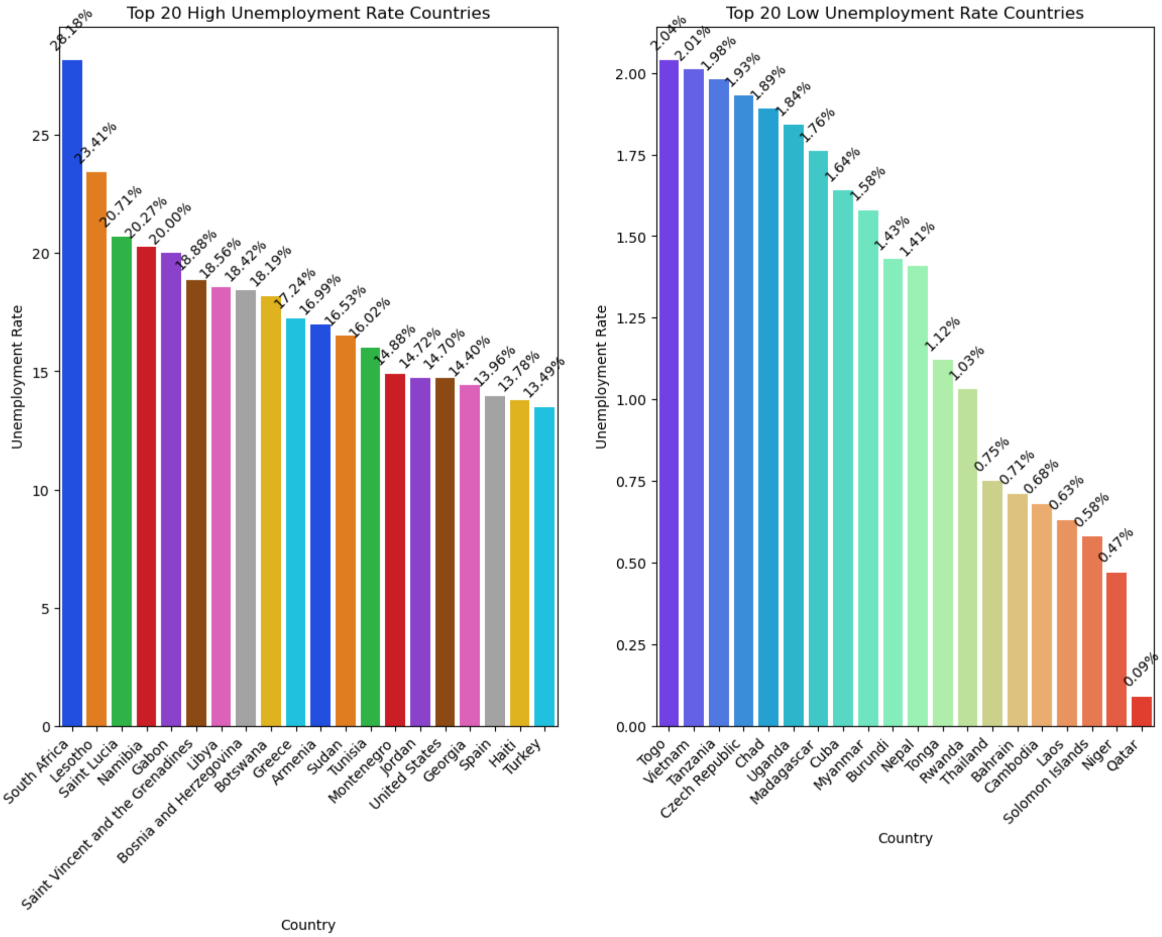
In [6]:
```
# List of columns with missing values
columns_with_missing = df.columns[df.isnull().any()]

# Impute numerical columns with mean
numerical_columns = df.select_dtypes(include=['float64'])
numerical_columns = numerical_columns.columns[numerical_columns.isnull().any
df[numerical_columns] = df[numerical_columns].fillna(df[numerical_columns].m

# Impute categorical columns with mode
categorical_columns = df.select_dtypes(include=['object'])
categorical_columns = categorical_columns.columns[categorical_columns.isnull
df[categorical_columns] = df[categorical_columns].fillna(df[categorical_colu

# Verify if all missing values are handled
missing_counts = df.isnull().sum()
print(missing_counts)
```

```
Country                                      0
Density\n(P/Km2)                             0
Abbreviation                                 0
Agricultural Land( %)                        0
Land Area(Km2)                               0
Armed Forces size                            0
Birth Rate                                   0
Calling Code                                 0
Capital/Major City                           0
Co2-Emissions                                0
CPI                                          0
CPI Change (%)                               0
Currency-Code                                0
Fertility Rate                               0
Forested Area (%)                            0
Gasoline Price                               0
GDP                                          0
Gross primary education enrollment (%)       0
Gross tertiary education enrollment (%)      0
Infant mortality                             0
Largest city                                 0
Life expectancy                              0
Maternal mortality ratio                     0
Minimum wage                                 0
Official language                            0
Out of pocket health expenditure             0
Physicians per thousand                      0
Population                                   0
Population: Labor force participation (%)    0
Tax revenue (%)                              0
Total tax rate                               0
Unemployment rate                            0
Urban_population                             0
Latitude                                     0
Longitude                                    0
dtype: int64
```

2| DATA VISUALIZATION 📊

3| Top 20 Countries: Highest Unemployment

In [7]:
```
sorted_df = df.sort_values(by = 'Unemployment rate', ascending = False)

top_high_unemployment = sorted_df.head(20)
top_low_unemployment = sorted_df.tail(20)

# Create a figure with two subplots (side by side)
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 9))

# Plot for high unemployment countries
sns.barplot(data=top_high_unemployment, x='Country', y='Unemployment rate', 
axes[0].set_title('Top 20 High Unemployment Rate Countries')
axes[0].set_xlabel('Country')
axes[0].set_ylabel('Unemployment Rate')
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')
for p in axes[0].patches:
    axes[0].annotate(f'{p.get_height():.2f}%', (p.get_x() + p.get_width() / 
                     ha='center', va='bottom', fontsize=10, color='black', x
                     textcoords='offset points', rotation = 45)

# Plot for low unemployment countries
sns.barplot(data=top_low_unemployment, x='Country', y='Unemployment rate', p
axes[1].set_title('Top 20 Low Unemployment Rate Countries')
axes[1].set_xlabel('Country')
axes[1].set_ylabel('Unemployment Rate')
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right')
for p in axes[1].patches:
    axes[1].annotate(f'{p.get_height():.2f}%', (p.get_x() + p.get_width() / 
                     ha='center', va='bottom', fontsize=10, color='black', x
                     textcoords='offset points', rotation = 45)

# Show the plots
plt.show()
```



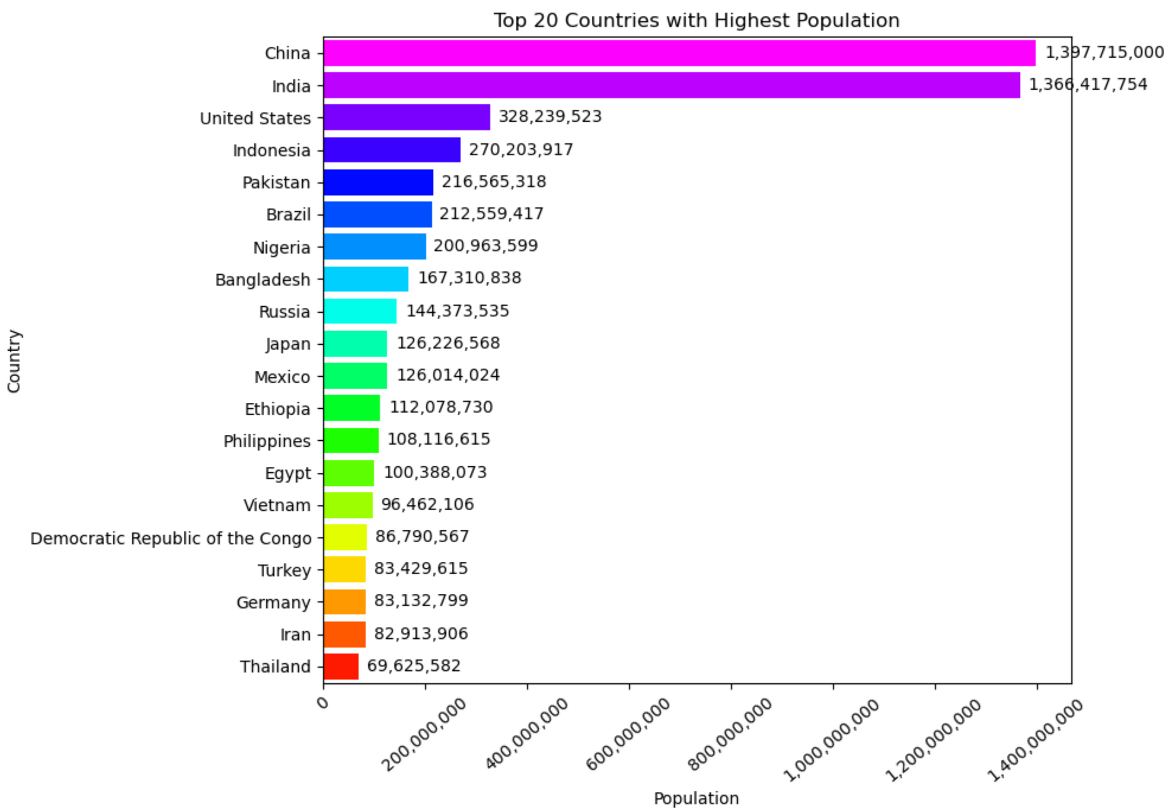
✨Insights 😃😃

Top 20 Countries with Highest Unemployment Rates: The left plot displays the countries with the highest unemployment rates. South Africa has the highest unemployment rate at 28.18%, followed by Lesotho and Saint Lucia. The United States also appears on this list with a relatively high unemployment rate.

Top 20 Countries with Lowest Unemployment Rates: The right plot illustrates the countries with the lowest unemployment rates. These countries have remarkably low unemployment rates, with some even less than 1%. Qatar, Niger and Solomon islands, and Loas are among the countries with the lowest unemployment rates.

4| Top 20 Countries: Highest Population

In [8]:
```python
import matplotlib.ticker as ticker

sorted_df = df.sort_values(by='Population', ascending=False)

# Get the top 20 countries with the highest population
top_population_country = sorted_df.head(20)

# Set up the figure and axes for the subplots
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(10, 7))

# Plot for top population countries
sns.barplot(data=top_population_country, x='Population', y='Country', palett
axes.set_title('Top 20 Countries with Highest Population')
axes.set_xlabel('Population')
axes.set_ylabel('Country')
axes.set_xticklabels(['{:,}'.format(int(x)) for x in axes.get_xticks()], rot
for p in axes.patches:
    axes.annotate(f'{p.get_width():,.0f}', (p.get_width(), p.get_y() + p.get_
                 xytext=(5, 0), textcoords='offset points', ha='left', v

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



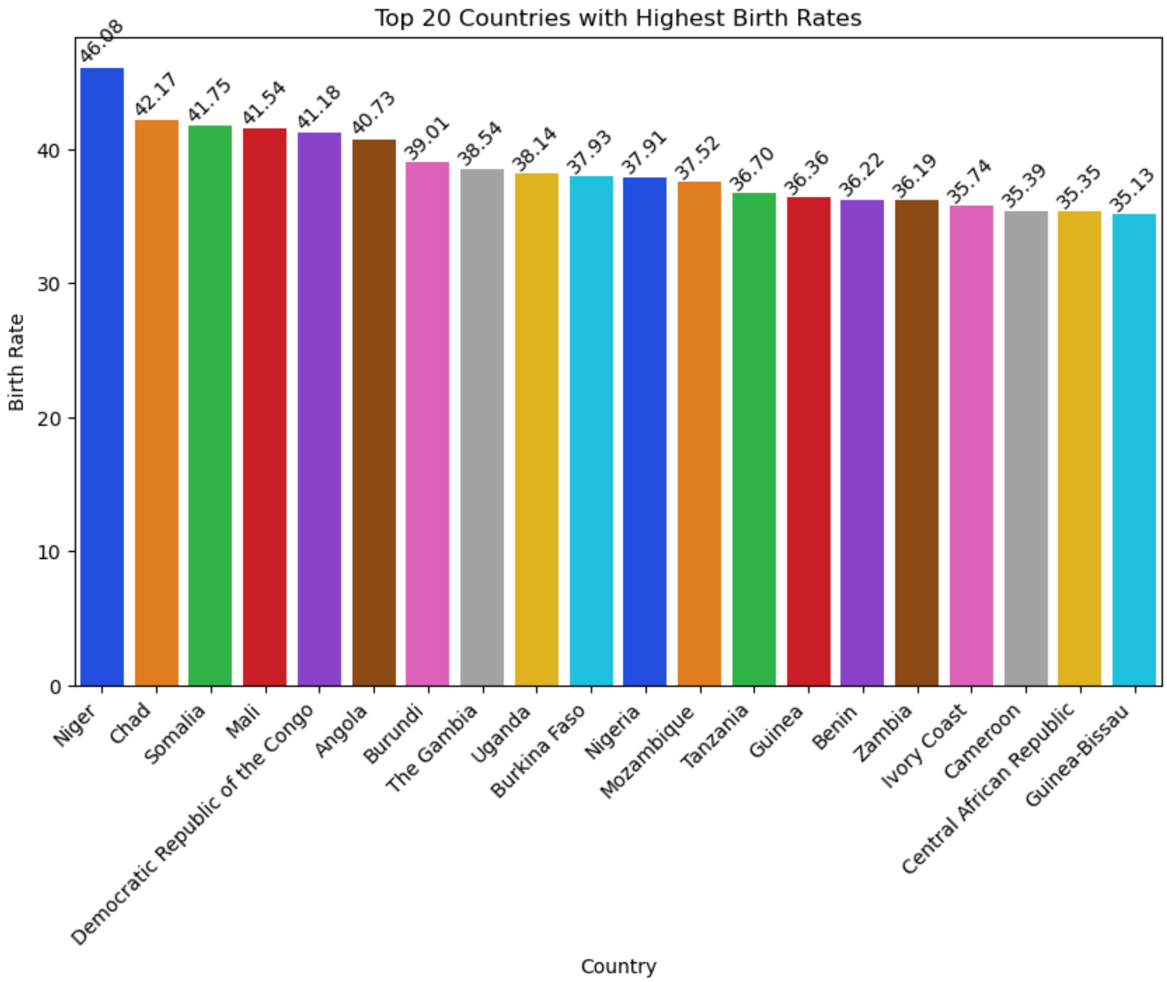
✨Insights 😃 😃

Top 20 Countries with Highest Population: The plot displays the top 20 countries with the highest populations. China and India have the two highest populations, with around 1.4 billion people each. The United States follows with over 320 million people.

5| Top 20 Countries: Highest Birth Rates

In [9]:

```
# Sort the dataframe by 'Birth Rate' column in descending order
sorted_df = df.sort_values(by='Birth Rate', ascending=False)

# Get the top 20 countries with the highest birth rates
top_country_birth = sorted_df.head(20)

# Create a bar plot to visualize the top 20 countries with high birth rates
plt.figure(figsize=(10, 6))
sns.barplot(data=top_country_birth, x='Country', y='Birth Rate', palette='br

# Add title and labels
plt.title('Top 20 Countries with Highest Birth Rates')
plt.xlabel('Country')
plt.ylabel('Birth Rate')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Display data labels on top of each bar
for index, value in enumerate(top_country_birth['Birth Rate']):
    plt.text(index, value, f'{value:.2f}', ha='center', va='bottom', fontsiz

# Show the plot
plt.show()
```

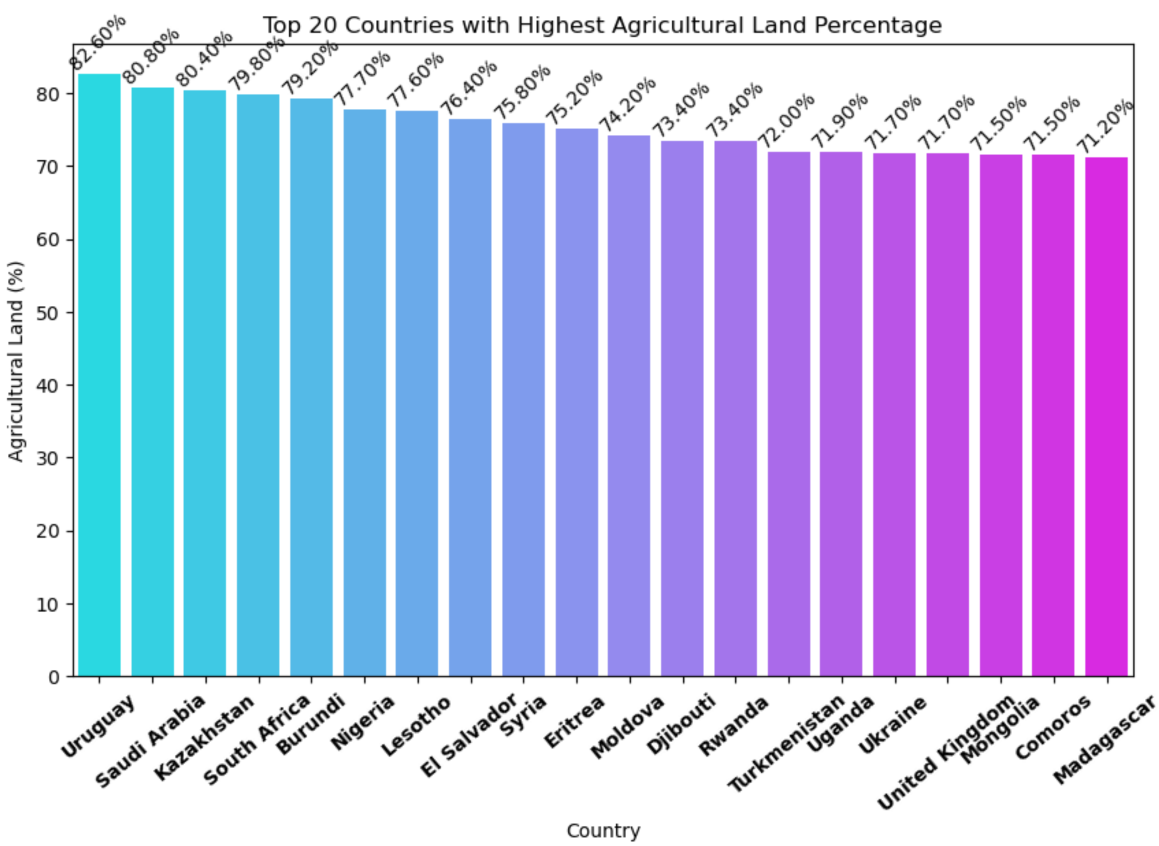


✨Insights 😃 😃

Countries with Highest Birth Rates: This visualization highlights the top 20 countries with the highest birth rates. Niger has the highest birth rate at 46.08 births per 1000 people, followed by Mali and the Democratic Republic of the Congo. It gives us insight into the population growth dynamics in these nations.

6| Top 20 Countries: Highest Agricultural

In [10]:
```
# Sort the dataframe by 'Agricultural Land (%)' column in descending order
sorted_df = df.sort_values(by='Agricultural Land( %)', ascending=False)

# Get the top 20 countries with the highest agricultural land percentages
top_country_Agri = sorted_df.head(20)

# Create a bar plot to visualize the top 20 countries with high agricultural
plt.figure(figsize=(10, 6))
sns.barplot(data=top_country_Agri, x='Country', y='Agricultural Land( %)', pa

# Add title and labels
plt.title('Top 20 Countries with Highest Agricultural Land Percentage')
plt.xlabel('Country')
plt.ylabel('Agricultural Land (%)')

# Rotate x-axis labels for better readability
plt.xticks(rotation=40,fontweight = 'bold',fontsize = 10 )

# Annotate the bars with actual values
for index, value in enumerate(top_country_Agri['Agricultural Land( %)']):
    plt.text(index, value, f'{value:.2f}%', ha='center', va='bottom', fontsi


# Show the plot
plt.show()
```



✨Insights 😃😃

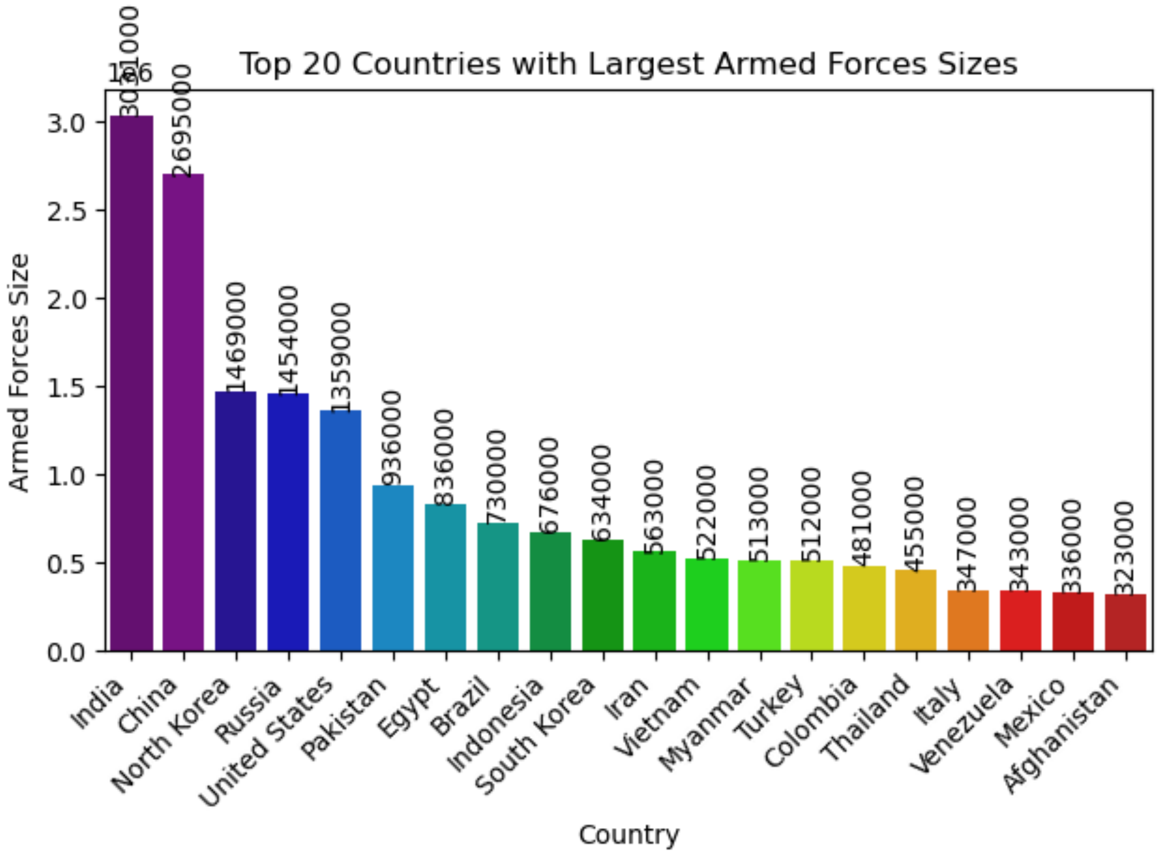
Countries with Most Farming Land: This graph shows the top 20 countries that use the most land for farming. Uruguay is at the top with 82.6% of its land used for agriculture. Saudi Arabia and Kazakhstan are also high on the list.

Agricultural Land Across Countries: The chart helps us compare how much land each country uses for farming. Uruguay leads, followed by Saudi Arabia and Kazakhstan. This tells us how much land is dedicated to farming in each of these countries.

7| Top 20 Countries: Largest Armed Forces

In [11]:

```
# Sort the DataFrame by 'Armed Forces size' column in descending order
sorted_df = df.sort_values(by='Armed Forces size', ascending=False)

# Get the top 20 countries with the largest armed forces sizes
top10 = sorted_df.head(20)

# Create a bar plot to visualize the top 20 countries with the largest armed
sns.barplot(data=top10, x='Country', y='Armed Forces size', palette='nipy_sp

# Add title and labels
plt.title('Top 20 Countries with Largest Armed Forces Sizes')
plt.xlabel('Country')
plt.ylabel('Armed Forces Size')

# Rotate x-axis labels for better readability
plt.xticks(rotation=45, ha='right')

# Annotate the bars with actual values
for index, value in enumerate(top10['Armed Forces size']):
    plt.text(index, value, f'{value:.0f}', ha='center', va='bottom', fontsiz

# Show the plot
plt.tight_layout()
plt.show()
```

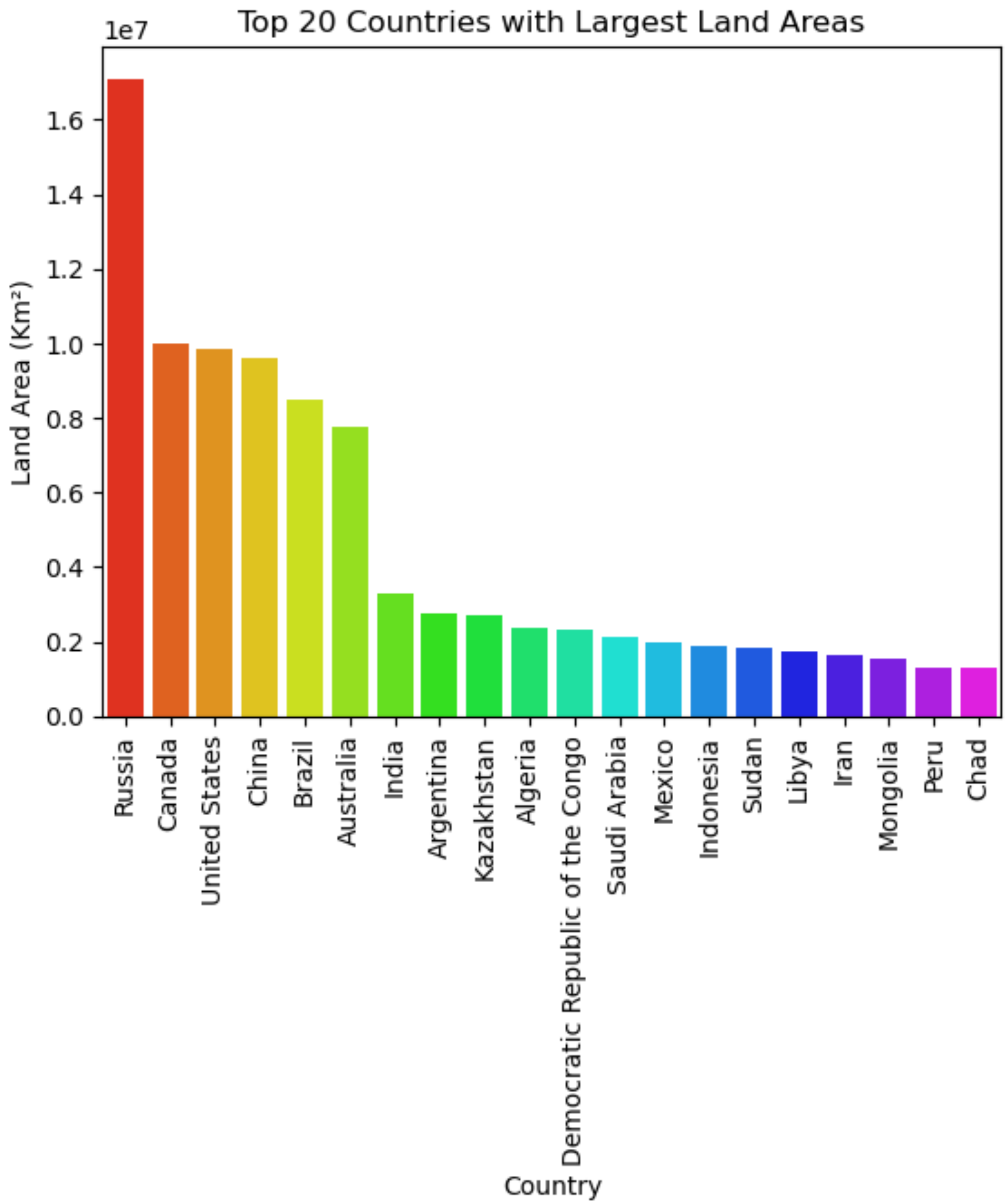


✨Insights 😃😃

Top 20 Countries with Largest Armed Forces Sizes: The graph shows the sizes of the armies in the top 20 countries. India has the biggest army, followed by China, Russia, United States and pakistan. This graph helps us see how different these countries' armies are.

8| Top 20 Countries: Largest Land Areas

In [12]:
```
# Step 02: Sort the dataframe by 'Land Area(Km2)' column in descending order
sorted_df = df.sort_values(by='Land Area(Km2)', ascending=False)

# Step 03: Get the top 20 countries with the largest land areas
top_land_area_countries = sorted_df.head(20)
top_land_vs_population_countries = sorted_df.head(20)
# Create subplots for both bar plot and scatter plot

# Bar plot of top countries with largest land areas
sns.barplot(data=top_land_area_countries, x='Country', y='Land Area(Km2)', pa
plt.title('Top 20 Countries with Largest Land Areas')
plt.xlabel('Country')
plt.ylabel('Land Area (Km²)')
plt.xticks(rotation = 90)

# Show the plots

plt.show()
```


Top 20 Countries with Largest Land Areas
1e7
Land Area (Km²)
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Russia
Canada
United States
China
Brazil
Australia
India
Argentina
Kazakhstan
Algeria
Democratic Republic of the Congo
Saudi Arabia
Mexico
Indonesia
Sudan
Libya
Iran
Mongolia
Peru
Chad
Country

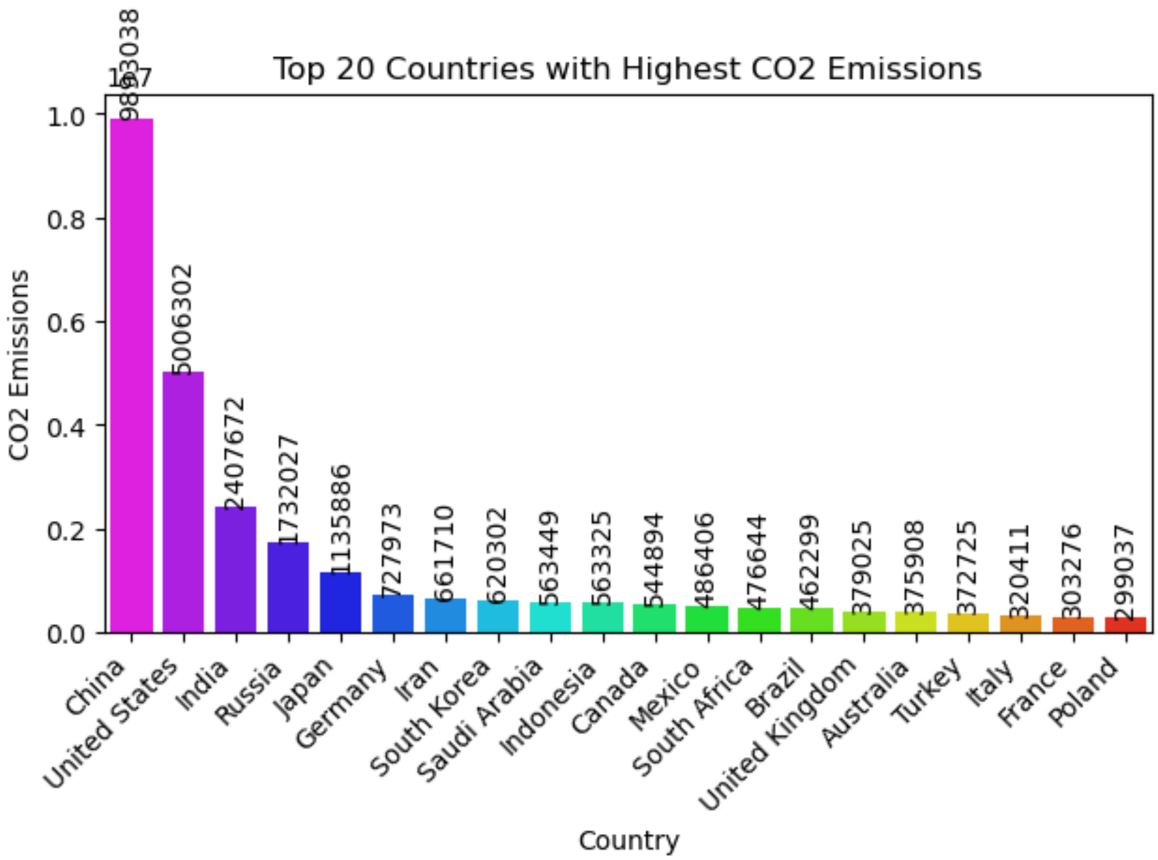
✨Insights 😃😃

The visualization showcases the land area distribution of the top 20 countries, highlighting Russia as the leader with the largest land area, followed by Canada, the United States, and China. This graphical representation effectively illustrates the significant geographical extent of these nations compared to others.

9| Top 20 Countries: Highest CO2 Emissions

In [13]:

```
# Sort the DataFrame by CO2 emissions column in descending order and get the
top_co2_emissions_countries = df.sort_values(by='Co2-Emissions', ascending=F

# Create a bar plot to visualize CO2 emissions for top countries
sns.barplot(data=top_co2_emissions_countries, x='Country', y='Co2-Emissions'
plt.title('Top 20 Countries with Highest CO2 Emissions')
plt.xlabel('Country')
plt.ylabel('CO2 Emissions')
plt.xticks(rotation=45, ha='right')

for index , value in enumerate(top_co2_emissions_countries['Co2-Emissions'])
    # plt.text(index, value, f'{value:.0f}', ha = 'center',va = 'bottom', fo
    plt.text(index, value,f'{value:.0f}',ha = 'center',va = 'bottom', fontsi
plt.tight_layout()
plt.show()
```

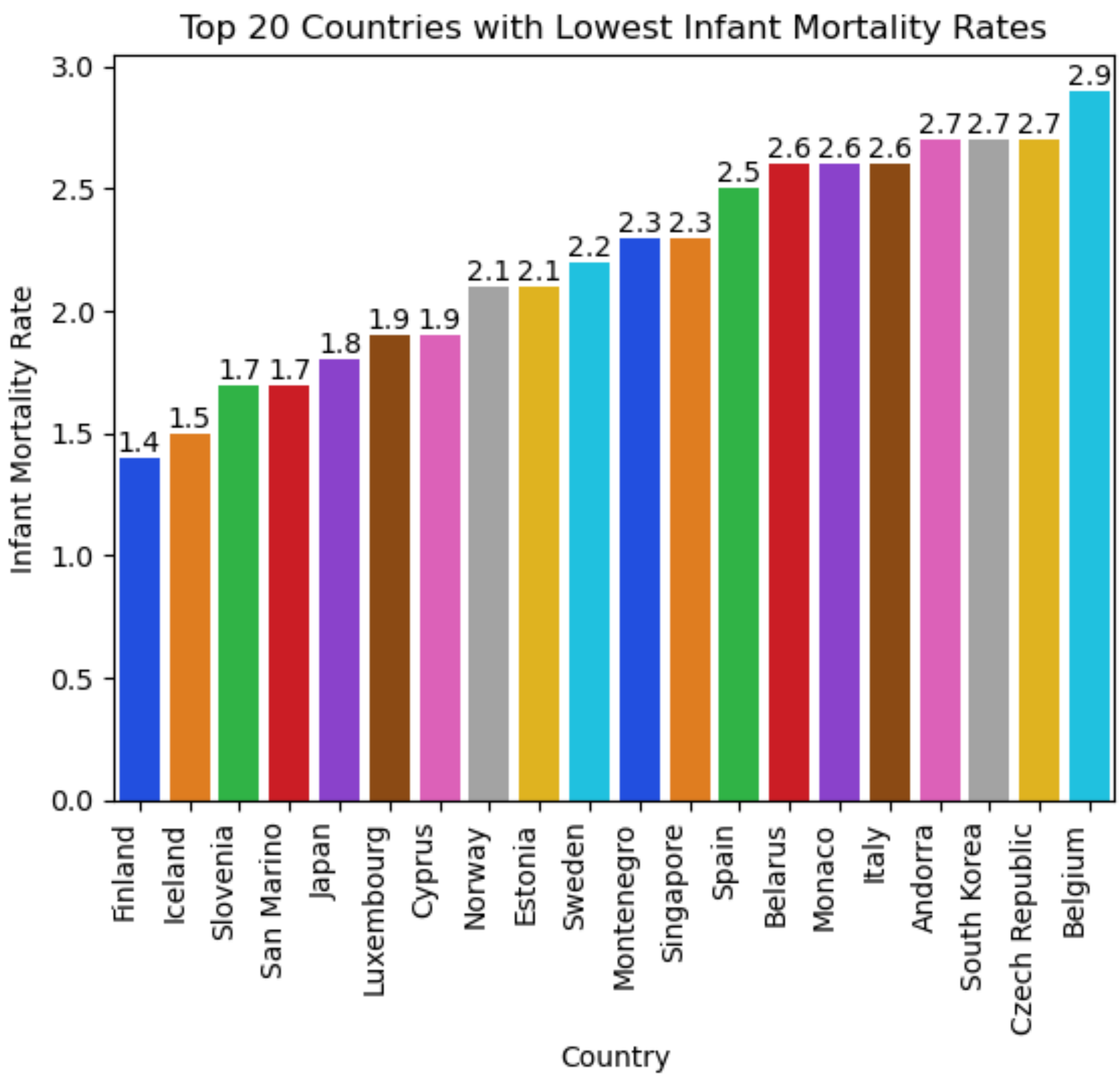


✨Insights 😃 😃

The bar plot showcases the top 20 countries with the highest CO2 emissions. China has the highest CO2 emissions, followed by the United States and India. This visualization highlights the significant carbon dioxide emissions from these countries, indicating their impact on global environmental concerns such as climate change.

10| Top 20 Countries: Low Infant Mortality

In [14]:
```
# Sort the DataFrame by infant mortality column in ascending order and get th
top_infant_mortality_countries = df.sort_values(by='Infant mortality', ascen

# Create a bar plot to visualize infant mortality rates for top countries
sns.barplot(data=top_infant_mortality_countries, x='Country', y='Infant mort
plt.title('Top 20 Countries with Lowest Infant Mortality Rates')
plt.xlabel('Country')
plt.ylabel('Infant Mortality Rate')
plt.xticks(rotation=90, ha='right')

for index, value in enumerate(top_infant_mortality_countries['Infant mortali
    plt.text(index, value, f'{value}', ha='center', va='bottom', fontsize=10
```

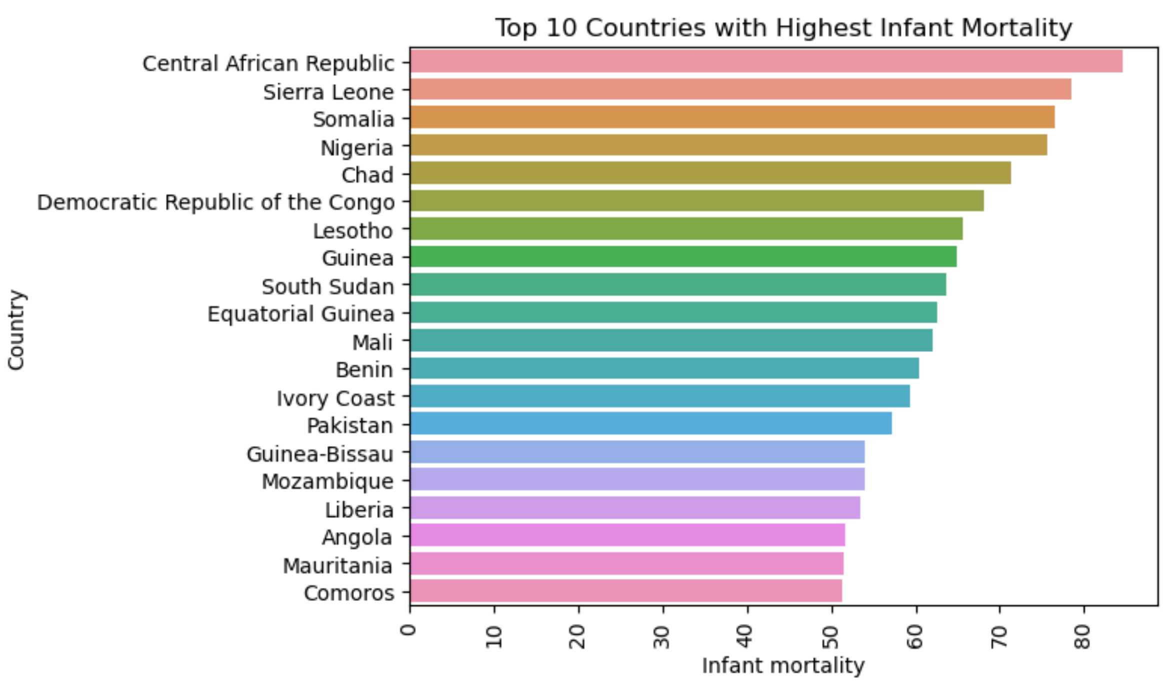


✨Insights 😃😃

Bar graph to show the 20 countries with the lowest rates (between 1.2 and 2.9 for every 1000 babies). This helps us see which countries are doing well in keeping babies healthy and where there's room for improvement.

11| Top 10 Countries:High Infant Mortality

In [15]:
```
top_infant_mortality = df.sort_values(by='Infant mortality', ascending=False
sns.barplot(x='Infant mortality', y='Country', data=top_infant_mortality)
plt.title('Top 10 Countries with Highest Infant Mortality')
plt.xticks(rotation=90)
plt.show()
```



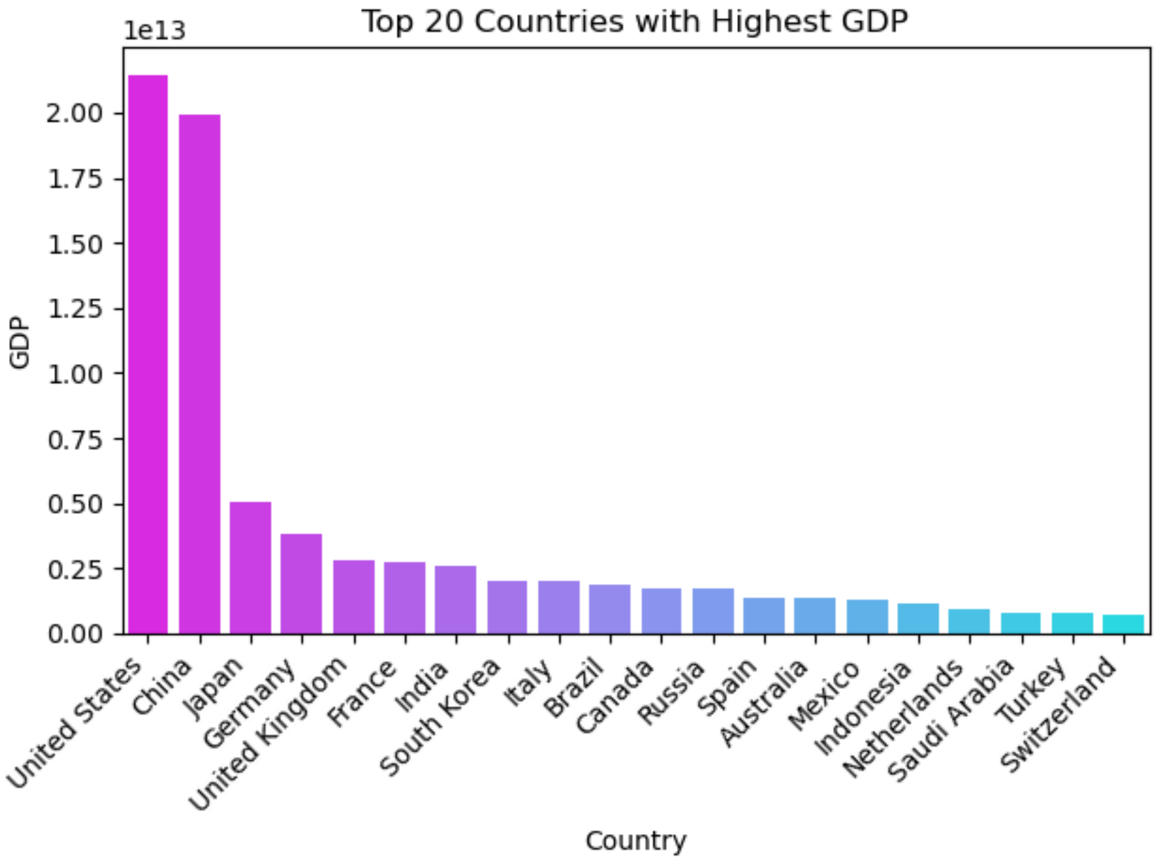
✨Insights 😃😃

High infant mortality rates (50.6 to 80.0 per 1000 live births) reveal healthcare disparities among the top 10 countries. Urgent action and international collaboration are needed to improve conditions and reduce these rates.

12| Top 20 Countries: Highest GDP

In [16]:

```
# Sort the DataFrame by GDP column in descending order and get the top 20 rov
top_gdp_countries = df.sort_values(by='GDP', ascending=False).head(20)

# Create a bar plot to visualize GDP for top countries
sns.barplot(data=top_gdp_countries, x='Country', y='GDP', palette='cool_r')
plt.title('Top 20 Countries with Highest GDP')
plt.xlabel('Country')
plt.ylabel('GDP')
plt.xticks(rotation=45, ha='right')

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



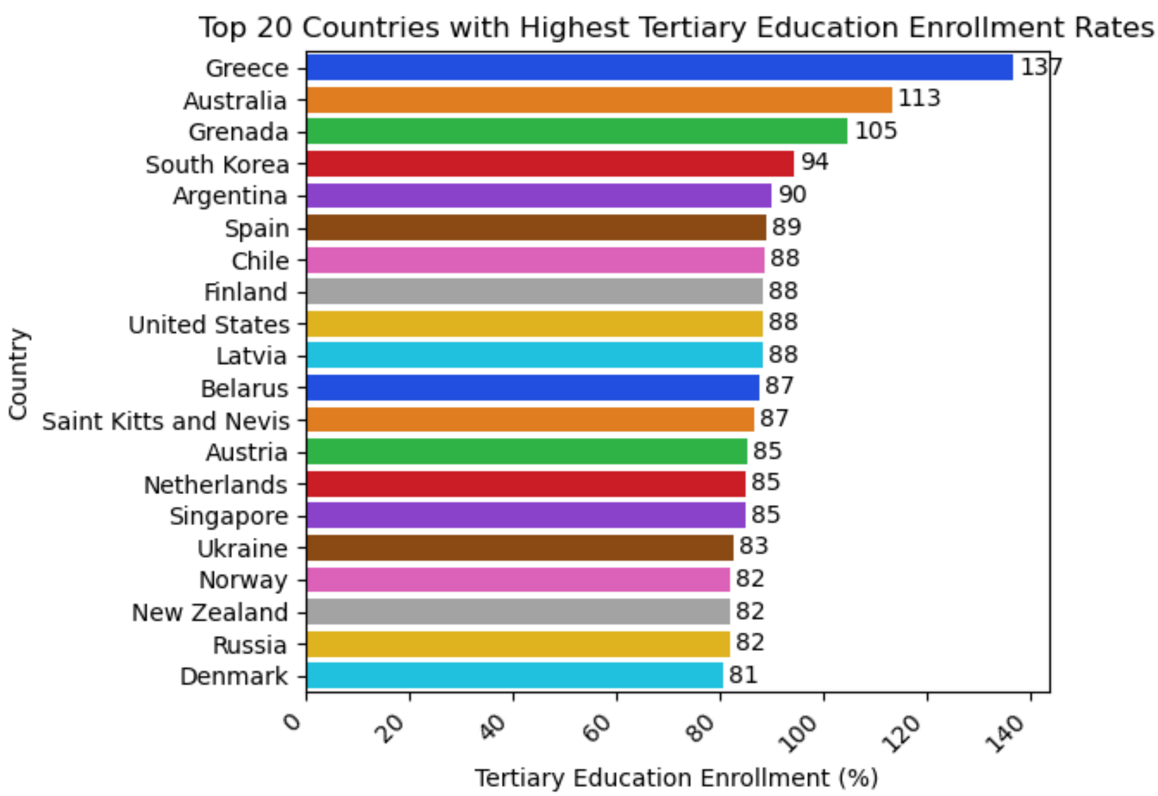
✨Insights 😃😃

A bar graph illustrates their GDP values, ranging from billions to trillions, showcasing leading economies. The bar plot visualizes the top 20 countries with the highest Gross Domestic Product (GDP). The United States leads with the highest GDP, followed by China, Germany, and the United Kingdom, showcasing their significant economic strength. The graph offers a clear comparison of GDP values among these countries.

13| Top 20 Countries: Highest Tertiary Education Enrollment Rates

In [17]:

```
# Sort the DataFrame by gross tertiary education enrollment column in descend
top_tertiary_enrollment_countries = df.sort_values(by='Gross tertiary educat

# Create a bar plot to visualize tertiary education enrollment for top countr
ax = sns.barplot(data=top_tertiary_enrollment_countries, x='Gross tertiary ed
plt.title('Top 20 Countries with Highest Tertiary Education Enrollment Rates
plt.xlabel('Tertiary Education Enrollment (%)')
plt.ylabel('Country')
plt.xticks(rotation=45, ha='right')

# Annotate each bar with the exact tertiary enrollment value using plt.text
for index, value in enumerate(top_tertiary_enrollment_countries['Gross terti
    ax.text(value + 1, index, f'{value:.0f}', va='center', color='black')

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



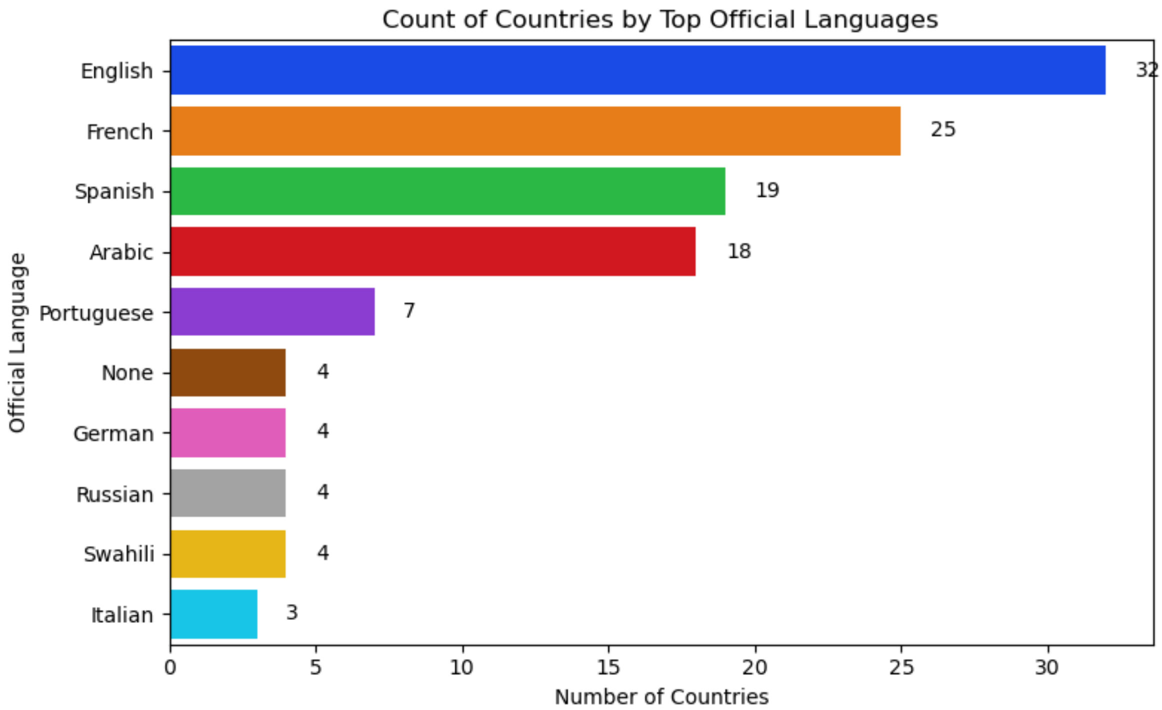
✨Insights 😃😃

The bar plot visualizes the top 20 countries with the highest gross tertiary education enrollment rates. Notably, Greece holds the highest rate at 136.6%, followed by Australia, South Korea, and Argentina. The graph highlights the significant disparities in tertiary education enrollment across these nations, showcasing their dedication to higher education.

14| Countries by Top Languages

In [18]:

```
# Specify the number of top languages to display
top_languages_count = 10

# Get the top N official languages
top_languages = df['Official language'].value_counts().nlargest(top_language

# Filter the DataFrame to include only the top languages
df_top_languages = df[df['Official language'].isin(top_languages)]

# Count of Countries by Top Official Languages
plt.figure(figsize=(8, 5))
sns.countplot(data=df_top_languages, y='Official language', order=df_top_lan
plt.title('Count of Countries by Top Official Languages')
plt.xlabel('Number of Countries')
plt.ylabel('Official Language')
plt.tight_layout()

# Add annotations to the bars
for index, value in enumerate(df_top_languages['Official language'].value_co
    plt.text(value + 1, index, f'{value}', va='center')

plt.show()
```



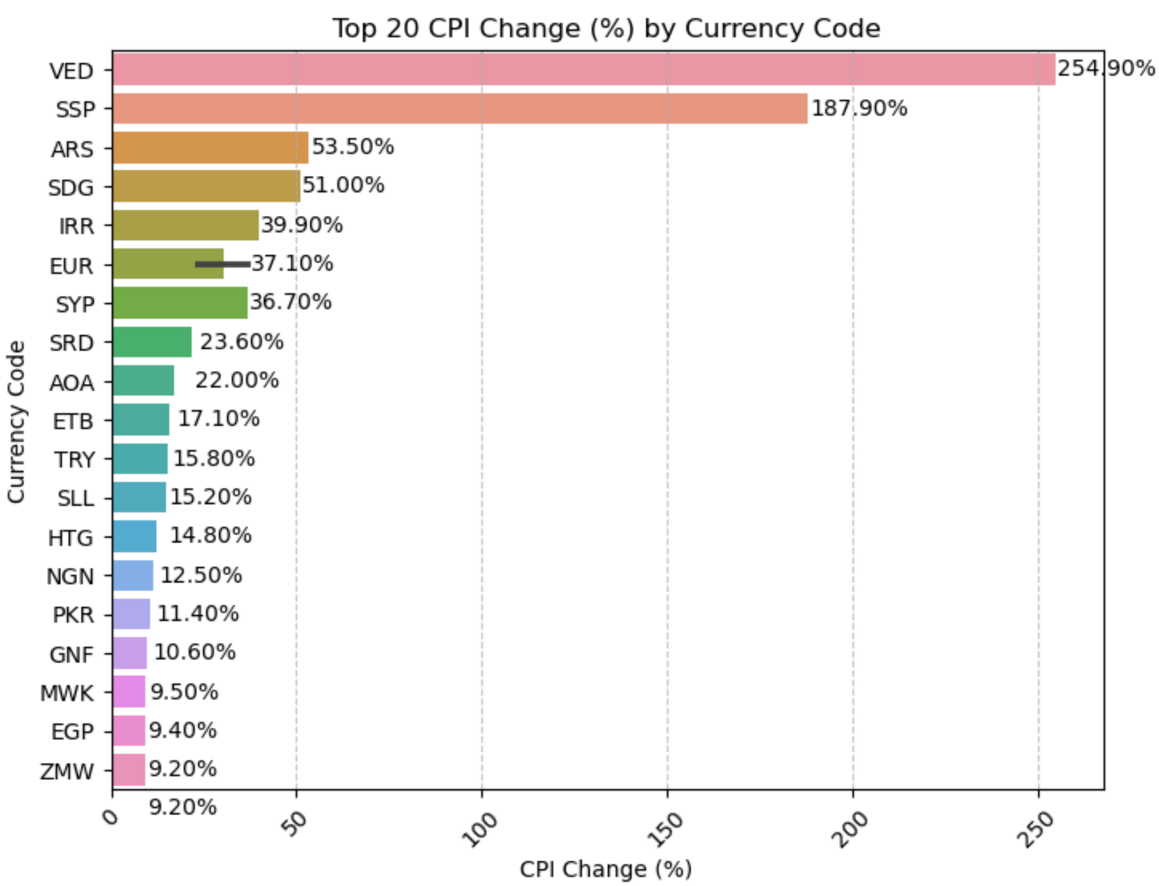
✨Insights 😃 😃

Graphs showing the count of countries by top official languages:

- French, English, and Spanish are the most common official languages among the top 10 countries.
- Arabic and Portuguese are also widely spoken as official languages, each being the primary language in around 10 countries.
- There are a few countries with None as their official language, which might indicate linguistic diversity or multilingualism.
- Russian, Swahili, Persian, and Romanian are also represented, albeit in smaller numbers.

15| Top 20 CPI Change (%): Currency Code

In [19]:
```python
# Select top N currencies with the highest CPI changes
top_n_currencies = 20
top_currencies = df.nlargest(top_n_currencies, 'CPI Change (%)')

# Create the bar plot
plt.figure(figsize=(8, 6))
sns.set_palette("viridis")  # Use a color palette for better distinction
sns.barplot(x='CPI Change (%)', y='Currency-Code', data=top_currencies)
plt.title('Top {} CPI Change (%) by Currency Code'.format(top_n_currencies))
plt.xlabel('CPI Change (%)')
plt.ylabel('Currency Code')
plt.xticks(rotation=45)  # Rotate currency code labels for better readability

# Add data labels to the bars
for index, value in enumerate(top_currencies['CPI Change (%)']):
    plt.text(value + 0.5, index, f'{value:.2f}%', va='center')

# Add horizontal grid lines
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```



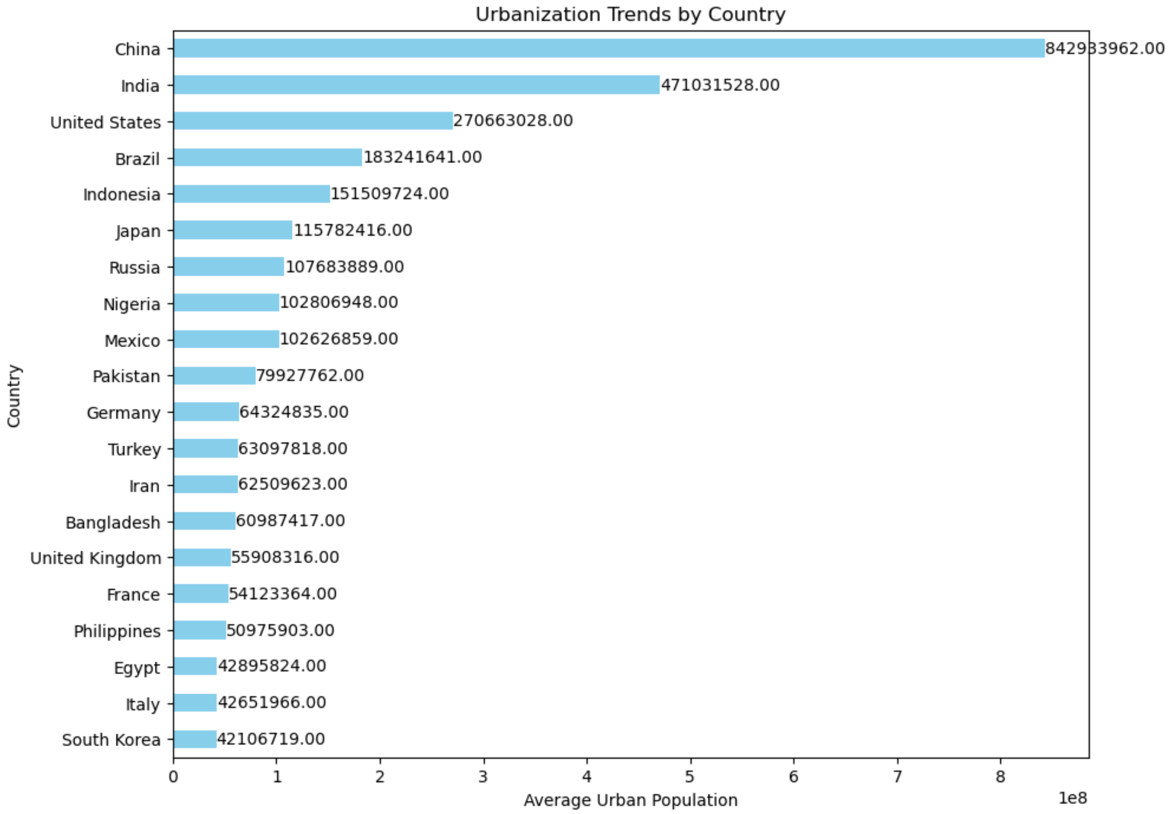
✨Insights 😃😃

A bar graph displays these changes, ranging from 9.2% to 254.9%, revealing economic trends and variations among currencies.

The graph highlights varying CPI changes across currencies, indicating economic conditions and inflation trends. Currencies with high positive CPI changes might suggest inflationary pressures and economic growth, while negative changes could reflect deflationary concerns.

16| Urbanization Trends by Country

In [20]:
```
subset_countries = 20  # Number of top countries to display
urbanization_by_country = df.groupby('Country')['Urban_population'].mean().s

plt.figure(figsize=(10, 8))
ax = urbanization_by_country.plot(kind='barh', color='skyblue')
plt.title('Urbanization Trends by Country')
plt.xlabel('Average Urban Population')
plt.ylabel('Country')
plt.gca().invert_yaxis()  # Invert y-axis to have the highest value at the t

# Add data labels to the bars
for index, value in enumerate(urbanization_by_country):
    ax.text(value + 2, index, f'{value:.2f}', va='center', color='black')  #

plt.show()
```



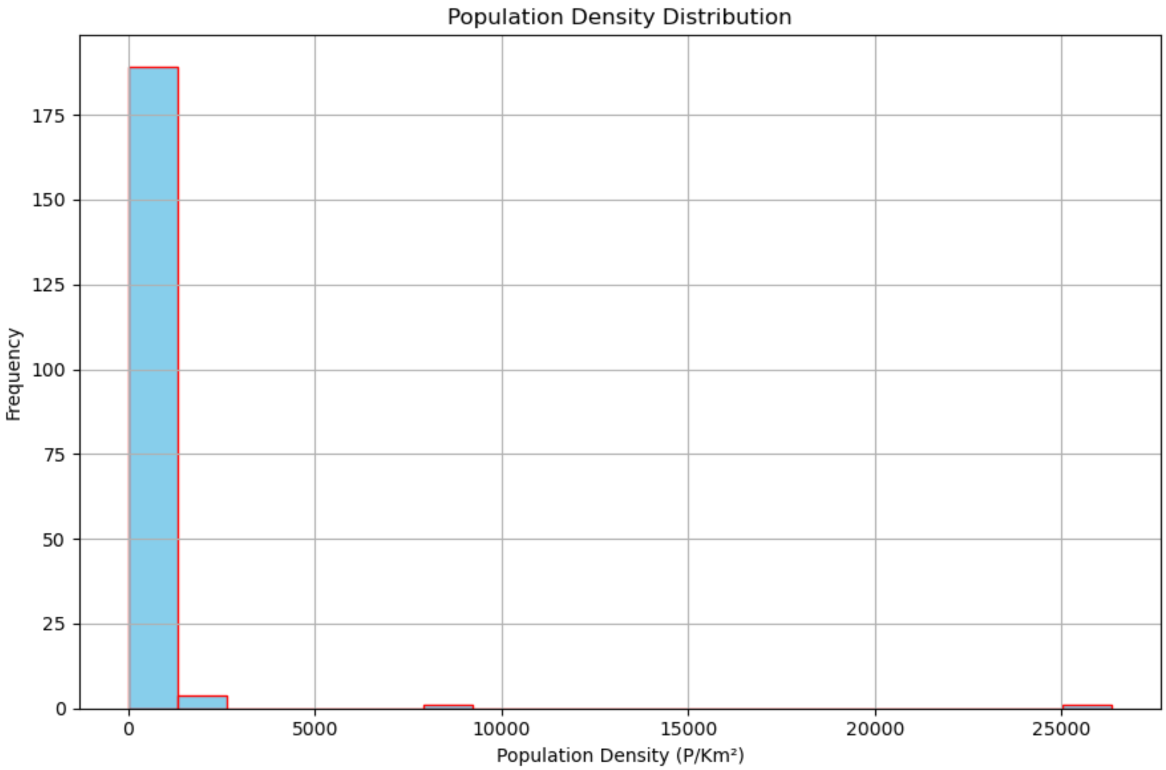
✨Insights 😃😃

Notable entries include China with around 842 million, India with about 471 million, and the United States with approximately 270 million urban inhabitants.

The bar chart highlights the top countries with the highest average urban populations. China, India, and the United States lead, each with urban populations exceeding hundreds of millions, while Brazil, Indonesia, and Russia follow closely in terms of urbanization.

17| Population Density Distribution

In [21]:
```
plt.figure(figsize=(9, 6))
plt.hist(df['Density\n(P/Km2)'], bins=20, color='skyblue', edgecolor='red')
plt.title('Population Density Distribution')
plt.xlabel('Population Density (P/Km²)')
plt.ylabel('Frequency')
plt.grid(True)
plt.tight_layout()
plt.show()
```

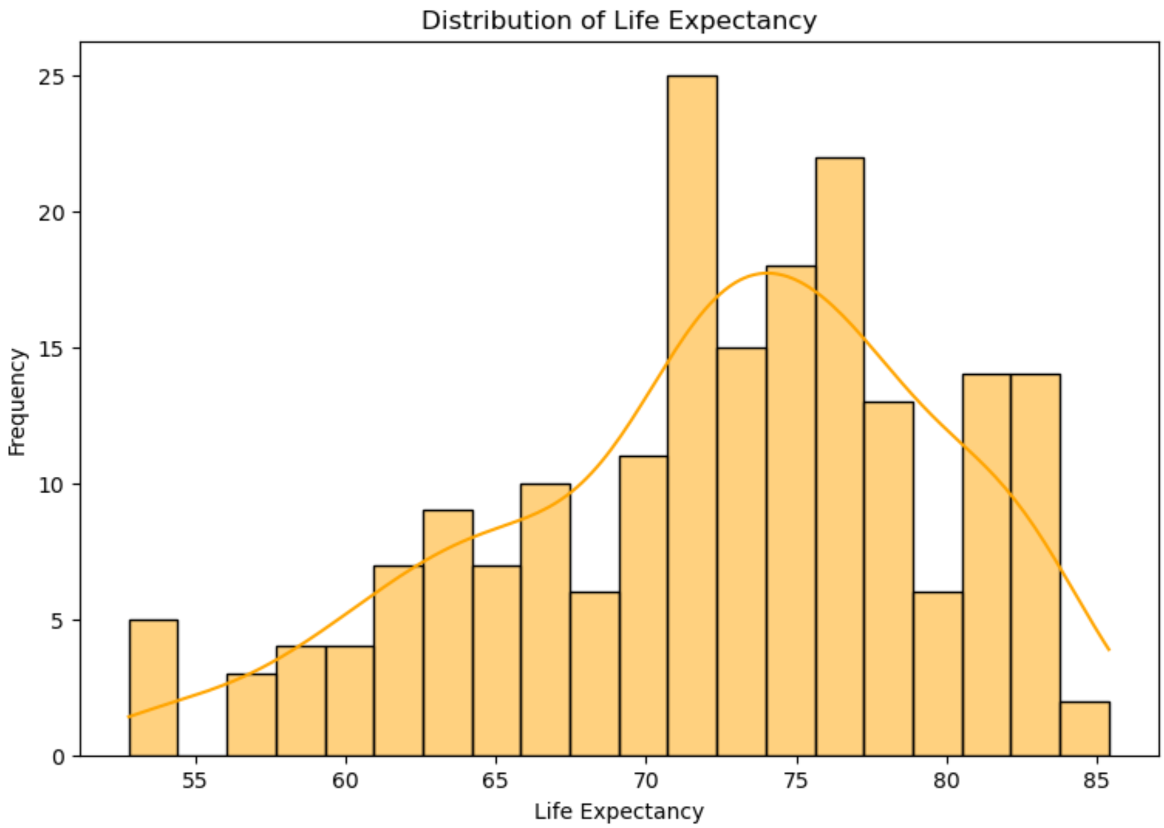


✨Insights 😃😃

The histogram indicates that a higher number of countries have relatively lower population densities, while fewer countries have higher population densities exceeding 1000 people per square kilometer. This is evident from the taller bars in the lower range of population density values compared to the higher values, which leads to the right-skewed distribution.

18| Distribution of Life Expectancy

In [22]:
```
plt.figure(figsize=(9, 6))
sns.histplot(data=df, x='Life expectancy', bins=20, kde=True, color='Orange'
plt.title('Distribution of Life Expectancy')
plt.xlabel('Life Expectancy')
plt.ylabel('Frequency')
plt.show()
```



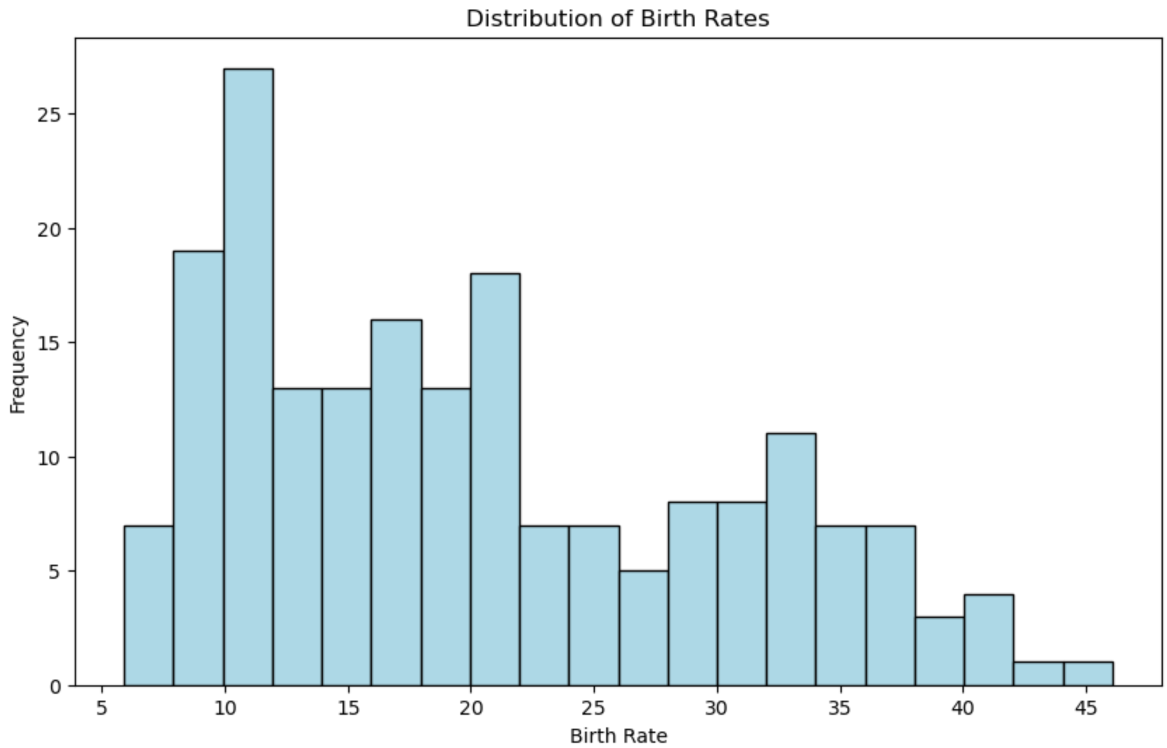
✨Insights 😃😃

The distribution of life expectancy is skewed to the left, with a peak around 75-80 years. Most countries have life expectancies between 60 and 85 years

18| Distribution of Birth Rates

In [23]:

```
plt.figure(figsize=(10, 6))
plt.hist(df['Birth Rate'], bins=20, color='lightblue', edgecolor='black')
plt.title('Distribution of Birth Rates')
plt.xlabel('Birth Rate')
plt.ylabel('Frequency')
plt.show()
```

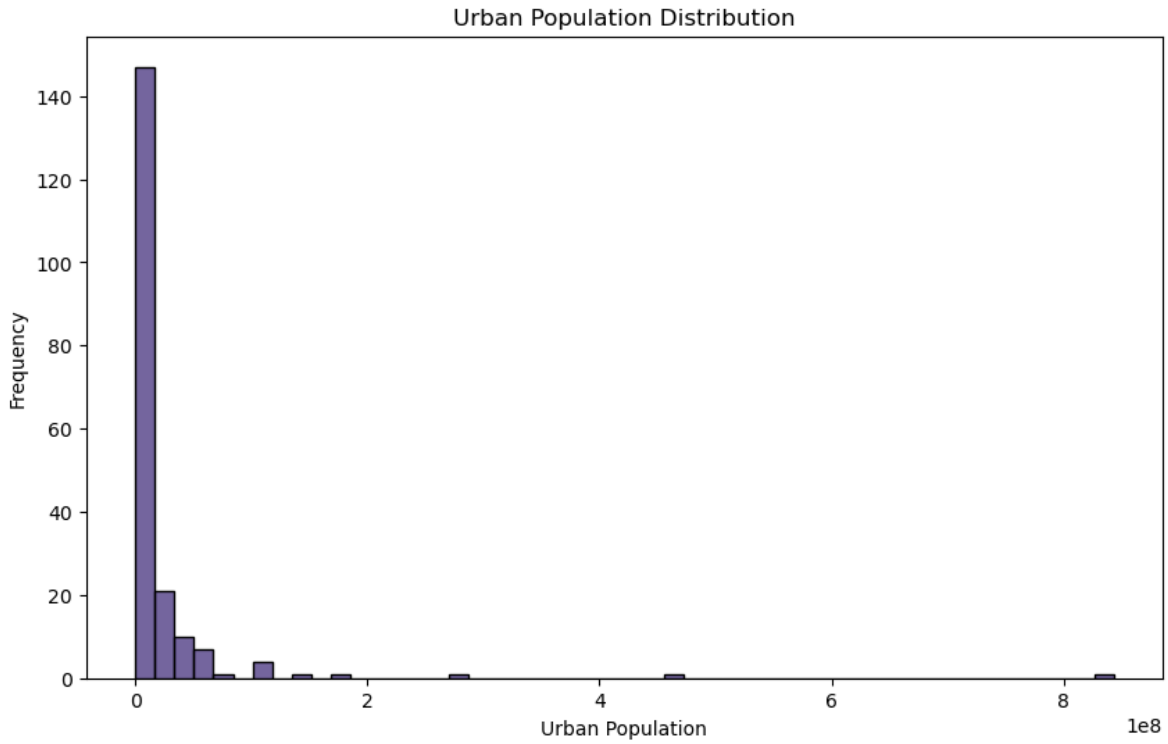


✨Insights 😃😃

The histogram of birth rates indicates a skewed distribution, with fewer countries having higher birth rates and a larger proportion having lower birth rates.

19| Urban Population Distribution:

In [31]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df['Urban_population'], bins=50)
plt.title('Urban Population Distribution')
plt.xlabel('Urban Population')
plt.ylabel('Frequency')
plt.show()
```

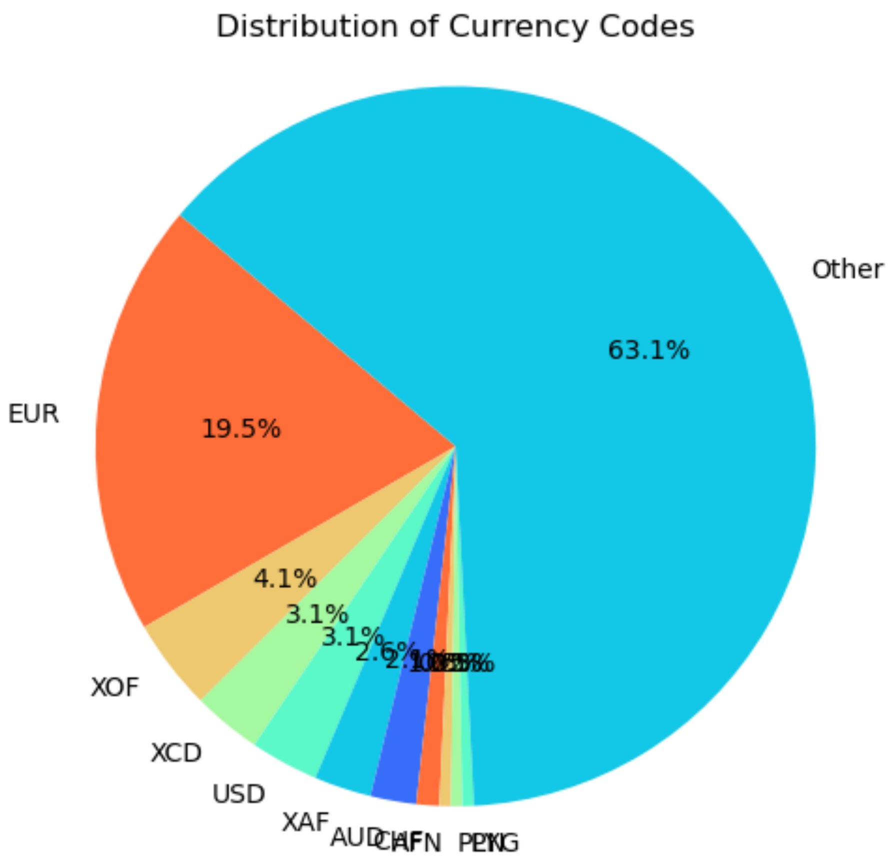


✨Insights 😃😃

The urban population distribution exhibits a right-skewed pattern, with a higher concentration of countries having smaller urban populations.

20| Distribution of Currency Codes

In [25]:
```
# Get the top N currency codes (e.g., top 10)
top_n_currency = 10
currency_counts = df['Currency-Code'].value_counts().head(top_n_currency)

# Calculate the sum of remaining counts
remaining_counts = df['Currency-Code'].value_counts().sum() - currency_count:

# Create a new Series for the top currency codes and an "Other" category
currency_counts = currency_counts.append(pd.Series([remaining_counts], index:

# Plot the pie chart
color = ['red', 'green', 'blue', 'cyan','orange','grey']
plt.pie(currency_counts, labels=currency_counts.index, autopct='%1.1f%%', st:
plt.title('Distribution of Currency Codes')
plt.axis('equal')
plt.tight_layout()
plt.show()
```

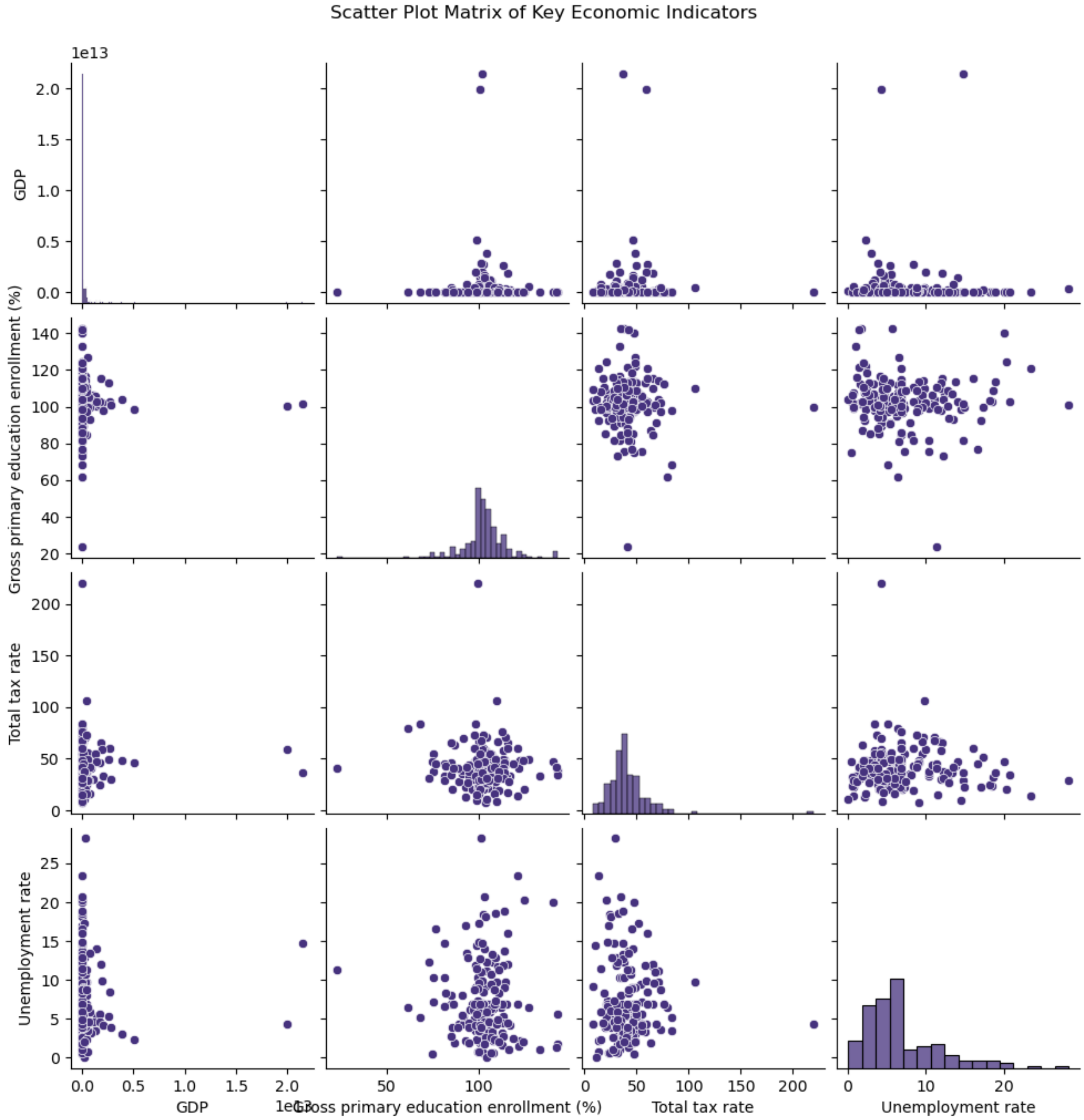


✨Insights 😃 😃

The currency distribution includes EUR (19.5%), XOF (4.1%), XAF (3.1%), USD (3.1%) etc , and others (63.1%).

21| Economic Indicators Scatter Matrix:

In [26]:
```
economic_indicators = df[['GDP', 'Gross primary education enrollment (%)', '
sns.pairplot(economic_indicators)
plt.suptitle('Scatter Plot Matrix of Key Economic Indicators', y=1.02)
plt.show()
```

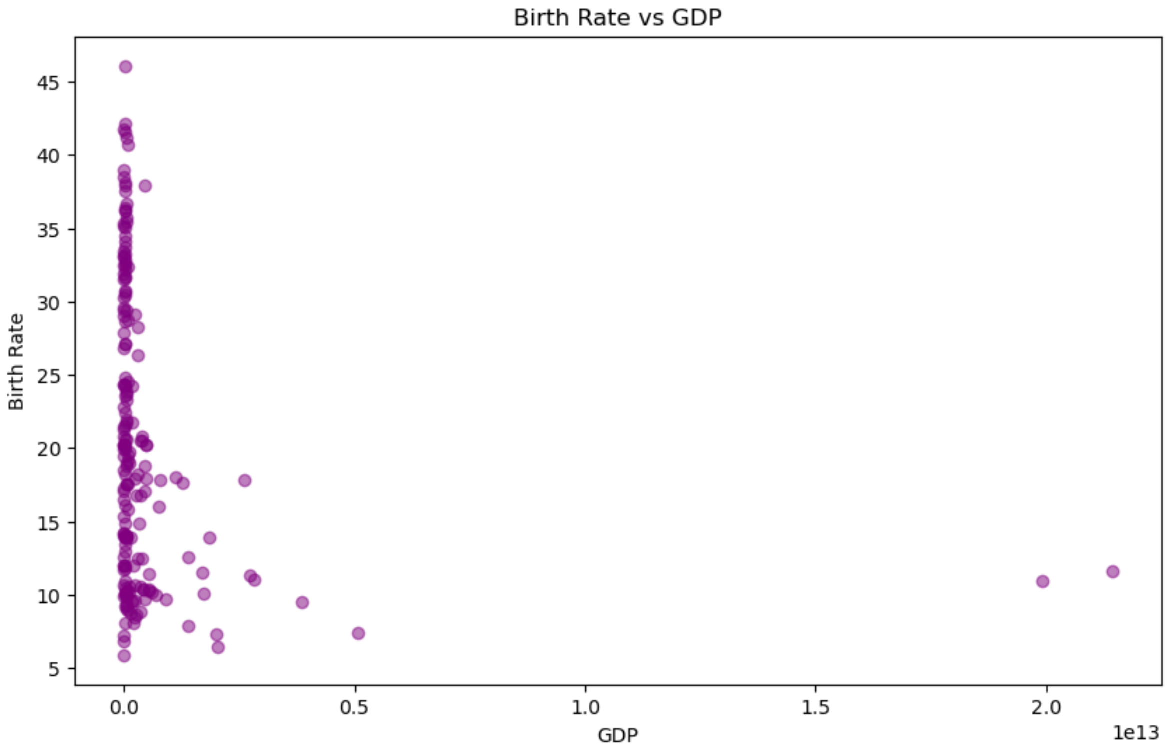


✨Insights 😃 😃

The pair plot indicating potential correlations and trends in economic indicators.

22| Birth Rate vs GDP

In [27]:
```
plt.figure(figsize=(10, 6))
plt.scatter(df['GDP'], df['Birth Rate'], color='purple', alpha=0.5)
plt.title('Birth Rate vs GDP')
plt.xlabel('GDP')
plt.ylabel('Birth Rate')
plt.show()
```

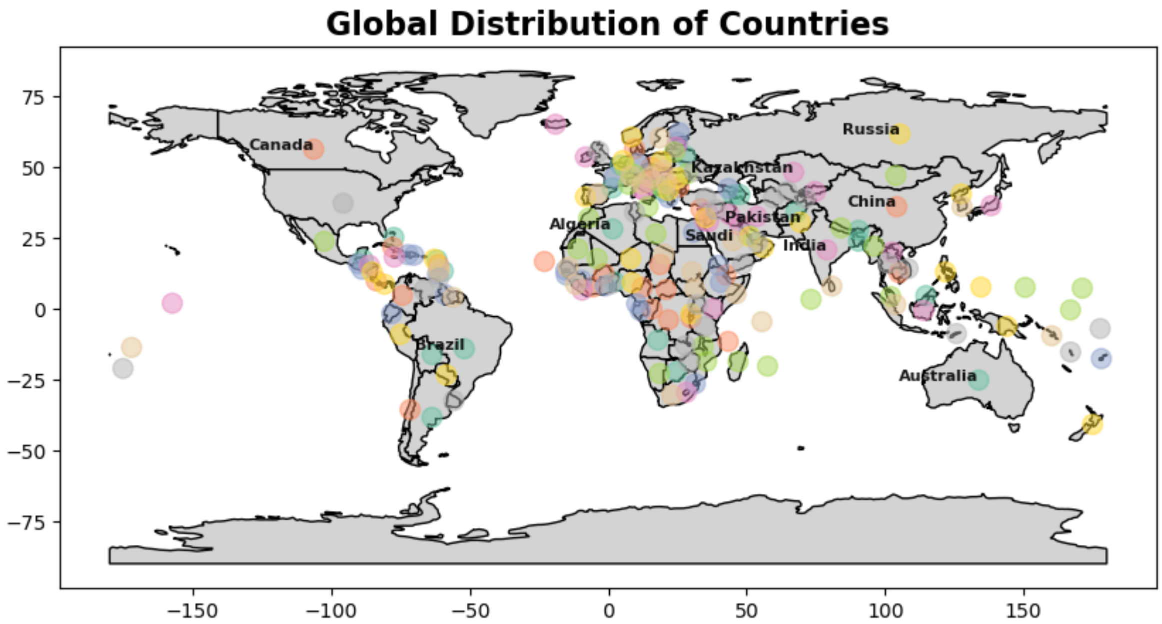


✨Insights 😃😃

This trend indicates that countries with lower GDPs tend to have higher birth rates, possibly influenced by socio-economic factors and development status.

23 | Global Distribution of Countries

In [29]:
```
import geopandas as gpd
from shapely.geometry import Point

# Create GeoDataFrame
geometry = [Point(xy) for xy in zip(df['Longitude'], df['Latitude'])]
gdf = gpd.GeoDataFrame(df, geometry=geometry, crs='EPSG:4326')

# World map
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
fig, ax = plt.subplots(figsize=(10, 6))

# Plot world map
world.plot(ax=ax, color='lightgrey', edgecolor='black')

# Plot country points with a color map
scatter = gdf.plot(ax=ax, markersize=100, legend=True, cmap='Set2', alpha=0.5

# Annotate country names
for x, y, label in zip(gdf.geometry.x, gdf.geometry.y, gdf['Country']):
    if label in ['United States of America', 'Canada', 'Russia',
                 'China', 'Australia','Pakistan','India','Brazil', 'Kazakhsta
        ax.text(x, y, label.split(' ')[0], fontsize=8, ha='right', color='bla
    else:
        ax.text(x, y, '', fontsize=8, ha='right', color='darkslategrey', wei

# Set a title
plt.title('Global Distribution of Countries', fontsize=16, fontweight='bold'




# Display the plot
plt.show()
```



24 | Conclusion

✨Insights 😃 😃

The compilation of visualizations offers a comprehensive panorama of diverse facets in different countries, granting insights into their economic, demographic, and environmental realms:

🌐 Unemployment Rates

From countries grappling with high unemployment rates like Gabon to those enjoying remarkably low rates such as Germany, these visualizations underline the varied state of global labor markets.

🌍 Population Dynamics

China and India emerge as demographic behemoths, while the visual representation showcases the profound contrasts in population sizes across nations.

🌱 Birth Rates and Urbanization

Through the spotlight on countries with elevated birth rates like Niger, the data elucidates population growth dynamics. Furthermore, urbanization trends come to the fore, delineating nations with substantial urban populations.

🌾 Agriculture and Armed Forces

Uruguay's extensive agricultural land and the magnitude of armed forces in countries like India, China, and the United States underscore their prioritization of these domains.

🌍 CO2 Emissions and Environmental Impact

The juxtaposition of CO2 emissions in China, the United States, and India underscores their momentous contributions to global environmental concerns.

💰 Economic Strength and GDP

The GDP visualization showcases economic powerhouses like the United States and China, magnifying their significant economic sway.

📚 Tertiary Education Priorities

Greece's robust tertiary education enrollment rate and the disparities across countries underscore their dedication to higher learning.

🌎 Linguistic Diversity

The linguistic landscape visualization unveils the prevalence of official languages such as French, English, and Spanish, while simultaneously showcasing the tapestry of linguistic diversity.

💱 Currency Trends and Inflation

The depiction of CPI changes among currencies furnishes insights into economic climates and patterns of inflation.

🏙 Urban Population

China, India, and the United States command the lead in urban populations, evincing varying degrees of urbanization.

🏞 Population Density and Life Expectancy

The histogram on population density encapsulates a spectrum of densities, while the distribution of life expectancy shines a light on health conditions across nations.

📊 GDP and CO2 Emissions Relationship

The connection between GDP and CO2 emissions underscores the interrelationship between economic prosperity and environmental challenges.

📈 Correlations and Economic Trends

The pair plot charts potential correlations and trends within economic indicators, enriching the analytical depth.

📉 GDP and Birth Rates Relationship

The interplay between GDP and birth rates suggests the intricate influence of economic factors on population dynamics.

In [ ]: