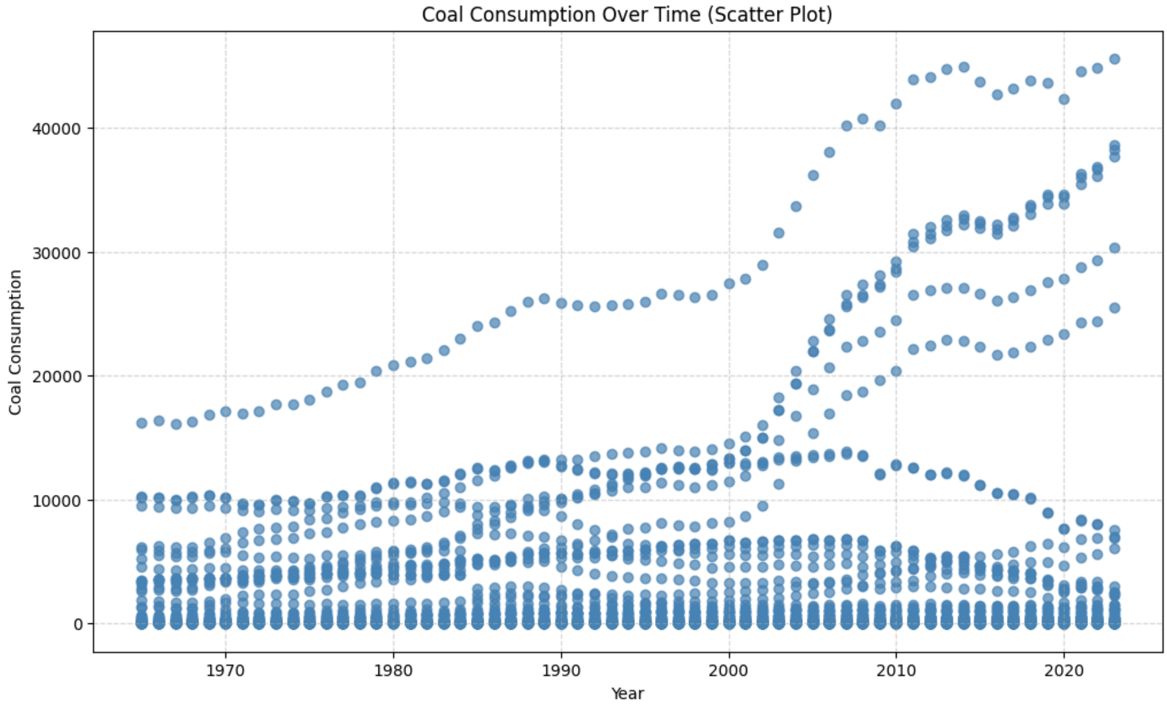
## MAIN FORECASTING

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.stattools import adfuller
```

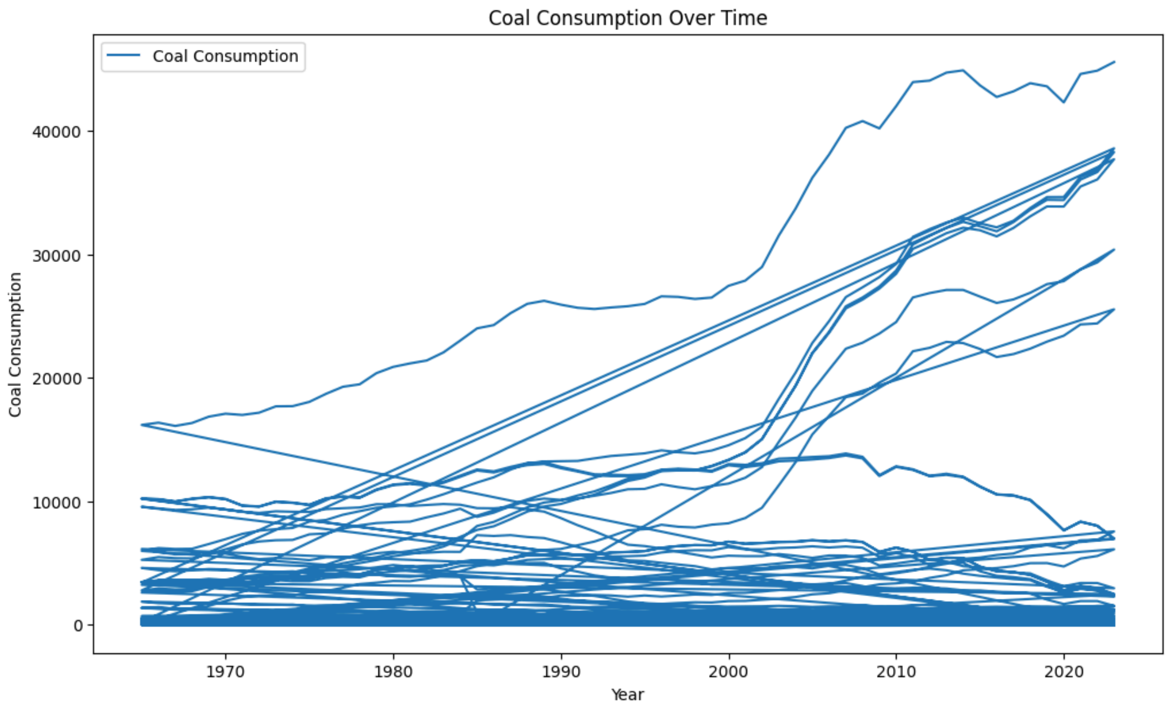
In [7]:
```
# Load the dataset and strip column names of extra spaces
data = pd.read_excel(r"C:\Users\KARTHIKEYA\Desktop\Mini Project\Datasets\
data.columns = data.columns.str.strip()  # Remove leading/trailing spaces

# Display the first few rows and check column names
print("Columns in dataset:", data.columns)
print(data.head())

# Ensure 'Year' is in datetime format and set as index
if 'Year' in data.columns:
    data['Year'] = pd.to_datetime(data['Year'], format='%Y', errors='coer
    data.set_index('Year', inplace=True)
else:
    print("Error: 'Year' column not found!")

# Identify correct column name for coal consumption
coal_col = None
for col in data.columns:
    if "coal consumption" in col.lower():  # Case-insensitive match
        coal_col = col
        break

if coal_col:
    time_series = data[coal_col]
    print("Coal Consumption Data Extracted Successfully")
else:
    print("Error: Coal Consumption column not found! Available columns:",
```

```
Columns in dataset: Index(['Entity', 'Year', 'Coal consumption - TWh'], dt
ype='object')
   Entity  Year  Coal consumption - TWh
0  Africa  1965               323.49615
1  Africa  1966               323.12220
2  Africa  1967               330.29156
3  Africa  1968               343.51290
4  Africa  1969               346.64288
Coal Consumption Data Extracted Successfully
```

In [49]:
```
#SCATTER PLOT SHOWING CONSUMPTION OF COAL FROM 1965 - 2023

plt.figure(figsize=(12, 7))
plt.scatter(time_series.index, time_series, color='steelblue', alpha=0.7)
plt.title("Coal Consumption Over Time (Scatter Plot)")
plt.xlabel("Year")
plt.ylabel("Coal Consumption")
plt.grid(True, linestyle="--", alpha=0.5)
plt.show()
```

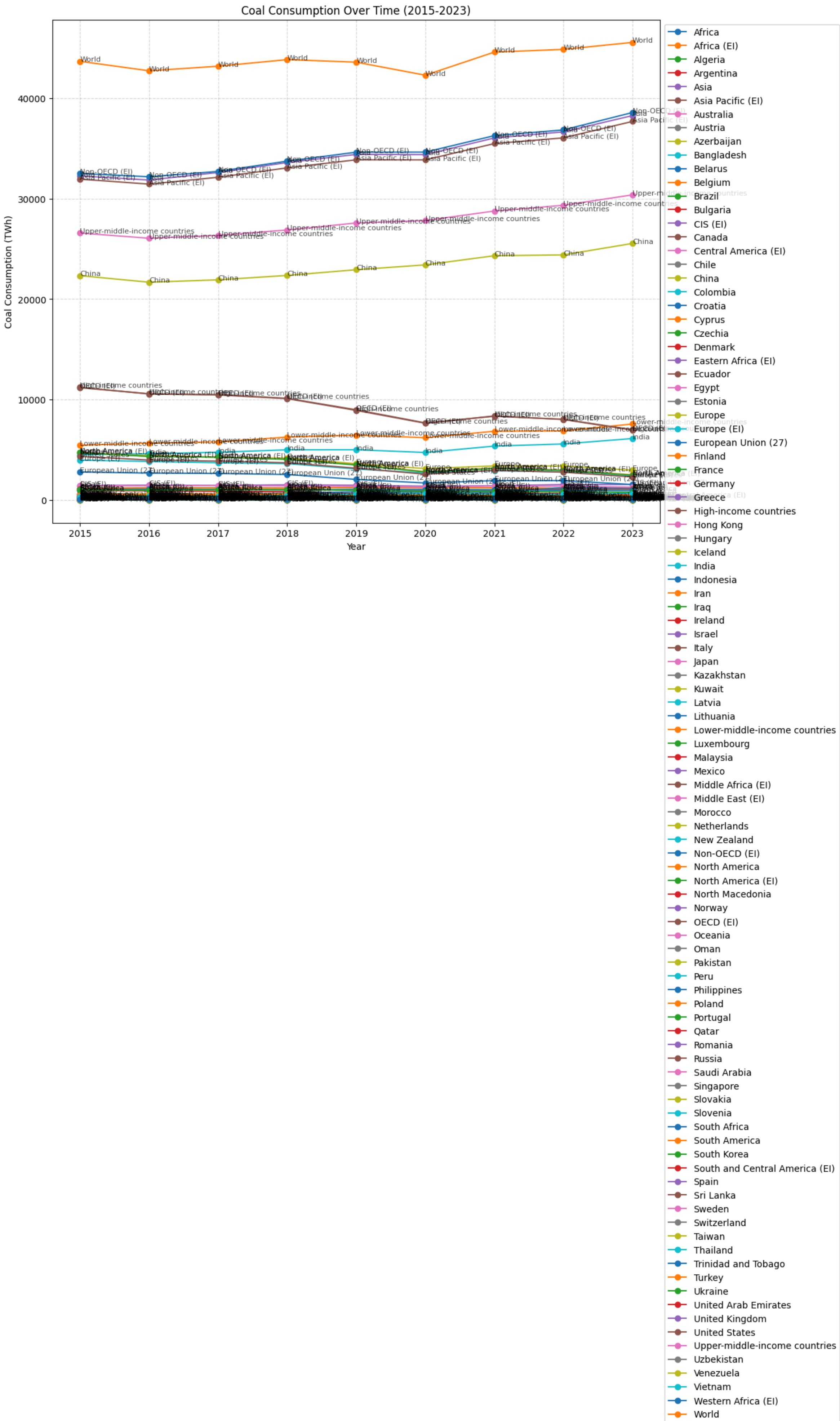



In [54]:
```
#TIME SERIES PLOT(LINE GRAPH) SHOWING CONSUMPTION OF COAL FROM 1965 - 202
# Visualize the data
plt.figure(figsize=(12, 7))
plt.plot(time_series, label="Coal Consumption")
plt.title("Coal Consumption Over Time")
plt.xlabel("Year")
plt.ylabel("Coal Consumption")
plt.legend()
plt.show()
```




In [50]:
```
#COUNTRY WISE CONSUMPTION OF PAST 8 YEARS

import matplotlib.pyplot as plt

# Filter for years 2015-2023
start_year, end_year = 2015, 2023
```

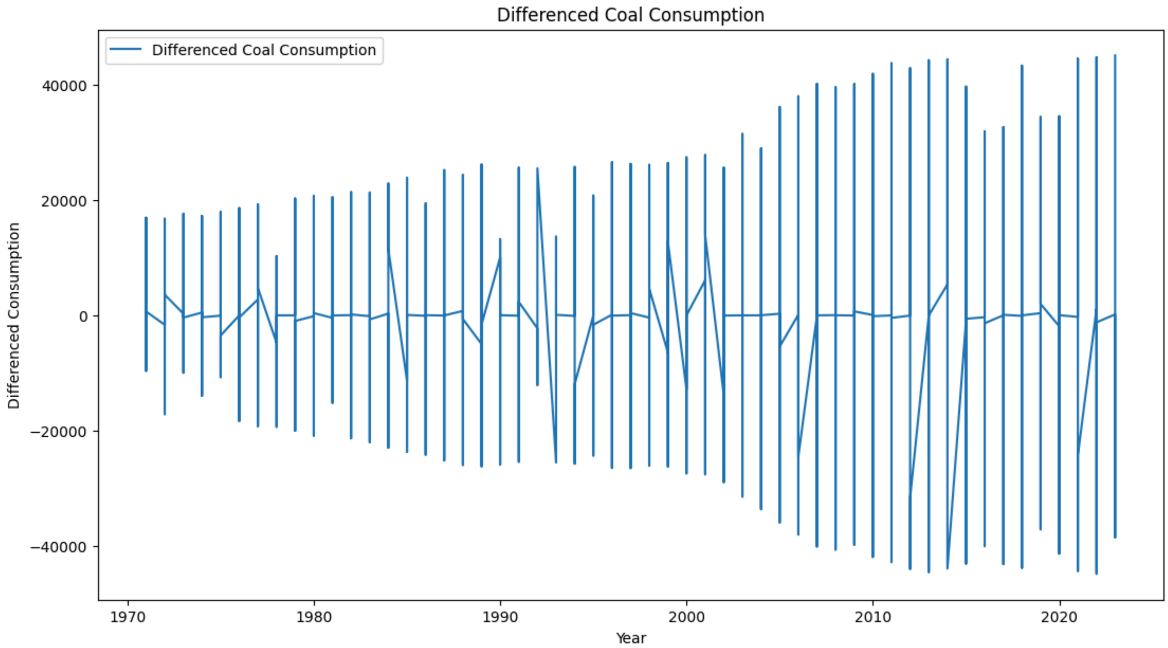
```
filtered_data = data[(data["Year"] >= start_year) & (data["Year"] <= end_

# Get unique countries
countries = filtered_data["Entity"].unique()

# Plot multiple countries with different colors
plt.figure(figsize=(12, 10))

for country in countries:
    country_data = filtered_data[filtered_data["Entity"] == country]
    plt.plot(country_data["Year"], country_data["Coal consumption - TWh"]

# Scatter plot with country labels
for _, row in filtered_data.iterrows():
    plt.text(row["Year"], row["Coal consumption - TWh"], row["Entity"], f

# Improve visualization
plt.title("Coal Consumption Over Time (2015-2023)")
plt.xlabel("Year")
plt.ylabel("Coal Consumption (TWh)")
plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
plt.grid(True, linestyle="--", alpha=0.5)



# Show plot
plt.show()
```


Coal Consumption Over Time (2015-2023)
Coal Consumption (TWh)
Year
0
10000
20000
30000
40000
2015
2016
2017
2018
2019
2020
2021
2022
2023
Africa
Africa (EI)
Algeria
Argentina
Asia
Asia Pacific (EI)
Australia
Austria
Azerbaijan
Bangladesh
Belarus
Belgium
Brazil
Bulgaria
CIS (EI)
Canada
Central America (EI)
Chile
China
Colombia
Croatia
Cyprus
Czechia
Denmark
Eastern Africa (EI)
Ecuador
Egypt
Estonia
Europe
Europe (EI)
European Union (27)
Finland
France
Germany
Greece
High-income countries
Hong Kong
Hungary
Iceland
India
Indonesia
Iran
Iraq
Ireland
Israel
Italy
Japan
Kazakhstan
Kuwait
Latvia
Lithuania
Lower-middle-income countries
Luxembourg
Malaysia
Mexico
Middle Africa (EI)
Middle East (EI)
Morocco
Netherlands
New Zealand
Non-OECD (EI)
North America
North America (EI)
North Macedonia
Norway
OECD (EI)
Oceania
Oman
Pakistan
Peru
Philippines
Poland
Portugal
Qatar
Romania
Russia
Saudi Arabia
Singapore
Slovakia
Slovenia
South Africa
South America
South Korea
South and Central America (EI)
Spain
Sri Lanka
Sweden
Switzerland
Taiwan
Thailand
Trinidad and Tobago
Turkey
Ukraine
United Arab Emirates
United Kingdom
United States
Upper-middle-income countries
Uzbekistan
Venezuela
Vietnam
Western Africa (EI)
World

In [118…

```
# Check for stationarity using ADF (Augumented Dickey-Fuller) test
adf_test = adfuller(time_series)
print("ADF Test Results:")
print(f"p-value: {adf_test[1]}")

if adfuller(time_series)[1] <= 0.05:
    print("\033[1mTHE DATA IS STATIONARY.\033[0m")
else:
    print("\033[1mTHE DATA IS NOT STATIONARY, APPLYING DIFFERENCING...\03

# Apply differencing if necessary
time_series_diff = time_series.diff().dropna()

# Plot differenced data
plt.figure(figsize=(13, 7))
plt.plot(time_series_diff, label="Differenced Coal Consumption")
plt.title("Differenced Coal Consumption")
plt.xlabel("Year")
plt.ylabel("Differenced Consumption")
plt.legend()
plt.show()
```

```
ADF Test Results:
p-value: 0.0
THE DATA IS STATIONARY.
```




In [67]:

```
import pandas as pd

# Load the dataset
df = pd.read_excel(r"C:\Users\KARTHIKEYA\Desktop\Mini Project\Datasets\CO

# Print the first few rows to check column names
print(df.head())

# Ensure the column names match your dataset
df.rename(columns=lambda x: x.strip(), inplace=True)  # Strip any extra s

# Assign time series data
india_data = df  # Assigning to a variable for consistency
time_series = india_data["Coal consumption - TWh"]
```

```
   Entity  Year  Coal consumption - TWh
0  Africa  1965              323.49615
1  Africa  1966              323.12220
2  Africa  1967              330.29156
3  Africa  1968              343.51290
4  Africa  1969              346.64288
```

In [69]:

```
# TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP T
# import pandas as pd

# # Load the dataset
# file_path = r"C:\Users\KARTHIKEYA\Desktop\Mini Project\Datasets\COAL Co
# df = pd.read_excel(file_path)

# # Clean column names (strip spaces)
# df.columns = df.columns.str.strip()

# # Ensure the correct column name is used
# column_name = "Coal consumption - TWh"  # Adjust if needed
# if column_name not in df.columns:
#     print(f"Column '{column_name}' not found. Available columns: {df.co
#     exit()

# # Assign time series data
# time_series = df[column_name].dropna()
```

In [80]:

```
# Fit ARIMA model
p, d, q = 1, 2, 1  # Example parameters (can be tuned)
arima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(0, 0,
arima_results = arima_model.fit()

# Summary of ARIMA model
print(arima_results.summary())

# Forecast next 5 years using ARIMA
forecast_arima = arima_results.get_forecast(steps=5)
forecast_values_arima = forecast_arima.predicted_mean
confidence_intervals_arima = forecast_arima.conf_int()
```

```
                                     SARIMAX Results
==========================================================================
========
Dep. Variable:     Coal consumption - TWh   No. Observations:
5521
Model:                   SARIMAX(1, 2, 1)   Log Likelihood              -4
6480.771
Date:                    Fri, 14 Feb 2025   AIC                          9
2967.543
Time:                            23:44:06   BIC                          9
2987.390
Sample:                                 0   HQIC                         9
2974.464
                                   - 5521
Covariance Type:                      opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1         -0.0076      0.035     -0.220      0.826      -0.076
0.060
ma.L1         -0.9999      0.005   -213.604      0.000      -1.009      -
0.991
sigma2      1.209e+06   6481.975    186.467      0.000     1.2e+06    1.22
e+06
==========================================================================
=========
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):          149
065679.55
Prob(Q):                              1.00   Prob(JB):
0.00
Heteroskedasticity (H):               0.37   Skew:
-24.47
Prob(H) (two-sided):                  0.00   Kurtosis:
806.64
==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
```

In [87]:

```
# Fit SARIMA model
P, D, Q, s = 1, 1, 1, 2  # Example seasonal parameters (can be tuned)
sarima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(P, D
sarima_results = sarima_model.fit()

# Summary of SARIMA model
print(sarima_results.summary())

# Forecast next 5 years using SARIMA
forecast_sarima = sarima_results.get_forecast(steps=5)
forecast_values_sarima = forecast_sarima.predicted_mean
confidence_intervals_sarima = forecast_sarima.conf_int()
```

```
                                      SARIMAX Results
==========================================================================
================
Dep. Variable:            Coal consumption - TWh   No. Observations:
5521
Model:             SARIMAX(1, 2, 1)x(1, 1, 1, 2)   Log Likelihood
-46488.942
Date:                           Fri, 14 Feb 2025   AIC
92987.885
Time:                                   23:46:25   BIC
93020.963
Sample:                                        0   HQIC
92999.421
                                          - 5521
Covariance Type:                             opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1         -0.0074      0.033     -0.223      0.824      -0.072
0.057
ma.L1         -1.0000      0.833     -1.201      0.230      -2.632
0.632
ar.S.L2        0.0118      0.028      0.420      0.675      -0.043
0.067
ma.S.L2       -1.0000      0.833     -1.201      0.230      -2.632
0.632
sigma2      1.104e+06   2.53e-08   4.36e+13      0.000     1.1e+06     1.1
e+06
==========================================================================
=========
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):         151
179498.25
Prob(Q):                              0.98   Prob(JB):
0.00
Heteroskedasticity (H):               0.37   Skew:
-24.62
Prob(H) (two-sided):                  0.00   Kurtosis:
812.47
==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
[2] Covariance matrix is singular or near-singular, with condition number
4.68e+29. Standard errors may be unstable.
```

In [128…

```
# Print forecasts (ALL COUNTRIES)
print("\nARIMA Forecast for Next 5 Years:")
print(forecast_values_arima)
print("\nSARIMA Forecast for Next 5 Years:")
print(forecast_values_sarima)
```

```
ARIMA Forecast for Next 5 Years:
5521    45569.594535
5522    45579.532620
5523    45589.430468
5524    45599.328623
5525    45609.226775
Name: predicted_mean, dtype: float64

SARIMA Forecast for Next 5 Years:
2024-01-01    45947.859348
2025-01-01    46691.167951
2026-01-01    47111.347328
2027-01-01    47886.204829
2028-01-01    48319.895327
Freq: YS-JAN, Name: predicted_mean, dtype: float64
```

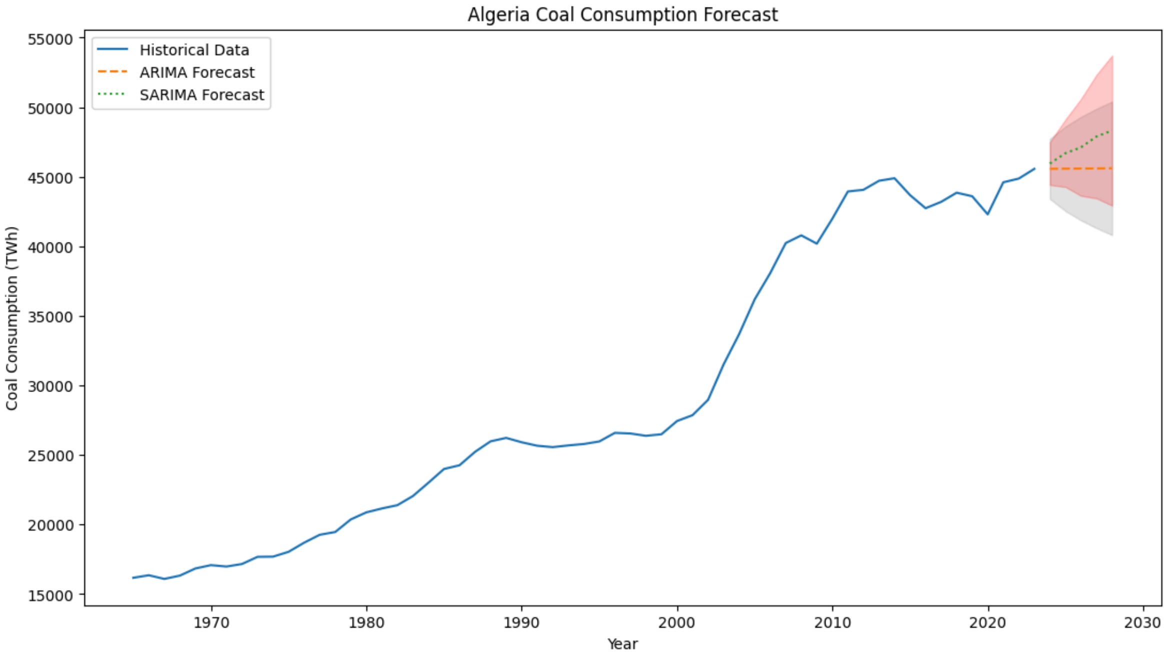
In [111…

```
# TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP TEMP T
# import matplotlib.pyplot as plt

# # Generate future years for plotting
# future_years = pd.date_range(start=time_series.index[-1] + pd.DateOffse

# plt.figure(figsize=(10, 6))
# plt.plot(time_series, label="Historical Data")
# plt.plot(future_years, forecast_values_arima, label="ARIMA Forecast", l
# plt.plot(future_years, forecast_values_sarima, label="SARIMA Forecast",
# plt.fill_between(future_years, confidence_intervals_arima.iloc[:, 0], c
# plt.fill_between(future_years, confidence_intervals_sarima.iloc[:, 0],
# plt.title(f"{entity} Coal Consumption Forecast")
# plt.xlabel("Year")
# plt.ylabel("Coal Consumption (TWh)")
# plt.legend()
# plt.show()
```

In [134…

```
# Assuming you have loaded your data and filtered for a SPECIFIC COUNTRY
entity = "Algeria"

# Your existing code for loading, preprocessing, and fitting models...

# Forecast next 5 years using ARIMA
forecast_arima = arima_results.get_forecast(steps=5)
forecast_values_arima = forecast_arima.predicted_mean
confidence_intervals_arima = forecast_arima.conf_int()

# Forecast next 5 years using SARIMA
forecast_sarima = sarima_results.get_forecast(steps=5)
forecast_values_sarima = forecast_sarima.predicted_mean
confidence_intervals_sarima = forecast_sarima.conf_int()

# Generate future years for plotting
future_years = pd.date_range(
    start=time_series.index[-1] + pd.offsets.YearBegin(),
    periods=5,
    freq='YS'
)

# Plot forecasts
plt.figure(figsize=(13, 7))
plt.plot(time_series, label="Historical Data")
plt.plot(future_years, forecast_values_arima, label="ARIMA Forecast", lin
```

```
plt.plot(future_years, forecast_values_sarima, label="SARIMA Forecast", l
plt.fill_between(future_years, confidence_intervals_arima.iloc[:, 0], con
plt.fill_between(future_years, confidence_intervals_sarima.iloc[:, 0], co
plt.title(f"{entity} Coal Consumption Forecast")
plt.xlabel("Year")
plt.ylabel("Coal Consumption (TWh)")
plt.legend()
plt.show()
```




**WHOLE CODE FOR ANY RANDOM COUNTRY REPORT GENERATION**

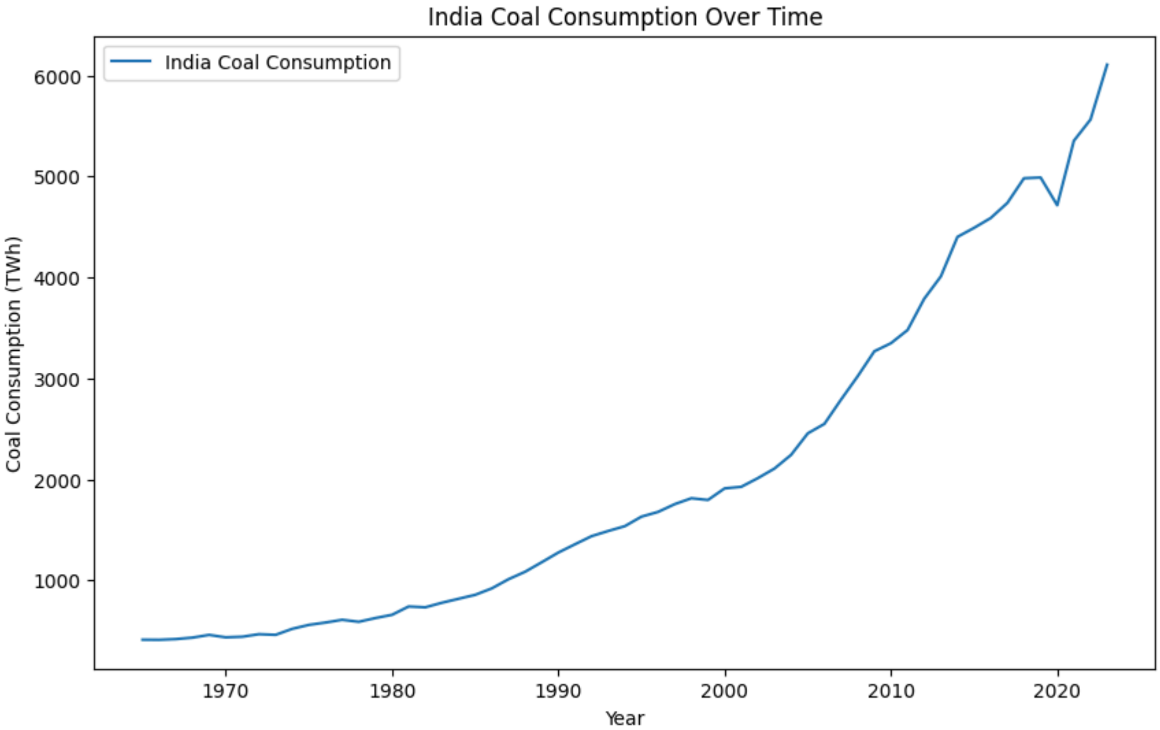
In [139…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.stattools import adfuller

# Load the dataset
# file_path = "3c681988-d6d8-4378-ba4c-2486974e9c91_COAL Consumption.xlsx
# sheet_name = "coal-consumption-by-country-ter"
# data = pd.read_excel(file_path, sheet_name=sheet_name)

data = pd.read_excel(r"C:\Users\KARTHIKEYA\Desktop\Mini Project\Datasets\

# Display the first few rows of the dataset
print(data.head())

# Function to preprocess and analyze data for a given entity
def analyze_entity(entity):
    # Filter data for the specific entity
    entity_data = data[data['Entity'] == entity].copy()

    # Ensure 'Year' is datetime and set as index
    entity_data['Year'] = pd.to_datetime(entity_data['Year'], format='%Y'
    entity_data.set_index('Year', inplace=True)

    # Extract the coal consumption column
    time_series = entity_data['Coal consumption - TWh']
```

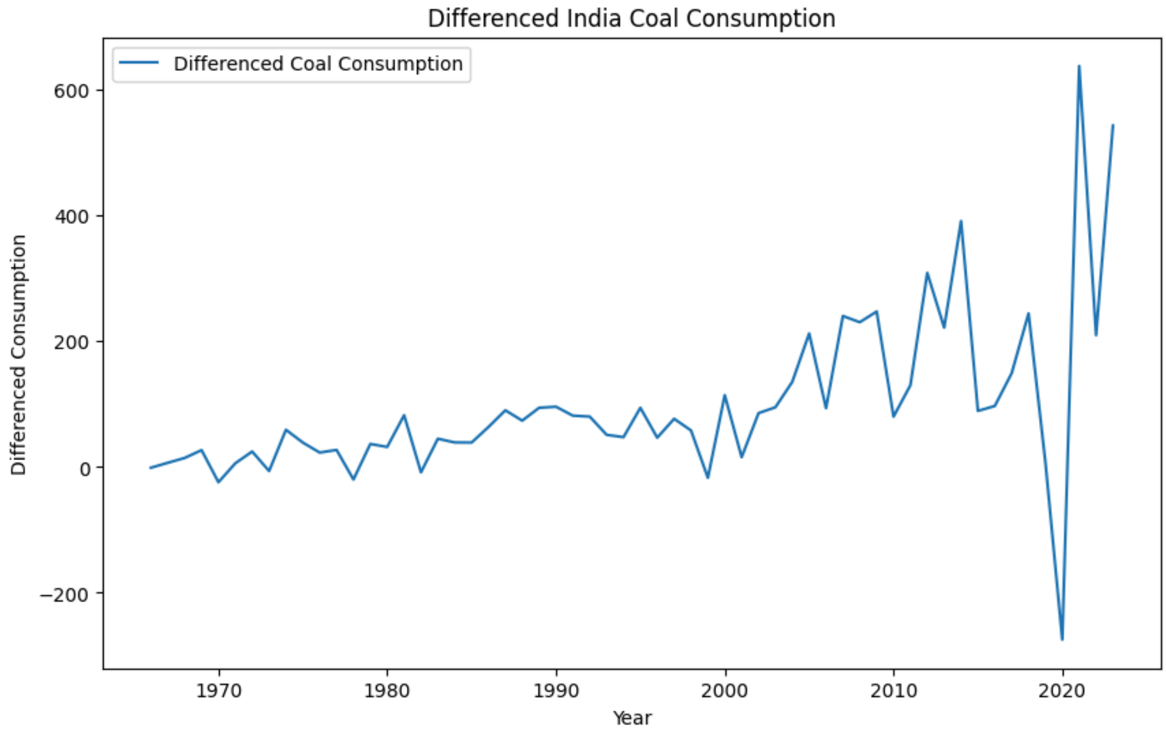
```
    # Check if there is enough data to proceed
    if len(time_series) < 20:
        print(f"Not enough data for {entity}. Please select another count
        return

    # Visualize the data
    plt.figure(figsize=(10, 6))
    plt.plot(time_series, label=f"{entity} Coal Consumption")
    plt.title(f"{entity} Coal Consumption Over Time")
    plt.xlabel("Year")
    plt.ylabel("Coal Consumption (TWh)")
    plt.legend()
    plt.show()

    # Check for stationarity using ADF test
    adf_test = adfuller(time_series)
    print("ADF Test Results:")
    print(f"p-value: {adf_test[1]}")
    if adf_test[1] <= 0.05:
        print("The data is stationary.")
    else:
        print("The data is non-stationary. Applying differencing...")

    # Apply differencing if necessary
    time_series_diff = time_series.diff().dropna()

    # Plot differenced data
    plt.figure(figsize=(10, 6))
    plt.plot(time_series_diff, label="Differenced Coal Consumption")
    plt.title(f"Differenced {entity} Coal Consumption")
    plt.xlabel("Year")
    plt.ylabel("Differenced Consumption")
    plt.legend()
    plt.show()

    # Fit ARIMA model
    p, d, q = 1, 1, 1  # Example parameters (can be tuned)
    arima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(0
    arima_results = arima_model.fit()

    # Summary of ARIMA model
    print(arima_results.summary())

    # Forecast next 5 years using ARIMA
    forecast_arima = arima_results.get_forecast(steps=5)
    forecast_values_arima = forecast_arima.predicted_mean
    confidence_intervals_arima = forecast_arima.conf_int()

    # Fit SARIMA model
    P, D, Q, s = 1, 1, 1, 2  # Example seasonal parameters (can be tuned)
    sarima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(
    sarima_results = sarima_model.fit()

    # Summary of SARIMA model
    print(sarima_results.summary())

    # Forecast next 5 years using SARIMA
    forecast_sarima = sarima_results.get_forecast(steps=5)
    forecast_values_sarima = forecast_sarima.predicted_mean
    confidence_intervals_sarima = forecast_sarima.conf_int()
```

```
    # Generate future years for plotting
    future_years = pd.date_range(
        start=time_series.index[-1] + pd.offsets.YearBegin(),
        periods=5,
        freq='YS'
    )

    # Plot forecasts
    plt.figure(figsize=(13, 7))
    plt.plot(time_series, label="Historical Data")
    plt.plot(future_years, forecast_values_arima, label="ARIMA Forecast",
    plt.plot(future_years, forecast_values_sarima, label="SARIMA Forecast
    plt.fill_between(future_years, confidence_intervals_arima.iloc[:, 0],
    plt.fill_between(future_years, confidence_intervals_sarima.iloc[:, 0]
    plt.title(f"{entity} Coal Consumption Forecast")
    plt.xlabel("Year")
    plt.ylabel("Coal Consumption (TWh)")
    plt.legend()
    plt.show()

# Example usage: Analyze data for India
entity = "India"
analyze_entity(entity)
```

```
   Entity  Year  Coal consumption - TWh
0  Africa  1965               323.49615
1  Africa  1966               323.12220
2  Africa  1967               330.29156
3  Africa  1968               343.51290
4  Africa  1969               346.64288
```




```
ADF Test Results:
p-value: 1.0
The data is non-stationary. Applying differencing...
```

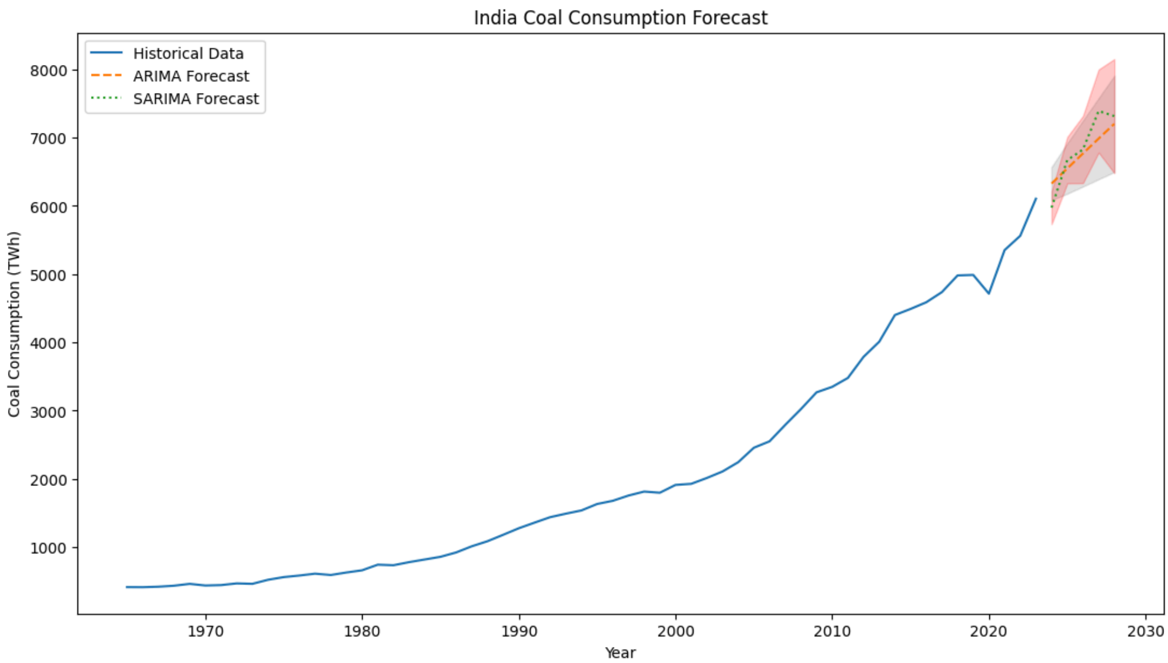



```
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting paramete
rs.
  warn('Non-stationary starting autoregressive parameters'
```

```
                               SARIMAX Results
==========================================================================
========
Dep. Variable:     Coal consumption - TWh   No. Observations:
59
Model:                   SARIMAX(1, 1, 1)   Log Likelihood
-362.543
Date:                    Sat, 15 Feb 2025   AIC
731.087
Time:                            00:37:01   BIC
737.268
Sample:                        01-01-1965   HQIC
733.495
                             - 01-01-2023
Covariance Type:                      opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1          0.9927      0.017     60.113      0.000       0.960
1.025
ma.L1         -0.8489      0.068    -12.493      0.000      -0.982      -
0.716
sigma2      1.527e+04   1603.095      9.523      0.000    1.21e+04    1.84
e+04
==========================================================================
=========
Ljung-Box (L1) (Q):                   1.46   Jarque-Bera (JB):
171.07
Prob(Q):                              0.23   Prob(JB):
0.00
Heteroskedasticity (H):              59.17   Skew:
0.91
Prob(H) (two-sided):                  0.00   Kurtosis:
11.21
==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
```

```
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
```

```
                                     SARIMAX Results
==========================================================================
===============
Dep. Variable:            Coal consumption - TWh   No. Observations:
59
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 2)   Log Likelihood
-349.252
Date:                           Sat, 15 Feb 2025   AIC
708.505
Time:                                   00:37:02   BIC
718.631
Sample:                               01-01-1965   HQIC
712.431
                                    - 01-01-2023
Covariance Type:                             opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1         -0.9907     12.344     -0.080      0.936    -25.185      2
3.204
ma.L1          0.9977     25.259      0.039      0.968    -48.510      5
0.505
ar.S.L2       -0.8222      0.185     -4.443      0.000     -1.185      -
0.460
ma.S.L2        0.3034      0.289      1.051      0.293     -0.262
0.869
sigma2      1.493e+04   1.95e+05      0.077      0.939  -3.67e+05    3.97
e+05
==========================================================================
=========
Ljung-Box (L1) (Q):                   0.07   Jarque-Bera (JB):
121.41
Prob(Q):                              0.80   Prob(JB):
0.00
Heteroskedasticity (H):              33.48   Skew:
0.72
Prob(H) (two-sided):                  0.00   Kurtosis:
10.07
==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
```




**WHOLE CODE FOR ANY RANDOM COUNTRY REPORT GENERATION WITH EVALUATION METRICS (MAE, RMSE, MAPE)**

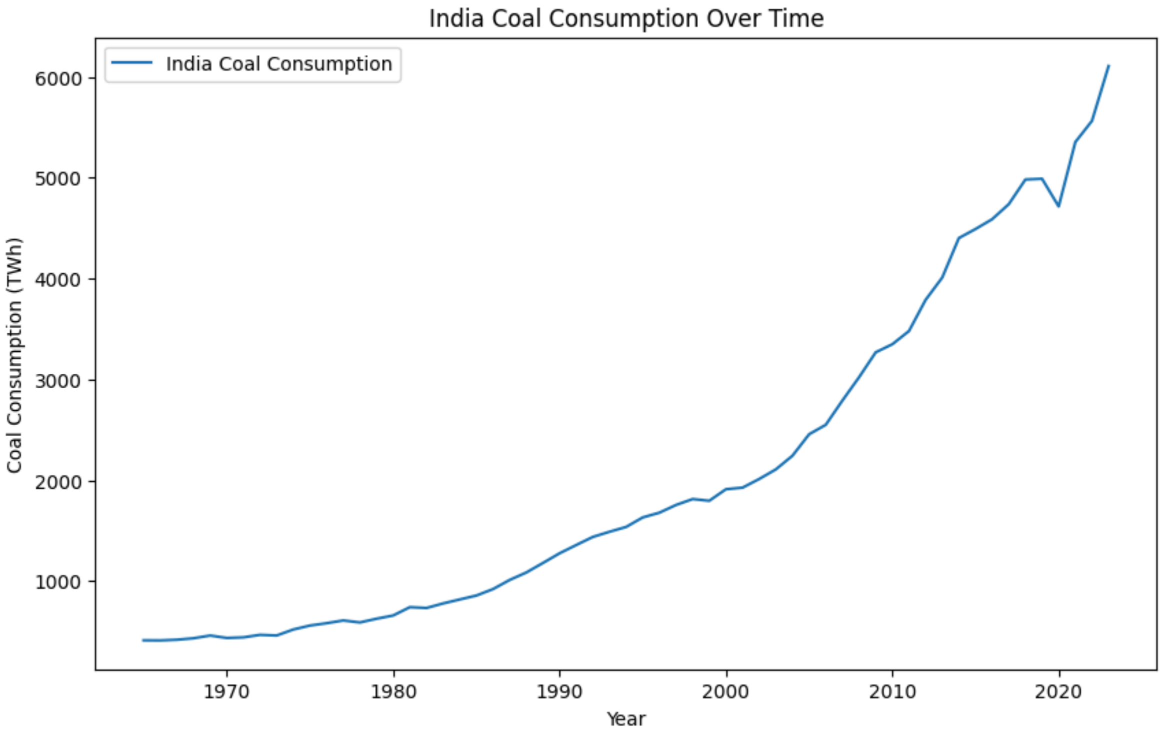
In [144…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.stattools import adfuller

# Load the dataset
data = pd.read_excel(r"C:\Users\KARTHIKEYA\Desktop\Mini Project\Datasets\


# Display the first few rows of the dataset
print(data.head())

# Function to preprocess and analyze data for a given entity
def analyze_entity(entity):
    # Filter data for the specific entity
    entity_data = data[data['Entity'] == entity].copy()

    # Ensure 'Year' is datetime and set as index
    entity_data['Year'] = pd.to_datetime(entity_data['Year'], format='%Y'
    entity_data.set_index('Year', inplace=True)

    # Extract the coal consumption column
    time_series = entity_data['Coal consumption - TWh']

    # Check if there is enough data to proceed
    if len(time_series) < 20:
        print(f"Not enough data for {entity}. Please select another count
        return

    # Visualize the data
    plt.figure(figsize=(10, 6))
    plt.plot(time_series, label=f"{entity} Coal Consumption")
    plt.title(f"{entity} Coal Consumption Over Time")
    plt.xlabel("Year")
```

```
plt.ylabel("Coal Consumption (TWh)")
plt.legend()
plt.show()

# Check for stationarity using ADF test
adf_test = adfuller(time_series)
print("ADF Test Results:")
print(f"p-value: {adf_test[1]}")
if adf_test[1] <= 0.05:
    print("The data is stationary.")
else:
    print("The data is non-stationary. Applying differencing...")

# Apply differencing if necessary
time_series_diff = time_series.diff().dropna()

# Fit ARIMA model
p, d, q = 1, 1, 1  # Example parameters (can be tuned)
arima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(0
arima_results = arima_model.fit()

# Summary of ARIMA model
print(arima_results.summary())

# Forecast next 5 years using ARIMA
forecast_arima = arima_results.get_forecast(steps=5)
forecast_values_arima = forecast_arima.predicted_mean
confidence_intervals_arima = forecast_arima.conf_int()

# Fit SARIMA model
P, D, Q, s = 1, 1, 1, 2  # Example seasonal parameters (can be tuned)
sarima_model = SARIMAX(time_series, order=(p, d, q), seasonal_order=(
sarima_results = sarima_model.fit()

# Summary of SARIMA model
print(sarima_results.summary())

# Forecast next 5 years using SARIMA
forecast_sarima = sarima_results.get_forecast(steps=5)
forecast_values_sarima = forecast_sarima.predicted_mean
confidence_intervals_sarima = forecast_sarima.conf_int()

# Calculate performance metrics
actual_values = time_series.values
forecast_values_arima = forecast_values_arima.values
forecast_values_sarima = forecast_values_sarima.values

# Mean Absolute Error (MAE) for ARIMA and SARIMA
mae_arima = np.mean(np.abs(actual_values[-len(forecast_values_arima):
mae_sarima = np.mean(np.abs(actual_values[-len(forecast_values_sarima

# Root Mean Squared Error (RMSE) for ARIMA and SARIMA
rmse_arima = np.sqrt(np.mean((actual_values[-len(forecast_values_arim
rmse_sarima = np.sqrt(np.mean((actual_values[-len(forecast_values_sar

# Mean Absolute Percentage Error (MAPE) for ARIMA and SARIMA
mape_arima = np.mean(np.abs((actual_values[-len(forecast_values_arima
mape_sarima = np.mean(np.abs((actual_values[-len(forecast_values_sari

# Calculate performance metrics as percentages
```

```
    total_actual_sum = np.sum(actual_values)
    mae_arima_percentage = (mae_arima / total_actual_sum) * 100
    rmse_arima_percentage = (rmse_arima / total_actual_sum) * 100
    mape_arima_percentage = mape_arima / 100

    mae_sarima_percentage = (mae_sarima / total_actual_sum) * 100
    rmse_sarima_percentage = (rmse_sarima / total_actual_sum) * 100
    mape_sarima_percentage = mape_sarima / 100

    # Print performance metrics
    print("\nPerformance Metrics for ARIMA:")
    print(f"MAE (Percentage): {mae_arima_percentage:.2f}%")
    print(f"RMSE (Percentage): {rmse_arima_percentage:.2f}%")
    print(f"MAPE (Percentage): {mape_arima_percentage:.2f}%")

    print("\nPerformance Metrics for SARIMA:")
    print(f"MAE (Percentage): {mae_sarima_percentage:.2f}%")
    print(f"RMSE (Percentage): {rmse_sarima_percentage:.2f}%")
    print(f"MAPE (Percentage): {mape_sarima_percentage:.2f}%")

    # Generate future years for plotting
    future_years = pd.date_range(
        start=time_series.index[-1] + pd.offsets.YearBegin(),
        periods=5,
        freq='YS'
    )

    # Plot forecasts
    plt.figure(figsize=(13, 7))
    plt.plot(time_series, label="Historical Data")
    plt.plot(future_years, forecast_values_arima, label="ARIMA Forecast",
    plt.plot(future_years, forecast_values_sarima, label="SARIMA Forecast
    plt.fill_between(future_years, confidence_intervals_arima.iloc[:, 0],
    plt.fill_between(future_years, confidence_intervals_sarima.iloc[:, 0]
    plt.title(f"{entity} Coal Consumption Forecast")
    plt.xlabel("Year")
    plt.ylabel("Coal Consumption (TWh)")
    plt.legend()
    plt.show()

# Example usage: Analyze data for India
entity = "India"
analyze_entity(entity)
```

```
   Entity  Year  Coal consumption - TWh
0  Africa  1965               323.49615
1  Africa  1966               323.12220
2  Africa  1967               330.29156
3  Africa  1968               343.51290
4  Africa  1969               346.64288
```




```
ADF Test Results:
p-value: 1.0
The data is non-stationary. Applying differencing...
```

```
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
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C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
ges\statsmodels\tsa\statespace\sarimax.py:966: UserWarning: Non-stationary
starting autoregressive parameters found. Using zeros as starting paramete
rs.
  warn('Non-stationary starting autoregressive parameters'
```

```
                               SARIMAX Results
==========================================================================
========
Dep. Variable:     Coal consumption - TWh   No. Observations:
59
Model:                   SARIMAX(1, 1, 1)   Log Likelihood
-362.543
Date:                    Sat, 15 Feb 2025   AIC
731.087
Time:                            00:42:43   BIC
737.268
Sample:                        01-01-1965   HQIC
733.495
                             - 01-01-2023
Covariance Type:                      opg
==========================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
--------------------------------------------------------------------------
----
ar.L1          0.9927      0.017     60.113      0.000       0.960
1.025
ma.L1         -0.8489      0.068    -12.493      0.000      -0.982      -
0.716
sigma2      1.527e+04   1603.095      9.523      0.000    1.21e+04    1.84
e+04
==========================================================================
=========
Ljung-Box (L1) (Q):                   1.46   Jarque-Bera (JB):
171.07
Prob(Q):                              0.23   Prob(JB):
0.00
Heteroskedasticity (H):              59.17   Skew:
0.91
Prob(H) (two-sided):                  0.00   Kurtosis:
11.21
==========================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).
```

```
C:\Users\KARTHIKEYA\AppData\Local\Programs\Python\Python312\Lib\site-packa
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ges\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency info
rmation was provided, so inferred frequency YS-JAN will be used.
  self._init_dates(dates, freq)
```
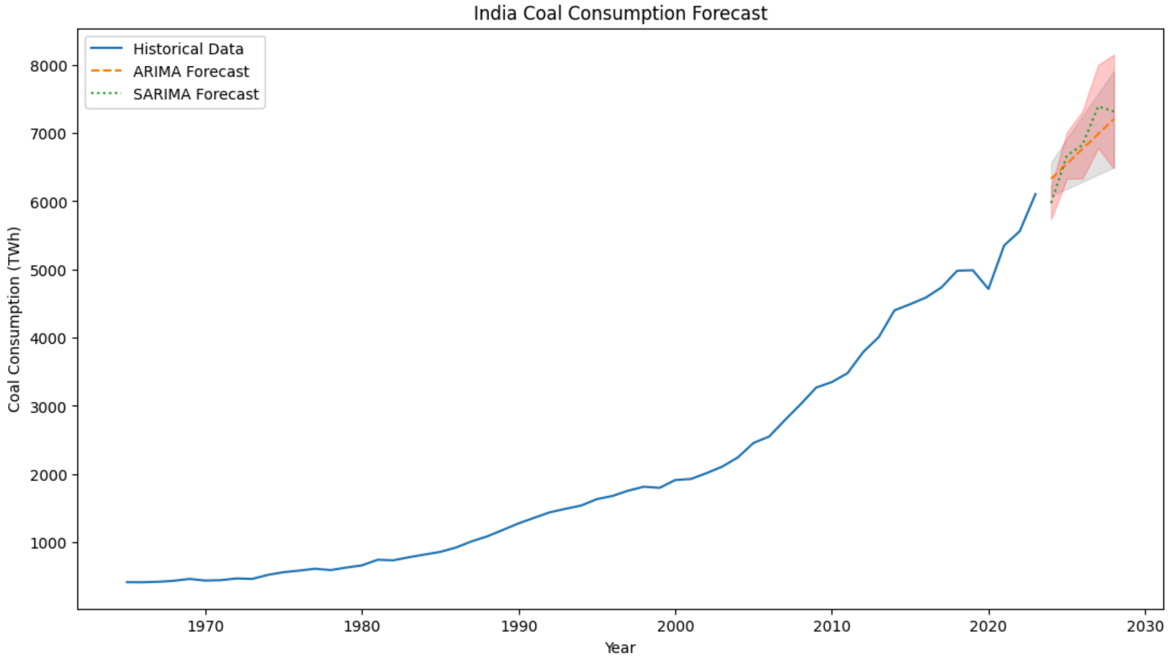

```
                                      SARIMAX Results                                       
==========================================================================================
==============
Dep. Variable:           Coal consumption - TWh   No. Observations:                       
59
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 2)   Log Likelihood                      
-349.252
Date:                           Sat, 15 Feb 2025   AIC                                 
708.505
Time:                                   00:42:43   BIC                                 
718.631
Sample:                               01-01-1965   HQIC                                
712.431
                                    - 01-01-2023                                       
Covariance Type:                             opg                                       
==========================================================================================
====
                 coef    std err          z      P>|z|      [0.025      0.
975]
------------------------------------------------------------------------------------------
----
ar.L1         -0.9907     12.344     -0.080      0.936     -25.185      2
3.204
ma.L1          0.9977     25.259      0.039      0.968     -48.510      5
0.505
ar.S.L2       -0.8222      0.185     -4.443      0.000      -1.185      -
0.460
ma.S.L2        0.3034      0.289      1.051      0.293      -0.262       
0.869
sigma2      1.493e+04   1.95e+05      0.077      0.939   -3.67e+05    3.97
e+05
==========================================================================================
=========
Ljung-Box (L1) (Q):                   0.07   Jarque-Bera (JB):                
121.41
Prob(Q):                              0.80   Prob(JB):                        
0.00
Heteroskedasticity (H):              33.48   Skew:                            
0.72
Prob(H) (two-sided):                  0.00   Kurtosis:                        
10.07
==========================================================================================
=========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (com
plex-step).

Performance Metrics for ARIMA:
MAE (Percentage): 1.18%
RMSE (Percentage): 1.19%
MAPE (Percentage): 0.27%

Performance Metrics for SARIMA:
MAE (Percentage): 1.23%
RMSE (Percentage): 1.27%
MAPE (Percentage): 0.28%
```


India Coal Consumption Forecast
Historical Data
ARIMA Forecast
SARIMA Forecast
Coal Consumption (TWh)
1000
2000
3000
4000
5000
6000
7000
8000
1970
1980
1990
2000
2010
2020
2030
Year