```
# This Python 3 environment comes with many helpful analytics libraries installe
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/doc
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets
# You can also write temporary files to /kaggle/temp/, but they won't be saved o
```

```
/kaggle/input/climate-change-earth-surface-temperature-data/GlobalTemperatu
/kaggle/input/climate-change-earth-surface-temperature-data/GlobalLandTempe
/kaggle/input/climate-change-earth-surface-temperature-data/GlobalLandTempe
/kaggle/input/climate-change-earth-surface-temperature-data/GlobalLandTempe
/kaggle/input/climate-change-earth-surface-temperature-data/GlobalLandTempe
```

```
print("this is the the GlobalTemperatures file")
df1 = pd.read_csv('/kaggle/input/climate-change-earth-surface-temperature-data/G
df1.dataframeName = 'GlobalLandTemperaturesByCity.csv'
nRow, nCol = df1.shape
print(f'There are {nRow} rows and {nCol} columns')
```

```
this is the the GlobalTemperatures file
There are 3192 rows and 9 columns
```

```
df1
```

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandM
0	1750-01-01	3.034	3.574	
1	1750-02-01	3.083	3.702	
2	1750-03-01	5.626	3.076	
3	1750-04-01	8.490	2.451	
4	1750-05-01	11.573	2.072	
...	...	...	...	
3187	2015-08-01	14.755	0.072	
3188	2015-09-01	12.999	0.079	
3189	2015-10-01	10.801	0.102	
3190	2015-11-01	7.433	0.119	
3191	2015-12-01	5.518	0.100	

3192 rows × 9 columns

Null imputation:

We will check the null rates and explain the nulls. After that consider ways to impute them

```
null_rate = df1['LandAverageTemperatureUncertainty'].isnull().sum()

# Calculate the null rate as a percentage of the total number of rows
total_rows = len(df1)
null_rate_percentage = (null_rate / total_rows) * 100

print(f"Null rate for 'LandAverageTemperature': {null_rate} rows ({null_rate_per
```

```
Null rate for 'LandAverageTemperature': 12 rows (0.38%)
```

```
null_rate = df1['LandAverageTemperature'].isnull().sum()

# Calculate the null rate as a percentage of the total number of rows
total_rows = len(df1)
null_rate_percentage = (null_rate / total_rows) * 100

print(f"Null rate for 'LandAverageTemperature': {null_rate} rows ({null_rate_per
```

```
Null rate for 'LandAverageTemperature': 12 rows (0.38%)
```

LandAverageTemperatureUncertainty and LandAverageTemperature matches Since it's only 12 rows, we decided to drop them

```
df1.dropna(subset=['LandAverageTemperature'], inplace=True)
len(df1)
```

```
3180
```

```
null_rate = df1['LandMaxTemperature'].isnull().sum()

# Calculate the null rate as a percentage of the total number of rows
total_rows = len(df1)
null_rate_percentage = (null_rate / total_rows) * 100

print(f"Null rate for 'LandMaxTemperature': {null_rate} rows ({null_rate_percent
```

```
Null rate for 'LandMaxTemperature': 1188 rows (37.36%)
```

Since it's really high, we want to impute it.Let's the rows with nulls first

```
null_rows = df1[df1['LandMaxTemperature'].isnull()]
null_rows.describe()
```

	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTem
count	1188.000000	1188.000000	
mean	8.044657	2.048162	
std	4.555287	1.080738	
min	-2.080000	0.428000	
25%	4.038000	1.269000	
50%	8.084000	1.800500	
75%	12.311750	2.591250	
max	19.021000	7.880000	

```
LandAverageTemperature = df1[['LandAverageTemperature', "LandAverageTemperatureU
LandAverageTemperature #this is for the use of LandAverageTemperature
```

	LandAverageTemperature	LandAverageTemperatureUncertainty	dt
0	3.034	3.574	1750-01-01
1	3.083	3.702	1750-02-01
2	5.626	3.076	1750-03-01
3	8.490	2.451	1750-04-01
4	11.573	2.072	1750-05-01
...	...	...	...
3187	14.755	0.072	2015-08-01
3188	12.999	0.079	2015-09-01
3189	10.801	0.102	2015-10-01
3190	7.433	0.119	2015-11-01
3191	5.518	0.100	2015-12-01

3180 rows × 3 columns

```
df1.dropna(subset=['LandMaxTemperature'], inplace=True)
len(df1)
```

```
1992
```

```
is_null_free = not df1.isnull().any().any()

if is_null_free:
    print("The DataFrame df1 is null-free.")
else:
    print("The DataFrame df1 contains null values.")
```

```
The DataFrame df1 is null-free.
```

df1: null free data frame contains all columns

LandAverageTemperature: null free data frame contains information about LandAverageTemperature

Now let's start visualize it

```
#all imports
import matplotlib.pyplot as plt
import datetime as dt
from scipy.stats import pearsonr
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
```

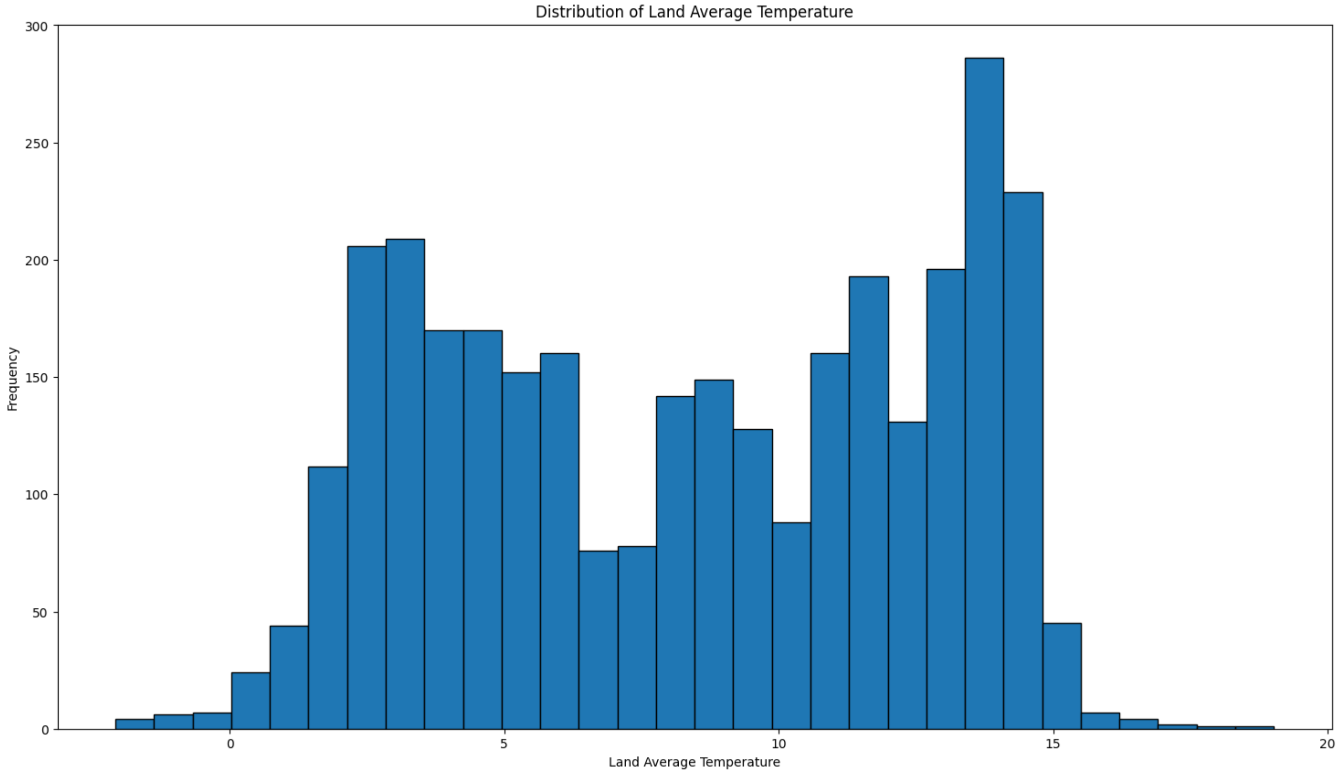
Basic statistics for 'LandAverageTemperature' and 'LandAverageTemperatureUncertainty'

temperature_stats = LandAverageTemperature['LandAverageTemperature'].describe()
uncertainty_stats =
LandAverageTemperature['LandAverageTemperatureUncertainty'].describe()

print("Temperature Statistics:\n", temperature_stats) print("\nUncertainty Statistics:\n", uncertainty_stats)

```
plt.figure(figsize=(18, 10))  # Optional: Adjust the figure size

# Create a histogram of the 'LandAverageTemperature' column
plt.hist(LandAverageTemperature['LandAverageTemperature'], bins=30, edgecolor='k

# Add labels and a title
plt.xlabel('Land Average Temperature')
plt.ylabel('Frequency')
plt.title('Distribution of Land Average Temperature')
print("the mean of LandAverageTemperature is", LandAverageTemperature['LandAvera
# Show the plot
plt.show()
```

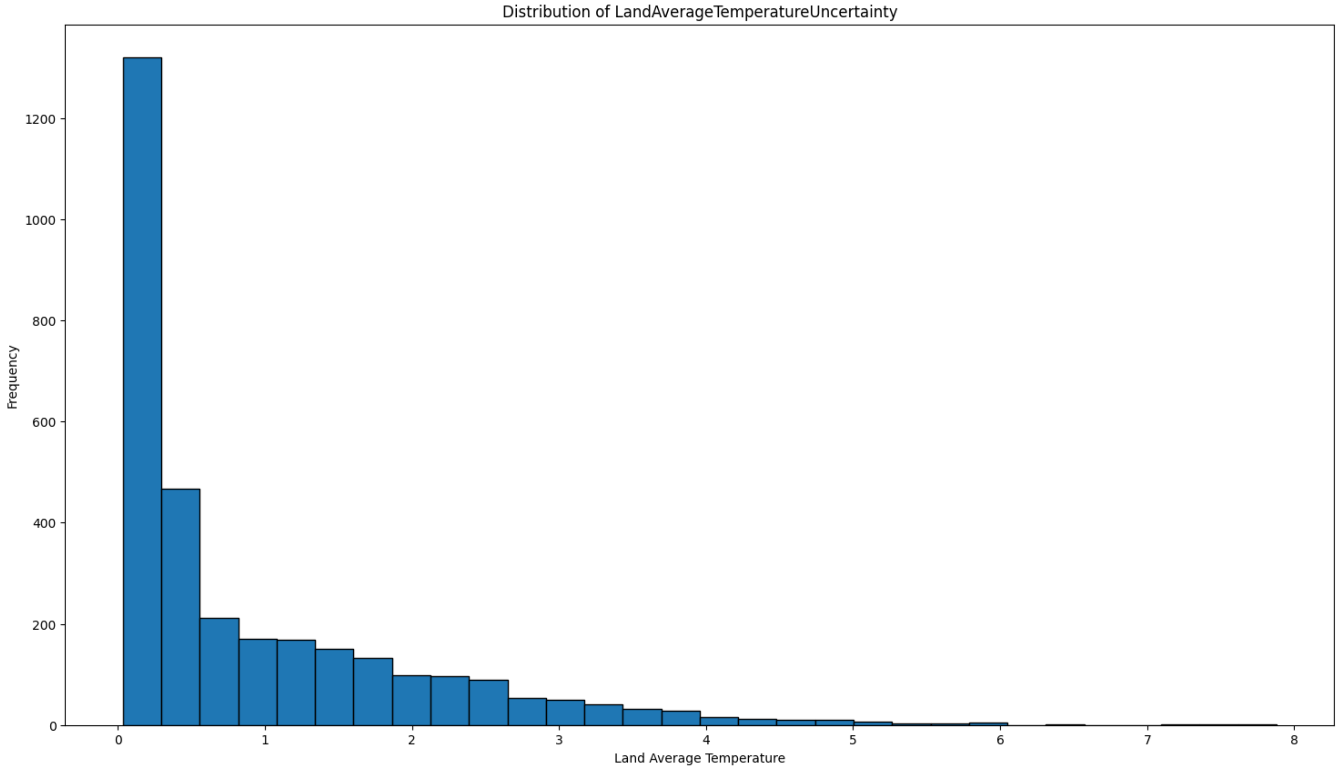
```
the mean of LandAverageTemperature is 8.374731132075471
```



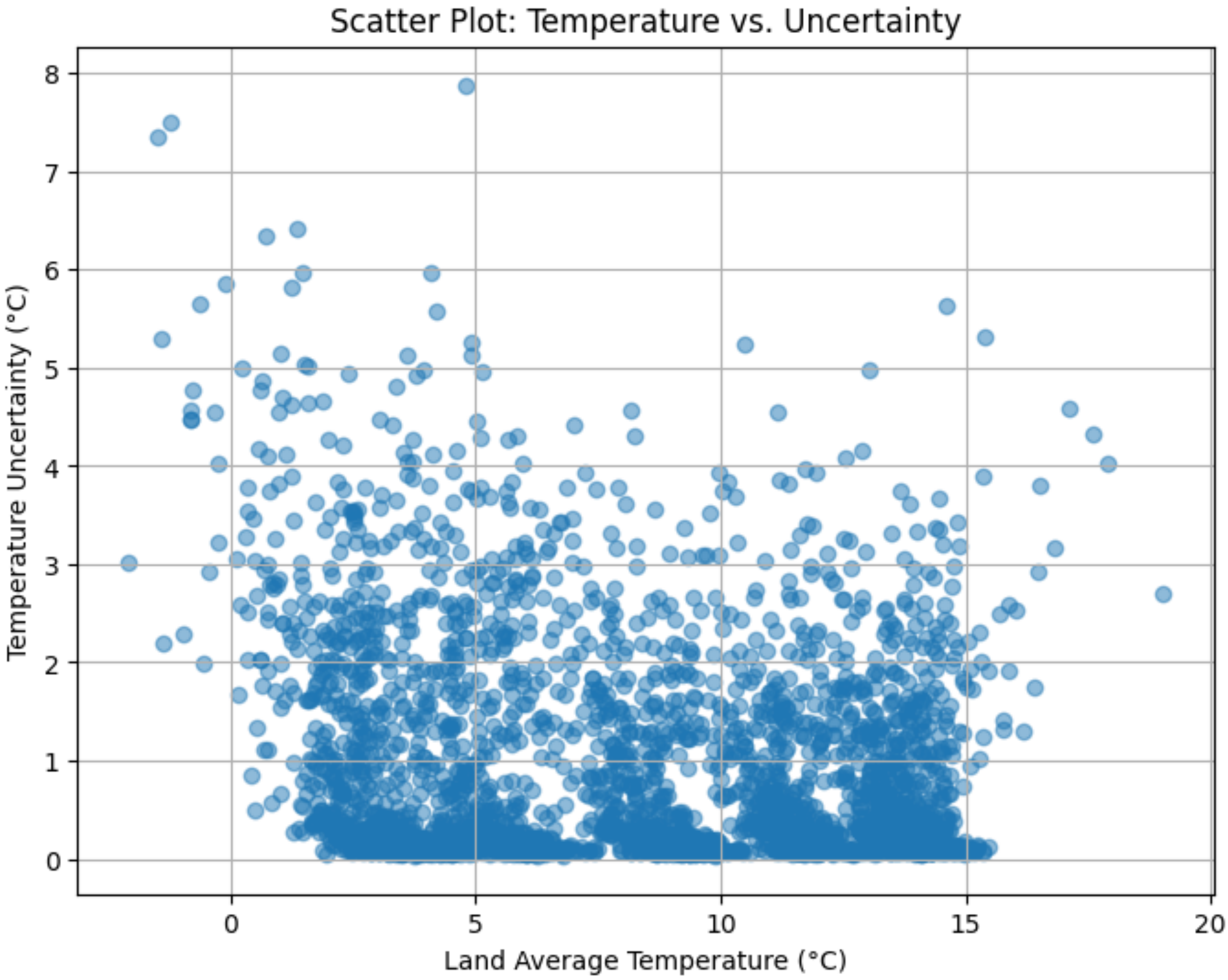

```
plt.figure(figsize=(18, 10))  # Optional: Adjust the figure size

# Create a histogram of the 'LandAverageTemperature' column
plt.hist(LandAverageTemperature['LandAverageTemperatureUncertainty'], bins=30, e
```

```
# Add labels and a title
plt.xlabel('Land Average Temperature')
plt.ylabel('Frequency')
plt.title('Distribution of LandAverageTemperatureUncertainty')
print("the mean of LandAverageTemperatureUncertainty is", LandAverageTemperature
# Show the plot
plt.show()
```

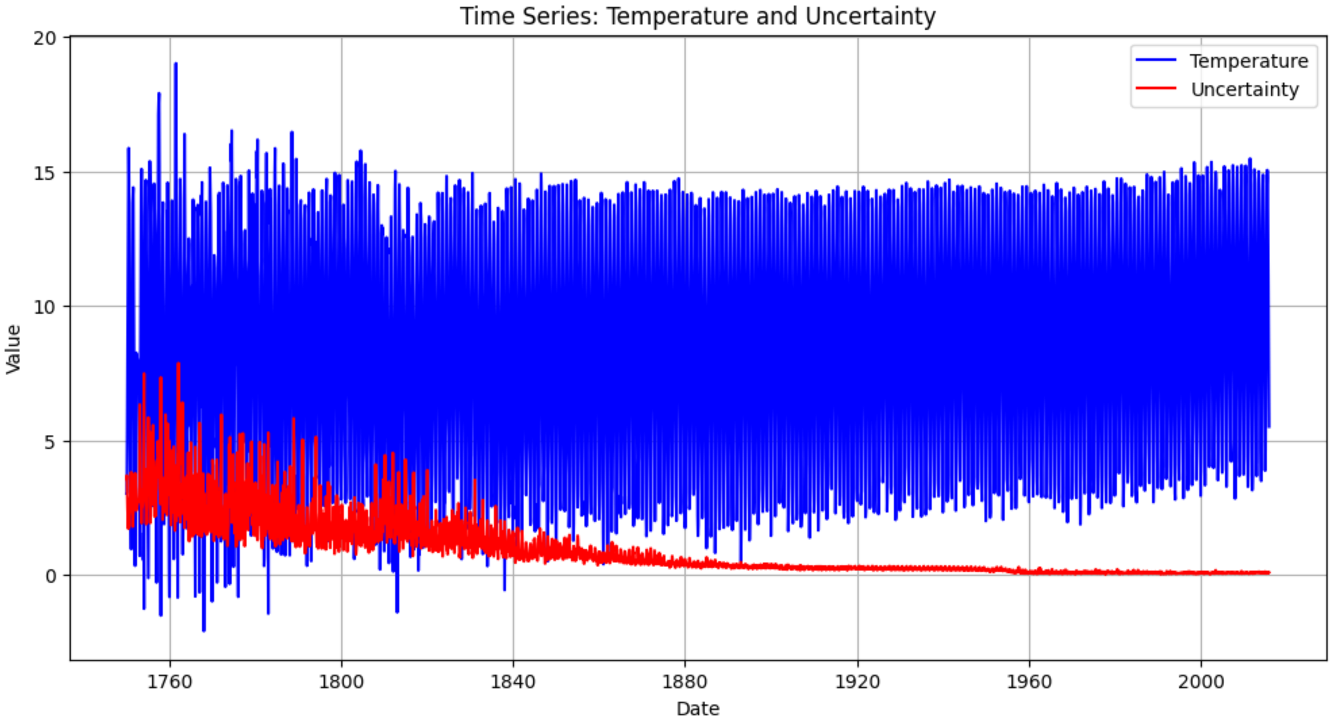
```
the mean of LandAverageTemperatureUncertainty is 0.938467924528302
```



```
plt.figure(figsize=(8, 6))
plt.scatter(LandAverageTemperature['LandAverageTemperature'], LandAverageTempera
plt.xlabel('Land Average Temperature (°C)')
plt.ylabel('Temperature Uncertainty (°C)')
plt.title('Scatter Plot: Temperature vs. Uncertainty')
plt.grid(True)
plt.show()
```



```
# Assuming you have a date or timestamp column 'Date'
LandAverageTemperature.loc[:, 'Date'] = pd.to_datetime(LandAverageTemperature['d

plt.figure(figsize=(12, 6))
plt.plot(LandAverageTemperature['Date'], LandAverageTemperature['LandAverageTemp
plt.plot(LandAverageTemperature['Date'], LandAverageTemperature['LandAverageTemp
plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Time Series: Temperature and Uncertainty')
plt.legend()
plt.grid(True)
plt.show()
```




```
import plotly.graph_objs as go
```

```
import plotly.offline as py


LandAverageTemperature.loc[:,'dt'] = pd.to_datetime(LandAverageTemperature['dt']
LandAverageTemperature.loc[:,'dt'] = LandAverageTemperature['dt'].apply(lambda x
global1 = LandAverageTemperature.groupby(['dt'])['LandAverageTemperature'].mean(

# Create a Plotly line plot
trace = go.Scatter(
    x=global1['dt'],
    y=global1['LandAverageTemperature'],
    mode='lines',
)

data = [trace]

# Plot the data
py.iplot(data, filename='line-mode')
```

Analysis on possible reasons:

Inverse Relationship: The fact that uncertainty is decreasing while temperature is increasing suggests an inverse relationship between temperature and uncertainty. This means that as global land temperatures rise, the uncertainty around those temperature measurements is decreasing.(**unlikely by common sense**)

Improved Measurement Techniques: The decreasing uncertainty could indicate advancements in temperature measurement techniques, data collection, or data processing. It may reflect increased accuracy and confidence in temperature measurements.

Climate Change: As we progress in time, our ability to measure and predict temperature changes due to climate change has improved. Additionally, **global warming** could causes the temperature to goes up

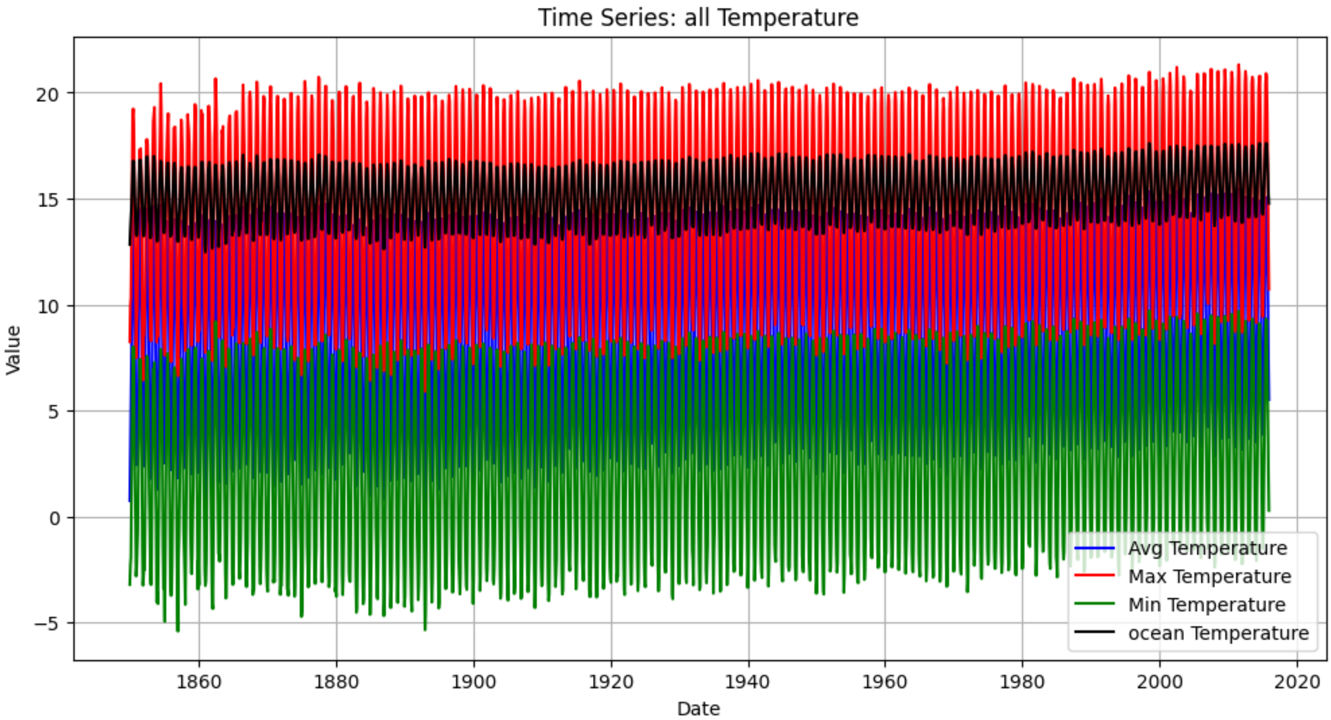
```
df1.head()
```

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandM
1200	1850-01-01	0.749	1.105	
1201	1850-02-01	3.071	1.275	
1202	1850-03-01	4.954	0.955	
1203	1850-04-01	7.217	0.665	
1204	1850-05-01	10.004	0.617	

```
LandMaxTemperature_stats = df1['LandAverageTemperature'].describe()
LandMaxTemperatureUncertainty_stats = df1['LandAverageTemperatureUncertainty'].d

print("LandMaxTemperature Statistics:\n", LandMaxTemperature_stats)
print("\nLandMaxemperatureUncertainty Statistics:\n", LandMaxTemperatureUncertai
```

```
LandMaxTemperature Statistics:
 count    1992.000000
mean        8.571583
std         4.263193
min         0.404000
25%         4.430000
50%         8.850500
75%        12.858500
max        15.482000
Name: LandAverageTemperature, dtype: float64

LandMaxemperatureUncertainty Statistics:
 count    1992.000000
mean        0.276663
std         0.224030
min         0.034000
25%         0.099750
50%         0.230000
75%         0.347250
max         1.492000
Name: LandAverageTemperatureUncertainty, dtype: float64
```

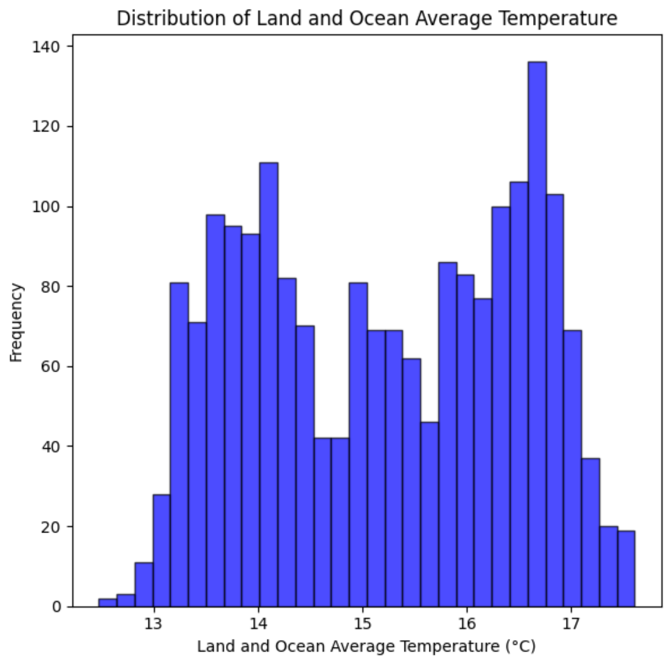
```
df1.loc[:, 'Date'] = pd.to_datetime(df1['dt'])

plt.figure(figsize=(12, 6))
plt.plot(df1['Date'], df1['LandAverageTemperature'], label='Avg Temperature', co
plt.plot(df1['Date'], df1['LandMaxTemperature'], label='Max Temperature', color=
plt.plot(df1['Date'], df1['LandMinTemperature'], label='Min Temperature', color=
plt.plot(df1['Date'], df1['LandAndOceanAverageTemperature'], label='ocean Temper

plt.xlabel('Date')
plt.ylabel('Value')
plt.title('Time Series: all Temperature')
plt.legend()
plt.grid(True)
plt.show()
```

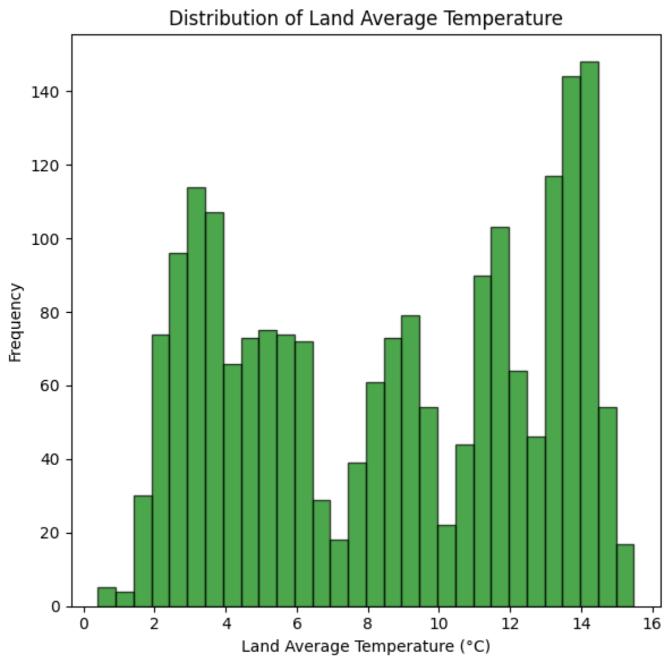


```
df1.loc[:,'dt'] = pd.to_datetime(df1['dt']).dt.strftime('%d/%m/%Y')
df1.loc[:,'dt'] = df1['dt'].apply(lambda x: x[6:])
global1 = df1.groupby(['dt'])['LandAndOceanAverageTemperature'].mean().reset_ind

# Create a Plotly line plot
trace = go.Scatter(
    x=global1['dt'],
    y=global1['LandAndOceanAverageTemperature'],
    mode='lines',
)

data = [trace]

# Plot the data
py.iplot(data, filename='line-mode')
```

```
plt.figure(figsize=(12, 6))
```

```
# Plot the distribution of 'LandAndOceanAverageTemperature'
plt.subplot(1, 2, 1)
plt.hist(df1['LandAndOceanAverageTemperature'].dropna(), bins=30, edgecolor='k',
plt.xlabel('Land and Ocean Average Temperature (°C)')
plt.ylabel('Frequency')
plt.title('Distribution of Land and Ocean Average Temperature')

# Plot the distribution of 'LandAverageTemperature'
plt.subplot(1, 2, 2)
plt.hist(df1['LandAverageTemperature'].dropna(), bins=30, edgecolor='k', alpha=0
plt.xlabel('Land Average Temperature (°C)')
plt.ylabel('Frequency')
plt.title('Distribution of Land Average Temperature')

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






```
land_avg_temp = df1['LandAverageTemperature'].mean()
land_ocean_avg_temp = df1['LandAndOceanAverageTemperature'].mean()

print(f"Mean Land Average Temperature: {land_avg_temp:.2f} °C")
print(f"Mean Land and Ocean Average Temperature: {land_ocean_avg_temp:.2f} °C")
```

```
Mean Land Average Temperature: 8.57 °C
Mean Land and Ocean Average Temperature: 15.21 °C
```

Further investigation is needed to explore the geographic differences and potential explanations. Utilizing additional datasets in the form of CSV files could provide valuable insights.

Moreover, it's worth noting that the increasing trend appears to be more pronounced in the **land-ocean temperature data**.