Statement :- Time Series Analysis on LandAverageTemperature dataset and forecast the future trend.

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Import Required Libraries

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [ ]:

```
import plotly.graph_objs as go
import plotly.express as px
```

In [ ]:

```
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [ ]:

```
from statsmodels.tsa.stattools import adfuller
```

In [ ]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [ ]:

```
from statsmodels.tsa.ar_model import AR
```

In [ ]:
```
pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.7/dist-packages (1.8.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (1.24.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (1.0.1)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (56.0.0)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (1.4.1)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (0.22.2.post1)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (1.1.5)
Requirement already satisfied: numpy~=1.19.0 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (1.19.5)
Requirement already satisfied: statsmodels!=0.12.0,>=0.11 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (0.12.2)
Requirement already satisfied: Cython!=0.29.18,>=0.29 in /usr/local/lib/python3.7/dist-packages (from pmdarima) (0.29.22)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.19->pmdarima) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.19->pmdarima) (2018.9)
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.7/dist-packages (from statsmodels!=0.12.0,>=0.11->pmdarima) (0.5.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.7.3->pandas>=0.19->pmdarima) (1.15.0)
```

In [ ]:
```
from pmdarima import auto_arima
```

In [ ]:
```
from statsmodels.tsa.arima_model import ARIMA
```

Read the Data

In [ ]:
```
df = pd.read_csv("GlobalLandTemperatures.csv", parse_dates = ["dt"],
```

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

Out[182]:

dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
1750-01-01	3.034	3.574	NaN	
1750-02-01	3.083	3.702	NaN	
1750-03-01	5.626	3.076	NaN	
1750-04-01	8.490	2.451	NaN	
1750-05-01	11.573	2.072	NaN	

In [ ]:
```
df.tail()
```

Out[183]:

dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
2015-08-01	14.755	0.072	20.699	
2015-09-01	12.999	0.079	18.845	
2015-10-01	10.801	0.102	16.450	
2015-11-01	7.433	0.119	12.892	
2015-12-01	5.518	0.100	10.725	

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3192 entries, 1750-01-01 to 2015-12-01
Data columns (total 8 columns):
 #   Column                                     Non-Null Count  Dtyp
e
---  ------                                     --------------  ----
-
 0   LandAverageTemperature                     3180 non-null   floa
t64
 1   LandAverageTemperatureUncertainty          3180 non-null   floa
t64
 2   LandMaxTemperature                         1992 non-null   floa
t64
 3   LandMaxTemperatureUncertainty              1992 non-null   floa
t64
 4   LandMinTemperature                         1992 non-null   floa
t64
 5   LandMinTemperatureUncertainty              1992 non-null   floa
t64
 6   LandAndOceanAverageTemperature             1992 non-null   floa
t64
 7   LandAndOceanAverageTemperatureUncertainty  1992 non-null   floa
t64
dtypes: float64(8)
memory usage: 224.4 KB
```

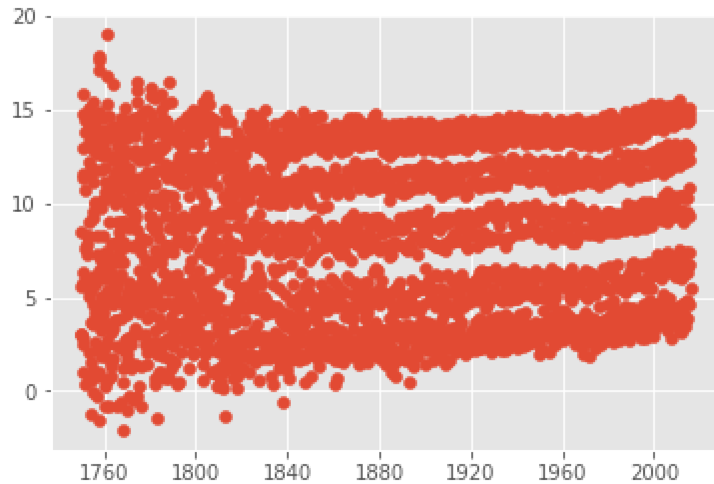
Interpretation :- In this data, there are 3192 rows and 8 columns. Also the data collected from 01-01-1750 to 01-12-2015.

In [ ]:
```
df.isna().sum()
```

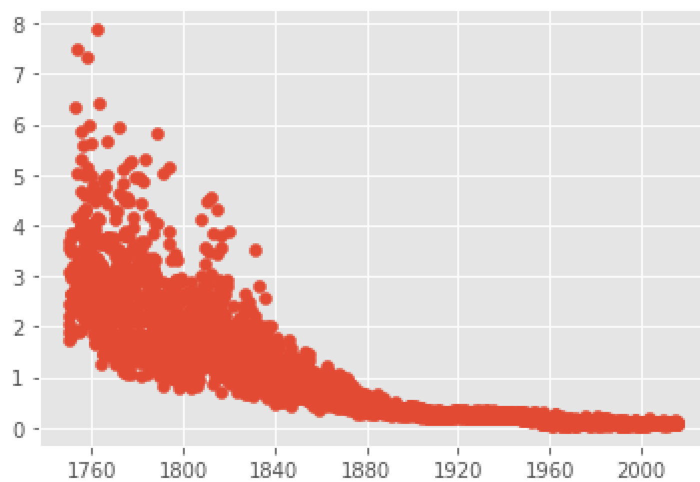
Out[185]:
```
LandAverageTemperature                         12
LandAverageTemperatureUncertainty              12
LandMaxTemperature                           1200
LandMaxTemperatureUncertainty                1200
LandMinTemperature                           1200
LandMinTemperatureUncertainty                1200
LandAndOceanAverageTemperature               1200
LandAndOceanAverageTemperatureUncertainty    1200
dtype: int64
```

Interpretation :- 30% data are missing in dataset. so we have to fill the missing values by mean, median or mode.

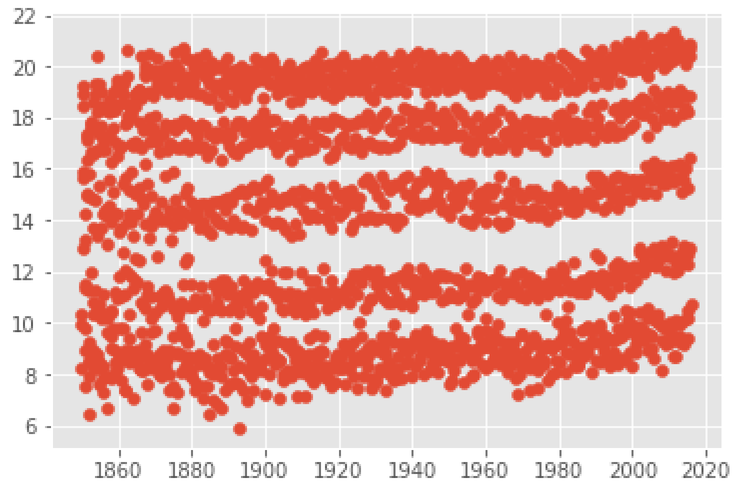
In [ ]:
```
plt.scatter(df.index, df["LandAverageTemperature"])
plt.show()
```



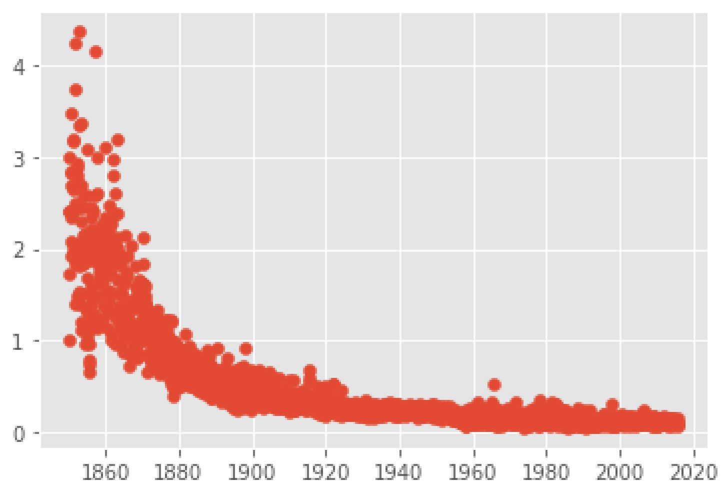
In [ ]:
```
plt.scatter(df.index, df["LandAverageTemperatureUncertainty"])
plt.show()
```



In [ ]:
```
plt.scatter(df.index, df["LandMaxTemperature"])
plt.show()
```

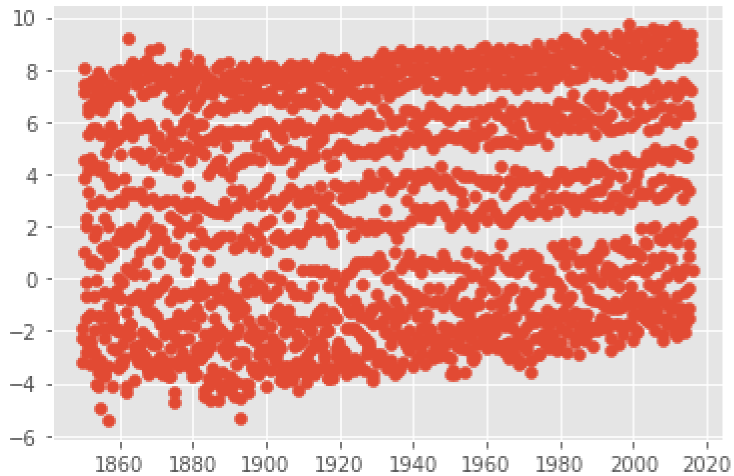


In [ ]:
```
plt.scatter(df.index, df["LandMaxTemperatureUncertainty"])
plt.show()
```



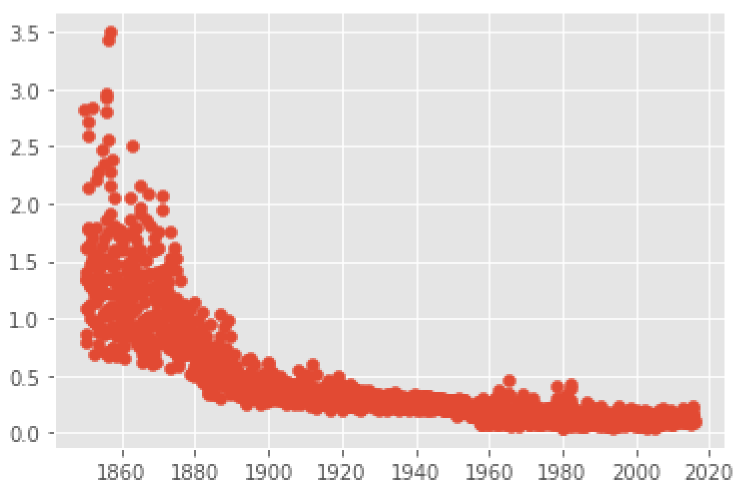
In [ ]:

```
plt.scatter(df.index, df["LandMinTemperature"])
plt.show()
```

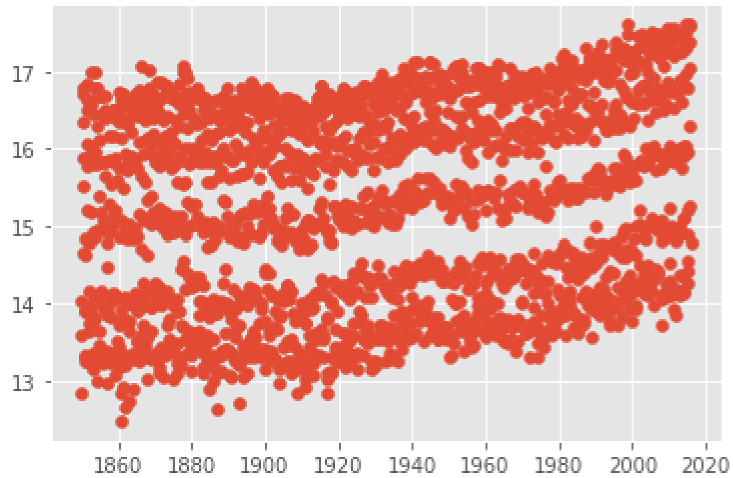


In [ ]:

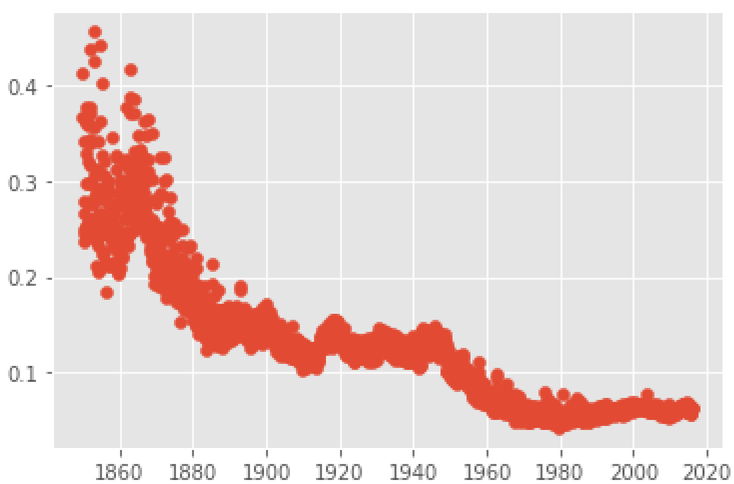
```
plt.scatter(df.index, df["LandMinTemperatureUncertainty"])
plt.show()
```



In [ ]:
```
plt.scatter(df.index, df["LandAndOceanAverageTemperature"])
plt.show()
```



In [ ]:
```
plt.scatter(df.index, df["LandAndOceanAverageTemperatureUncertainty"]
plt.show()
```



Interpretation :- From all above graphs we can say that, for all columns all points are stated close so we are replace missing values by mean with respect to that column.

In [ ]:

```
df["LandAverageTemperature"] = df["LandAverageTemperature"].fillna(df

df["LandAverageTemperatureUncertainty"] = df["LandAverageTemperatureU

df["LandMaxTemperature"] = df["LandMaxTemperature"].fillna(df["LandMa

df["LandMaxTemperatureUncertainty"] = df["LandMaxTemperatureUncertain

df["LandMinTemperature"] = df["LandMinTemperature"].fillna(df["LandMi

df["LandMinTemperatureUncertainty"] = df["LandMinTemperatureUncertain

df["LandAndOceanAverageTemperature"] = df["LandAndOceanAverageTempera

df["LandAndOceanAverageTemperatureUncertainty"] = df["LandAndOceanAve
```

In [ ]:

```
df.isna().sum()
```

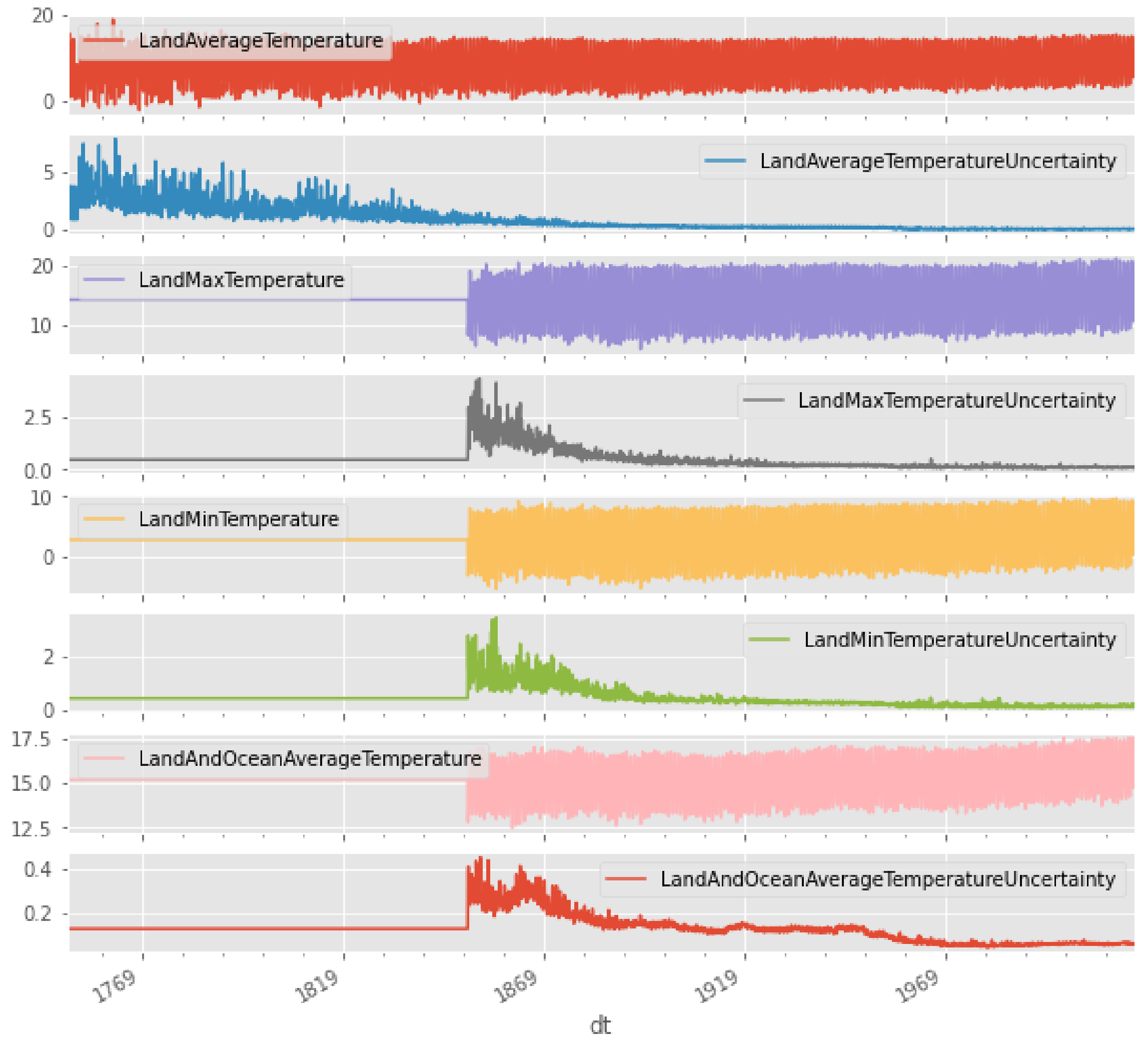
Out[195]:

```
LandAverageTemperature                       0
LandAverageTemperatureUncertainty            0
LandMaxTemperature                           0
LandMaxTemperatureUncertainty                0
LandMinTemperature                           0
LandMinTemperatureUncertainty                0
LandAndOceanAverageTemperature               0
LandAndOceanAverageTemperatureUncertainty    0
dtype: int64
```

Interpretation :- Now we have zero missing values. and that's important for time series analysis.

Graphical Visualisation of Data

In [ ]:
```
df.plot(subplots = True,figsize = (10,10))
plt.show()
```



Interpretation :- In the above figure, the graph is in straight line from year 1750 to year 1850. It happens because of missing values.

In [ ]:

```
fig = go.Figure([go.Scatter(x = df.index,
                            y = df.LandAverageTemperature)])
fig.show()
```

In [ ]:

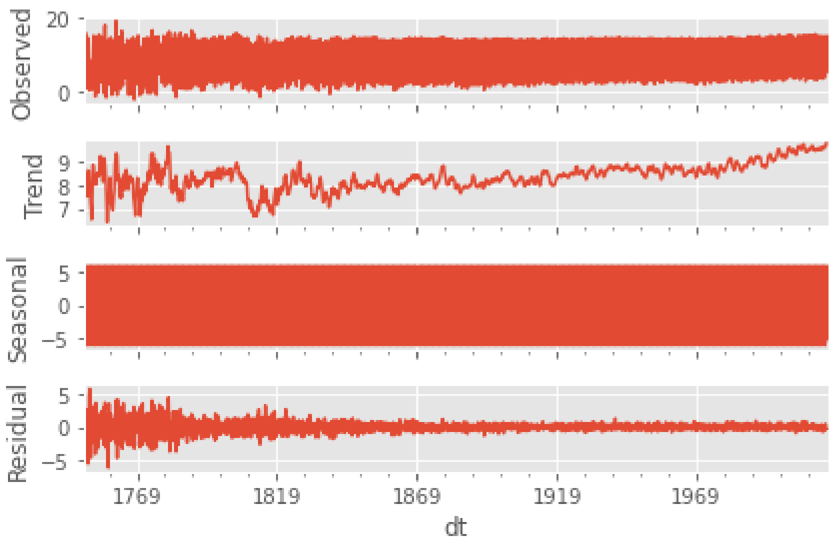
```
fig = px.bar(df, x = df.index,
             y = "LandAverageTemperature")
fig.show()
```

In [ ]:

```
fig = px.line(df, x = df.index,
              y = df.LandAverageTemperature,
              title = 'Custum Tick Labels')
fig.update_xaxes(dtick = "M1")
fig.show()
```

Decomposition

```python
decomposition = sm.tsa.seasonal_decompose(df["LandAverageTemperature"
fig = decomposition.plot()
```



Conclusion :- We can see that the entire series is taken as the trend component and that there is same seasonality from start to end. We can also see that the residual plot between -5 to 5.

Stationarity

Constant statistical properties -> mean, variance, std with does not change over time

H0 : It is Non Stationary

H1 : It is Stationary

P value > 0.05 Fail to reject null hypothesis -> Non Stationary

P value < 0.05 it is Stationary

In [ ]:
```
output = adfuller(df["LandAverageTemperature"])
output
```

Out[201]:
```
(-4.036039785872673,
 0.0012331195770598 26,
 29,
 3162,
 {'1%': -3.4324197712239393,
  '10%': -2.5672568084635663,
  '5%': -2.862454498112156},
 7457.668033159485)
```

In [ ]:
```
p_val = output[1]
```

In [ ]:
```
if p_val > 0.05:
    print("Non Stationary")
else:
    print("Stationary")
```

```
Stationary
```

Conclusion :- P value is 0.001. and from our hypothesis, P value is less than 0.05. so our data column is stationary

Moving Average

In [ ]:
```
df_avgTemp = pd.DataFrame(df.iloc[:,0])
```

In [ ]:
```
df_avgTemp.head()
```

Out[205]:

dt	LandAverageTemperature
1750-01-01	3.034
1750-02-01	3.083
1750-03-01	5.626
1750-04-01	8.490
1750-05-01	11.573

1. Simple Moving Average

In [ ]:
```
df_avgTemp["SMA_3"] = df_avgTemp["LandAverageTemperature"].rolling(wi
```

In [ ]:
```
df_avgTemp
```
Out[207]:

	LandAverageTemperature	SMA_3
dt		
1750-01-01	3.034	NaN
1750-02-01	3.083	NaN
1750-03-01	5.626	3.914333
1750-04-01	8.490	5.733000
1750-05-01	11.573	8.563000
...	...	...
2015-08-01	14.755	14.770333
2015-09-01	12.999	14.268333
2015-10-01	10.801	12.851667
2015-11-01	7.433	10.411000
2015-12-01	5.518	7.917333

3192 rows × 2 columns

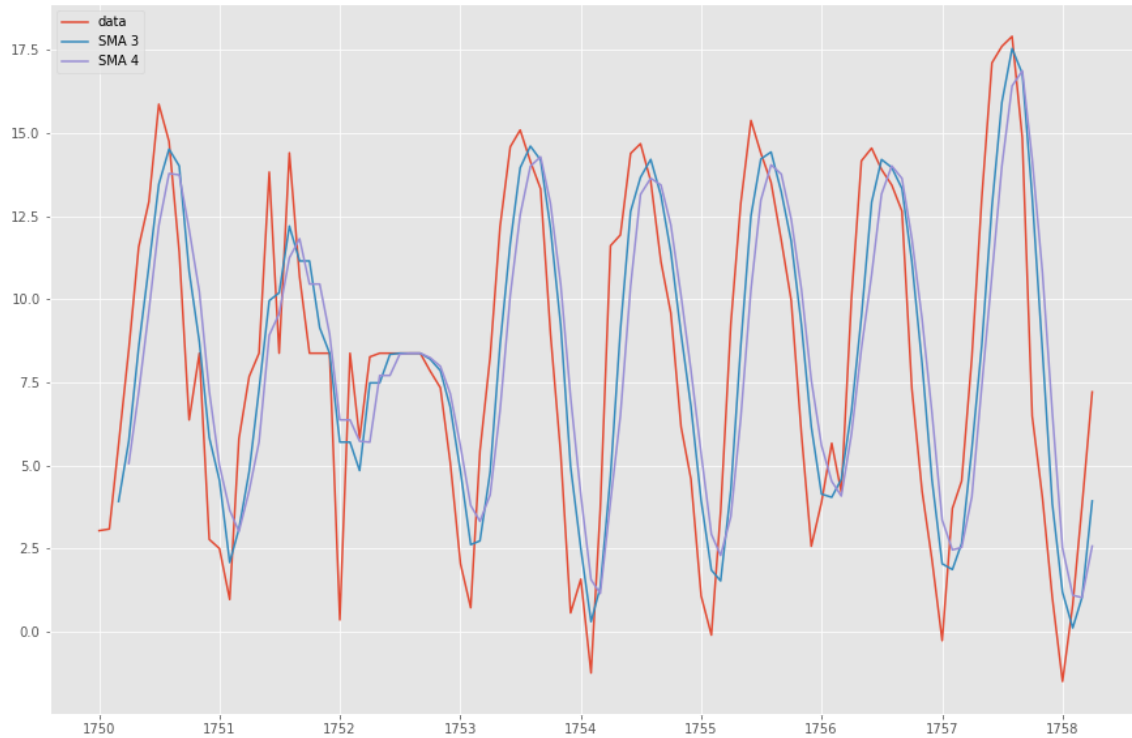
In [ ]:
```
df_avgTemp["SMA_4"] = df_avgTemp["LandAverageTemperature"].rolling(wi
```
In [ ]:
```
df_avgTemp
```
Out[209]:

	LandAverageTemperature	SMA_3	SMA_4
dt			
1750-01-01	3.034	NaN	NaN
1750-02-01	3.083	NaN	NaN
1750-03-01	5.626	3.914333	NaN
1750-04-01	8.490	5.733000	5.05825
1750-05-01	11.573	8.563000	7.19300
...	...	...	...
2015-08-01	14.755	14.770333	14.15575
2015-09-01	12.999	14.268333	14.32750
2015-10-01	10.801	12.851667	13.40150
2015-11-01	7.433	10.411000	11.49700
2015-12-01	5.518	7.917333	9.18775

3192 rows × 3 columns

In [ ]:
```
df_aT = df_avgTemp.head(100)
```

In [ ]:
```
plt.figure(figsize=[15,10])
plt.grid(True)
plt.plot(df_aT['LandAverageTemperature'], label = 'data')
plt.plot(df_aT['SMA_3'], label = 'SMA 3')
plt.plot(df_aT['SMA_4'], label = 'SMA 4')
plt.legend(loc = 2)
plt.show()
```



Interpretation :- When the temperature is moving upward or downward, so is the moving average line, albeit with a lag. After a temperature turning point, the temperature crosses the moving average line. At the V-shaped bottom on the preceding figure, for example, temperature are below the line until the gap (ellipse), and then temperature cross above the line.

2. Cumulative Moving Average

In [ ]:
```
df_avgTemp['CMA_4'] = df_avgTemp["LandAverageTemperature"].expanding(
```

In [ ]:
```
df_avgTemp
```

Out[213]:

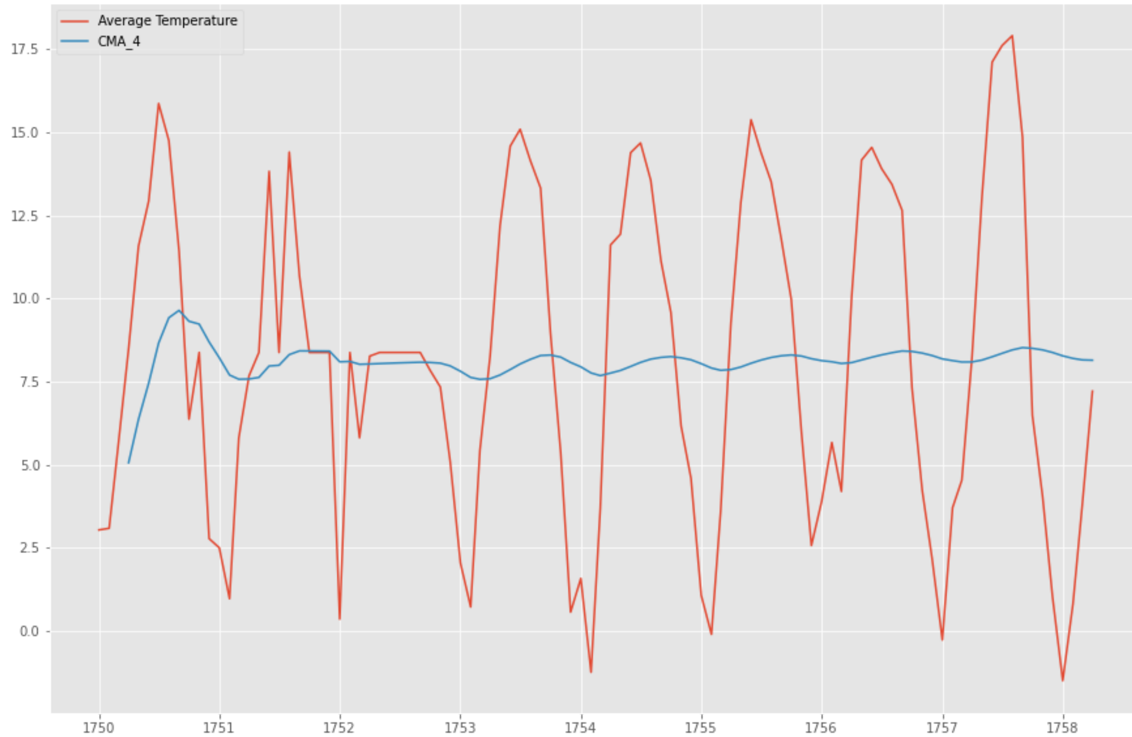
	LandAverageTemperature	SMA_3	SMA_4	CMA_4
dt				
1750-01-01	3.034	NaN	NaN	NaN
1750-02-01	3.083	NaN	NaN	NaN
1750-03-01	5.626	3.914333	NaN	NaN
1750-04-01	8.490	5.733000	5.05825	5.058250
1750-05-01	11.573	8.563000	7.19300	6.361200
...	...	...	...	...
2015-08-01	14.755	14.770333	14.15575	8.373711
2015-09-01	12.999	14.268333	14.32750	8.375161
2015-10-01	10.801	12.851667	13.40150	8.375922
2015-11-01	7.433	10.411000	11.49700	8.375626
2015-12-01	5.518	7.917333	9.18775	8.374731

3192 rows × 4 columns

In [ ]:
```
df_aT_cum = df_avgTemp.head(100)
```

In [ ]:

```
plt.figure(figsize = [15,10])
plt.grid(True)
plt.plot(df_aT_cum['LandAverageTemperature'], label = 'Average Temper
plt.plot(df_aT_cum['CMA_4'], label = 'CMA_4')
plt.legend(loc = 2)
plt.show()
```



3. Exponential Moving Average

In [ ]:

```
df_avgTemp['EMA'] = df_avgTemp["LandAverageTemperature"].ewm(span=40,
```

In [ ]:
```
df_avgTemp
```

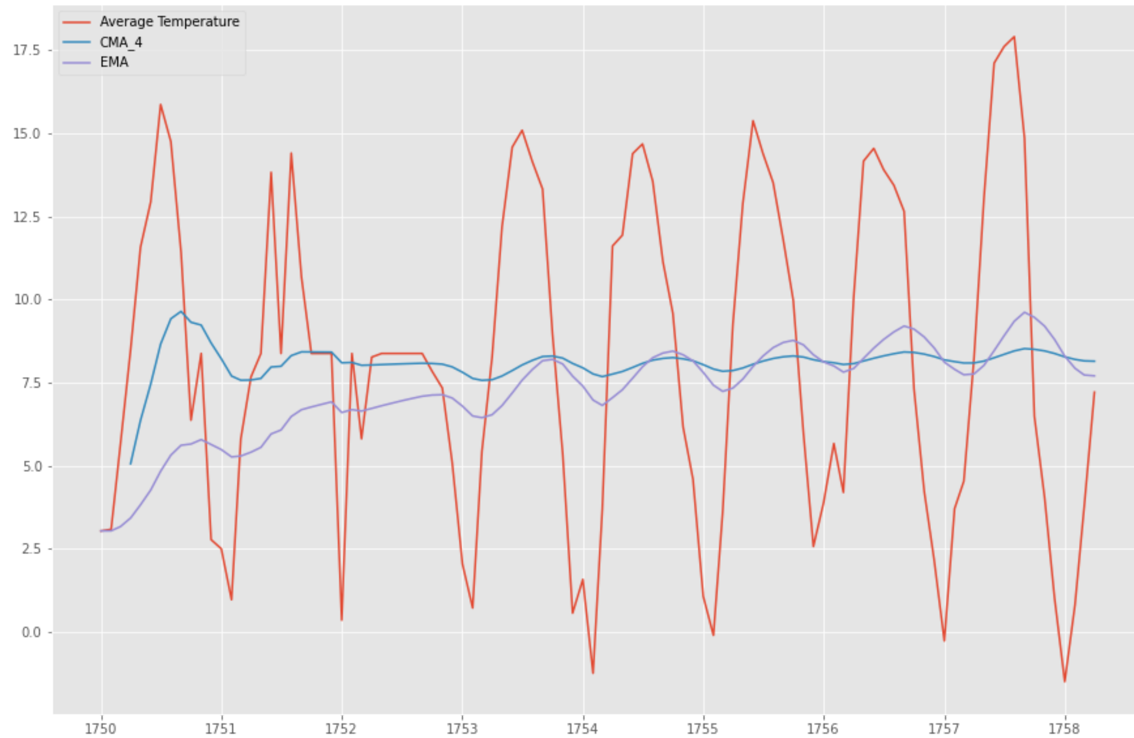
Out[217]:

	LandAverageTemperature	SMA_3	SMA_4	CMA_4	EMA
dt					
1750-01-01	3.034	NaN	NaN	NaN	3.034000
1750-02-01	3.083	NaN	NaN	NaN	3.036390
1750-03-01	5.626	3.914333	NaN	NaN	3.162713
1750-04-01	8.490	5.733000	5.05825	5.058250	3.422580
1750-05-01	11.573	8.563000	7.19300	6.361200	3.820162
...	...	...	...	...	...
2015-08-01	14.755	14.770333	14.15575	8.373711	10.017136
2015-09-01	12.999	14.268333	14.32750	8.375161	10.162593
2015-10-01	10.801	12.851667	13.40150	8.375922	10.193734
2015-11-01	7.433	10.411000	11.49700	8.375626	10.059064
2015-12-01	5.518	7.917333	9.18775	8.374731	9.837549

3192 rows × 5 columns

In [ ]:
```
df_aT_ema = df_avgTemp.head(100)
```

In [ ]:
```
plt.figure(figsize = [15,10])
plt.grid(True)
plt.plot(df_aT_ema['LandAverageTemperature'], label = 'Average Temper
plt.plot(df_aT_ema['CMA_4'], label = 'CMA_4')
plt.plot(df_aT_ema['EMA'], label = 'EMA')
plt.legend(loc = 2)
plt.show()
```



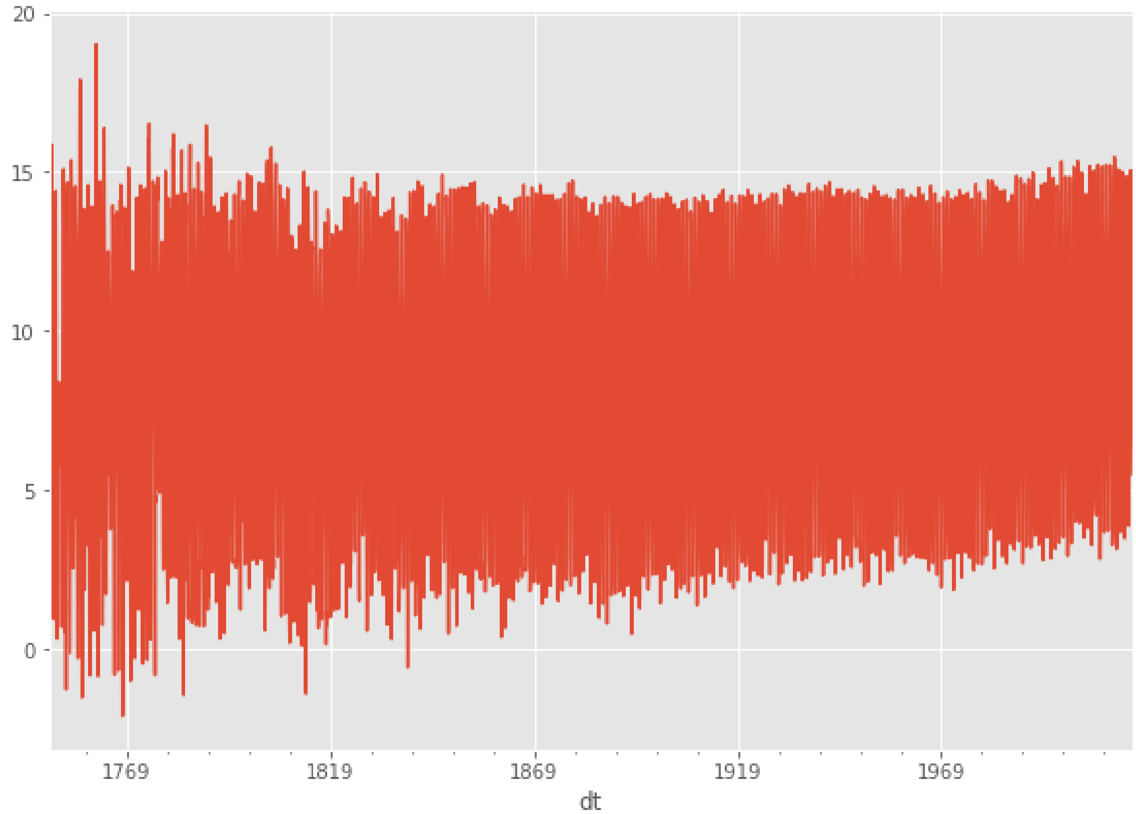
Auto Regression

In [ ]:
```
df = df["LandAverageTemperature"]
```

Conclusion :- In this project, our main focus on Land Average Temperature, because we want to forecast Land Average Temperature for future, so that's why we select one column.

In [ ]:

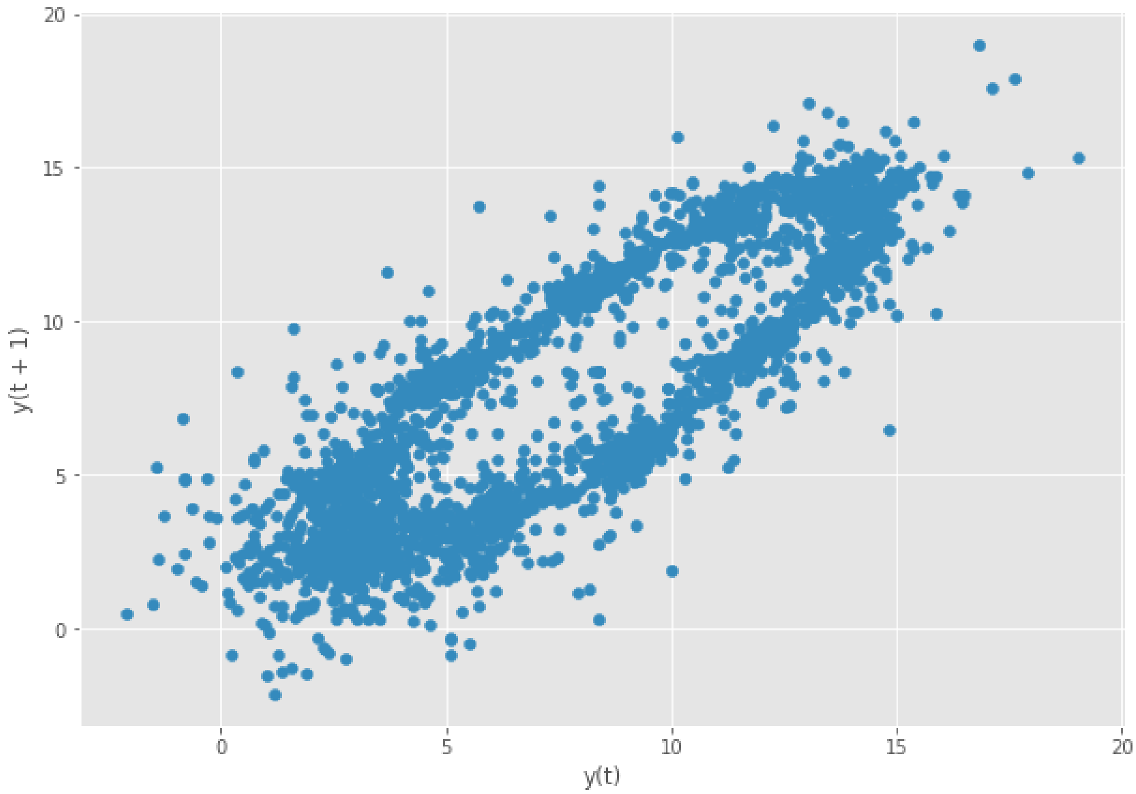
```
plt.rcParams['figure.figsize']=(10,7)
plt.style.use('ggplot')

df.plot()
plt.show()
```



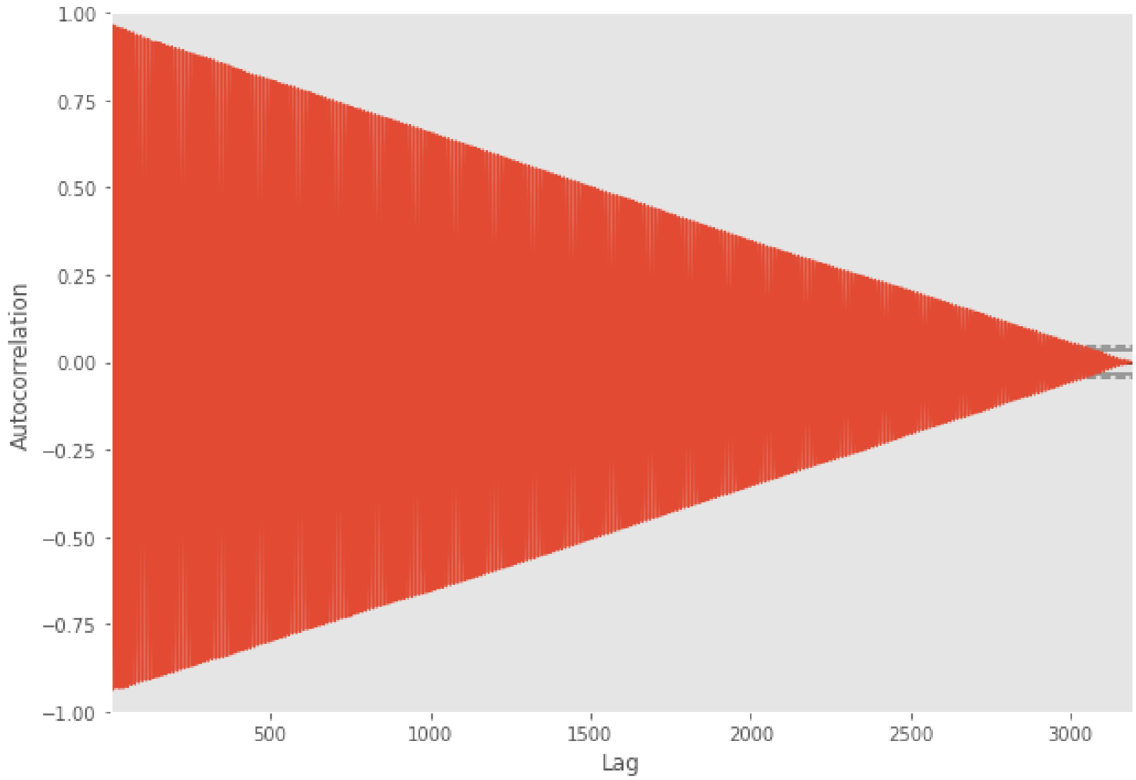
Conclusion :- graph shows that whole data points lise between the 0 to 15. but sometimes for year 1770 it's goes high and also goes down the zero.

In [ ]:

```
pd.plotting.lag_plot(df)
plt.show()
```



In [ ]:
```
pd.plotting.autocorrelation_plot(df)
plt.show()
```



In [ ]:
```
model = AR(df)

model_fit = model.fit()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_mode
l.py:165: ValueWarning:

No frequency information was provided, so inferred frequency MS will
be used.
```

In [ ]:

```
print('The lag value chose is: %s' % model_fit.k_ar)

print('The coefficients of the model are:\n %s' % model_fit.params)
```

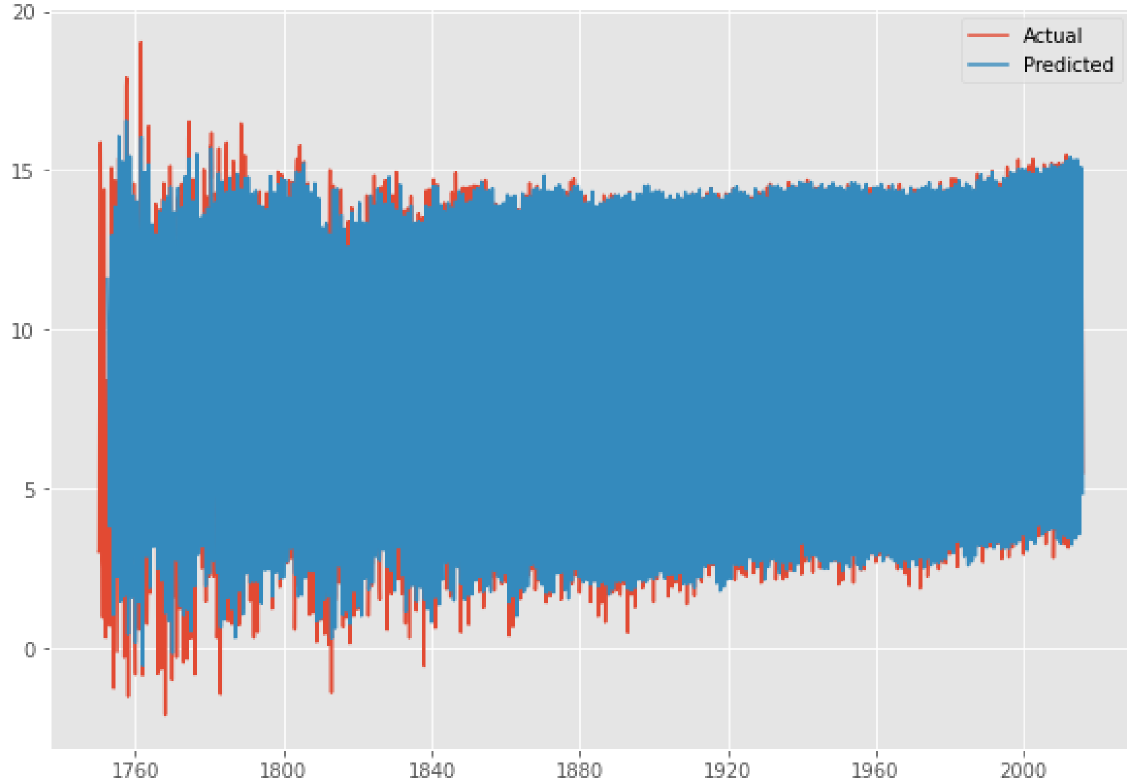
```
The lag value chose is: 29
The coefficients of the model are:
 const                          0.881397
L1.LandAverageTemperature     0.404223
L2.LandAverageTemperature     0.093370
L3.LandAverageTemperature     0.000443
L4.LandAverageTemperature    -0.104205
L5.LandAverageTemperature    -0.054776
L6.LandAverageTemperature    -0.036547
L7.LandAverageTemperature     0.031555
L8.LandAverageTemperature    -0.000573
L9.LandAverageTemperature     0.038456
L10.LandAverageTemperature    0.046108
L11.LandAverageTemperature    0.055164
L12.LandAverageTemperature    0.167969
L13.LandAverageTemperature    0.061250
L14.LandAverageTemperature   -0.033238
L15.LandAverageTemperature    0.015883
L16.LandAverageTemperature   -0.011632
L17.LandAverageTemperature    0.045604
L18.LandAverageTemperature    0.041991
L19.LandAverageTemperature   -0.017348
L20.LandAverageTemperature   -0.070361
L21.LandAverageTemperature    0.055874
L22.LandAverageTemperature    0.049755
L23.LandAverageTemperature    0.078548
L24.LandAverageTemperature    0.081391
L25.LandAverageTemperature   -0.022227
L26.LandAverageTemperature    0.044483
L27.LandAverageTemperature    0.021048
L28.LandAverageTemperature   -0.029365
L29.LandAverageTemperature   -0.057637
dtype: float64
```

Conclusion :- The model choosing the 29 lag value.

In [ ]:

```
pred = model_fit.predict()
```

In [ ]:
```
plt.plot(df,label="Actual")
plt.plot(pred,label="Predicted")
plt.legend()
plt.show()
```

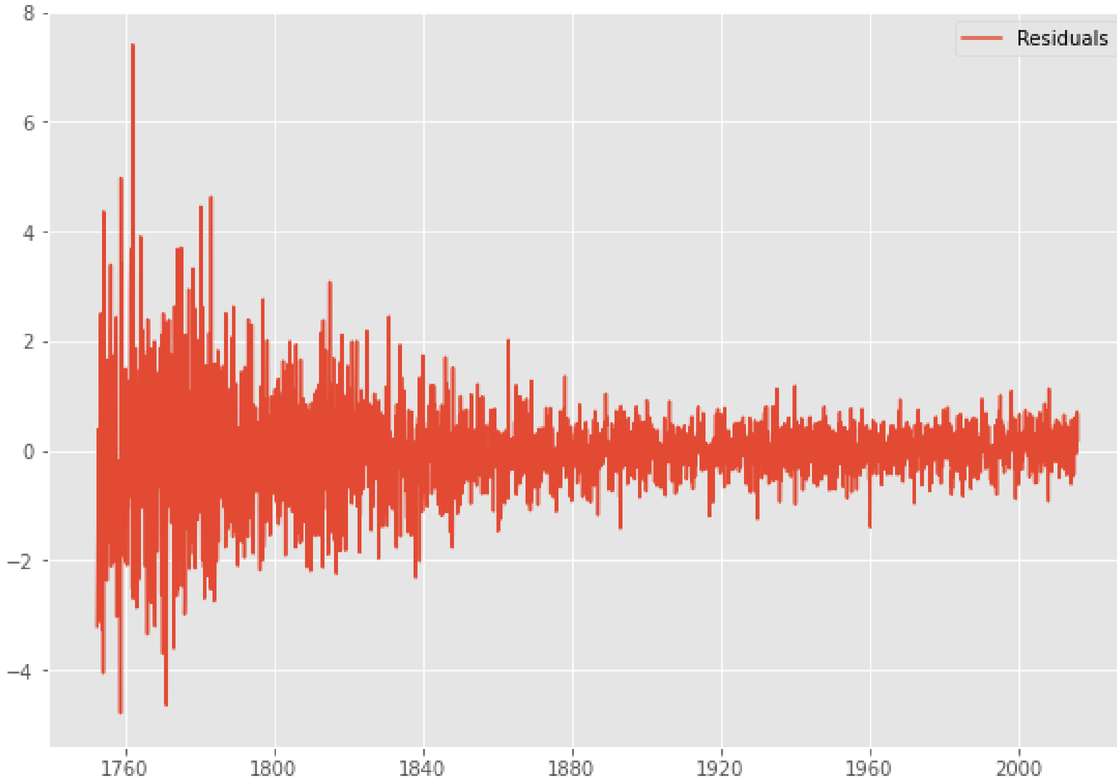


Conclusion :- Here we can see the Actual temperatures and Predicted temperatures are almost same for all year.

In [ ]:
```
residual=model_fit.resid
```

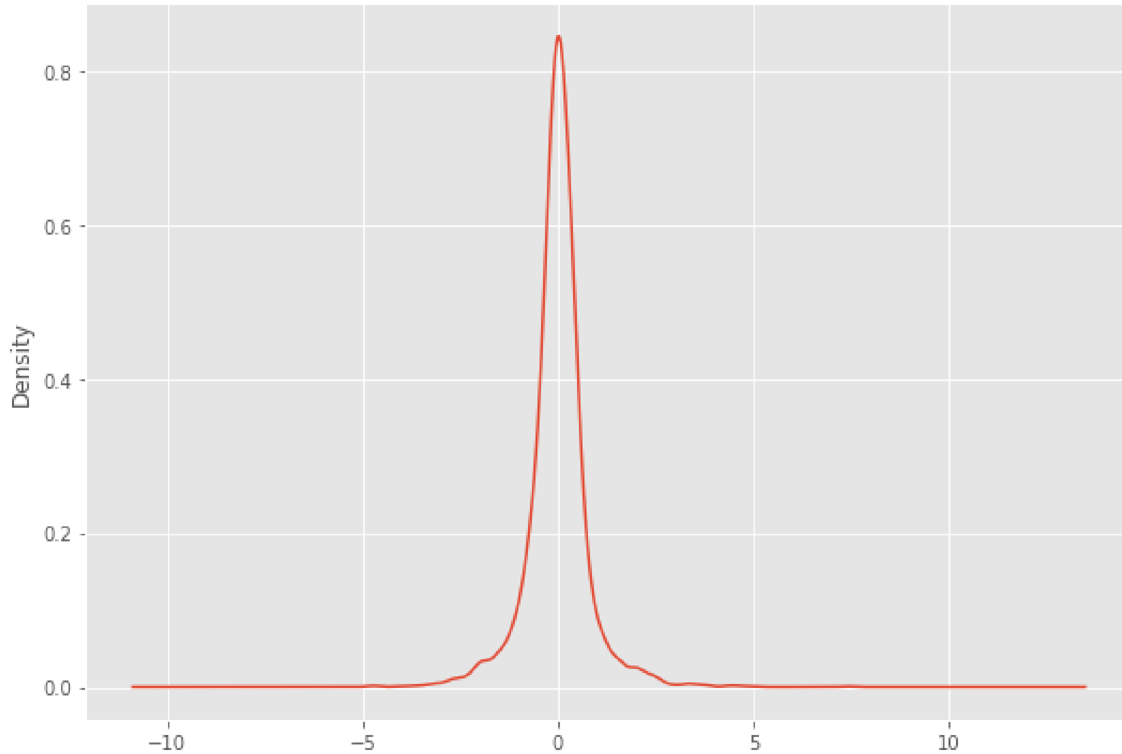
In [ ]:

```
plt.plot(residual, label = "Residuals")
plt.legend()
plt.show()
```



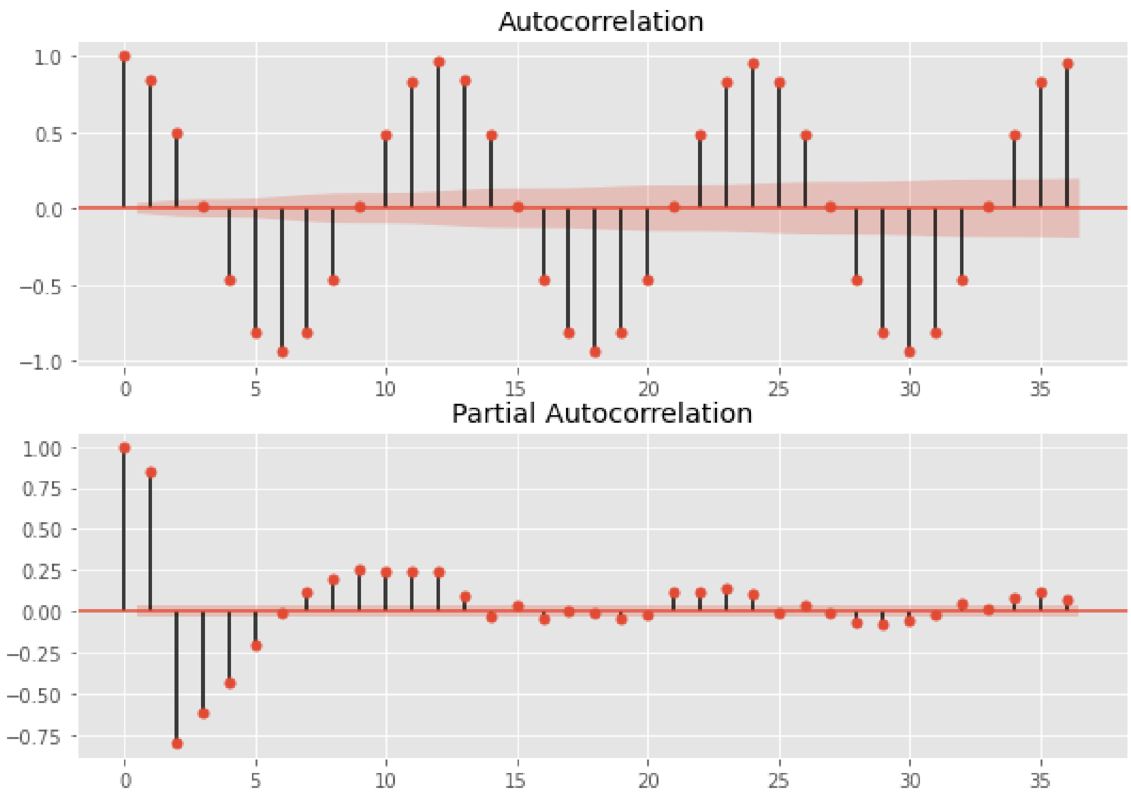
In [ ]:

```
residual.plot(kind="kde")
plt.show()
```



In [ ]:

```
fig, axs = plt.subplots(2)

axs[0].set_title("ACF plot")
plot_acf(df, ax = axs[0])

axs[1].set_title("PACF plot")
plot_pacf(df, ax = axs[1])

plt.show()
```



ARIMA

In [ ]:
```
auto_model = auto_arima(df, trace = True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=8966.142, Time=5.59 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=14689.182, Time=0.10 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=12872.363, Time=0.21 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=13537.798, Time=0.51 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=14687.182, Time=0.09 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept   : AIC=inf, Time=4.62 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept   : AIC=12844.370, Time=1.49 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept   : AIC=8439.487, Time=6.89 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept   : AIC=inf, Time=6.03 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept   : AIC=8526.038, Time=9.66 sec
 ARIMA(3,1,3)(0,0,0)[0] intercept   : AIC=inf, Time=9.09 sec
 ARIMA(2,1,3)(0,0,0)[0] intercept   : AIC=8045.200, Time=6.70 sec
 ARIMA(1,1,3)(0,0,0)[0] intercept   : AIC=12193.044, Time=2.57 sec
 ARIMA(2,1,4)(0,0,0)[0] intercept   : AIC=inf, Time=9.71 sec
 ARIMA(1,1,4)(0,0,0)[0] intercept   : AIC=inf, Time=7.90 sec
 ARIMA(3,1,4)(0,0,0)[0] intercept   : AIC=7914.051, Time=11.34 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept   : AIC=inf, Time=12.83 sec
 ARIMA(3,1,5)(0,0,0)[0] intercept   : AIC=7842.248, Time=14.12 sec
 ARIMA(2,1,5)(0,0,0)[0] intercept   : AIC=inf, Time=15.16 sec
 ARIMA(4,1,5)(0,0,0)[0] intercept   : AIC=7889.034, Time=15.87 sec
 ARIMA(3,1,5)(0,0,0)[0]             : AIC=7804.675, Time=5.66 sec
 ARIMA(2,1,5)(0,0,0)[0]             : AIC=7736.078, Time=5.59 sec
 ARIMA(1,1,5)(0,0,0)[0]             : AIC=inf, Time=4.15 sec
 ARIMA(2,1,4)(0,0,0)[0]             : AIC=7762.627, Time=3.76 sec
 ARIMA(1,1,4)(0,0,0)[0]             : AIC=inf, Time=2.92 sec
 ARIMA(3,1,4)(0,0,0)[0]             : AIC=7899.752, Time=3.96 sec

Best model:  ARIMA(2,1,5)(0,0,0)[0]
Total fit time: 166.565 seconds
```

Conclusion :- Auto arima gives us p, d, and q values for ARIMA. and find out p,d, and q value manually is quite difficult. Here; p = 2, d = 1, q = 5.

In [ ]:
```
auto_model.summary()
```

Out[233]:

Statespace Model Results

Dep. Variable:	y	**No. Observations:**	3192
Model:	SARIMAX(2, 1, 5)	**Log Likelihood**	-3860.039
Date:	Sun, 02 May 2021	**AIC**	7736.078
Time:	03:57:15	**BIC**	7784.623
Sample:	0	**HQIC**	7753.485
	- 3192		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.7319	0.000	1.13e+04	0.000	1.732	1.732
ar.L2	-0.9997	0.000	-8572.650	0.000	-1.000	-0.999
ma.L1	-2.4160	0.008	-288.842	0.000	-2.432	-2.400
ma.L2	2.0676	0.022	92.084	0.000	2.024	2.112
ma.L3	-0.6345	0.030	-21.223	0.000	-0.693	-0.576
ma.L4	0.1153	0.025	4.698	0.000	0.067	0.163
ma.L5	-0.1265	0.009	-13.574	0.000	-0.145	-0.108
sigma2	0.6379	0.007	87.605	0.000	0.624	0.652

Ljung-Box (Q):	182.11	**Jarque-Bera (JB):**	8978.35
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.07	**Skew:**	0.10
Prob(H) (two-sided):	0.00	**Kurtosis:**	11.22

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

Splitting Data into Train and Test

In [ ]:
```
df.shape
```

Out[234]: (3192,)

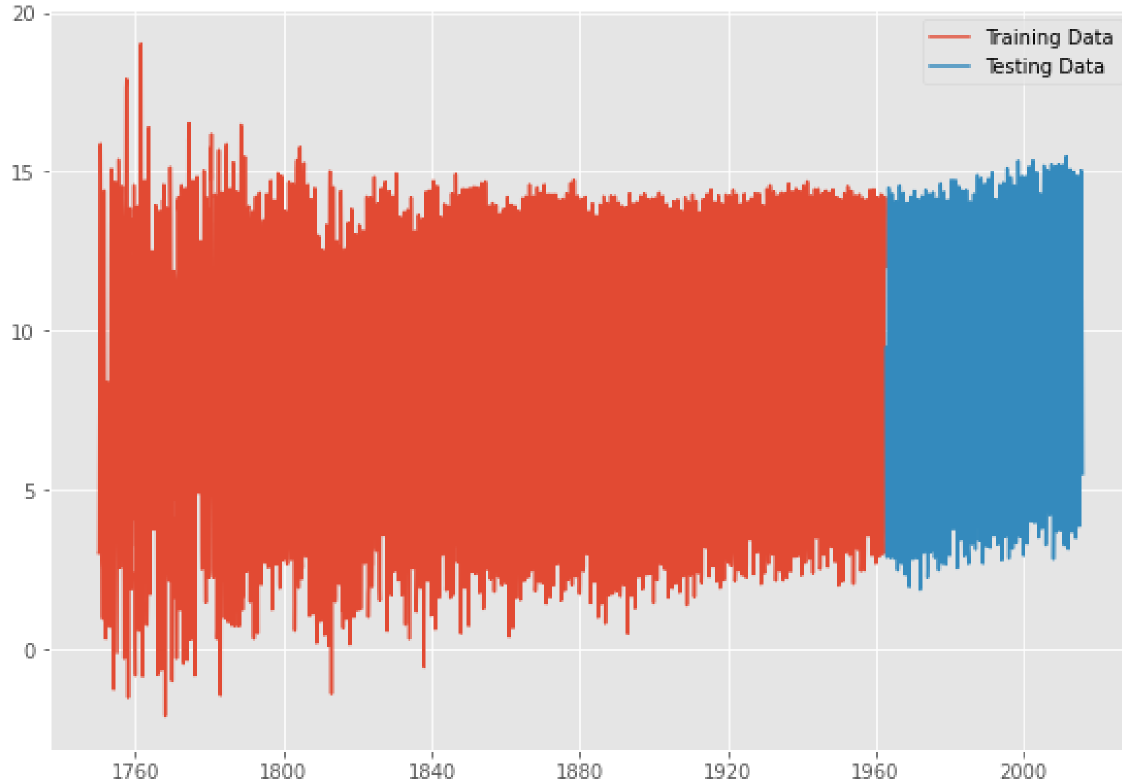
In [ ]:
```
train_len = int(0.8 * len(df))
train_len
```

Out[235]: 2553

In [ ]:
```
train = df[:train_len]
train.shape
```
Out[236]:
```
(2553,)
```
In [ ]:
```
train
```
Out[237]:
```
dt
1750-01-01     3.034
1750-02-01     3.083
1750-03-01     5.626
1750-04-01     8.490
1750-05-01    11.573
               ...
1962-05-01    11.128
1962-06-01    13.427
1962-07-01    14.205
1962-08-01    13.713
1962-09-01    12.018
Name: LandAverageTemperature, Length: 2553, dtype: float64
```
In [ ]:
```
test = df[train_len:]
test.shape
```
Out[238]:
```
(639,)
```
In [ ]:
```
test
```
Out[239]:
```
dt
1962-10-01     9.468
1962-11-01     6.283
1962-12-01     3.940
1963-01-01     2.901
1963-02-01     4.020
               ...
2015-08-01    14.755
2015-09-01    12.999
2015-10-01    10.801
2015-11-01     7.433
2015-12-01     5.518
Name: LandAverageTemperature, Length: 639, dtype: float64
```

In [ ]:

```
plt.plot(train, label = "Training Data")
plt.plot(test, label = "Testing Data")
plt.legend()
plt.show()
```



In [ ]:
```
# make a model

model = ARIMA(train, order =(2, 1, 5))
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_mode
l.py:165: ValueWarning:

No frequency information was provided, so inferred frequency MS will
be used.

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_mode
l.py:165: ValueWarning:

No frequency information was provided, so inferred frequency MS will
be used.
```

In [ ]:
```
model_fit = model.fit()

model_fit.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/arima_model.p
y:1441: RuntimeWarning:

invalid value encountered in sqrt
```

Interpretation :- AIC = 6602 with model = ARIMA(2,1,5), Lower the AIC better the model.

In [ ]:
```python
y_pred_train = model_fit.predict()
y_pred_train
```

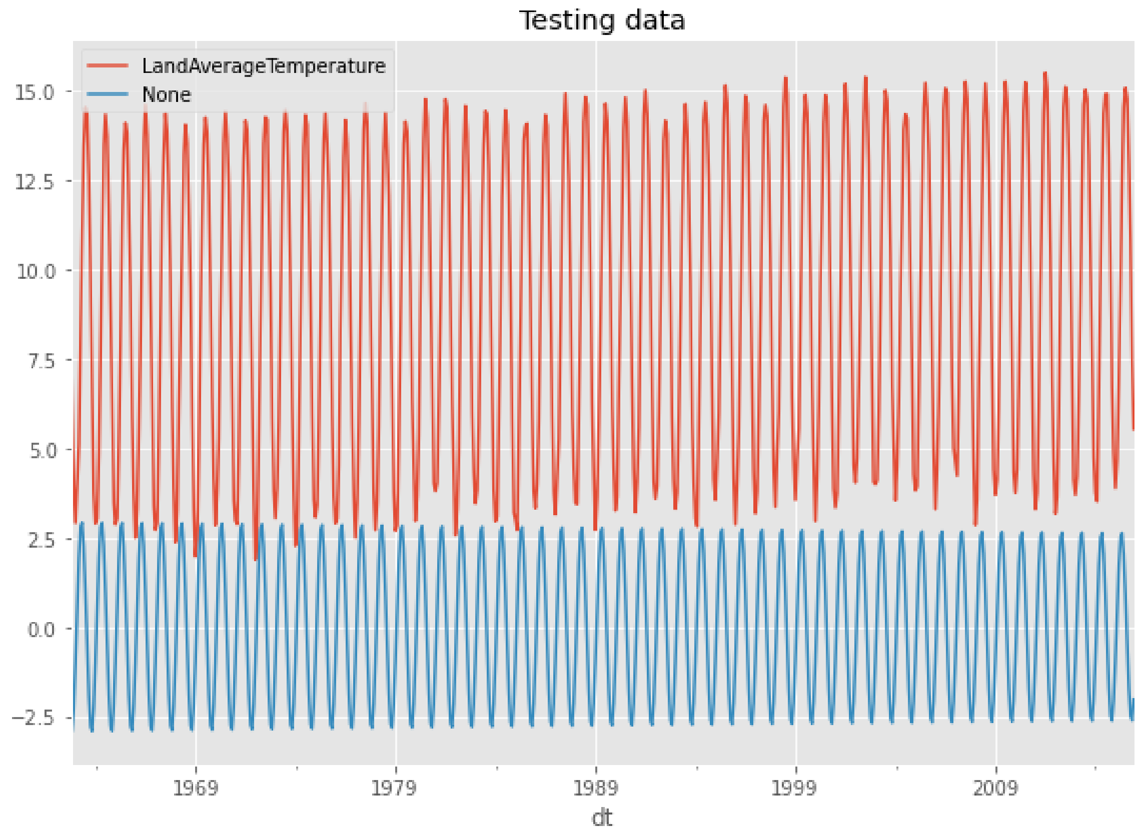
Out[243]:
```
1750-02-01    0.000194
1750-03-01    0.007188
1750-04-01    0.305939
1750-05-01    0.884255
1750-06-01    0.868201
                ...
1962-05-01    2.744426
1962-06-01    2.341728
1962-07-01    1.004735
1962-08-01   -0.375569
1962-09-01   -1.830524
Freq: MS, Length: 2552, dtype: float64
```

In [ ]:
```python
# predictions on test data set
# start -> len(train) & end -> len(train) - len(test) - 1 or len(x)-1
y_pred_test = model_fit.predict(start = len(train), end = len(df)-1)

y_pred_test
```

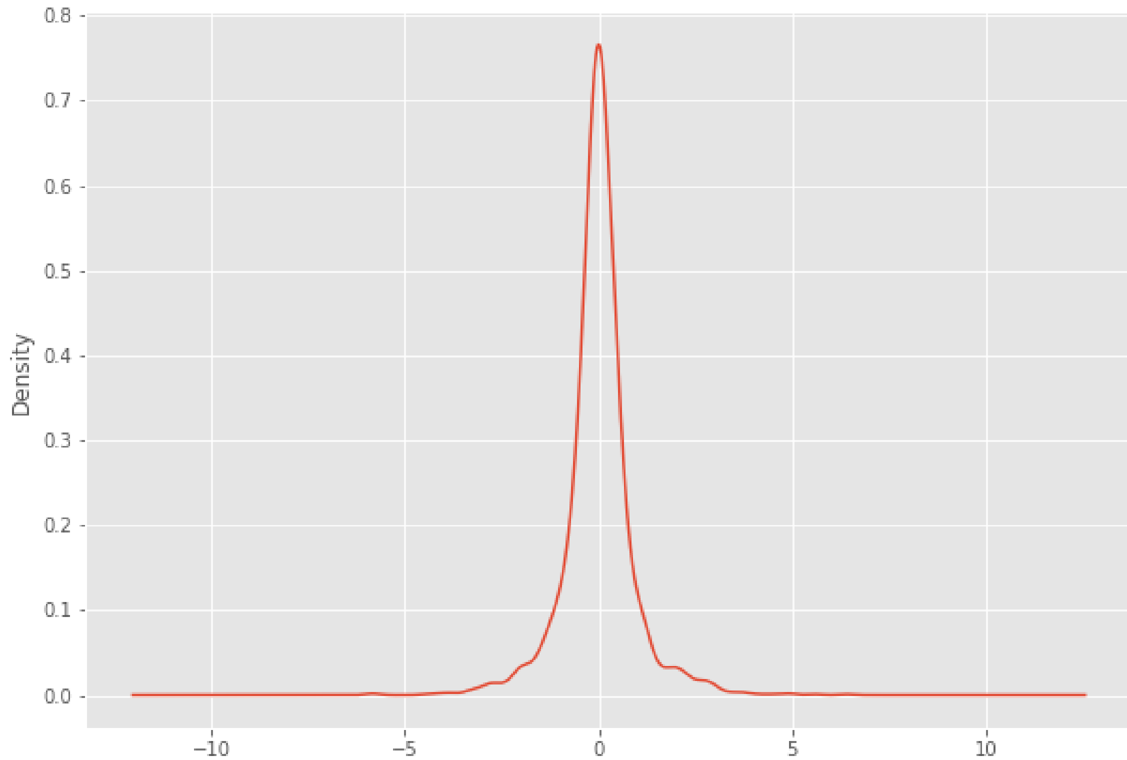
Out[244]:
```
1962-10-01   -2.859188
1962-11-01   -2.921608
1962-12-01   -2.268351
1963-01-01   -0.982761
1963-02-01    0.550456
                ...
2015-08-01   -0.466992
2015-09-01   -1.710221
2015-10-01   -2.494809
2015-11-01   -2.610738
2015-12-01   -2.027193
Freq: MS, Length: 639, dtype: float64
```

In [ ]:

```
test.plot(title = "Testing data")
y_pred_test.plot()
plt.legend()
plt.show()
```



In [ ]:
```
residuals = model_fit.resid
residuals.plot(kind = "kde")
plt.show()
```



In [ ]:
```
from sklearn.metrics import mean_squared_error

mse = mean_squared_error(test, y_pred_test)

print("MSE is :", mse)

print("RMSE is :", np.sqrt(mse))
```

```
MSE is : 98.85386926003595
RMSE is : 9.942528313262978
```

Predict 30 Future Values

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

Out[248]:
```
dt
1750-01-01     3.034
1750-02-01     3.083
1750-03-01     5.626
1750-04-01     8.490
1750-05-01    11.573
Name: LandAverageTemperature, dtype: float64
```

In [ ]:
```python
model = ARIMA(df , order = (2,1,5))

model_fit = model.fit()
```

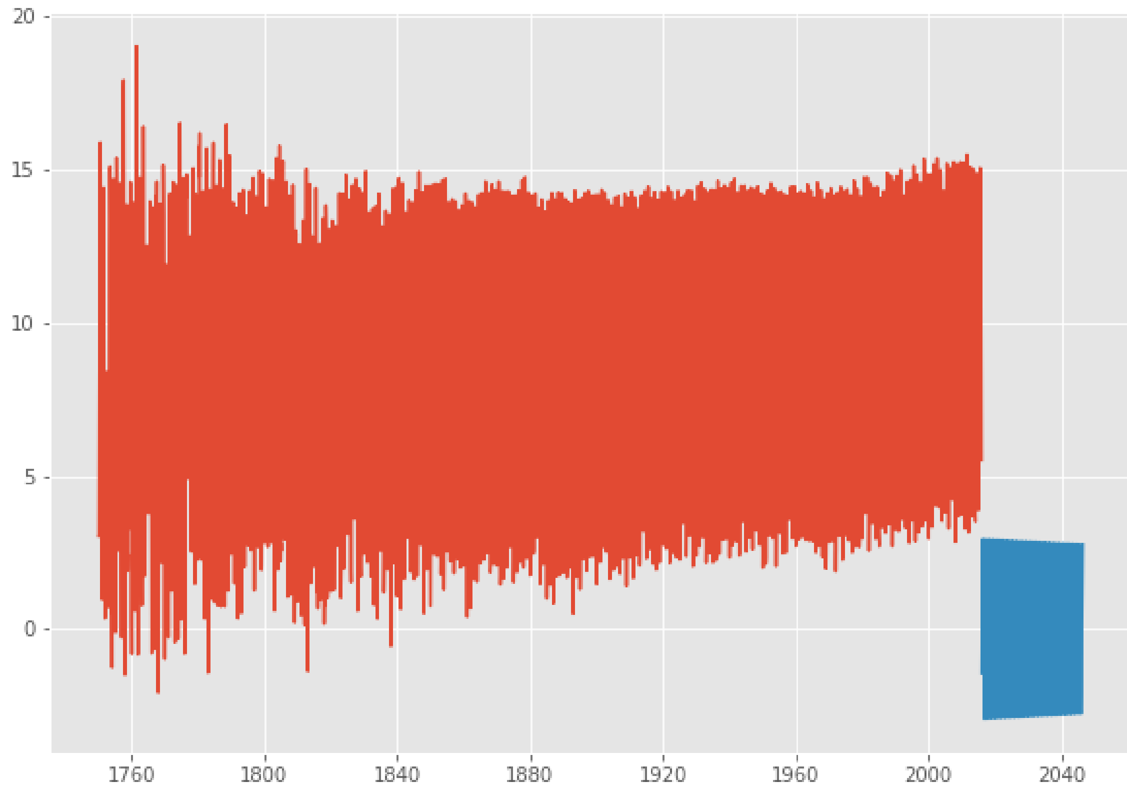
```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_mode
l.py:165: ValueWarning:

No frequency information was provided, so inferred frequency MS will
be used.

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/base/tsa_mode
l.py:165: ValueWarning:

No frequency information was provided, so inferred frequency MS will
be used.
```

In [ ]:
```python
forecast = model_fit.predict(start = len(df), end = len(df)+364)
forecast
```

Out[258]:
```
2016-01-01   -1.451985
2016-02-01    0.463870
2016-03-01    1.865606
2016-04-01    2.812980
2016-05-01    2.936771
                ...
2046-01-01   -0.970448
2046-02-01    0.474739
2046-03-01    1.792379
2046-04-01    2.629560
2046-05-01    2.762195
Freq: MS, Length: 365, dtype: float64
```

In [ ]:

```
plt.plot(df)
plt.plot(forecast)
plt.show()
```



Interpretation :- Above graph shows the trend of future value. From the graph we can say that the temperature fall down from the year 2016 to year 2040

Also we can forecast temperature by using resample method. Resample convert the data into Month, Year, Week, etc. And because of that we can forecast monthly, yearly and so on.

In [ ]:

```
df = pd.read_csv("GlobalLandTemperatures.csv", parse_dates = ["dt"],
```

In [ ]:

```
df["LandAverageTemperature"] = df["LandAverageTemperature"].fillna(df

df["LandAverageTemperatureUncertainty"] = df["LandAverageTemperatureU

df["LandMaxTemperature"] = df["LandMaxTemperature"].fillna(df["LandMa

df["LandMaxTemperatureUncertainty"] = df["LandMaxTemperatureUncertain

df["LandMinTemperature"] = df["LandMinTemperature"].fillna(df["LandMi

df["LandMinTemperatureUncertainty"] = df["LandMinTemperatureUncertain

df["LandAndOceanAverageTemperature"] = df["LandAndOceanAverageTempera

df["LandAndOceanAverageTemperatureUncertainty"] = df["LandAndOceanAve
```

In [ ]:
```
df.isna().sum()
```

Out[265]:
```
LandAverageTemperature                       0
LandAverageTemperatureUncertainty            0
LandMaxTemperature                           0
LandMaxTemperatureUncertainty                0
LandMinTemperature                           0
LandMinTemperatureUncertainty                0
LandAndOceanAverageTemperature               0
LandAndOceanAverageTemperatureUncertainty    0
dtype: int64
```

Resample Data into Month

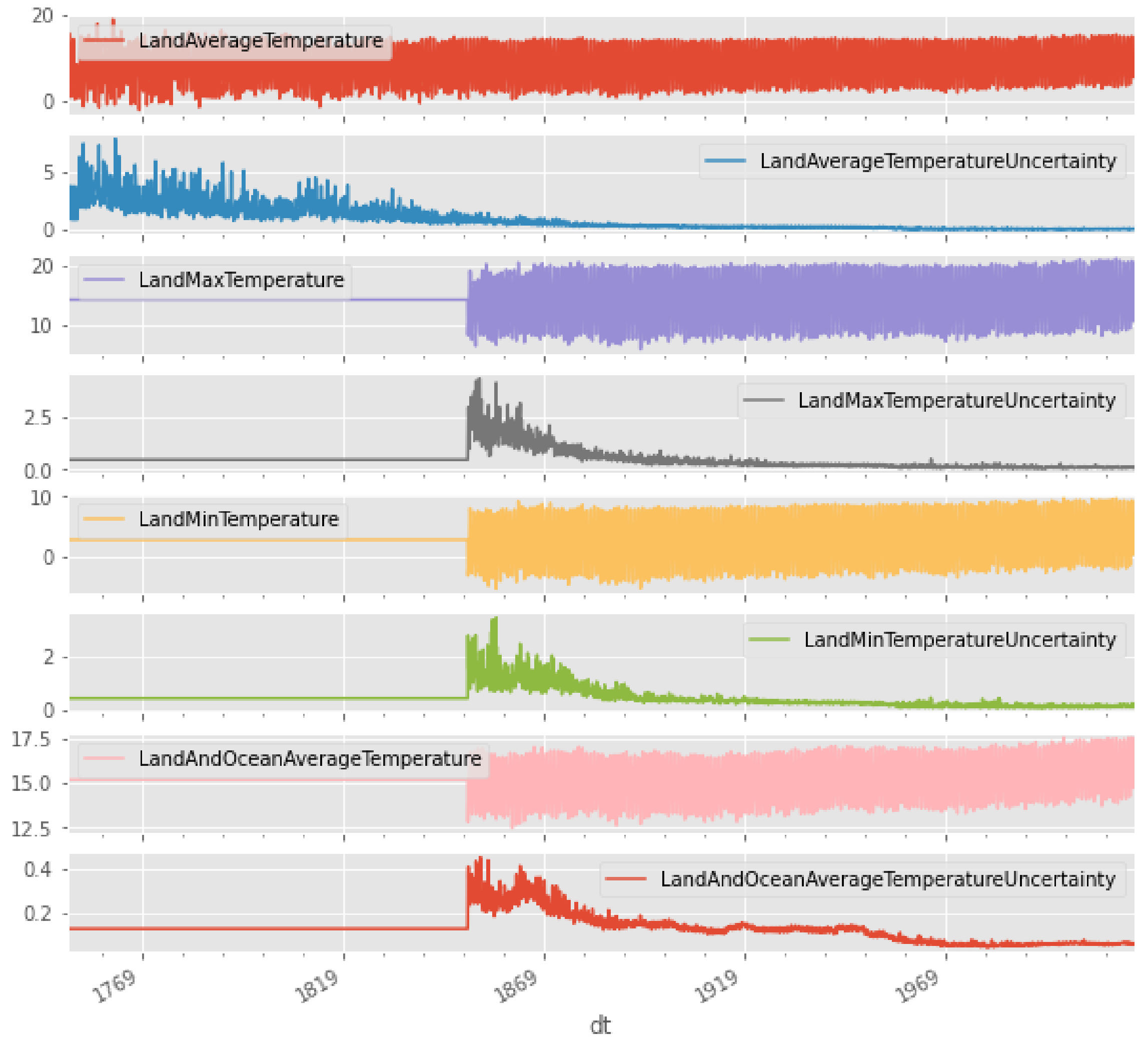
In [ ]:
```
month = df.resample("M").mean()
month.head()
```

Out[266]:

	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
dt				
1750-01-31	3.034	3.574	14.350601	
1750-02-28	3.083	3.702	14.350601	
1750-03-31	5.626	3.076	14.350601	
1750-04-30	8.490	2.451	14.350601	
1750-05-31	11.573	2.072	14.350601	

In [ ]:

```
month.plot(subplots = True, figsize = (10,10))
plt.show()
```



In [ ]:
```
fig = go.Figure([go.Scatter(x = month.index,
                            y = month.LandAverageTemperature)])
fig.show()
```

In [ ]:

```
fig = px.bar(month, x = month.index,
             y = "LandAverageTemperature")
fig.show()
```

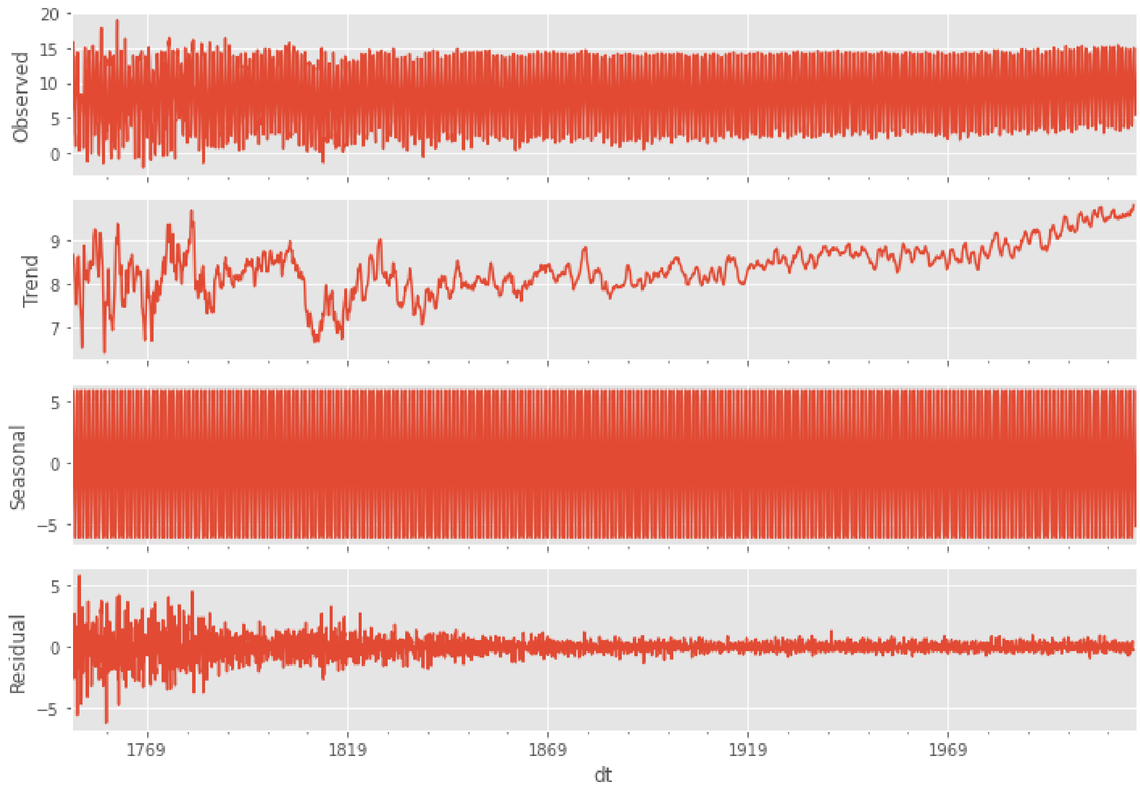
In [ ]:

```
fig = px.line(month, x = month.index,
              y = month.LandAverageTemperature,
              title = 'Custum Tick Labels')
fig.update_xaxes(dtick = "M1")
fig.show()
```

Decomposition

In [ ]:

```
decomposition = sm.tsa.seasonal_decompose(month["LandAverageTemperatu

fig = decomposition.plot()
```



Stationarity

Constant statistical properties -> mean, variance, std with does not change over time

H0 : It is Non Stationary H1 : It is Stationary

P value > 0.05 Fail to reject null hypothesis -> Non Stationary

P value < 0.05 it is Stationary

In [ ]:
```
output = adfuller(month["LandAverageTemperature"])
output
```

Out[274]:
```
(-4.036039785872673,
 0.0012331195770598 26,
 29,
 3162,
 {'1%': -3.4324197712239393,
  '10%': -2.5672568084635663,
  '5%': -2.862454498112156},
 7457.668033159485)
```

In [ ]:
```
p_val = output[1]
```

In [ ]:
```
if p_val > 0.05:
    print("Non Stationary")
else:
    print("Stationary")
```

```
Stationary
```

Conclusion :- P value is 0.001.. and from our hypothesis we can say our data column is stationary.

For monthly forecast, repeat the steps from AR to Auto Arima with the minor changes.

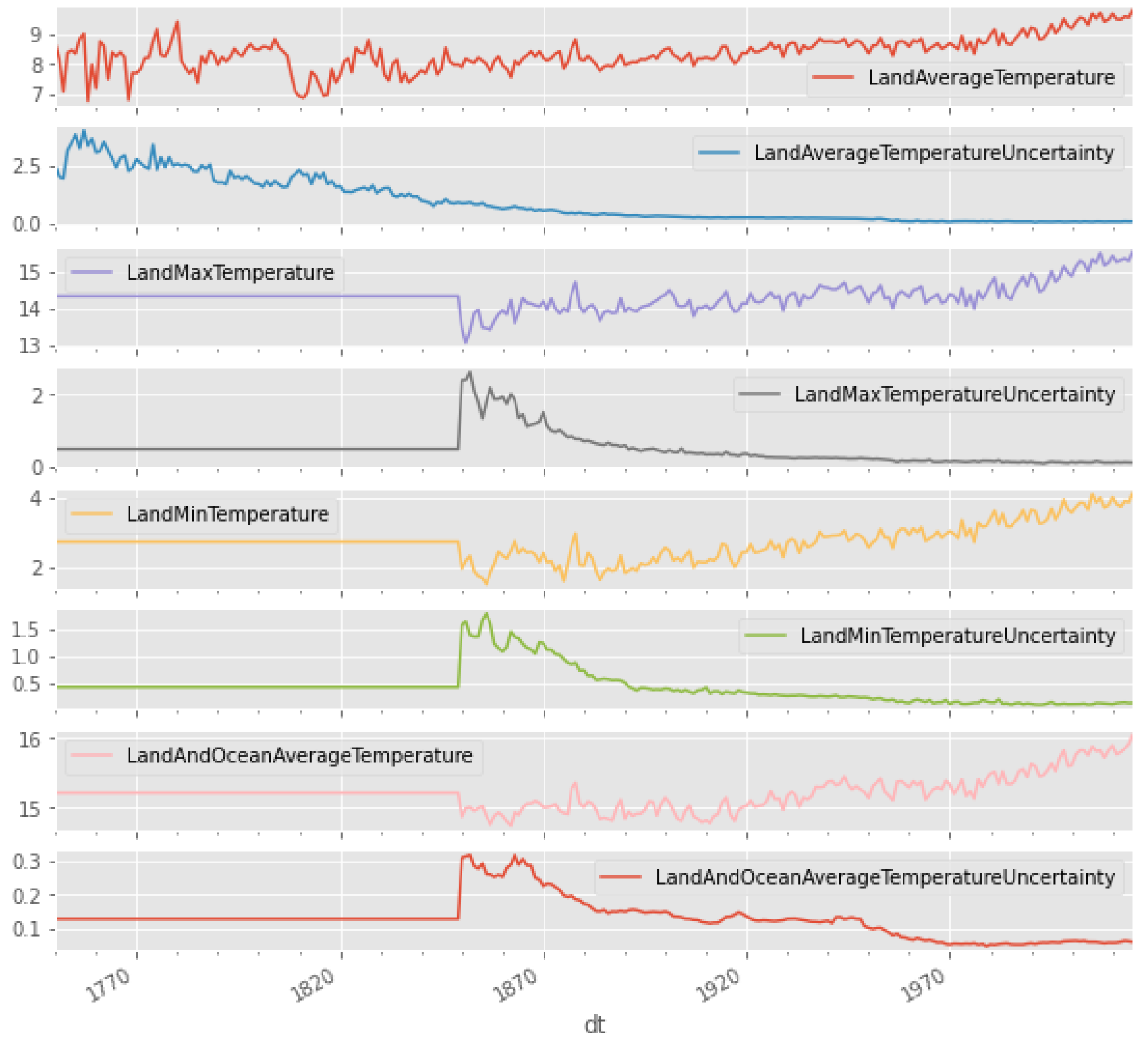
Resample Data into Year

In [ ]:
```
year = df.resample("Y").mean()
year.head()
```

Out[277]:

dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandM
1750-12-31	8.690644	2.496206	14.350601	
1751-12-31	8.142221	2.013362	14.350601	
1752-12-31	7.077282	1.957734	14.350601	
1753-12-31	8.388083	3.176000	14.350601	
1754-12-31	8.469333	3.494250	14.350601	

In [ ]:
```
year.plot(subplots = True, figsize = (10,10))
plt.show()
```



In [ ]:

```
fig = go.Figure([go.Scatter(x = year.index,
                            y = year.LandAverageTemperature)])
fig.show()
```

In [ ]:

```
fig = px.bar(year, x = year.index,
             y = "LandAverageTemperature")
fig.show()
```

In [ ]:
```
fig = px.line(year, x = year.index,
              y = year.LandAverageTemperature,
              title = 'Custum Tick Labels')
fig.update_xaxes(dtick = "M1")
fig.show()
```

Decomposition

In [ ]:

```
decomposition = sm.tsa.seasonal_decompose(year["LandAverageTemperatur
fig = decomposition.plot()
```

Stationarity

Constant statistical properties -> mean, variance, std with does not change over time

H0 : It is Non Stationary H1 : It is Stationary

P value > 0.05 Fail to reject null hypothesis -> Non Stationary

P value < 0.05 it is Stationary

```
In [ ]: output = adfuller(year["LandAverageTemperature"])
        output
```

```
Out[287]: (-0.8864293917075042,
           0.7924085576143398,
           12,
           253,
           {'1%': -3.4564641849494113,
            '10%': -2.572894516864816,
            '5%': -2.873032730098417},
           98.44937379415404)
```

```
In [ ]: p_val = output[1]
```

```
In [ ]: if p_val > 0.05:
            print("Non Stationary")
        else:
            print("Stationary")
```

```
Non Stationary
```

Conclusion :- Here p value is 0.79 and which is greater than the 0.05. so from our hypothesis 3can say that for our yearly data column is not stationary.

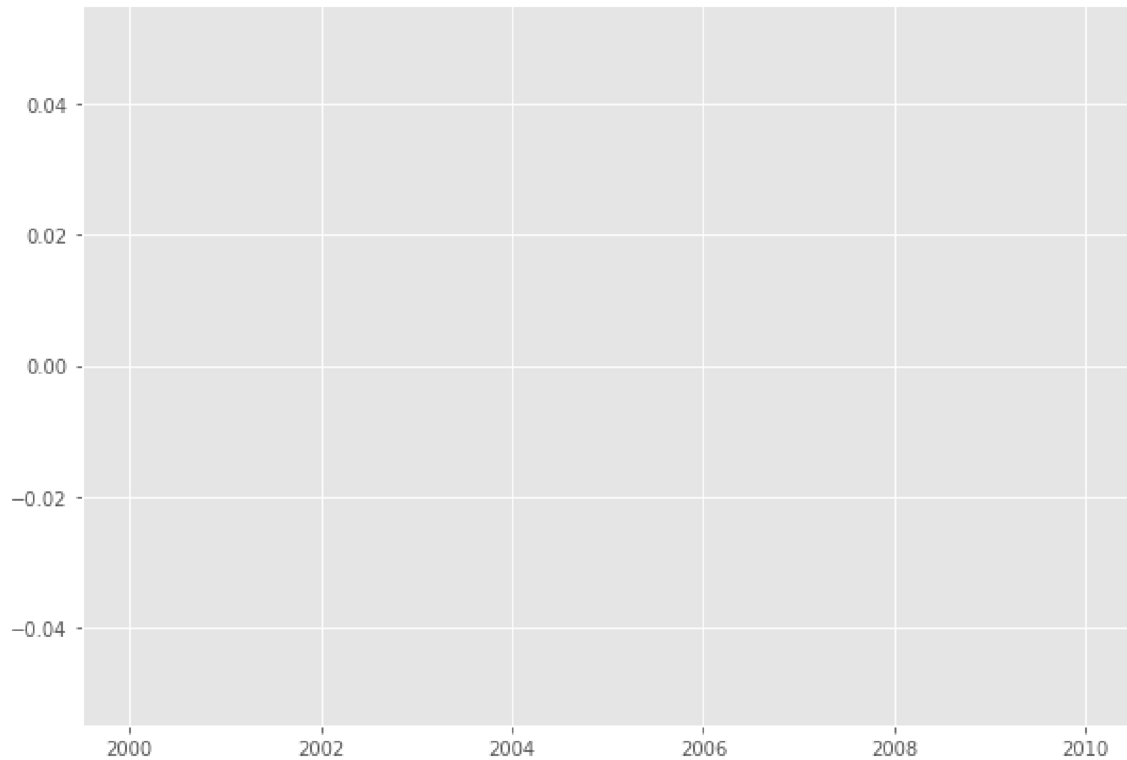
Now, we have to convert it in stationary. As below,

```
In [ ]: year["LandAverageTemperature_1"] = year["LandAverageTemperature"] - d
```

```
In [ ]: year = year.dropna()
```

In [ ]:

```python
plt.plot(year.index, year["LandAverageTemperature_1"])
plt.show()
```



Conclusion :- The graph is blank, because of size of yearly data. Our yearly data is very small, there are 216 rows only.

In [ ]:

```python
output = adfuller(year["LandAverageTemperature_1"])
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-294-6b3810c35bc3> in <module>()
----> 1 output = adfuller(year["LandAverageTemperature_1"])

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/stattools.py
 in adfuller(x, maxlag, regression, autolag, store, regresults)
    227     above a critical size, then we cannot reject that there
is a unit root.
    228
--> 229     The p-values are obtained through regression surface app
roximation from
    230     MacKinnon 1994, but using the updated 2010 tables. If th
e p-value is close
    231     to significant, then the critical values should be used
 to judge whether

ValueError: sample size is too short to use selected regression comp
onent
```

Conclusion :- Above error arise because of sample size. Above syntax gives us error but when you run "output", it gives valid output.

In [ ]:
```
output
```

Out[297]:
```
(-4.036039785872673,
 0.001233119577059826,
 29,
 3162,
 {'1%': -3.4324197712239393,
  '10%': -2.5672568084635663,
  '5%': -2.862454498112156},
 7457.668033159485)
```

In [ ]:
```
p_val = output[1]
```

In [ ]:
```
if p_val > 0.05:
    print("Non Stationary")
else:
    print("Stationary")
```

```
Stationary
```

Conclusion :- Now our data column becomes stationary.

For yearly forecast, repeat the steps from AR to Auto Arima with the minor changes.