In [82]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
%matplotlib Inline
```

In [2]:
```
data = 'E:\\SIMPLILEARN\\KAGGLE\\Air_Pollution\\data.csv'
with open(data) as f:
    print(f)

data = pd.read_csv(data, encoding='ISO-8859-1')
```

```
<_io.TextIOWrapper name='E:\\SIMPLILEARN\\KAGGLE\\Air_Pollution\\data.csv' mode=
'r' encoding='cp1252'>
```

In [3]:
```
# Extracting Tamil Nadu state data alone
df = data.query("state == 'Maharashtra'")
```

In [4]:
```
df.head(2)
```

Out[4]:

| | stn_code | sampling_date | state | location | agency | type | so2 | no2 | rspm |
|---|---|---|---|---|---|---|---|---|---|
| **197237** | 53.0 | 5/2/1987 | Maharashtra | Pune | Maharashtra Pollution Control Board | NaN | NaN | 10.4 | NaN |
| **197238** | 52.0 | 5/3/1987 | Maharashtra | Pune | Maharashtra Pollution Control Board | Industrial | 18.2 | 35.8 | NaN |

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60384 entries, 197237 to 257620
Data columns (total 13 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   stn_code                     42976 non-null  object
 1   sampling_date                60384 non-null  object
 2   state                        60384 non-null  object
 3   location                     60384 non-null  object
 4   agency                       41695 non-null  object
 5   type                         60090 non-null  object
 6   so2                          58322 non-null  float64
 7   no2                          59167 non-null  float64
 8   rspm                         55439 non-null  float64
 9   spm                          22345 non-null  float64
 10  location_monitoring_station  57529 non-null  object
 11  pm2_5                        0 non-null      float64
```

```
 12  date                        60382 non-null  object
dtypes: float64(5), object(8)
```

In [6]:
```
df.isna().sum().sort_values()
```

Out[6]:
```
sampling_date                    0
state                            0
location                         0
date                             2
type                           294
no2                           1217
so2                           2062
location_monitoring_station   2855
rspm                          4945
stn_code                     17408
agency                       18689
spm                          38039
pm2_5                        60384
dtype: int64
```

In [7]:
```
df.tail()
```

Out[7]:

| | stn_code | sampling_date | state | location | agency | type | so2 | no2 | rspm |
|---|---|---|---|---|---|---|---|---|---|
| **257616** | 711.0 | 27-12-15 | Maharashtra | Nagpur | Maharashtra State Pollution Control Board | Residential, Rural and other Areas | 12.0 | 48.0 | 134.0 |
| **257617** | 711.0 | 28-12-15 | Maharashtra | Nagpur | Maharashtra State Pollution Control Board | Residential, Rural and other Areas | 15.0 | 63.0 | 77.0 |
| **257618** | 711.0 | 29-12-15 | Maharashtra | Nagpur | Maharashtra State Pollution Control Board | Residential, Rural and other Areas | 11.0 | 33.0 | 51.0 |
| **257619** | 711.0 | 30-12-15 | Maharashtra | Nagpur | Maharashtra State Pollution Control Board | Residential, Rural and other Areas | 12.0 | 38.0 | 46.0 |
| **257620** | 711.0 | 31-12-15 | Maharashtra | Nagpur | Maharashtra State Pollution Control Board | Residential, Rural and other Areas | 12.0 | 38.0 | 51.0 |

In [8]:
```
df.describe()
```

Out[8]:

| | so2 | no2 | rspm | spm | pm2_5 |
|---|---|---|---|---|---|
| **count** | 58322.000000 | 59167.000000 | 55439.000000 | 22345.000000 | 0.0 |

| | so2 | no2 | rspm | spm | pm2_5 |
|---|---|---|---|---|---|
| **mean** | 17.366863 | 32.115370 | 101.479608 | 205.255823 | NaN |
| **std** | 13.541155 | 19.062558 | 61.460782 | 130.053447 | NaN |
| **min** | 0.000000 | 1.000000 | 1.000000 | 4.000000 | NaN |
| **25%** | 9.000000 | 18.000000 | 59.000000 | 114.000000 | NaN |
| **50%** | 14.000000 | 29.000000 | 90.000000 | 180.000000 | NaN |
| **75%** | 22.000000 | 41.000000 | 128.000000 | 265.000000 | NaN |

In [9]:
```
df['type'].replace("Industrial Areas","Industrial",inplace=True)
df['type'].replace("Industrial Area","Industrial",inplace=True)
df['type'].replace("Residential and others","Residential",inplace=True)
df['type'].replace("Residential, Rural and other Areas","Residential",inplace=Tr
df['type'].replace("Sensitive Areas", "Sensitive Area", inplace=True)
```

In [10]:
```
df['so2'].fillna(df['so2'].mean(), inplace=True)
df['no2'].fillna(df['no2'].mean(), inplace=True)
```

In [11]:
```
df['rspm'].fillna(df['rspm'].median(),inplace = True)
df['spm'].fillna(df['spm'].median(),inplace = True)
```

In [12]:
```
df['type']=df['type'].fillna(df['type'].mode()[0])
```

In [13]:
```
df.isna().sum()
```

Out[13]:
```
stn_code                       17408
sampling_date                      0
state                              0
location                           0
agency                         18689
type                               0
so2                                0
no2                                0
rspm                               0
spm                                0
location_monitoring_station     2855
pm2_5                          60384
date                               2
dtype: int64
```

In [14]:
```
df = df.sort_values(by='date')
```

In [15]:
```
df['date'].ffill(inplace=True)
```

In [16]:
```
df['date'] = pd.to_datetime(df['date'],format='%Y-%m-%d')
```

Dropping Columns like location_monitoring_station, pm2_5, date, Agency and stn_code

In [17]:
```
df.drop(columns=['location_monitoring_station', 'pm2_5', 'sampling_date', 'agenc
```

In [18]:
```
df.head()
```

Out[18]:

| | state | location | type | so2 | no2 | rspm | spm | date |
|---|---|---|---|---|---|---|---|---|
| **197243** | Maharashtra | Pune | Residential | 8.100000 | 9.0 | 90.0 | 180.0 | 1987-01-07 |
| **197244** | Maharashtra | Pune | Residential | 0.700000 | 47.6 | 90.0 | 293.0 | 1987-01-12 |
| **197237** | Maharashtra | Pune | Residential | 17.366863 | 10.4 | 90.0 | 180.0 | 1987-02-05 |
| **197239** | Maharashtra | Pune | Industrial | 11.300000 | 16.3 | 90.0 | 180.0 | 1987-02-06 |
| **197242** | Maharashtra | Pune | Industrial | 9.700000 | 10.9 | 90.0 | 180.0 | 1987-02-07 |

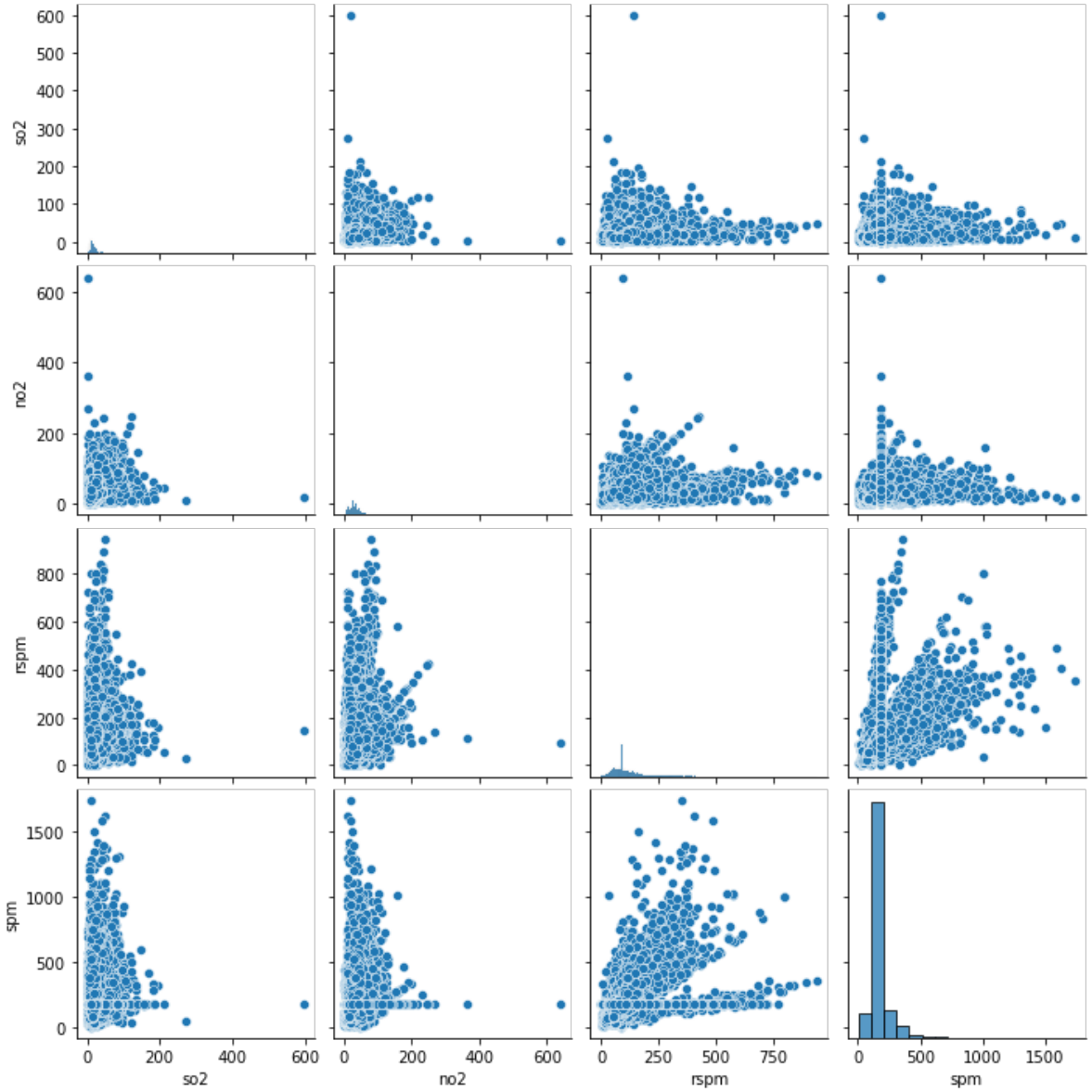
# Exploratory Data Analysis

In [19]:
```
plt.figure(figsize=(10,10))
plt.plot(df['date'], df[['no2', 'so2']])
plt.xlabel("Year")
plt.ylabel("SO2 & NO2")
```

Out[19]:
```
Text(0, 0.5, 'SO2 & NO2')
```

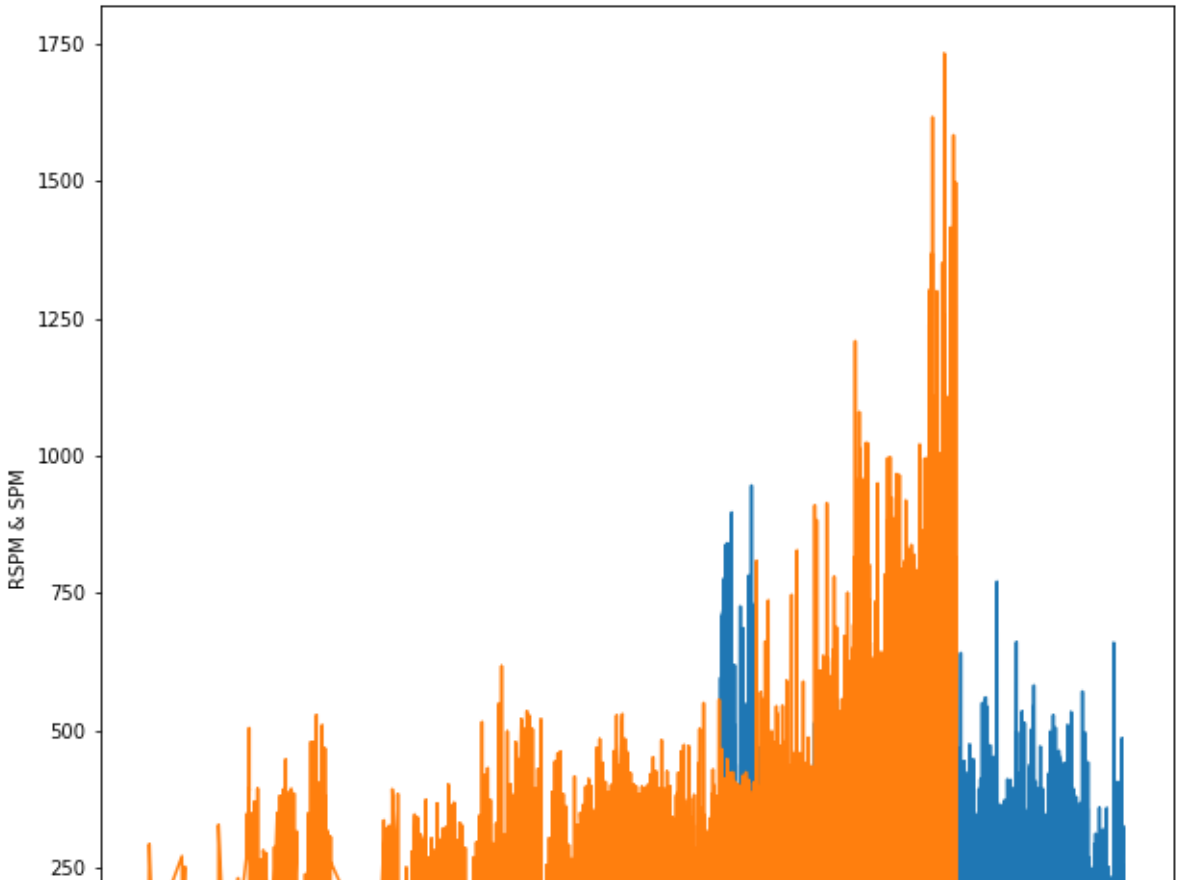
In [20]:
```
sns.pairplot(data=df)
```

Out[20]:
```
<seaborn.axisgrid.PairGrid at 0x1e0386dbe50>
```



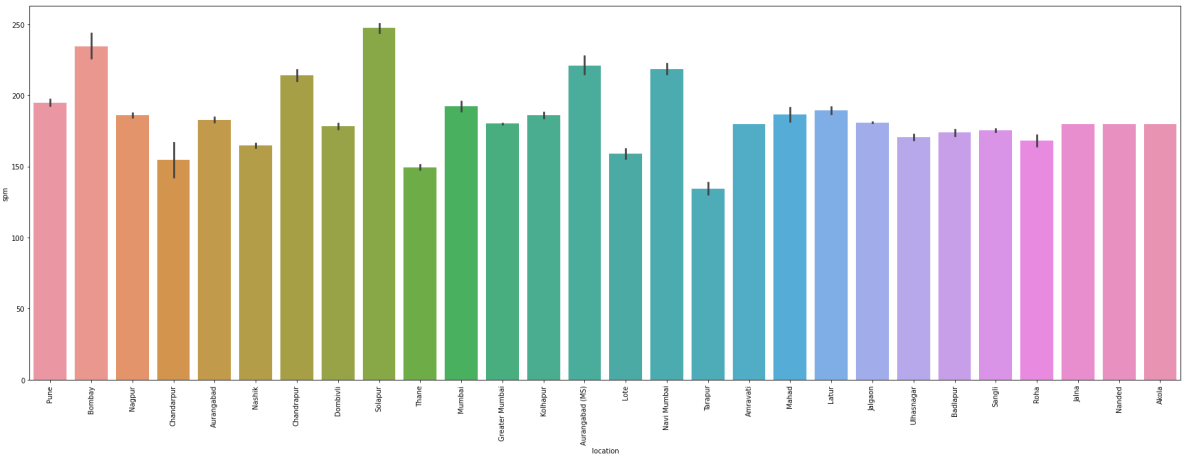

In [21]:
```
plt.figure(figsize=(10,10))
plt.plot(df['date'], df[['rspm', 'spm']])
plt.xlabel("Year")
plt.ylabel("RSPM & SPM")
```

Out[21]:
```
Text(0, 0.5, 'RSPM & SPM')
```



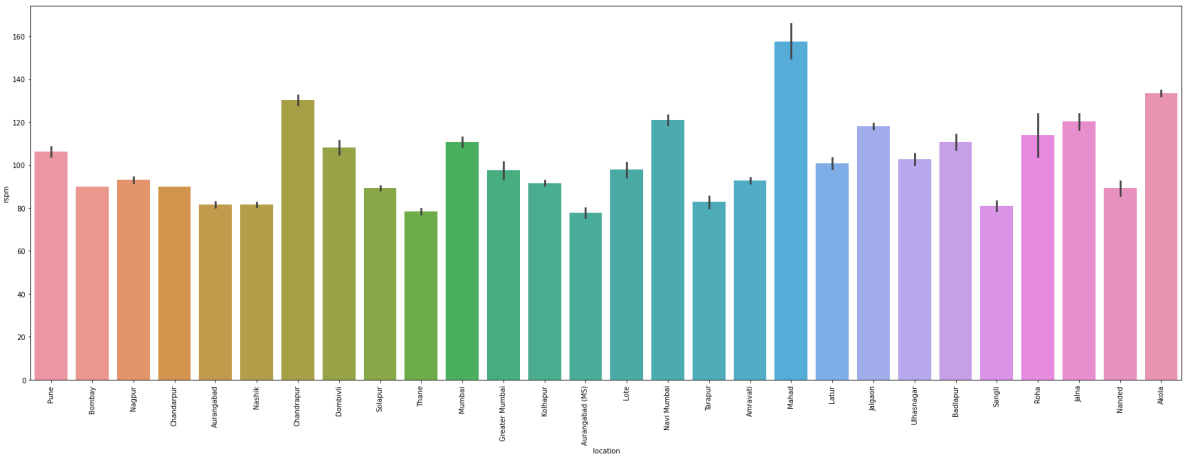

In [22]:

```
plt.figure(figsize=(30, 10))
plt.xticks(rotation=90)
sns.barplot(x='location',y='spm',data=df);
```

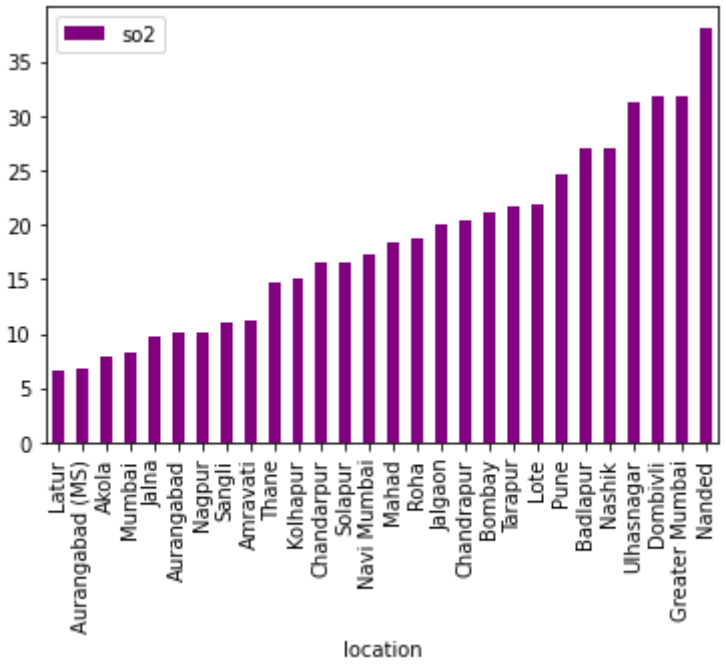



In [23]:

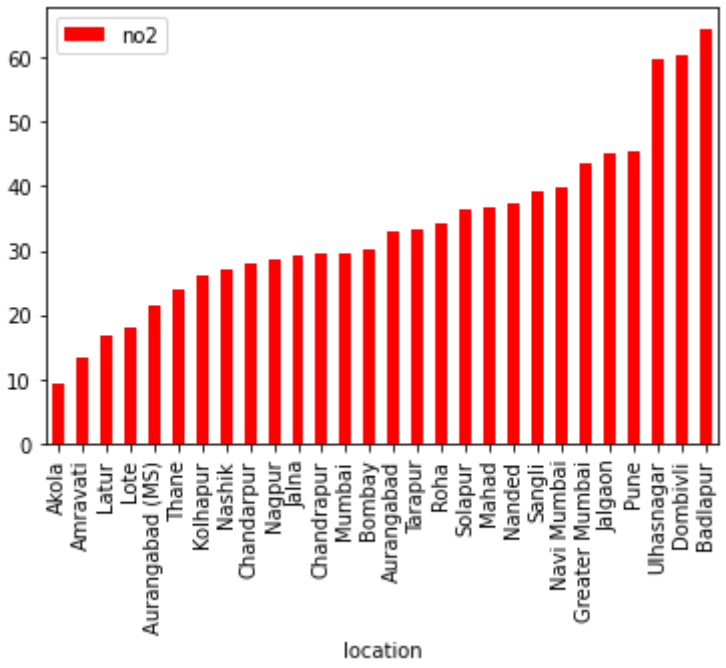
```
plt.figure(figsize=(30, 10))
plt.xticks(rotation=90)
sns.barplot(x='location',y='rspm',data=df);
```




In [24]:
```
df[['so2','location']].groupby(["location"]).mean().sort_values(by='so2').plot.b
plt.show()
```




In [25]:
```
df[['no2','location']].groupby(["location"]).mean().sort_values(by='no2').plot.b
plt.show()
```




In [26]:
```
loc = pd.pivot_table(df, values=['so2','no2','spm'],index='location')
loc
```

Out[26]:

| location | no2 | so2 | spm |
|---|---|---|---|
| **Akola** | 9.357824 | 7.937023 | 180.000000 |
| **Amravati** | 13.380021 | 11.138559 | 180.000000 |
| **Aurangabad** | 33.018726 | 10.016638 | 182.865231 |
| **Aurangabad (MS)** | 21.351419 | 6.815767 | 220.934524 |
| **Badlapur** | 64.451282 | 27.041370 | 173.935043 |
| **Bombay** | 30.061229 | 21.169740 | 234.602837 |
| **Chandarpur** | 27.834365 | 16.567540 | 154.779221 |
| **Chandrapur** | 29.483155 | 20.313778 | 214.248013 |
| **Dombivli** | 60.499191 | 31.839702 | 178.267231 |
| **Greater Mumbai** | 43.545930 | 31.843011 | 180.058055 |
| **Jalgaon** | 45.192121 | 20.052887 | 180.984350 |
| **Jalna** | 29.304250 | 9.686299 | 180.000000 |
| **Kolhapur** | 26.175916 | 15.091260 | 186.186164 |
| **Latur** | 16.856614 | 6.587331 | 189.265390 |
| **Lote** | 18.043252 | 21.907315 | 158.863114 |
| **Mahad** | 36.815866 | 18.395647 | 186.471455 |
| **Mumbai** | 29.660227 | 8.245033 | 192.484112 |
| **Nagpur** | 28.544353 | 10.032638 | 185.874141 |

| location | no2 | so2 | spm |
|---|---|---|---|
| **Nanded** | 37.185754 | 38.083357 | 180.000000 |
| **Nashik** | 27.205053 | 27.070612 | 164.791254 |
| **Navi Mumbai** | 39.788710 | 17.270234 | 218.691271 |
| **Pune** | 45.333006 | 24.659954 | 194.917552 |
| **Roha** | 34.291339 | 18.759843 | 168.283465 |
| **Sangli** | 39.231521 | 10.976787 | 175.430055 |
| **Solapur** | 36.335870 | 16.611888 | 247.254144 |
| **Tarapur** | 33.193643 | 21.770421 | 134.472973 |

# Air Quality index

In [27]:
```
# Calculate so2
def calculate_si(so2):
    si=0
    if (so2<=40):
     si= "s1"
    if (so2>40 and so2<=80):
     si= "s2"
    if (so2>80 and so2<=380):
     si= "s3"
    if (so2>380 and so2<=800):
     si= "s4"
    if (so2>800 and so2<=1600):
     si= "s5"
    if (so2>1600):
     si= "s6"
    return si
df['si']= df['so2'].apply(calculate_si)
ds= df[['so2','si']]
```

In [28]:
```
# Calculate No2
def calculate_ni(no2):
    ni=0
    if (no2<=40):
     ni= "n1"
    if (no2>40 and no2<=80):
     ni= "n2"
    if (no2>80 and no2<=180):
     ni= "n3"
    if (no2>180 and no2<=280):
     ni= "n4"
    if (no2>280 and no2<=400):
     ni= "n5"
    if (no2>400):
     ni= "n6"
    return ni
df['ni']= df['no2'].apply(calculate_ni)
dn= df[['no2','ni']]
```

In [29]:
```
# Calculate SPM
def calculate_spi(spm):
    spi=0
    if (spm<=40):
      spi= "sp1"
    if (spm>40 and spm<=80):
      spi= "sp2"
    if (spm>80 and spm<=180):
      spi= "sp3"
    if (spm>180 and spm<=280):
      spi= "sp4"
    if (spm>280 and spm<=400):
      spi= "sp5"
    if (spm>400):
      spi= "sp6"
    return  spi
df['spi']= df['spm'].apply(calculate_spi)
dsp= df[['spm','spi']]
```

In [30]:
```
# Calculate AQI
def calculate_aqi(si,ni,spi):
    aqi=0
    if(si>ni and si>spi):
     aqi=si
    if (spi>ni and spi>si):
     aqi=spi
    if(ni>si and ni>spi):
     aqi= ni
    return aqi
df['AQI']= df.apply(lambda x:calculate_aqi(x['so2'],x['no2'],x['spm']),axis=1)
```

In [31]:
```
df.head(3)
```

Out[31]:

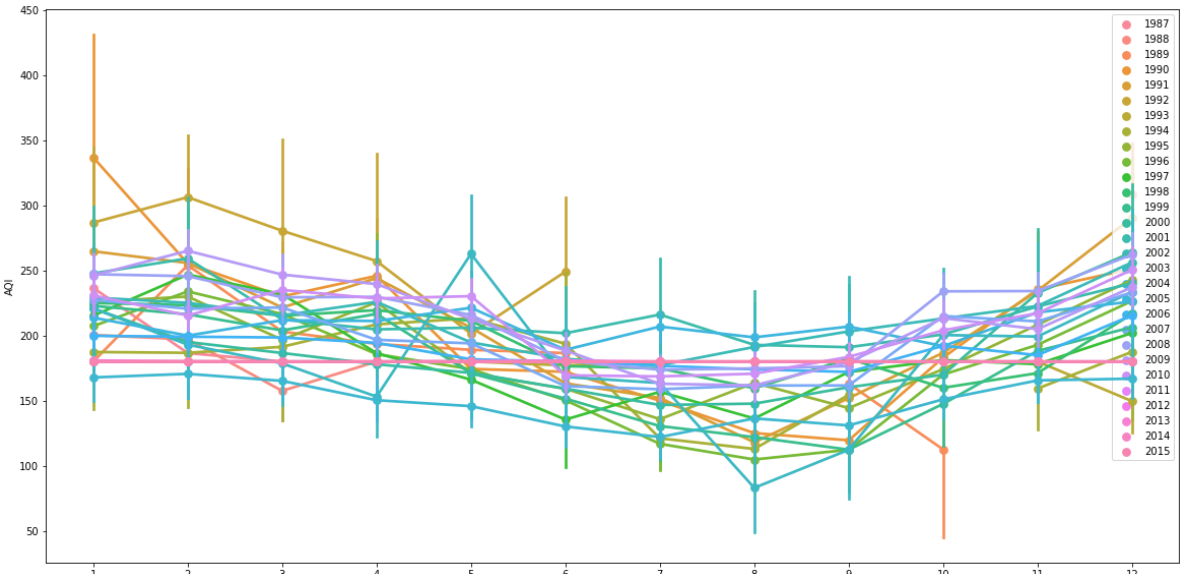
| | state | location | type | so2 | no2 | rspm | spm | date | si | ni | spi |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **197243** | Maharashtra | Pune | Residential | 8.100000 | 9.0 | 90.0 | 180.0 | 1987-01-07 | s1 | n1 | sp3 |
| **197244** | Maharashtra | Pune | Residential | 0.700000 | 47.6 | 90.0 | 293.0 | 1987-01-12 | s1 | n2 | sp5 |
| **197237** | Maharashtra | Pune | Residential | 17.366863 | 10.4 | 90.0 | 180.0 | 1987-02-05 | s1 | n1 | sp3 |

In [32]:
```
df['year'] = df['date'].dt.year
```

In [33]:
```
df['month'] = df['date'].dt.month
```

In [34]:
```
plt.figure(figsize=(20, 10))
sns.pointplot(x="month", y='AQI', hue="year", data=df, )
plt.xlabel("month")
plt.ylabel('AQI')
plt.legend(loc='upper right')
```

Out[34]:
```
<matplotlib.legend.Legend at 0x1e03f67ae50>
```




In [35]:
```
df.head()
```

Out[35]:

| | state | location | type | so2 | no2 | rspm | spm | date | si | ni | spi |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **197243** | Maharashtra | Pune | Residential | 8.100000 | 9.0 | 90.0 | 180.0 | 1987-01-07 | s1 | n1 | sp3 |
| **197244** | Maharashtra | Pune | Residential | 0.700000 | 47.6 | 90.0 | 293.0 | 1987-01-12 | s1 | n2 | sp5 |
| **197237** | Maharashtra | Pune | Residential | 17.366863 | 10.4 | 90.0 | 180.0 | 1987-02-05 | s1 | n1 | sp3 |
| **197239** | Maharashtra | Pune | Industrial | 11.300000 | 16.3 | 90.0 | 180.0 | 1987-02-06 | s1 | n1 | sp3 |
| **197242** | Maharashtra | Pune | Industrial | 9.700000 | 10.9 | 90.0 | 180.0 | 1987-02-07 | s1 | n1 | sp3 |

In [36]:
```
# Decomposing to see white noiise
decompose = df[['AQI']]
decompose.index =  df['date']
decompose = decompose[['AQI']]
decompose.head()
```

Out[36]:

| | AQI |
|---|---|
| **date** | |
| **1987-01-07** | 180.0 |
| **1987-01-12** | 293.0 |
| **1987-02-05** | 180.0 |
| **1987-02-06** | 180.0 |
| **1987-02-07** | 180.0 |

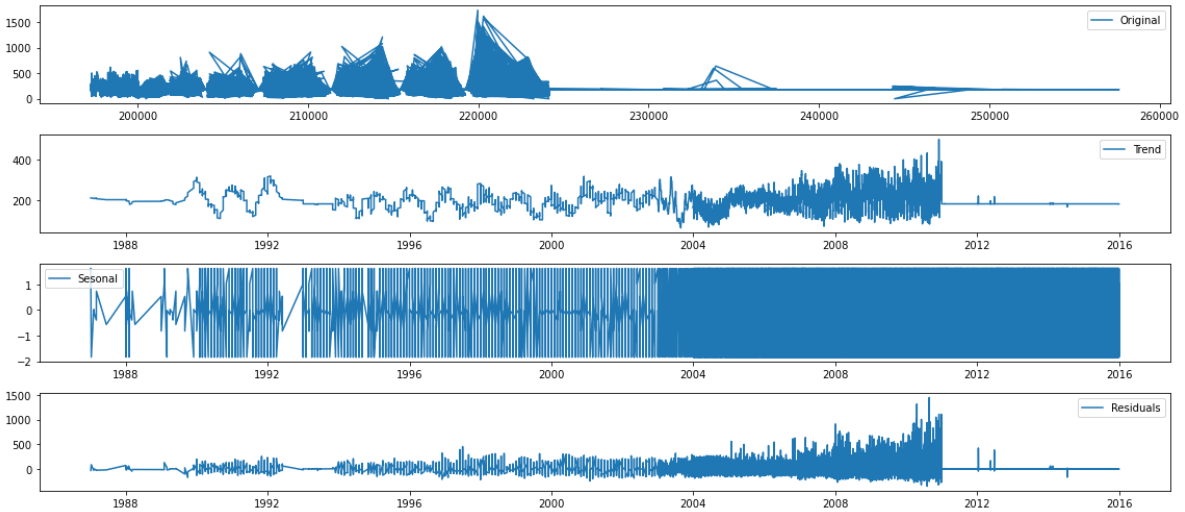
# Importing Decomposition model and plotting graph

## Trend, Sesonality & Residual

In [37]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(decompose, model='additive', freq=12, extrapo
```

In [38]:
```
trend = decomposition.trend
sesonal = decomposition.seasonal
resid = decomposition.resid
```

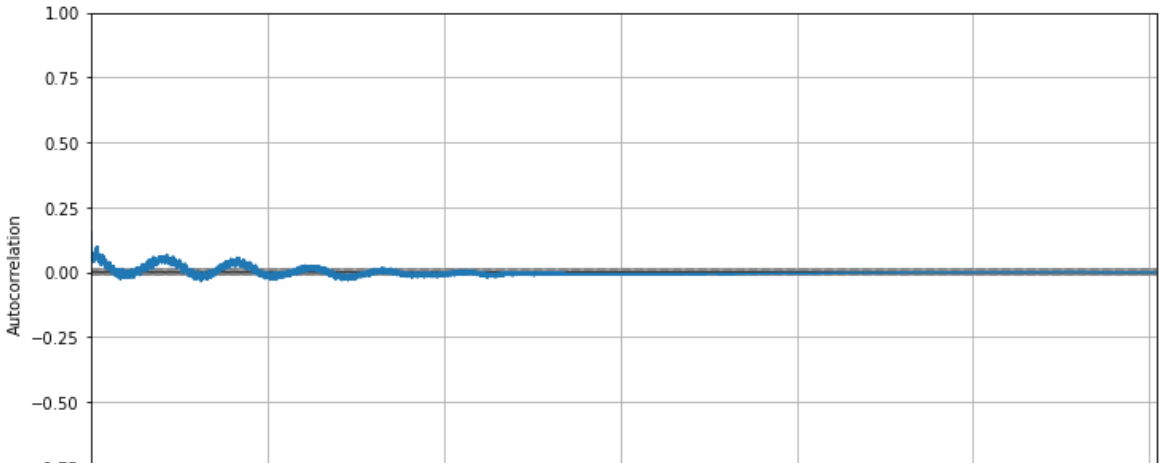
In [39]:
```
plt.figure(figsize=(16,7))
plt.subplot(411)
plt.plot(df['AQI'], label='Original')
plt.legend(loc='best')

plt.subplot(412)
plt.plot(trend, label='Trend')
plt.legend(loc='best')

plt.subplot(413)
plt.plot(sesonal, label='Sesonal')
plt.legend(loc='best')

plt.subplot(414)
plt.plot(resid, label='Residuals')
plt.legend(loc='best')

plt.tight_layout()
```




# AutoCorrelation

In [40]:
```
# Plotting Graph for autocorelation
from pandas.plotting import autocorrelation_plot
plt.figure(figsize=(12,6))
autocorrelation_plot(df['AQI'])
```

Out[40]:
```
<AxesSubplot:xlabel='Lag', ylabel='Autocorrelation'>
```




## Importing data

In [41]:
```
import datetime as dt
import math
from sklearn.metrics import mean_squared_error
```

In [64]:
```
ts = pd.pivot_table(df, values=['AQI'],index='date')
ts.head()
ts.shape
```

Out[64]:
```
(4686, 1)
```

In [66]:
```
# training Data and testing data
x_train = ts[ts.index < dt.datetime(2013,1,1,0,0,0)]
x_test = ts[ts.index >= dt.datetime(2013,1,1,0,0,0)]
print(x_train.shape)
print(x_test.shape)
```

```
(3591, 1)
(1095, 1)
```

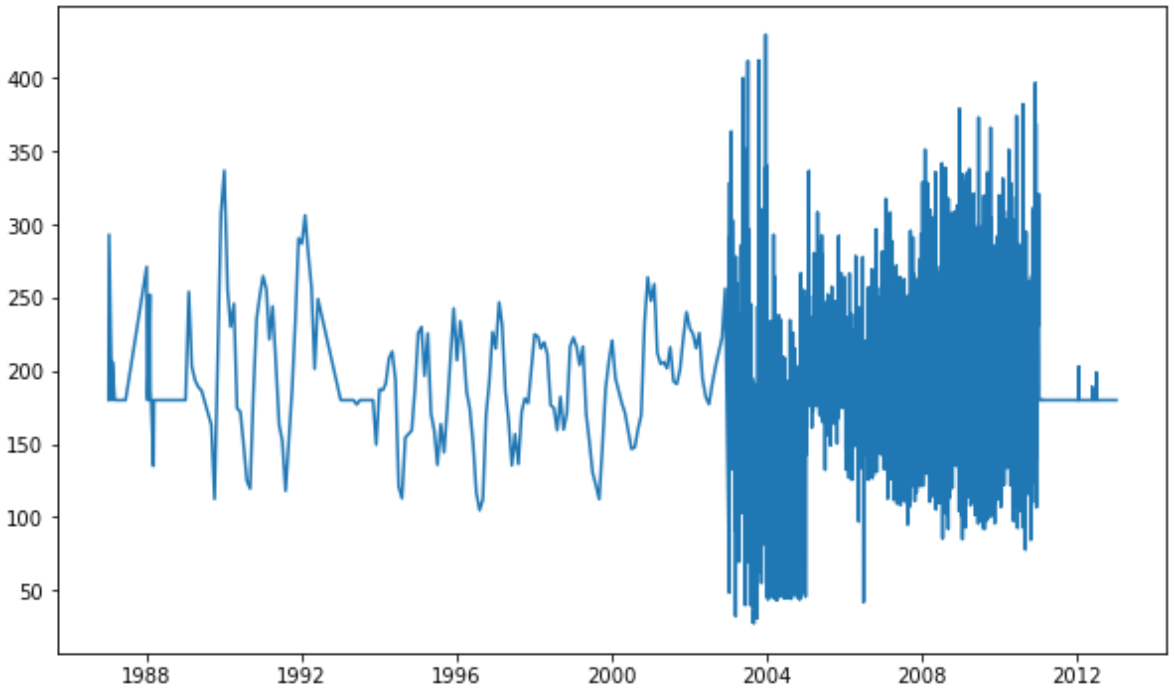
# Stationarity Check

For stationarity check we will use Augmented Dicky Fuller Test

In [67]:
```
from statsmodels.tsa.stattools import adfuller

def stationarity_check(data):
    df_test = adfuller(data.AQI, autolag='AIC')
    df_output = pd.Series(df_test[0:4], index= ['Test Static: ', 'P-Value: ','#I
    for key,value in df_test[4].items():
        df_output['Criticat Value (%s)'%key] = value
    print(df_output)

    plt.figure(figsize=(10,6))
    plt.plot(data.index, data.AQI)
    plt.show()
```

In [68]:
```
stationarity_check(x_train)
```

```
Test Static:                -3.616469
P-Value:                     0.005454
#Lags Used :                30.000000
No. Of Observation :      3560.000000
Criticat Value (1%)          -3.432188
Criticat Value (5%)          -2.862352
Criticat Value (10%)         -2.567202
dtype: float64
```

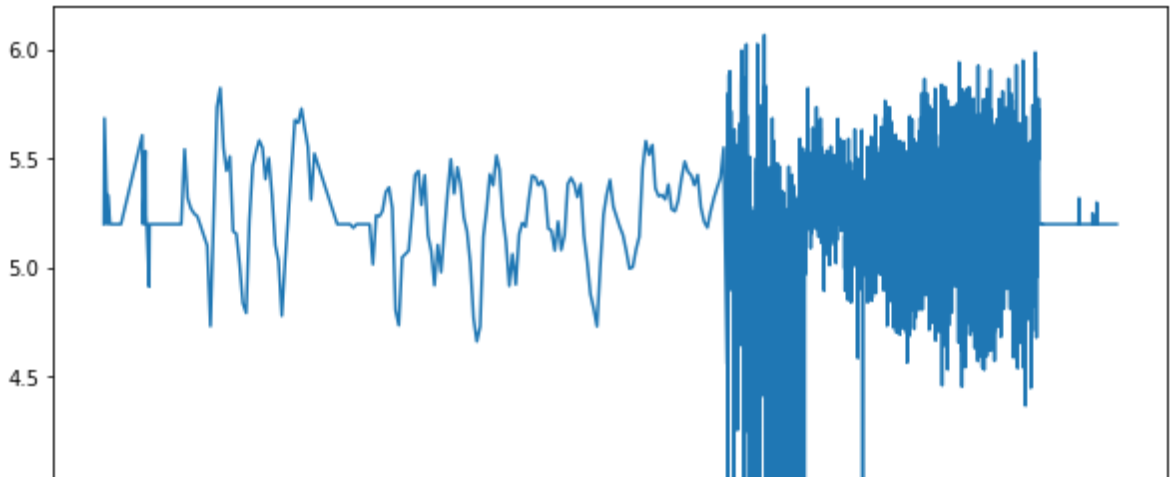



- Data is Highly stationary
- we need to apply log transformation to make variance constant

In [69]:
```
log_train = x_train
log_train = log_train['AQI'].apply(lambda x : math.log(x+1))
log_train = pd.DataFrame(log_train)
```

In [70]:
```
stationarity_check(log_train)
```

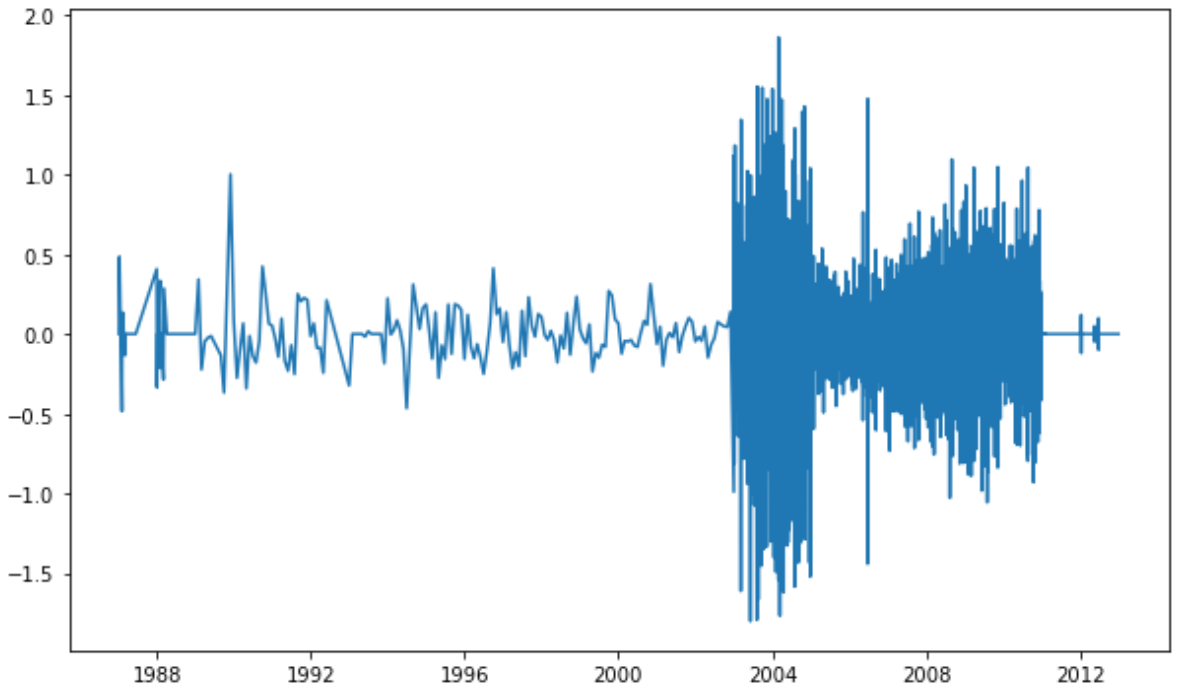
```
Test Static:                -3.814677
P-Value:                     0.002761
#Lags Used :                30.000000
No. Of Observation :      3560.000000
Criticat Value (1%)          -3.432188
Criticat Value (5%)          -2.862352
Criticat Value (10%)         -2.567202
dtype: float64
```




In [71]:
```
first_diff = log_train['AQI'] - log_train['AQI'].shift(1)
first_diff = first_diff.fillna(0)
first_diff = pd.DataFrame(first_diff)
```

In [72]:
```
stationarity_check(first_diff)
```

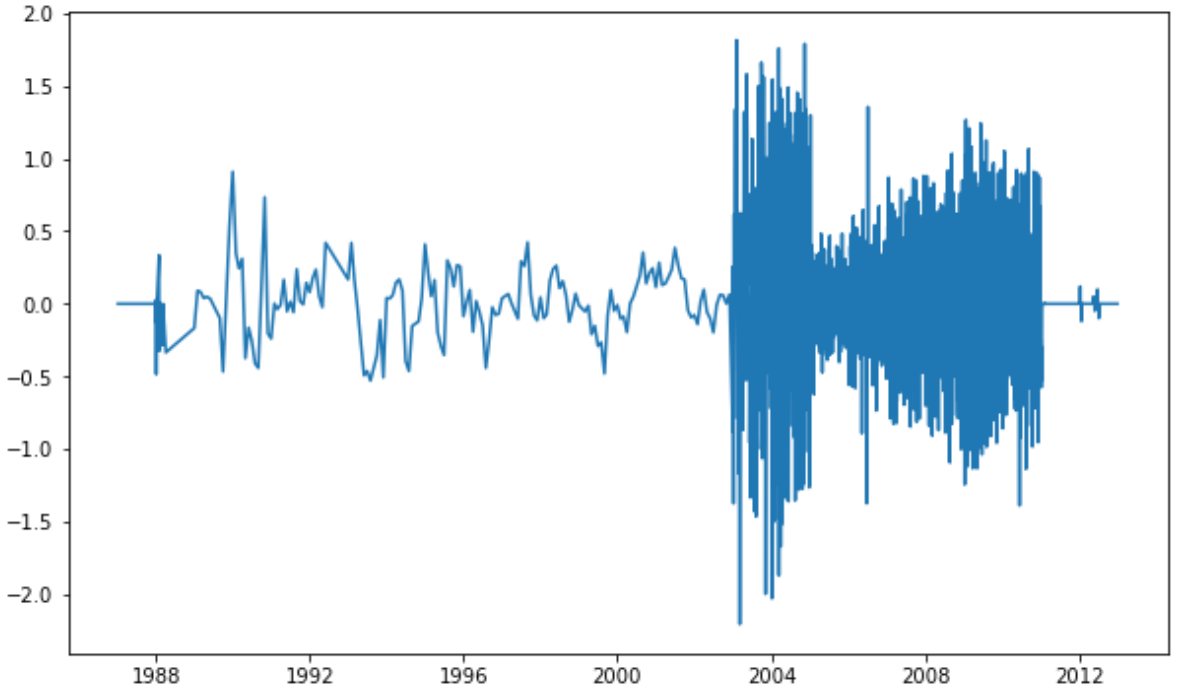
```
Test Static:             -21.733371
P-Value:                   0.000000
#Lags Used :              30.000000
No. Of Observation :    3560.000000
Criticat Value (1%)        -3.432188
Criticat Value (5%)        -2.862352
Criticat Value (10%)       -2.567202
dtype: float64
```




In [73]:
```
# Using Sesonality Difference
seasonal_diff = log_train['AQI'] - log_train['AQI'].shift(12)
seasonal_diff = seasonal_diff.fillna(0)
seasonal_diff = pd.DataFrame(seasonal_diff)
```

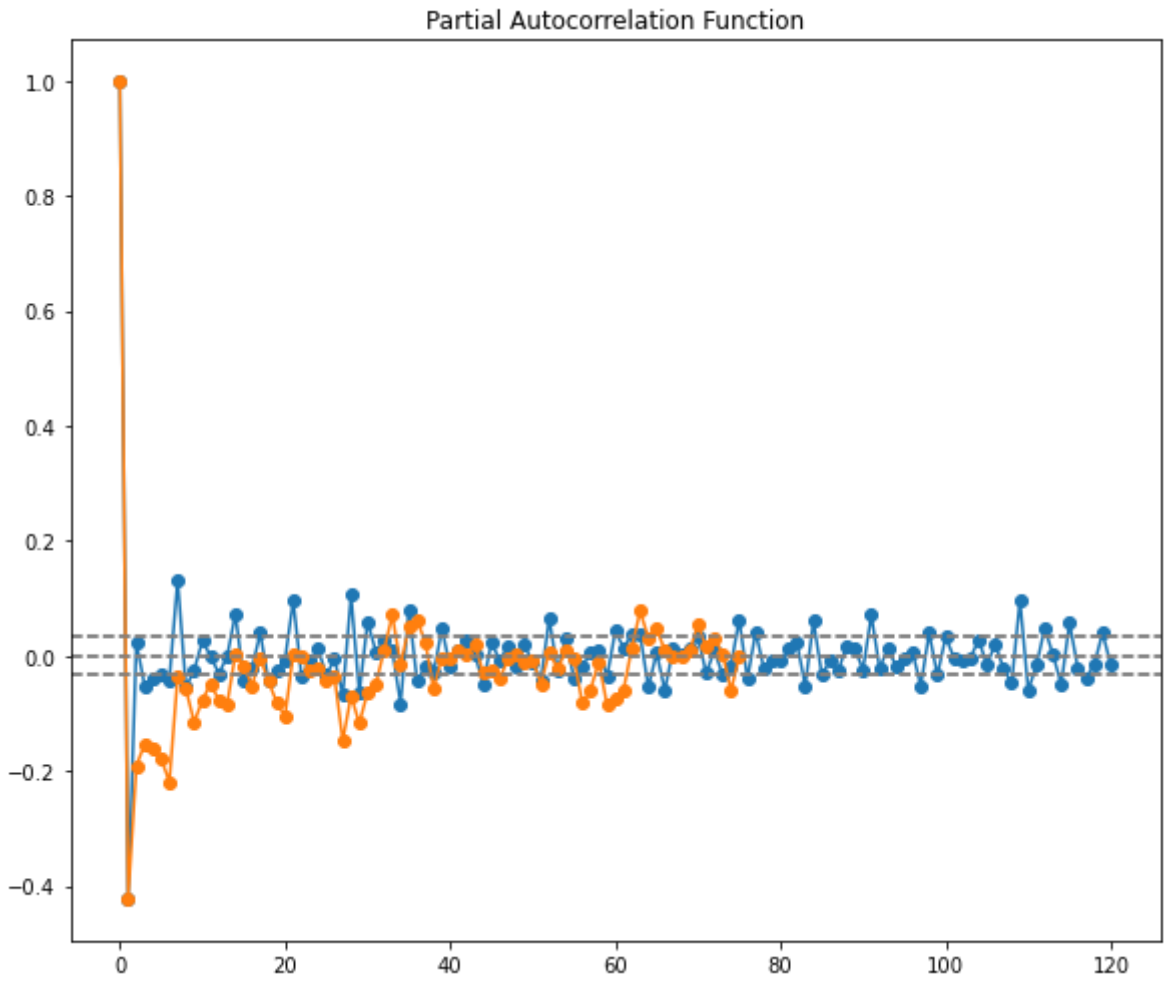
In [74]:
```
stationarity_check(seasonal_diff)
```

```
Test Static:           -1.132752e+01
P-Value:                1.133852e-20
#Lags Used :            3.000000e+01
No. Of Observation :    3.560000e+03
Criticat Value (1%)    -3.432188e+00
Criticat Value (5%)    -2.862352e+00
Criticat Value (10%)   -2.567202e+00
dtype: float64
```




## Plotting Acf and Pacf plots:

In [75]:
```
from statsmodels.tsa.stattools import acf, pacf
lag_Acf = acf(first_diff, nlags=120)
lag_Pacf = pacf(first_diff, nlags=75, method='ols')
plt.figure(figsize=(16,7))

# ACF Plot
plt.subplot(121)
plt.plot(lag_Acf, marker='o')
plt.axhline(y=0, linestyle='--', color='grey')
plt.axhline(y=-1.96/np.sqrt(len(first_diff)), linestyle='--', color='grey')
plt.axhline(y=1.96/np.sqrt(len(first_diff)), linestyle='--', color='grey')
plt.title("Autocorrelation Function")

# PACF Plot
plt.subplot(121)
plt.plot(lag_Pacf, marker='o')
plt.axhline(y=0, linestyle='--', color='grey')
plt.axhline(y=-1.96/np.sqrt(len(first_diff)), linestyle='--', color='grey')
plt.axhline(y=1.96/np.sqrt(len(first_diff)), linestyle='--', color='grey')
plt.title("Partial Autocorrelation Function")

plt.tight_layout()
```




# AR Model

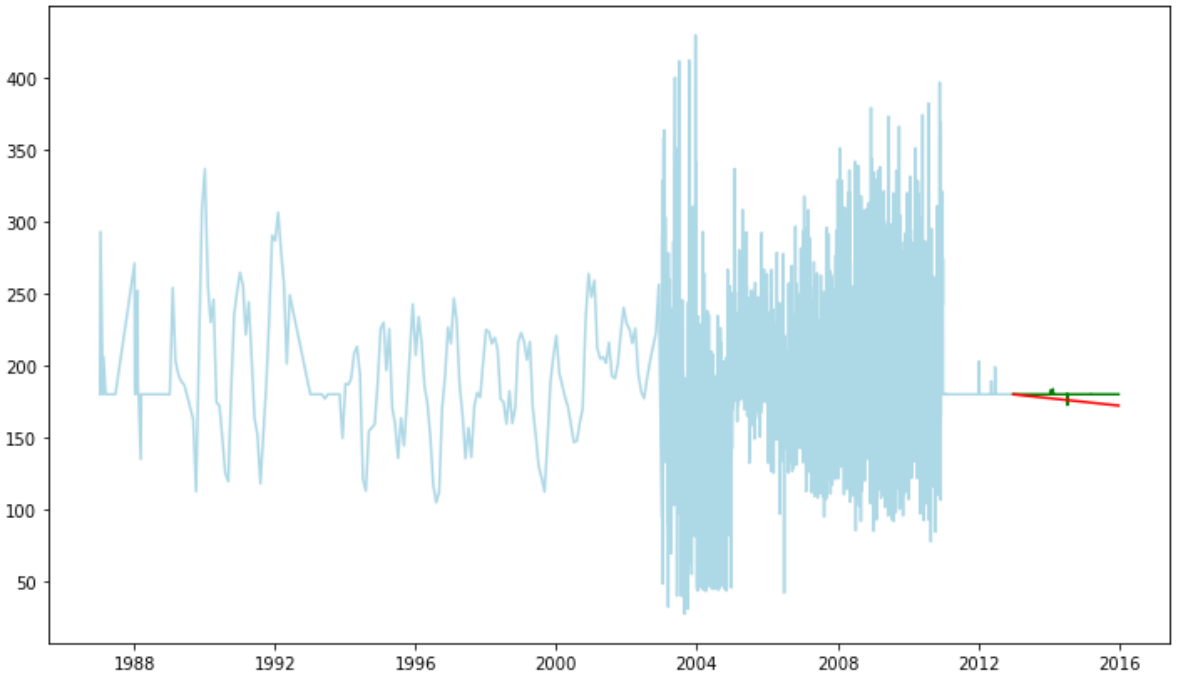
In [87]:
```
from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(log_train, order=(1,1,0))
result_arima = model.fit(disp=-1)
print(result_arima.summary())
```

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                   D.AQI   No. Observations:                 3590
Model:                 ARIMA(1, 1, 0)   Log Likelihood                -599.077
Method:                       css-mle   S.D. of innovations              0.286
Date:                Sat, 19 Nov 2022   AIC                           1204.154
Time:                        18:00:02   BIC                           1222.712
Sample:                             1   HQIC                          1210.768

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       -4.025e-05      0.003     -0.012      0.990      -0.007       0.007
ar.L1.D.AQI    -0.4240      0.015    -28.049      0.000      -0.454      -0.394
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -2.3583           +0.0000j            2.3583            0.5000
-----------------------------------------------------------------------------
```

In [77]:

```
plt.figure(figsize=(12,7))
plt.plot(x_train.index, x_train.values, color='lightblue')
plt.plot(x_test.index, x_test.values, color='green')

# For checking forecast
pred = pd.DataFrame(result_arima.forecast(len(x_test))[0])
pred.columns = ['yhat']
pred.index = x_test.index

# Converting from log to norm
pred['yhat'] = pred['yhat'].apply(lambda x : math.exp(x)-1)

measure = math.pow(mean_squared_error(x_test.values, pred.values), 0.5)
print(measure)
plt.plot(pred.index, pred.fillna(0).values, color='red')
plt.show()
```

```
4.5432006310227715
```




# MA Model

In [85]:

```
from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(log_train, order=(0,1,1))
result_ma = model.fit(disp=-1)
print(result_ma.summary())
```

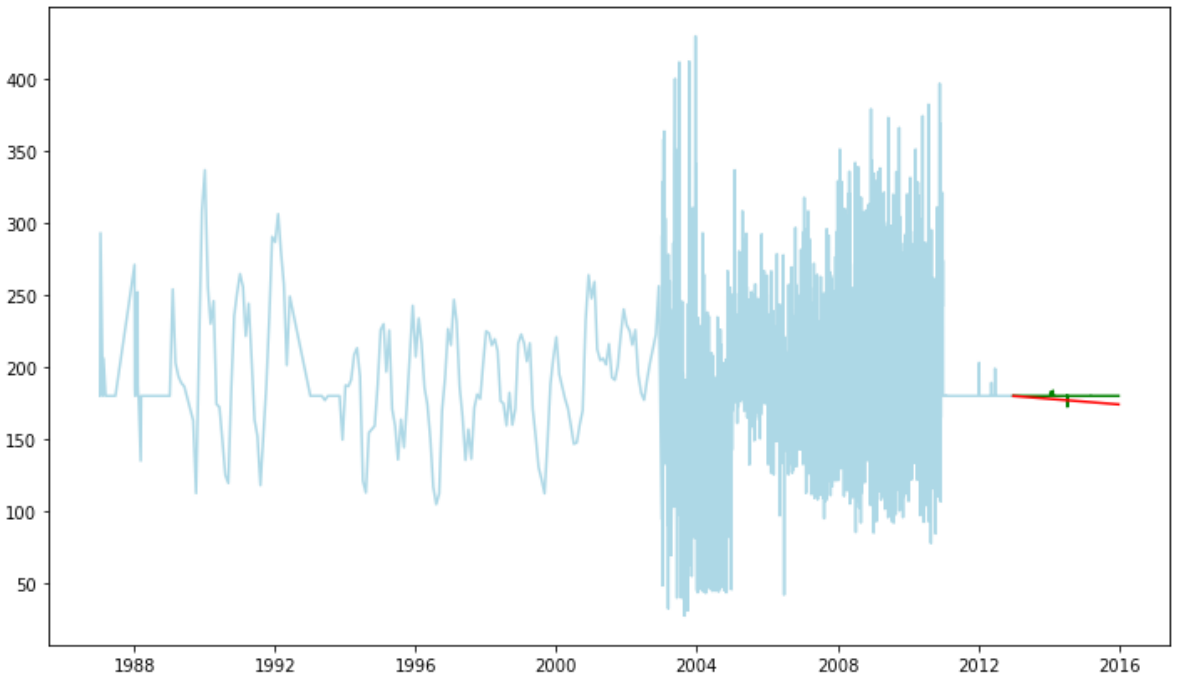
```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                  D.AQI   No. Observations:                 3590
Model:                 ARIMA(0, 1, 1)   Log Likelihood                -350.959
Method:                       css-mle   S.D. of innovations              0.267
Date:                Sat, 19 Nov 2022   AIC                            707.918
Time:                        17:59:53   BIC                            726.475
Sample:                             1   HQIC                           714.532

==============================================================================
```

```
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const       -3.003e-05      0.001     -0.041      0.967      -0.001       0.001
ma.L1.D.AQI    -0.8348      0.018    -45.578      0.000      -0.871      -0.799
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1            1.1979           +0.0000j            1.1979            0.0000
```

In [86]:

```
plt.figure(figsize=(12,7))
plt.plot(x_train.index, x_train.values, color='lightblue')
plt.plot(x_test.index, x_test.values, color='green')

# For checking forecast
pred = pd.DataFrame(result_ma.forecast(len(x_test))[0])
pred.columns = ['yhat']
pred.index = x_test.index

# Converting from log to norm
pred['yhat'] = pred['yhat'].apply(lambda x : math.exp(x)-1)

measure = math.pow(mean_squared_error(x_test.values, pred.values), 0.5)
print(measure)
plt.plot(pred.index, pred.fillna(0).values, color='red')
plt.show()
```

```
3.431366850928005
```




# ARIMA Model

In [83]:

```
from statsmodels.tsa.arima_model import ARIMA
model = ARIMA(log_train, order=(1,1,1))
result_arima = model.fit(disp=-1)
```

In [84]:

```
plt.figure(figsize=(12,7))
plt.plot(x_train.index, x_train.values, color='lightblue')
plt.plot(x_test.index, x_test.values, color='green')

# For checking forecast
pred = pd.DataFrame(result_arima.forecast(len(x_test))[0])
pred.columns = ['yhat']
pred.index = x_test.index

# Converting from log to norm
pred['yhat'] = pred['yhat'].apply(lambda x : math.exp(x)-1)

measure = math.pow(mean_squared_error(x_test.values, pred.values), 0.5)
print(measure)
plt.plot(pred.index, pred.fillna(0).values, color='red')
plt.show()
```

```
2.828188771834781
```