In [1]:
```python
# import pandas
import pandas as pd
# import numpy
import numpy as np
# import matplotlib
from matplotlib import pyplot as plt
from statsmodels.graphics.api import qqplot
import scipy.stats as stats
```

1

1.1

In [2]:
```python
Sig_Eqs=pd.read_csv("earthquakes-2023-11-01_21-47-02_+0800.tsv",sep = "\t")
```

print the top ten countries along with the total number of deaths

In [3]:
```
Sig_Eqs_1=Sig_Eqs[["Country","Deaths"]]
Sig_Eqs_1_sum=Sig_Eqs_1.groupby(['Country']).sum().sort_values("Deaths", ascending=False)
Sig_Eqs_1_sum.iloc[0:10]
```

Out[3]:

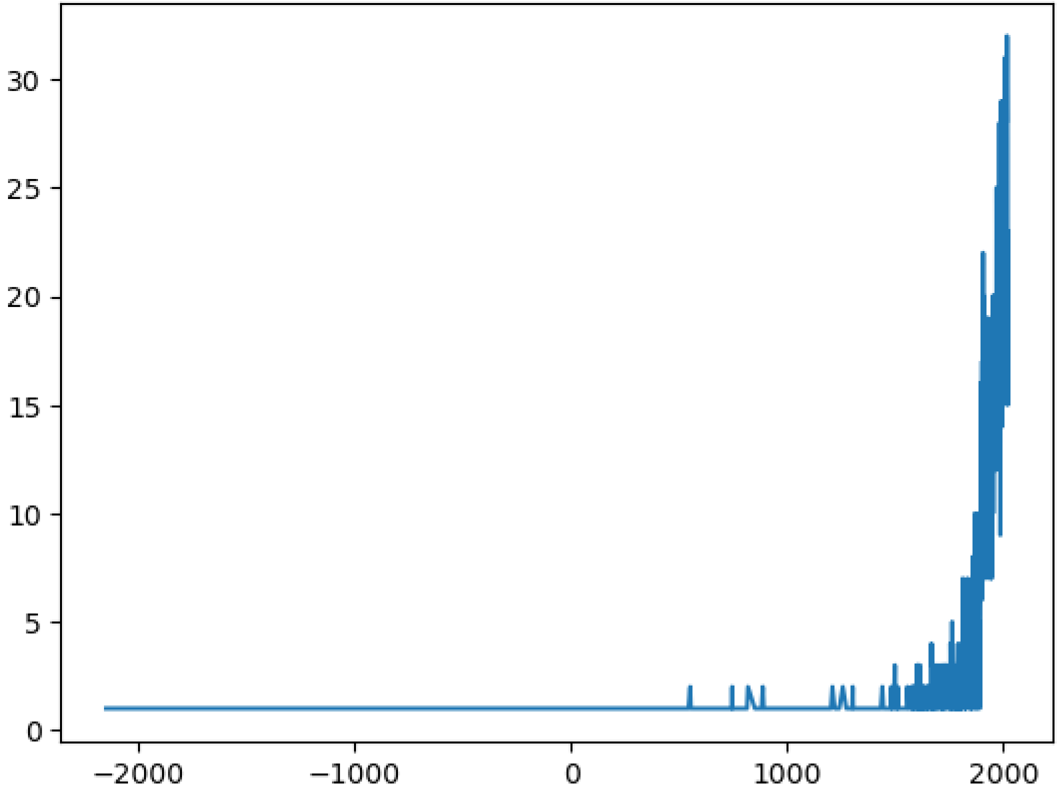
	Deaths
Country	
CHINA	2075045.0
TURKEY	1188881.0
IRAN	1011449.0
ITALY	498478.0
SYRIA	439224.0
HAITI	323478.0
AZERBAIJAN	317219.0
JAPAN	279085.0
ARMENIA	191890.0
PAKISTAN	145083.0

1.2

plot total number of earthquakes with magnitude larger than 6.0

In [4]:
```
Sig_Eqs_2=Sig_Eqs[["Year","Mag"]]
Sig_Eqs_2_new=Sig_Eqs_2.loc[Sig_Eqs_2["Mag"]>6.0]
Sig_Eqs_2_sum=Sig_Eqs_2_new.groupby(['Year']).count()
plt.plot(Sig_Eqs_2_sum)
```

Out[4]:
```
[<matplotlib.lines.Line2D at 0x13ee62269b0>]
```



Having an increasing trend. This may be due to the increase in historical records and the improvement of observational methods

1.3

In [5]:
```
Sig_Eqs=Sig_Eqs.dropna(subset="Country")
```

In [6]:
```
def CountEq_LargestEq(country, Sig_Eqs):
    Sig_Eqs_new=Sig_Eqs[["Year","Mo","Dy","Country","Mag"]]
    Sig_Eqs_count=Sig_Eqs_new.groupby(['Country']).count()['Year']
    Sig_Eqs_count=Sig_Eqs_count.rename('Count')
    Sig_Eqs_max=Sig_Eqs_new.groupby(['Country']).max()['Mag']
    Date=Sig_Eqs_new.loc[(Sig_Eqs_new['Country']==country) & (Sig_Eqs_new['Mag']==Sig_Eqs_max.loc[country])]
    Data=pd.merge(Date,Sig_Eqs_count,on=['Country'])
    return Data
```

show country which only have one largest earthquake

In [7]:
```
Data=CountEq_LargestEq("CHINA", Sig_Eqs)
Data
```

Out[7]:

	Year	Mo	Dy	Country	Mag	Count
0	1668.0	7.0	25.0	CHINA	8.5	620

show country which have more than one largest earthquakes

In [8]:
```
Data=CountEq_LargestEq("GREECE", Sig_Eqs)
Data
```

Out[8]:

	Year	Mo	Dy	Country	Mag	Count
0	365.0	7.0	21.0	GREECE	8.0	270
1	1303.0	8.0	8.0	GREECE	8.0	270

show all country with its' largest earthquakes

In [9]:
```
Sig_Eqs_3=Sig_Eqs['Country']
Sig_Eqs_3=Sig_Eqs_3.drop_duplicates()
Sig_Eqs_3.reset_index(drop=True, inplace=True)
Data=CountEq_LargestEq(Sig_Eqs_3[0], Sig_Eqs)
for i in range(1,Sig_Eqs_3.size):
    Data_new=CountEq_LargestEq(Sig_Eqs_3[i], Sig_Eqs)
    Data=pd.concat([Data,Data_new])
Data=Data.sort_values("Count", ascending=False)
Data.reset_index(drop=True, inplace=True)
Data
```

Out[9]:

	Year	Mo	Dy	Country	Mag	Count
0	1668.0	7.0	25.0	CHINA	8.5	620
1	2011.0	3.0	11.0	JAPAN	9.1	414
2	2004.0	12.0	26.0	INDONESIA	9.1	411
3	856.0	12.0	22.0	IRAN	7.9	384
4	2023.0	2.0	6.0	TURKEY	7.8	335
...	...	...	...	...	...	...
164	1921.0	9.0	16.0	CENTRAL AFRICAN REPUBLIC	4.8	1
165	1819.0	8.0	31.0	NORWAY	5.8	1
166	1914.0	10.0	23.0	PALAU	7.6	1
167	1848.0	7.0	12.0	FRENCH POLYNESIA	6.5	1
168	2018.0	5.0	15.0	COMOROS	5.9	1

169 rows × 6 columns

2

load 2281305.csv， only save DATE and WND, And seperate WND by ',' as direction, direction_code, type, speed, speed_code

In [10]:
```
wind=pd.read_csv('2281305.csv')
wind=wind[['DATE','WND']]
wind[['direction','direction_code','type','speed','speed_code']]=wind.WND.str.split(',',expand=True)
wind.drop(columns = 'WND',inplace=True)
wind['speed']=wind['speed'].astype(float)
wind
```

```
C:\Users\26576\AppData\Local\Temp\ipykernel_30544\590818858.py:1: DtypeWarning: Columns (4,8,9,12,15,21,22,24,26,31,33,34) have m
ixed types. Specify dtype option on import or set low_memory=False.
  wind=pd.read_csv('2281305.csv')
```

Out[10]:

	DATE	direction	direction_code	type	speed	speed_code
0	2010-01-02T00:00:00	040	1	N	20.0	1
1	2010-01-02T01:00:00	999	9	V	10.0	1
2	2010-01-02T02:00:00	999	9	C	0.0	1
3	2010-01-02T03:00:00	140	1	N	10.0	1
4	2010-01-02T04:00:00	300	1	N	40.0	1
...	...	...	...	...	...	...
111979	2020-09-11T17:00:00	170	1	N	30.0	1
111980	2020-09-11T18:00:00	180	1	N	40.0	1
111981	2020-09-11T19:00:00	220	1	V	30.0	1
111982	2020-09-11T20:00:00	260	1	N	30.0	1
111983	2020-09-11T21:00:00	310	1	V	20.0	1

111984 rows × 6 columns

delete the line if speed = 9999, and only these need to be deleted

In [11]:

```
wind=wind.loc[wind['speed']!=9999]
wind
```

Out[11]:

	DATE	direction	direction_code	type	speed	speed_code
0	2010-01-02T00:00:00	040	1	N	20.0	1
1	2010-01-02T01:00:00	999	9	V	10.0	1
2	2010-01-02T02:00:00	999	9	C	0.0	1
3	2010-01-02T03:00:00	140	1	N	10.0	1
4	2010-01-02T04:00:00	300	1	N	40.0	1
...	...	...	...	...	...	...
111979	2020-09-11T17:00:00	170	1	N	30.0	1
111980	2020-09-11T18:00:00	180	1	N	40.0	1
111981	2020-09-11T19:00:00	220	1	V	30.0	1
111982	2020-09-11T20:00:00	260	1	N	30.0	1
111983	2020-09-11T21:00:00	310	1	V	20.0	1

111346 rows × 6 columns

let year and month be a new line

In [12]:

```
wind['DATE']=pd.to_datetime(wind['DATE'])
wind['YYYY-MM']=wind['DATE'].dt.to_period('M')
wind.set_index('DATE',drop=True, inplace=True)
wind
```

```
C:\Users\26576\AppData\Local\Temp\ipykernel_30544\2778574480.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  wind['DATE']=pd.to_datetime(wind['DATE'])
C:\Users\26576\AppData\Local\Temp\ipykernel_30544\2778574480.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)
  wind['YYYY-MM']=wind['DATE'].dt.to_period('M')
```

Out[12]:

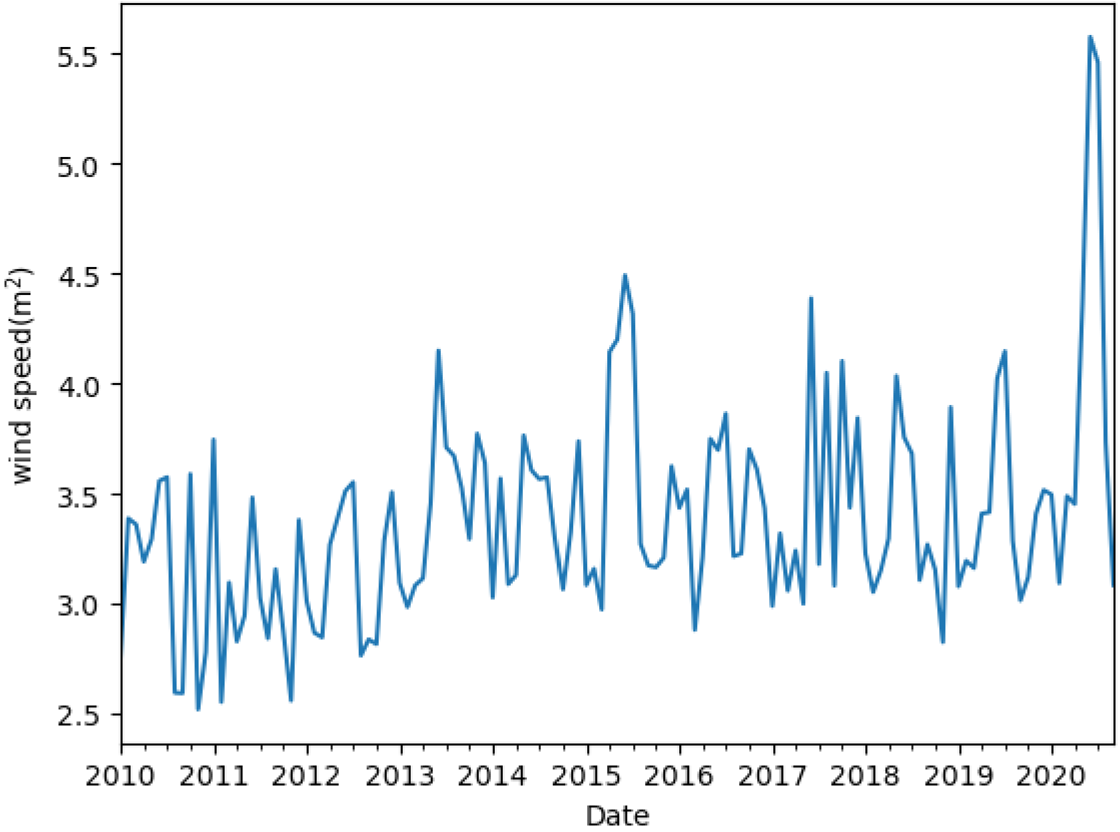
	direction	direction_code	type	speed	speed_code	YYYY-MM
DATE						
2010-01-02 00:00:00	040	1	N	20.0	1	2010-01
2010-01-02 01:00:00	999	9	V	10.0	1	2010-01
2010-01-02 02:00:00	999	9	C	0.0	1	2010-01
2010-01-02 03:00:00	140	1	N	10.0	1	2010-01
2010-01-02 04:00:00	300	1	N	40.0	1	2010-01
...	...	...	...	...	...	...
2020-09-11 17:00:00	170	1	N	30.0	1	2020-09
2020-09-11 18:00:00	180	1	N	40.0	1	2020-09
2020-09-11 19:00:00	220	1	V	30.0	1	2020-09
2020-09-11 20:00:00	260	1	N	30.0	1	2020-09
2020-09-11 21:00:00	310	1	V	20.0	1	2020-09

111346 rows × 6 columns

calculate monthly averaged wind speed and plot

In [13]:
```
wind_mon=wind[['YYYY-MM','speed']].groupby(['YYYY-MM']).mean()/10
wind_mon['speed'].plot()
plt.xlabel('Date')
plt.ylabel('wind speed(m$^2$)')
```

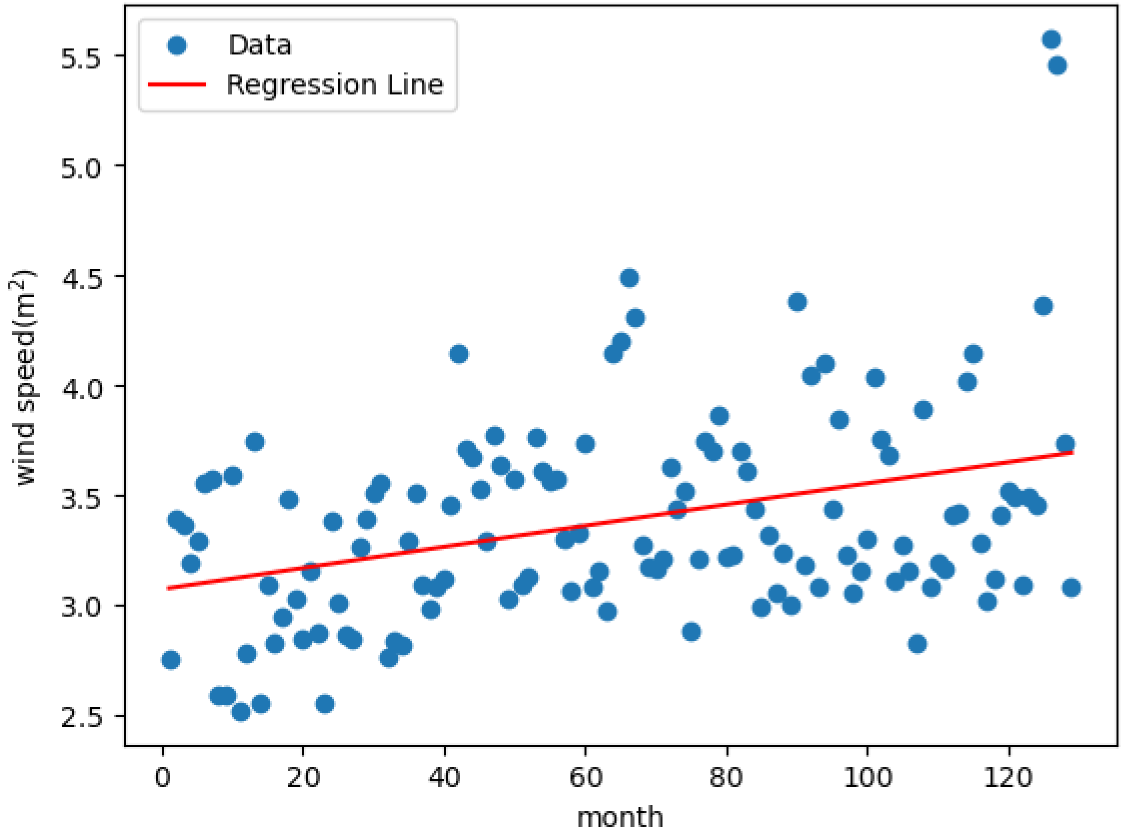
Out[13]:
```
Text(0, 0.5, 'wind speed(m$^2$)')
```



because we only do one-variable linear regression, we don't need to check whether the values satisfy normal distribution,

do linear regression and plot

In [14]:
```
y=wind_mon['speed'].to_numpy()
x=np.linspace(1,y.size,y.size)
slope, intercept, r_value, p_value, std_err = stats.linregress(x, y)
plt.scatter(x, y, label='Data')
plt.plot(x, intercept + slope * x, color='red', label='Regression Line')
plt.xlabel('month')
plt.ylabel('wind speed(m$^2$)')
plt.legend()
plt.show()
```



print linear regrassion parameters

In [15]:
```
print(f"Slope (斜率): {slope}")
print(f"Intercept (截距): {intercept}")
print(f"R-squared (相关系数的平方): {r_value**2}")
print(f"P-value (p-值): {p_value}")
```

```
Slope (斜率): 0.00481813862880326
Intercept (截距): 3.071759331411062
R-squared (相关系数的平方): 0.13543029389763156
P-value (p-值): 1.7814607055107157e-05
```

Because P-value < 0.05, we can refuse H0, so we can trust there is a linear relationship between the independent variable and the dependent variable, and the slope is not equal to zero. And the slope equals 0.0048, so there has a increasing trend.

3

3.1

the data is nitrite plus nitrate in station 01389005 from USGS

In [16]:
```
NOx=pd.read_csv('01389005.csv')
NOx
```

Out[16]:

	Unnamed: 0	agency_cd	site_no	Date	X_.from.right.intake_99133_00003	X_.from.right.intake_99133_00003_cd	X_.from.left.intake_99133_00003
0	1	USGS	1389005	2009-07-30	1.76	A	1.08
1	2	USGS	1389005	2009-07-31	1.41	A	0.99
2	3	USGS	1389005	2009-08-01	1.34	A	0.93
3	4	USGS	1389005	2009-08-02	1.05	A	0.90
4	5	USGS	1389005	2009-08-03	0.88	A	0.80
...	...	...	...	...	...	...	...
4778	4779	USGS	1389005	2023-10-06	0.64	P	1.12
4779	4780	USGS	1389005	2023-10-07	0.77	P	1.07
4780	4781	USGS	1389005	2023-10-08	0.98	P	1.00
4781	4782	USGS	1389005	2023-10-09	0.98	P	0.96
4782	4783	USGS	1389005	2023-10-10	0.97	P	0.97

4783 rows × 8 columns

remove error value or less quality value and rename

In [17]:
```
NOx=NOx.dropna(subset=["X_.from.right.intake_99133_00003","X_.from.left.intake_99133_00003"])
NOx=NOx.loc[NOx["X_.from.right.intake_99133_00003"]!= -999999]
NOx=NOx.loc[NOx["X_.from.left.intake_99133_00003"]!= -999999]
NOx=NOx.loc[NOx["X_.from.right.intake_99133_00003_cd"] != "A <"]
NOx=NOx.loc[NOx["X_.from.left.intake_99133_00003_cd"] != "A <"]
NOx.rename(columns={"X_.from.right.intake_99133_00003": "rightintake"}, inplace=True)
NOx.rename(columns={"X_.from.left.intake_99133_00003": "leftintake"}, inplace=True)
NOx.rename(columns={"X_.from.right.intake_99133_00003_cd": "rightintake_cd"}, inplace=True)
NOx.rename(columns={"X_.from.left.intake_99133_00003_cd": "leftintake_cd"}, inplace=True)
NOx
```

Out[17]:

	Unnamed: 0	agency_cd	site_no	Date	rightintake	rightintake_cd	leftintake	leftintake_cd
0	1	USGS	1389005	2009-07-30	1.76	A	1.08	A
1	2	USGS	1389005	2009-07-31	1.41	A	0.99	A
2	3	USGS	1389005	2009-08-01	1.34	A	0.93	A
3	4	USGS	1389005	2009-08-02	1.05	A	0.90	A
4	5	USGS	1389005	2009-08-03	0.88	A	0.80	A
...	...	...	...	...	...	...	...	...
4778	4779	USGS	1389005	2023-10-06	0.64	P	1.12	P
4779	4780	USGS	1389005	2023-10-07	0.77	P	1.07	P
4780	4781	USGS	1389005	2023-10-08	0.98	P	1.00	P
4781	4782	USGS	1389005	2023-10-09	0.98	P	0.96	P
4782	4783	USGS	1389005	2023-10-10	0.97	P	0.97	P

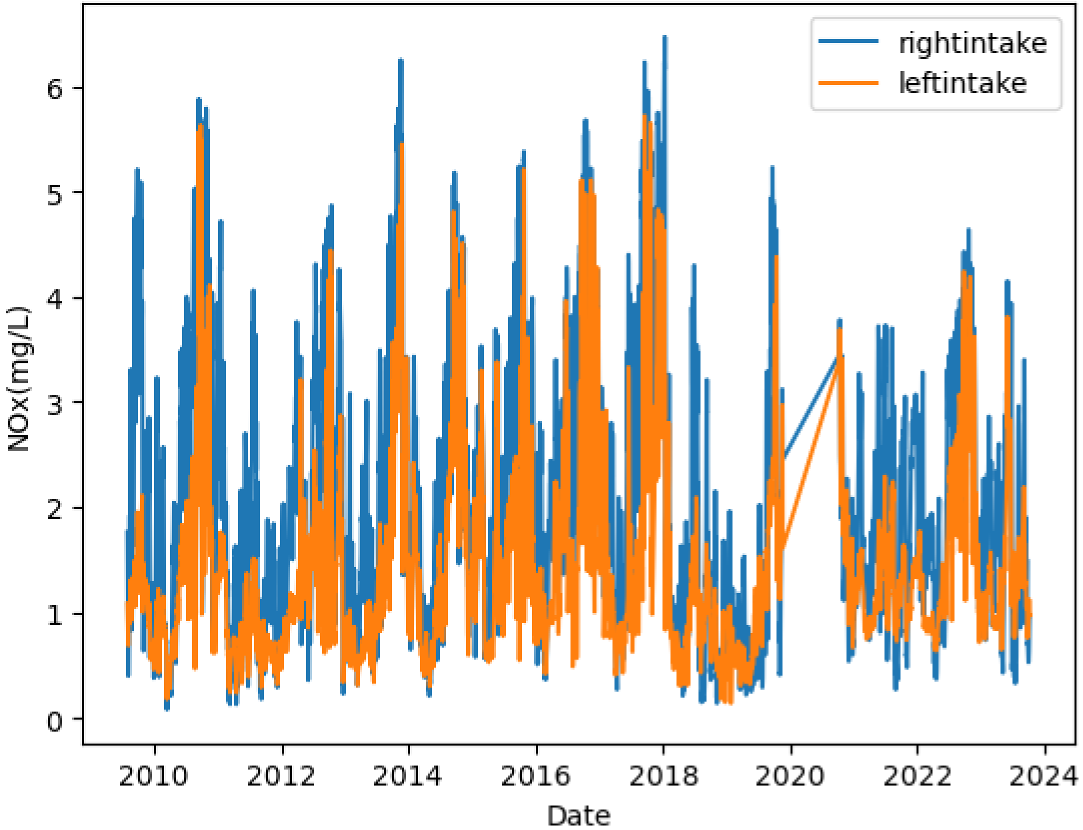
4698 rows × 8 columns

3.2

plot rightintake and leftintake

In [18]:
```
NOx['Date']=pd.to_datetime(NOx['Date'])
plt.plot(NOx['Date'],NOx['rightintake'])
plt.plot(NOx['Date'],NOx['leftintake'])
plt.xlabel('Date')
plt.ylabel('NOx(mg/L)')
plt.legend(['rightintake','leftintake'])
```

Out[18]: <matplotlib.legend.Legend at 0x13eed9ad480>



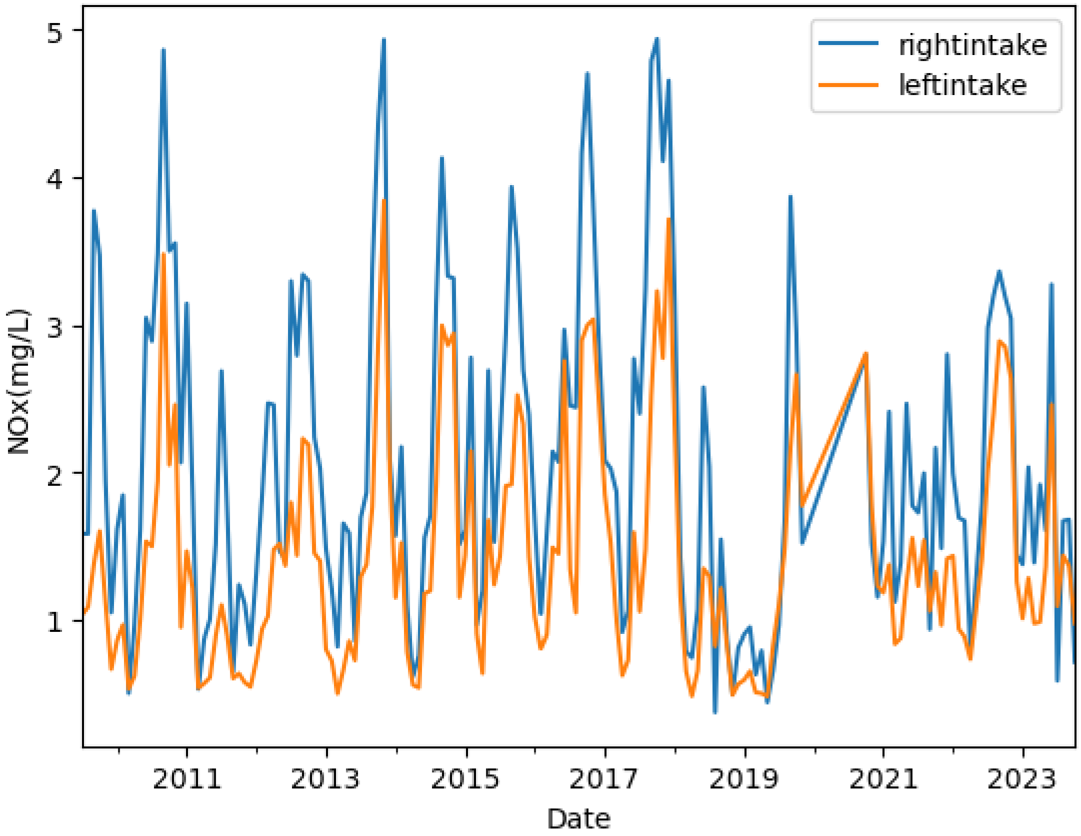
the abnormal between 2020 to 2021 because the value are lacked

3.3

calculate monthly averaged concentration of NOx and plot

In [19]:
```
NOx['YYYY-MM']=NOx['Date'].dt.to_period('M')
NOx_mon=NOx[['YYYY-MM','rightintake','leftintake']].groupby(['YYYY-MM']).mean()
NOx_mon.plot()
plt.xlabel('Date')
plt.ylabel('NOx(mg/L)')
plt.legend(['rightintake','leftintake'])
```

Out[19]: <matplotlib.legend.Legend at 0x13eed9af4f0>



we can see the concentration form right intake are always larger than left intake. And the data change seasonally.

show some simple statistics

In [20]:
```
NOx[['rightintake','leftintake']].describe()
```

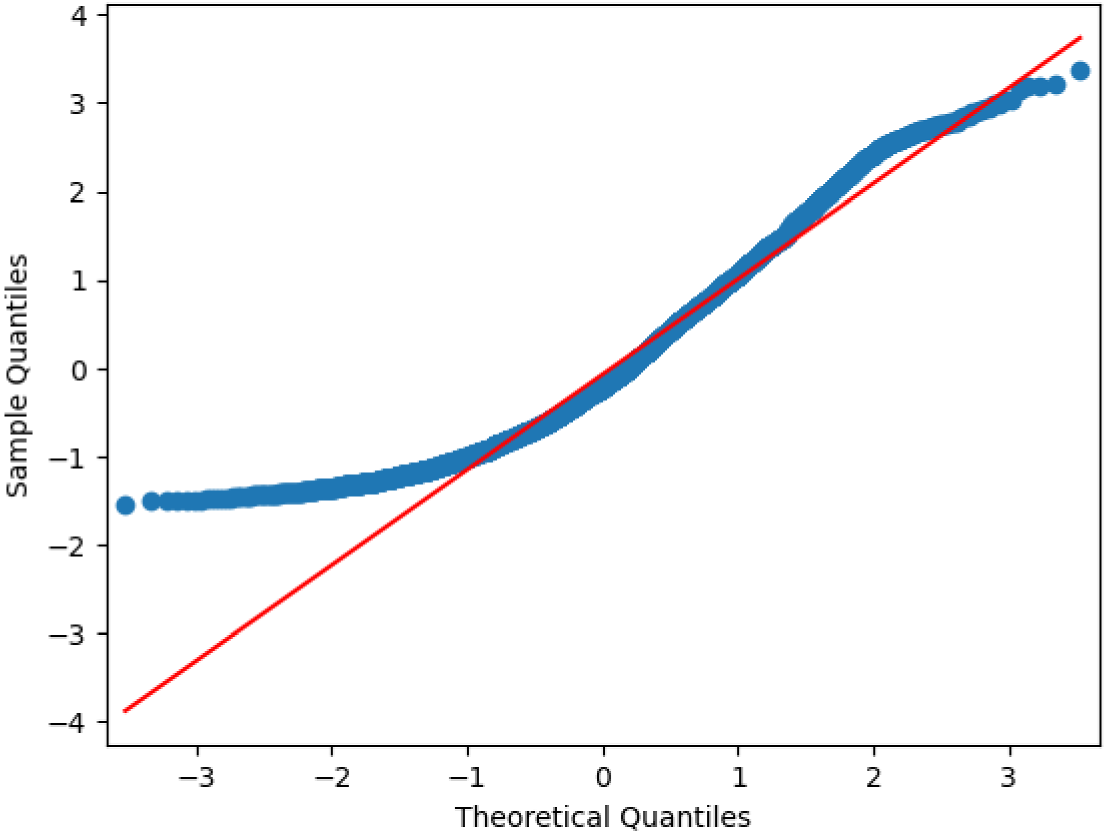
Out[20]:

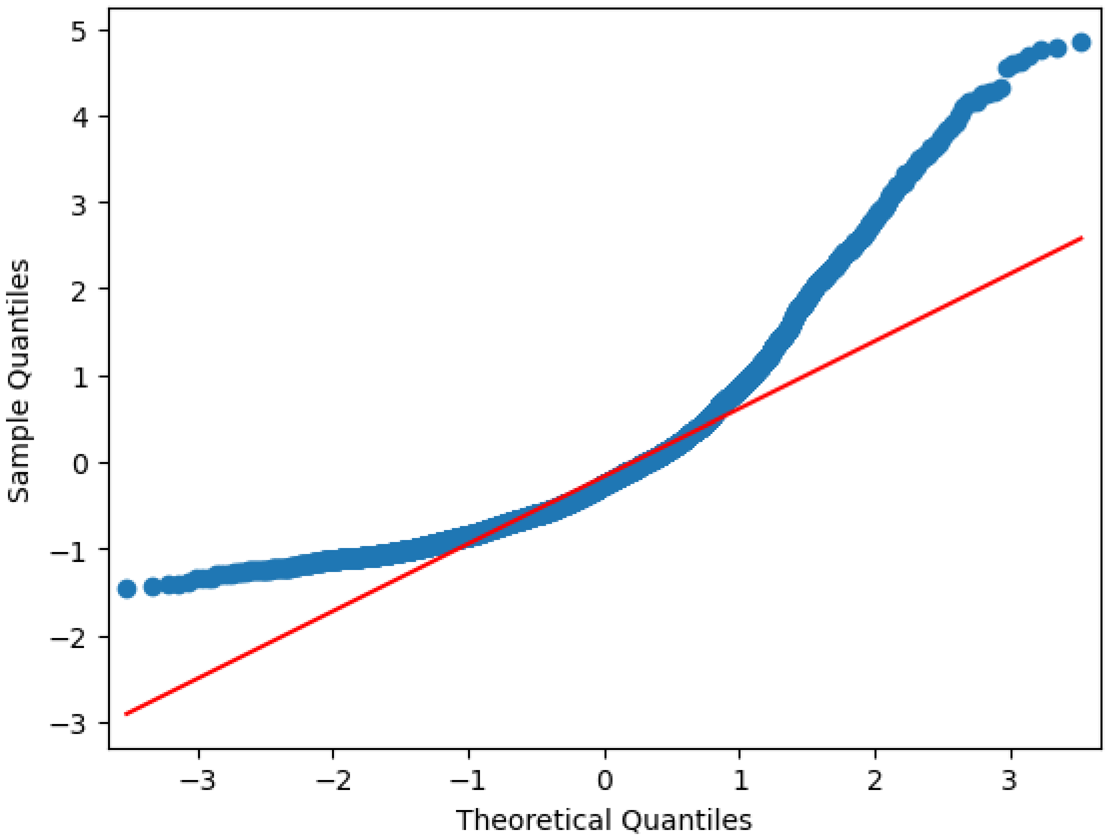
	rightintake	leftintake
count	4698.000000	4698.00000
mean	2.084985	1.42262
std	1.297827	0.88544
min	0.080000	0.14000
25%	1.050000	0.81000
50%	1.810000	1.19000
75%	2.940000	1.74000
max	6.470000	5.72000

The mean concentration and standard deviation of NOx at right intake is larger than left intake.

plot qqplot for concentration of NOx at right and left intake

In [21]:
```
fig = plt.figure()
ax = fig.add_subplot(111)
fig = qqplot(NOx['rightintake'], line="q", ax=ax, fit=True)
plt.show()
fig = plt.figure()
ax = fig.add_subplot(111)
fig = qqplot(NOx['leftintake'], line="q", ax=ax, fit=True)
plt.show()
```



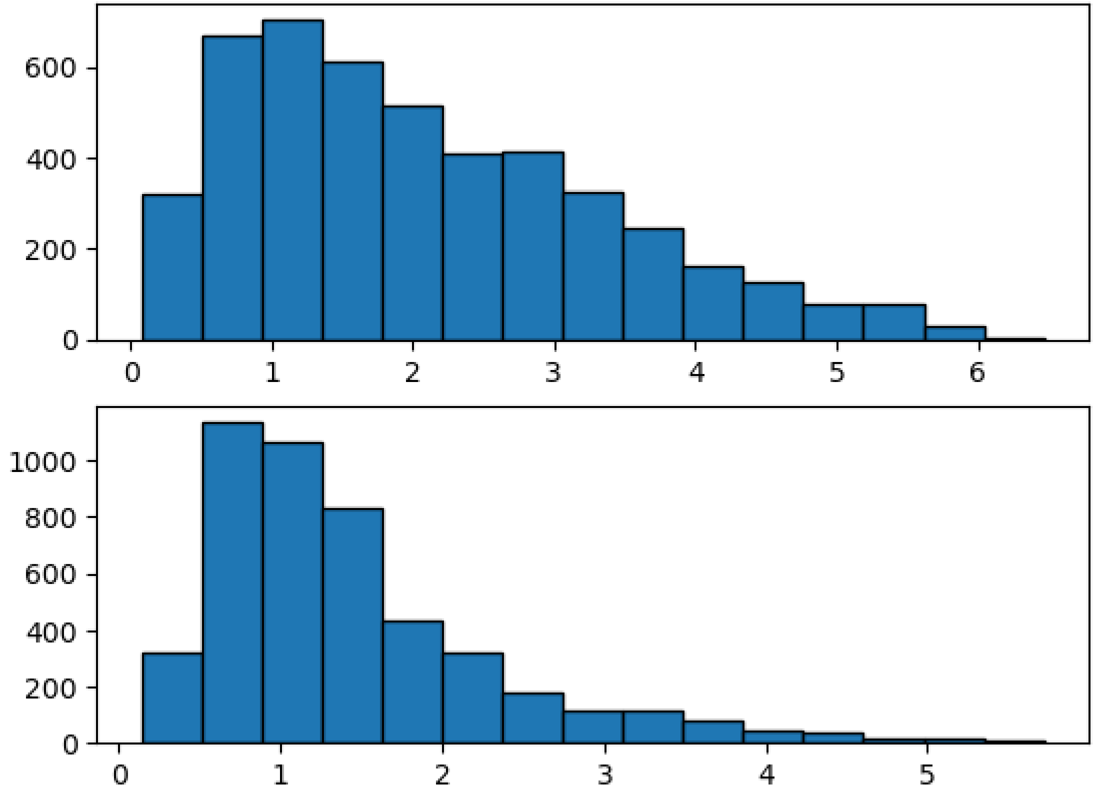


Both concentration of NOx at right and left intake are not satisfy normal distribution

plot concentration of NOx distribution for right and left intake

In [22]:
```
plt.subplot(211)
plt.hist(NOx["rightintake"], bins=15, edgecolor='black')
plt.subplot(212)
plt.hist(NOx["leftintake"], bins=15, edgecolor='black')
```

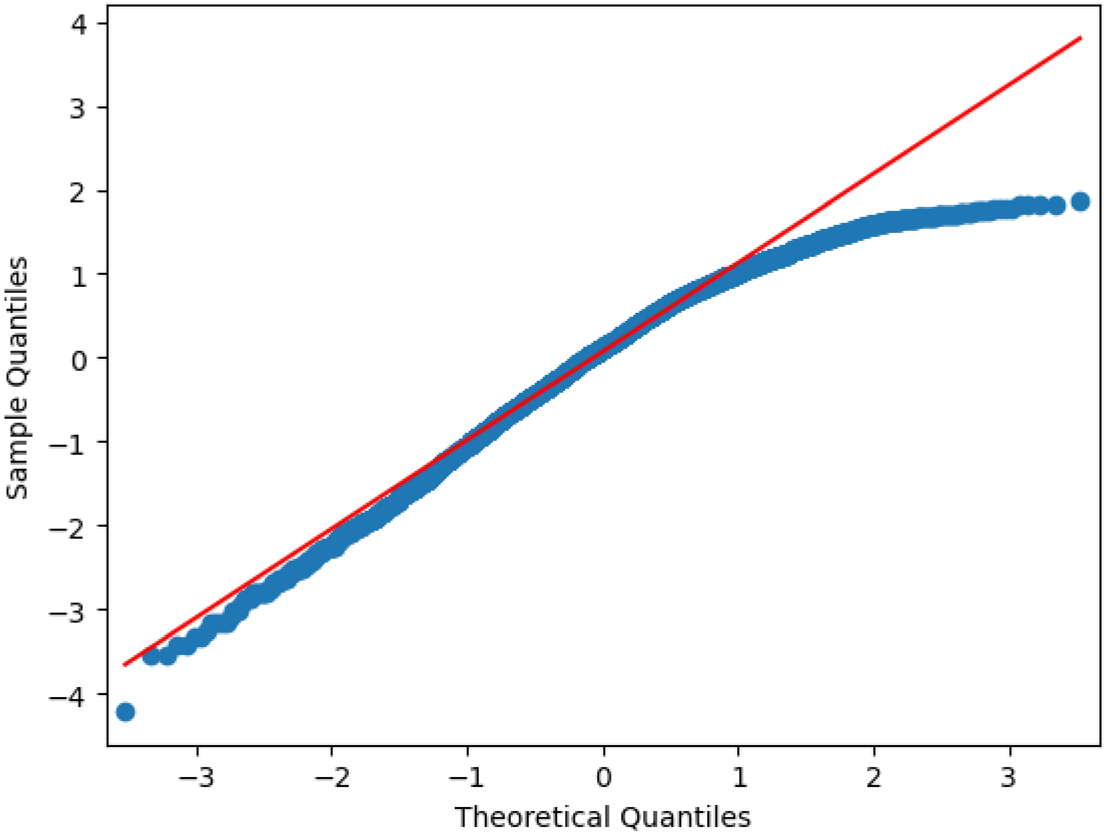
Out[22]:
```
(array([ 319., 1133., 1062.,  831.,  432.,  318.,  180.,  117.,  114.,
          77.,   43.,   34.,   18.,   13.,    7.]),
 array([0.14 , 0.512, 0.884, 1.256, 1.628, 2.   , 2.372, 2.744, 3.116,
        3.488, 3.86 , 4.232, 4.604, 4.976, 5.348, 5.72 ]),
 <BarContainer object of 15 artists>)
```

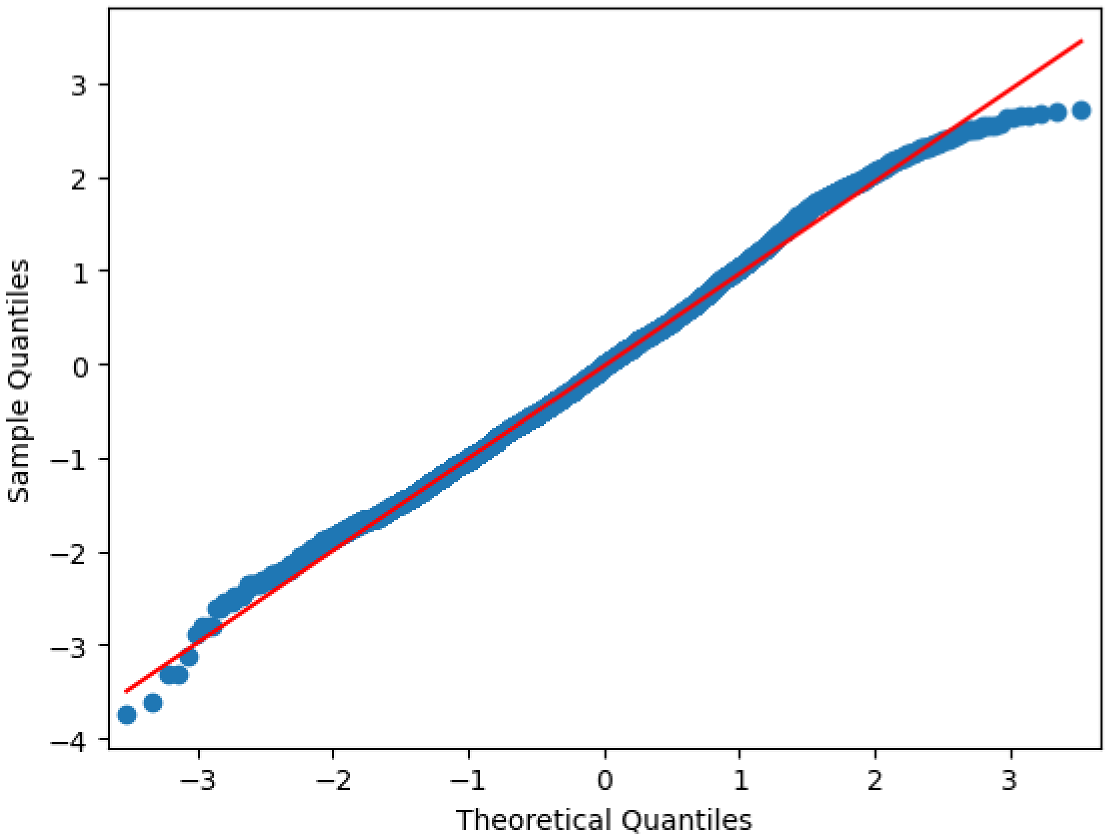


the concentration of NOx at right intake is positive skewness, the concentration of NOx at left intake is also positive skewness

plot qqplot for log concentration of NOx at right and left intake

In [23]:
```
fig = plt.figure()
ax = fig.add_subplot(111)
fig = qqplot(np.log(NOx['rightintake']), line="q", ax=ax, fit=True)
plt.show()
fig = plt.figure()
ax = fig.add_subplot(111)
fig = qqplot(np.log(NOx['leftintake']), line="q", ax=ax, fit=True)
plt.show()
```



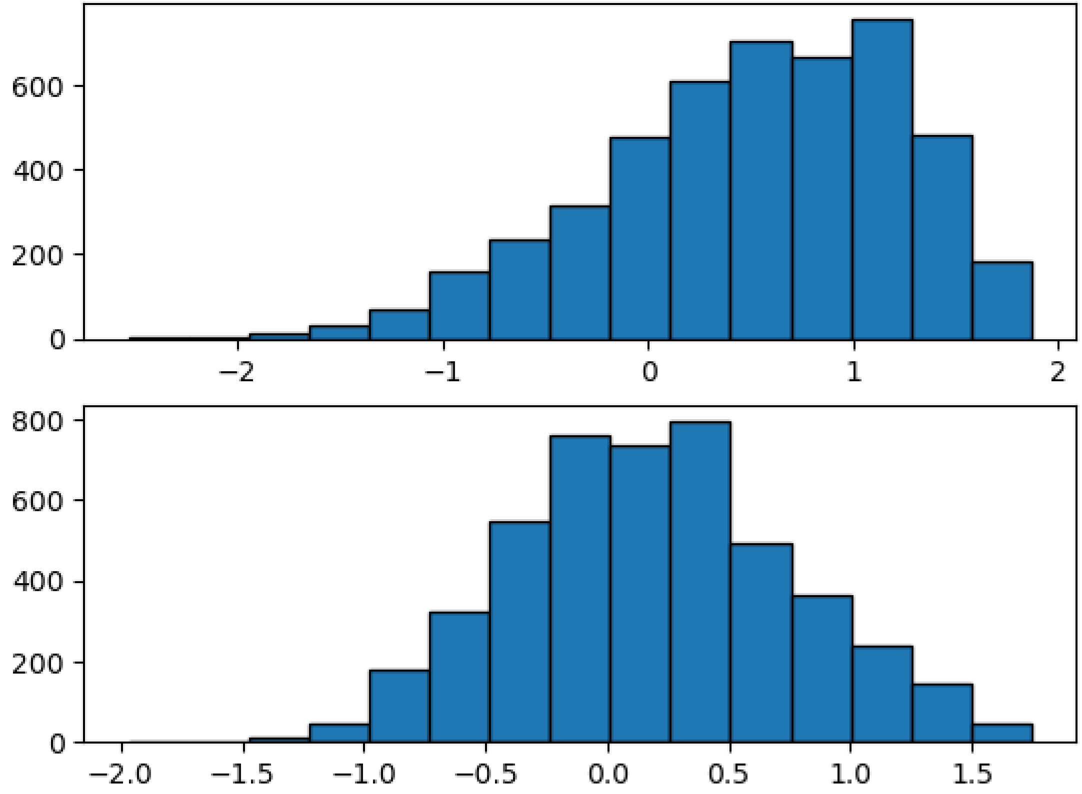


the log concentration of NOx at right intake is not normal, but at left intake is closer to normal

plot log concentration of NOx distribution for right and left intake

In [24]:
```
plt.subplot(211)
plt.hist(np.log(NOx["rightintake"]), bins=15, edgecolor='black')
plt.subplot(212)
plt.hist(np.log(NOx["leftintake"]), bins=15, edgecolor='black')
```

Out[24]:
```
(array([  2.,   3.,  13.,  48., 182., 325., 549., 760., 737., 793., 492.,
        363., 239., 144.,  48.]),
 array([-1.96611286, -1.71877408, -1.4714353 , -1.22409652, -0.97675775,
        -0.72941897, -0.48208019, -0.23474141,  0.01259736,  0.25993614,
         0.50727492,  0.7546137 ,  1.00195247,  1.24929125,  1.49663003,
         1.74396881]),
 <BarContainer object of 15 artists>)
```



the log concentration of NOx at right intake not normal, but at left intake is closer to normal calculate pearson correlation index

In [25]:
```
NOx[['rightintake','leftintake']].corr(method="pearson")
```

Out[25]:

	rightintake	leftintake
rightintake	1.000000	0.796005
leftintake	0.796005	1.000000

The correlation index is 0.796, meaning the two groups data have strong correlation. This is easy to understand because the two group data getted nearly in same station.

In [ ]: