Importing Libraries

In [2]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
from matplotlib import rcParams
import warnings
```

In [3]:

```
warnings.filterwarnings(action='ignore')
warnings.warn('this is a warning!')
```

Reading the Dataset

In [4]:

```
data = pd.read_csv(r'C:\Users\Cloud\Desktop\water quality
analysis\Data\water_dataX.csv',encoding='ISO-8859-1',low_memory=False)
```

Analysing the Data

In [5]:

```
data.head()
```

Out[5]:

	STATION CODE	LOCATIONS	STATE	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean	year
0	1393	DAMAN GANGA AT D/S OF MADHUBAN, DAMAN	DAMAN & DIU	30.6	6.7	7.5	203	NAN	0.1	11	27	2014
1	1399	ZUARI AT D/S OF PT. WHERE KUMBARJRIA CANAL JOI...	GOA	29.8	5.7	7.2	189	2	0.2	4953	8391	2014
2	1475	ZUARI AT PANCHAWADI	GOA	29.5	6.3	6.9	179	1.7	0.1	3243	5330	2014
3	3181	RIVER ZUARI AT	GOA	29.7	5.8	6.9	64	3.8	0.5	5382	8443	2014

	STATION CODE	LOCATIONS	STATE	Temp	D.O. (mg/l)	PH	CONDUCTIVITY (µmhos/cm)	B.O.D. (mg/l)	NITRATENAN N+ NITRITENANN (mg/l)	FECAL COLIFORM (MPN/100ml)	TOTAL COLIFORM (MPN/100ml)Mean	year
4	3182	BORIM BRIDGE RIVER ZUARI AT MARCAIM JETTY	GOA	29.5	5.8	7.3	83	1.9	0.4	3428	5500	2014

```
data.describe()
```

Out[6]:

	year
count	1991.000000
mean	2010.038172
std	3.057333
min	2003.000000
25%	2008.000000
50%	2011.000000
75%	2013.000000
max	2014.000000

In [7]:

```
data.info()
```

```
RangeIndex: 1991 entries, 0 to 1990
Data columns (total 12 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   STATION CODE                          1991 non-null   object
 1   LOCATIONS                             1991 non-null   object
 2   STATE                                 1991 non-null   object
 3   Temp                                  1991 non-null   object
 4   D.O. (mg/l)                           1991 non-null   object
```

```
 5   PH                                 1991 non-null   object
 6   CONDUCTIVITY (µmhos/cm)            1991 non-null   object
 7   B.O.D. (mg/l)                      1991 non-null   object
 8   NITRATENAN N+ NITRITENANN (mg/l)  1991 non-null   object
 9   FECAL COLIFORM (MPN/100ml)         1991 non-null   object
 10  TOTAL COLIFORM (MPN/100ml)Mean     1991 non-null   object
 11  year                               1991 non-null   int64
dtypes: int64(1), object(11)
memory usage: 186.8+ KB
data.shape
```

Out[8]:

```
(1991, 12)
```

Checking for missing values

In [9]:

```
data.isnull().any()
```

Out[9]:

```
STATION CODE                        False
LOCATIONS                           False
STATE                               False
Temp                                False
D.O. (mg/l)                         False
PH                                  False
CONDUCTIVITY (µmhos/cm)             False
B.O.D. (mg/l)                       False
NITRATENAN N+ NITRITENANN (mg/l)    False
FECAL COLIFORM (MPN/100ml)          False
TOTAL COLIFORM (MPN/100ml)Mean      False
year                                False
dtype: bool
```

In [10]:

```
data.isnull().sum()
```

Out[10]:

```
STATION CODE                        0
LOCATIONS                           0
STATE                               0
Temp                                0
D.O. (mg/l)                         0
PH                                  0
CONDUCTIVITY (µmhos/cm)             0
B.O.D. (mg/l)                       0
NITRATENAN N+ NITRITENANN (mg/l)    0
FECAL COLIFORM (MPN/100ml)          0
TOTAL COLIFORM (MPN/100ml)Mean      0
year                                0
dtype: int64
```

In [11]:

```
data.dtypes
```

```
STATION CODE                        object
LOCATIONS                           object
STATE                               object
Temp                                object
D.O. (mg/l)                         object
PH                                  object
CONDUCTIVITY (µmhos/cm)             object
```

```
B.O.D. (mg/l)                            object
NITRATENAN N+ NITRITENANN (mg/l)    object
FECAL COLIFORM (MPN/100ml)               object
TOTAL COLIFORM (MPN/100ml)Mean       object
year                                      int64
dtype: object
```

In [12]:

```
data['Temp']=pd.to_numeric(data['Temp'],errors='coerce')
data['D.O. (mg/l)']=pd.to_numeric(data['D.O. (mg/l)'],errors='coerce')
data['PH']=pd.to_numeric(data['PH'],errors='coerce')
data['B.O.D. (mg/l)']=pd.to_numeric(data['B.O.D. (mg/l)'],errors='coerce')
data['CONDUCTIVITY (µmhos/cm)']=pd.to_numeric(data['CONDUCTIVITY (µmhos/cm)'],errors='coerce')
data['NITRATENAN N+ NITRITENANN (mg/l)']=pd.to_numeric(data['NITRATENAN N+ NITRITENANN (mg/l)'],errors='coerce')
data['TOTAL COLIFORM (MPN/100ml)Mean']=pd.to_numeric(data['TOTAL COLIFORM (MPN/100ml)Mean'],errors='coerce')
data.dtypes
```

Out[12]:

```
STATION CODE                              object
LOCATIONS                                 object
STATE                                     object
Temp                                     float64
D.O. (mg/l)                              float64
PH                                       float64
CONDUCTIVITY (µmhos/cm)                  float64
B.O.D. (mg/l)                            float64
NITRATENAN N+ NITRITENANN (mg/l)    float64
FECAL COLIFORM (MPN/100ml)                object
TOTAL COLIFORM (MPN/100ml)Mean       float64
year                                       int64
dtype: object
data.isnull().sum()
```

Out[13]:

```
STATION CODE                            0
LOCATIONS                               0
STATE                                   0
Temp                                   92
D.O. (mg/l)                            31
PH                                      8
CONDUCTIVITY (µmhos/cm)                25
B.O.D. (mg/l)                          43
NITRATENAN N+ NITRITENANN (mg/l)    225
FECAL COLIFORM (MPN/100ml)              0
TOTAL COLIFORM (MPN/100ml)Mean       132
year                                    0
dtype: int64
```

Fill the Null Values

In [14]:

```
data['Temp'].fillna(data['Temp'].mean(),inplace=True)
data['D.O. (mg/l)'].fillna(data['D.O. (mg/l)'].mean(),inplace=True)
data['PH'].fillna(data['PH'].mean(),inplace=True)
data['CONDUCTIVITY (µmhos/cm)'].fillna(data['CONDUCTIVITY (µmhos/cm)'].mean(),inplace=True)
data['B.O.D. (mg/l)'].fillna(data['B.O.D. (mg/l)'].mean(),inplace=True)
```

```
data['NITRATENAN N+ NITRITENANN (mg/l)'].fillna(data['NITRATENAN N+
NITRITENANN (mg/l)'].mean(),inplace=True)
data['TOTAL COLIFORM (MPN/100ml)Mean'].fillna(data['TOTAL COLIFORM
(MPN/100ml)Mean'].mean(),inplace=True)
```

In [15]:

```
data.drop(["FECAL COLIFORM (MPN/100ml)"],axis=1,inplace=True)
```

Renaming the Column Names

In [16]:

```
data=data.rename(columns = {'D.O. (mg/l)': 'do'})
data=data.rename(columns = {'CONDUCTIVITY (µmhos/cm)': 'co'})
data=data.rename(columns = {'B.O.D. (mg/l)': 'bod'})
data=data.rename(columns = {'NITRATENAN N+ NITRITENANN (mg/l)': 'na'})
data=data.rename(columns = {'TOTAL COLIFORM (MPN/100ml)Mean': 'tc'})
data=data.rename(columns = {'STATION CODE': 'station'})
data=data.rename(columns = {'LOCATIONS': 'location'})
data=data.rename(columns = {'STATE': 'state'})
data=data.rename(columns = {'PH': 'ph'})
```

In [17]:

```
data
```

Out[17]:

	station	location	state	Temp	do	ph	co	bod	na	tc	year
0	1393	DAMANGANGA AT D/S OF MADHUBAN, DAMAN	DAMAN & DIU	30.600000	6.7	7.5	203.0	6.940049	0.100000	27.0	2014
1	1399	ZUARI AT D/S OF PT. WHERE KUMBARJRIA CANAL JOI...	GOA	29.800000	5.7	7.2	189.0	2.000000	0.200000	8391.0	2014
2	1475	ZUARI AT PANCHAWADI	GOA	29.500000	6.3	6.9	179.0	1.700000	0.100000	5330.0	2014
3	3181	RIVER ZUARI AT BORIM BRIDGE	GOA	29.700000	5.8	6.9	64.0	3.800000	0.500000	8443.0	2014
4	3182	RIVER ZUARI AT MARCAIM JETTY	GOA	29.500000	5.8	7.3	83.0	1.900000	0.400000	5500.0	2014
...	...	...	...	...	...	...	...	...	...	...	...
1986	1330	TAMBIRAPARANI AT	NAN	26.209814	7.9	738.0	7.2	2.700000	0.518000	202.0	2003

	station	location	state	Temp	do	ph	co	bod	na	tc	year
		ARUMUGANERI, TAMILNADU									
1987	1450	PALAR AT VANIYAMBADI WATER SUPPLY HEAD WORK, T...	NAN	29.000000	7.5	585.0	6.3	2.600000	0.155000	315.0	2003
1988	1403	GUMTI AT U/S SOUTH TRIPURA,TRIPURA	NAN	28.000000	7.6	98.0	6.2	1.200000	1.623079	570.0	2003
1989	1404	GUMTI AT D/S SOUTH TRIPURA, TRIPURA	NAN	28.000000	7.7	91.0	6.5	1.300000	1.623079	562.0	2003
1990	1726	CHANDRAPUR, AGARTALA D/S OF HAORA RIVER, TRIPURA	NAN	29.000000	7.6	110.0	5.7	1.100000	1.623079	546.0	2003

1991 rows × 11 columns

Water Quality Index (WQI) Calculation

a)Claculation of pH

In [18]:

```
data['npH']=data.ph.apply(lambda x: (100 if(8.5>=x>=7)
                                 else(80 if(8.6>=x>=8.5) or (6.9>=x>=6.8)
                                   else (60 if(8.8>=x>=8.6) or (6.8>=x>=6.7)
                                       else(40 if(9>=x>=8.8) or
(6.7>=x>=6.5)
                                           else 0)))))
```

b)calculation of dissolved oxygen

In [19]:

```
data['ndo']=data.do.apply(lambda x: (100 if(x>=6)
                                 else(80 if(6>=x>=5.1)
                                   else (60 if(5>=x>=4.1)
                                       else(40 if(4>=x>=3)
                                           else 0)))))
```

c)calculation of total coliform

In [20]:

```
data['nco']=data.tc.apply(lambda x: (100 if(5>=x>=0)
                                 else(80 if(50>=x>=5)
                                   else (60 if(500>=x>=50)
```

```
                                              else(40 if(10000>=x>=500)
                                                  else 0)))))
```

d)calculation of B.D.O

In [21]:

```
data['nbdo']=data.bod.apply(lambda x:(100 if(3>=x>=0)
                                      else(80 if(6>=x>=3)
                                        else (60 if(80>=x>=6)
                                            else(40 if(125>=x>=80)
                                                else 0)))))
```

e)calculation of electric conductivity

In [22]:

```
data['nec']=data.co.apply(lambda x:(100 if(75>=x>=0)
                                      else(80 if(150>=x>=75)
                                        else (60 if(225>=x>=150)
                                            else(40 if(300>=x>=225)
                                                else 0)))))
```

f)calculation of nitrate

In [23]:

```
data['nna']=data.na.apply(lambda x:(100 if(20>=x>=0)
                                      else(80 if(50>=x>=20)
                                        else (60 if(100>=x>=50)
                                            else(40 if(200>=x>=100)
                                                else 0)))))
```

Calculation of Water Quality Index WQI

```
data['wph']=data.npH*0.165
data['wdo']=data.ndo*0.281
data['wbdo']=data.nbdo*0.234
data['wec']=data.nec*0.009
data['wna']=data.nna*0.028
data['wco']=data.nco*0.281
data['wqi']=data.wph+data.wdo+data.wbdo+data.wec+data.wna+data.wco
data
```

Out[24]:

	station	location	state	Temp	do	ph	co	bod	na	tc	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi
0	1393	DAMANGANGA AT D/S OF MADHUBAN, DAMAN	DAMAN & DIU	30.600000	6.7	7.5	203.0	6.940049	0.100000	27.0	...	60	60	100	16.5	28.10	14.04	0.54	2.8	22.48	84.46
1	1399	ZUARI AT D/S OF PT. WHERE	GOA	29.800000	5.7	7.2	189.0	2.000000	0.200000	839	...	100	60	100	16.5	22.48	23.40	0.54	2.8	11.24	76.96

	station	location	state	Temp	do	ph	co	bod	na	tc	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi
		KUMBARJRIA CANAL JOI...								1.0											
2	1475	ZUARI AT PANCHAWADI	GOA	29.500000	6.3	6.9	179.0	1.700000	0.100000	5330.0	...	100	60	100	13.2	28.10	23.40	0.54	2.8	11.24	79.28
3	3181	RIVER ZUARI AT BORIM BRIDGE	GOA	29.700000	5.8	6.9	64.0	3.800000	0.500000	8443.0	...	80	100	100	13.2	22.48	18.72	0.90	2.8	11.24	69.34
4	3182	RIVER ZUARI AT MARCAIM JETTY	GOA	29.500000	5.8	7.3	83.0	1.900000	0.400000	5500.0	...	100	80	100	16.5	22.48	23.40	0.72	2.8	11.24	77.14
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1986	1330	TAMBIRAPARANI AT ARUMUGANERI, TAMILNADU	NAN	26.209814	7.9	738.0	7.2	2.700000	0.518000	202.0	...	100	100	100	0.0	28.10	23.40	0.90	2.8	16.86	72.06
1987	1450	PALAR AT VANIYAMBADI WATER SUPPLY HEAD	NAN	29.000000	7.5	585.0	6.3	2.600000	0.155000	315.0	...	100	100	100	0.0	28.10	23.40	0.90	2.8	16.86	72.06

	station	location	state	Temp	do	ph	co	bod	na	tc	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi
		WORK, T...																			
1988	1403	GUMTI AT U/S SOUTH TRIPURA,TRIPURA	NAN	28.000000	7.6	98.0	6.2	1.200000	1.623079	570.0	...	100	100	100	0.0	28.10	23.40	0.90	2.8	11.24	66.44
1989	1404	GUMTI AT D/S SOUTH TRIPURA, TRIPURA	NAN	28.000000	7.7	91.0	6.5	1.300000	1.623079	562.0	...	100	100	100	0.0	28.10	23.40	0.90	2.8	11.24	66.44
1990	1726	CHANDRAPUR, AGARTALA D/S OF HAORA RIVER, TRIPURA	NAN	29.000000	7.6	110.0	5.7	1.100000	1.623079	546.0	...	100	100	100	0.0	28.10	23.40	0.90	2.8	11.24	66.44

1991 rows × 24 columns

Calculation of overall WQI for each year

In [25]:

```
average = data.groupby('year')['wqi'].mean()
average.head()
```

Out[25]:

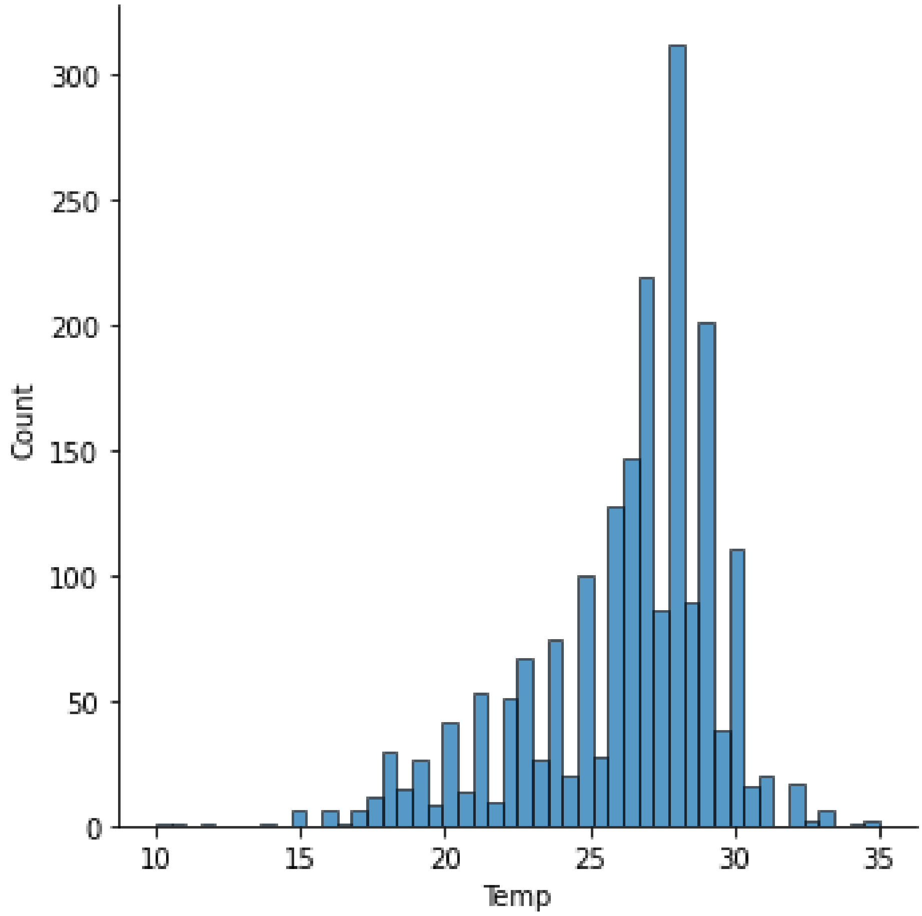
```
year
2003    66.239545
2004    61.290000
2005    73.762689
2006    72.909714
2007    74.233000
Name: wqi, dtype: float64
```

Data Visualization

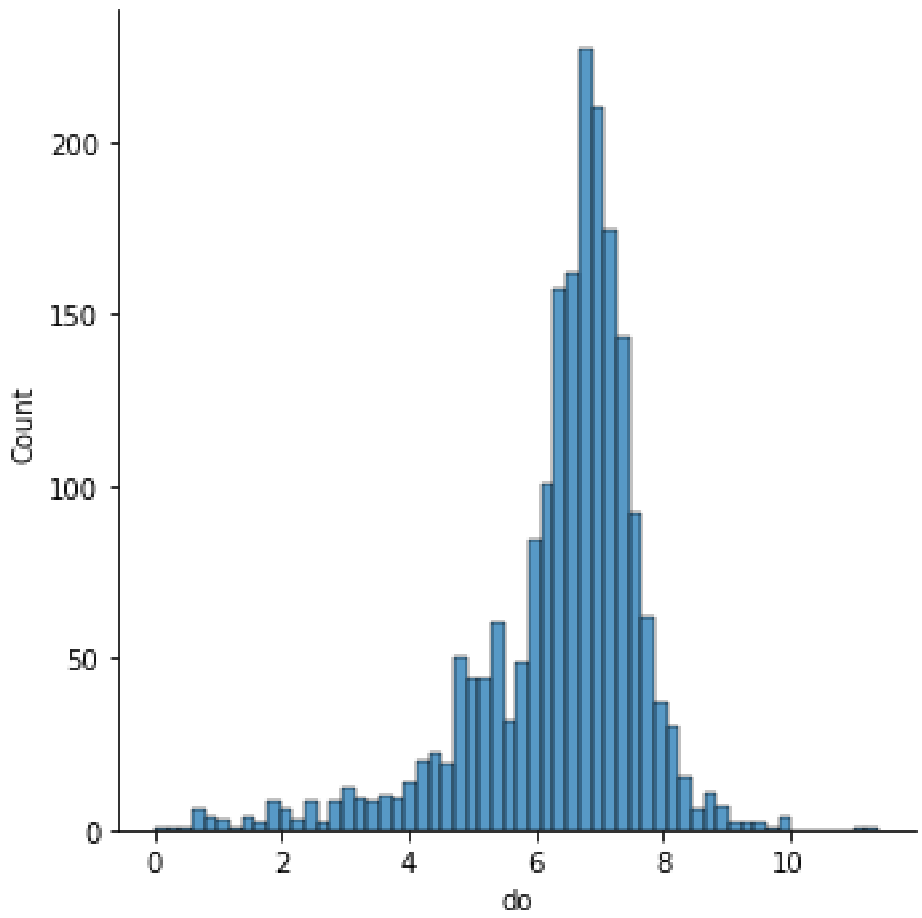
Univariate analysis

a)displot

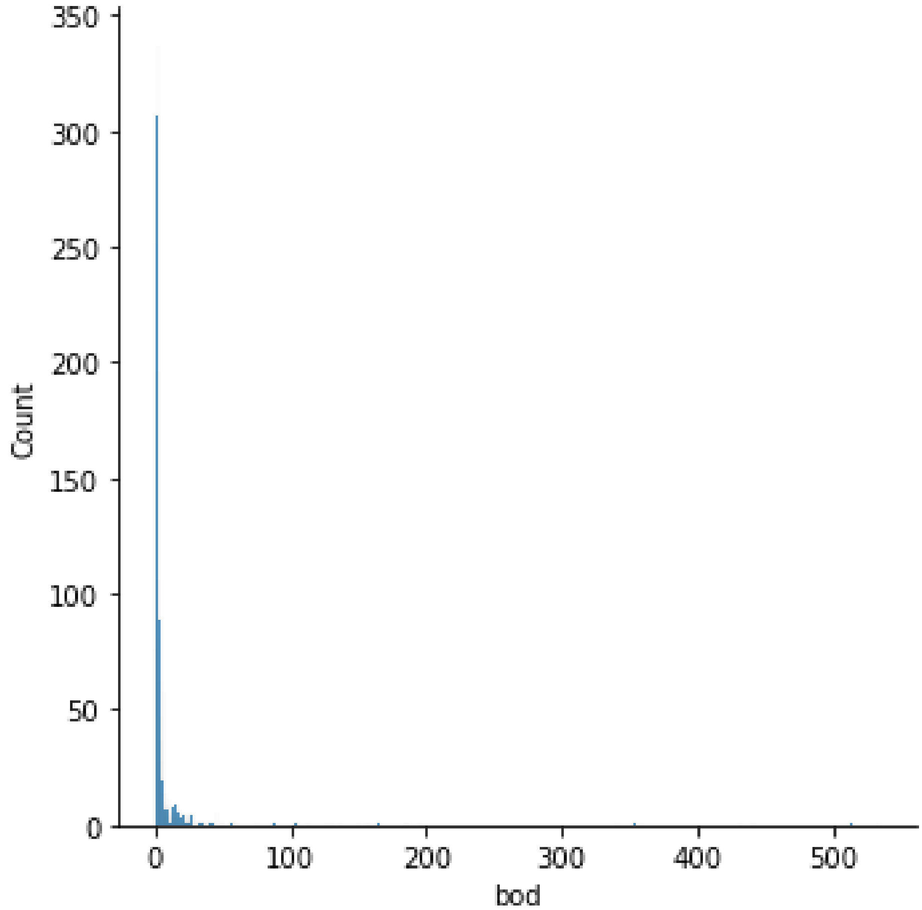
```
sns.displot(data.Temp)
plt.show()
```



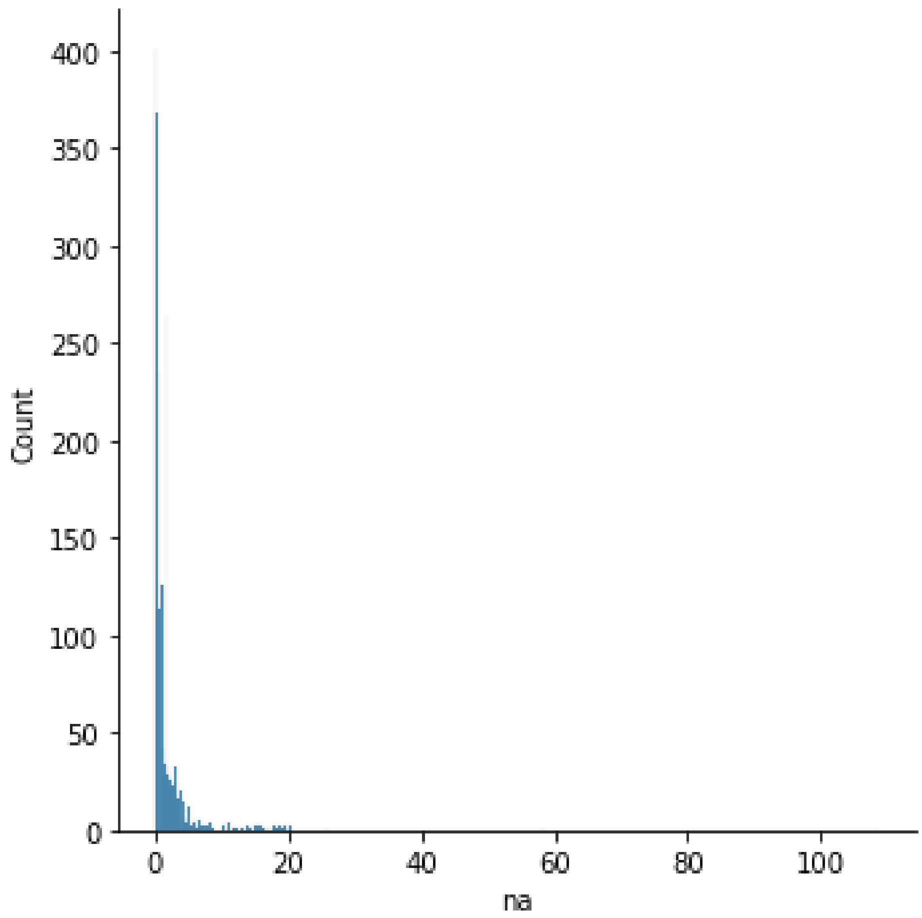

```
sns.displot(data.do)
plt.show()
```



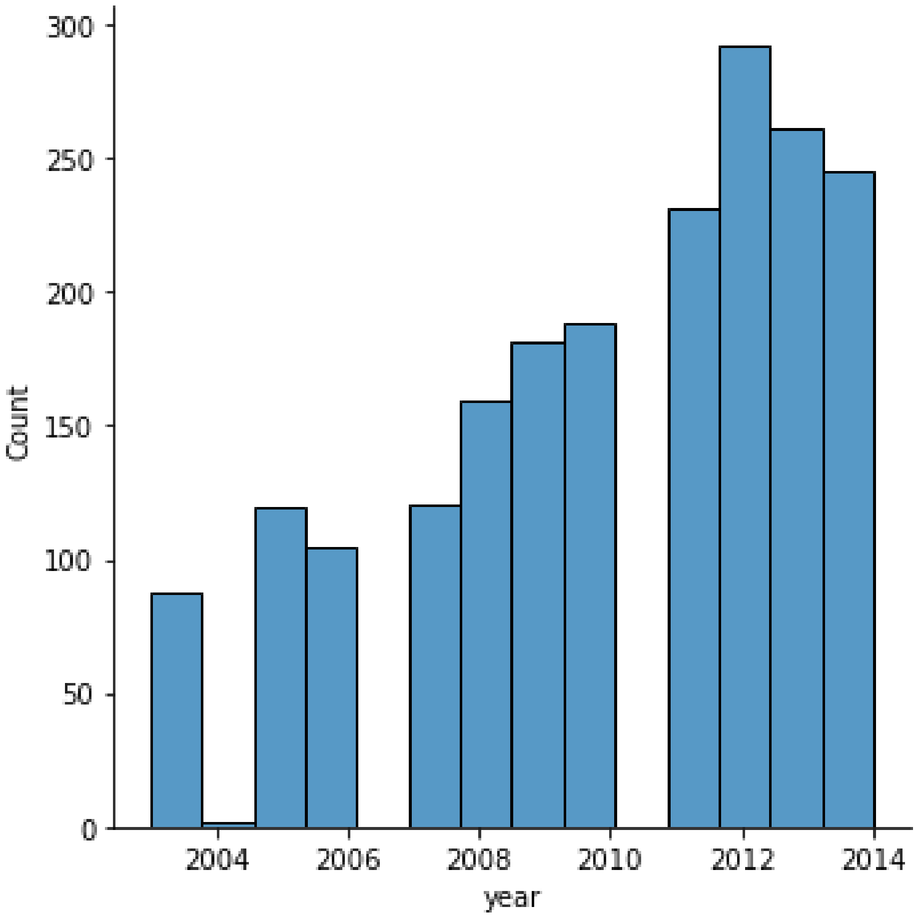

```
sns.displot(data.bod)
plt.show()
```



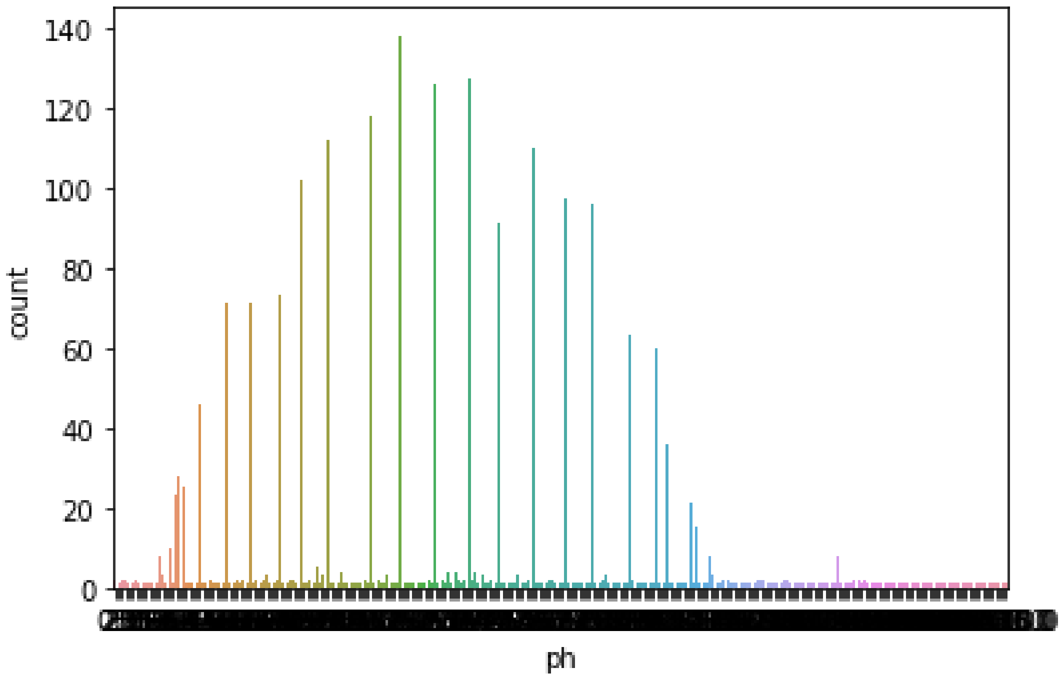

```
sns.displot(data.na)
plt.show()
```



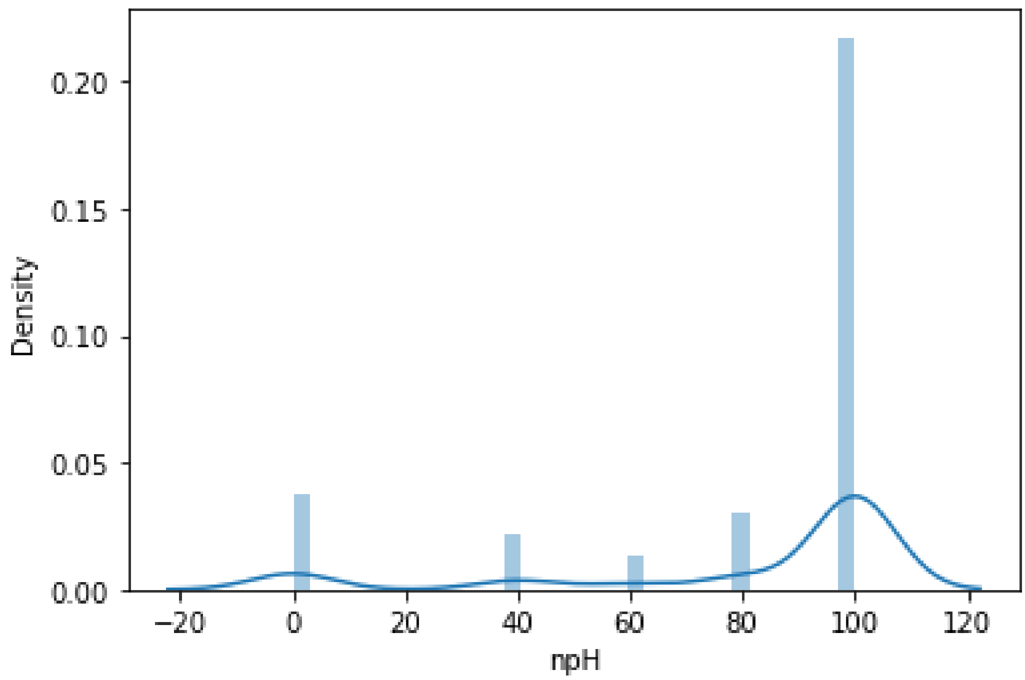

```
sns.displot(data.year)
plt.show()
```



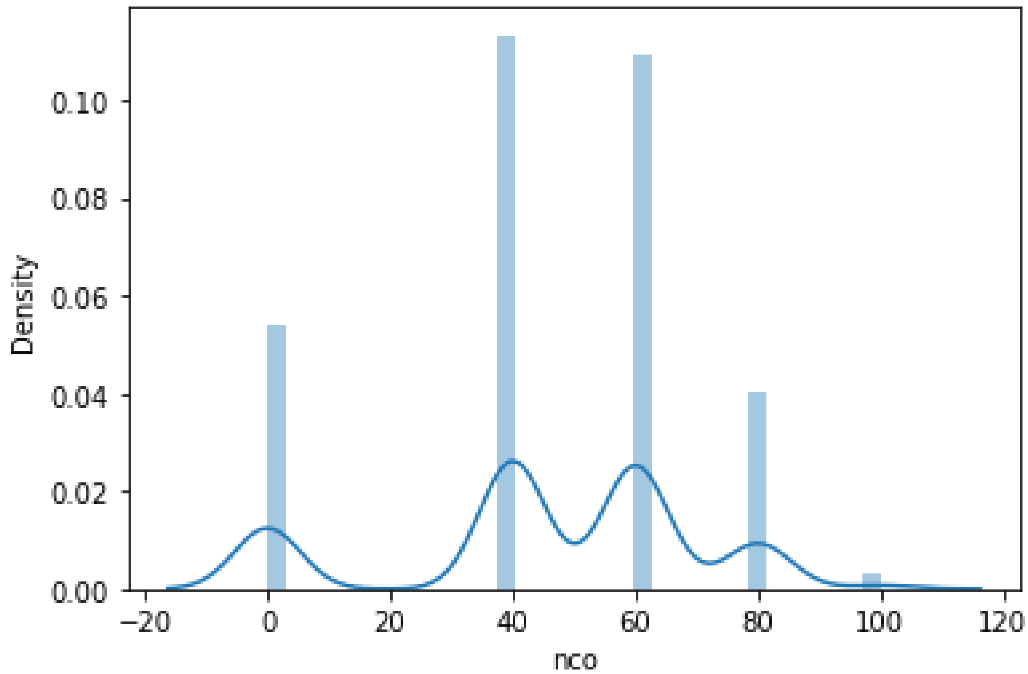
b)count



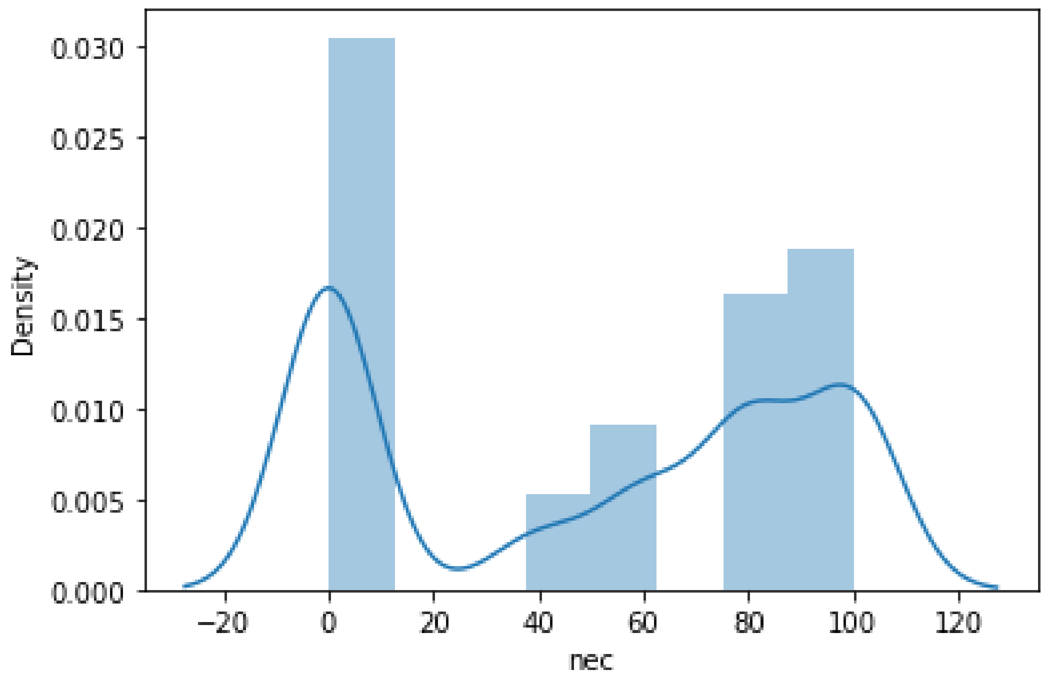

```
sns.distplot(data.npH)
plt.show()
```




```
sns.distplot(data.nco)
plt.show()
```



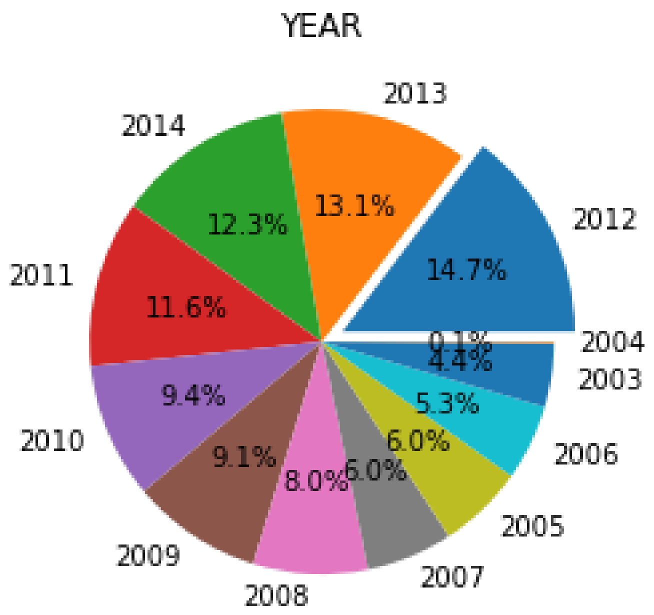

```
sns.distplot(data.nec)
plt.show()
```



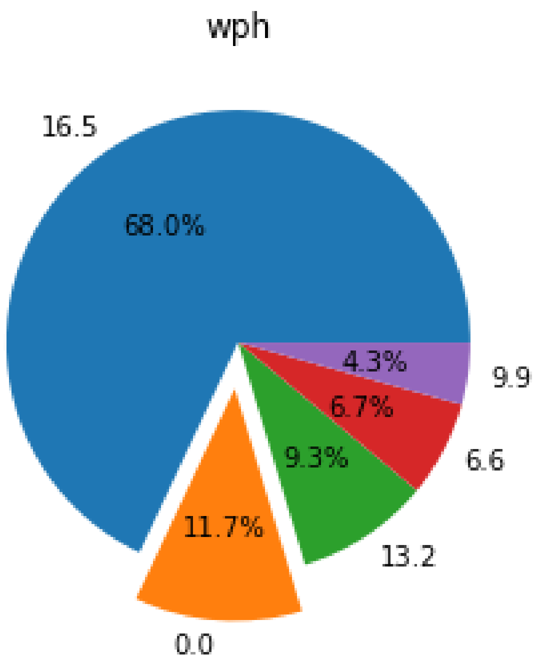
c)pie chart

In [35]:

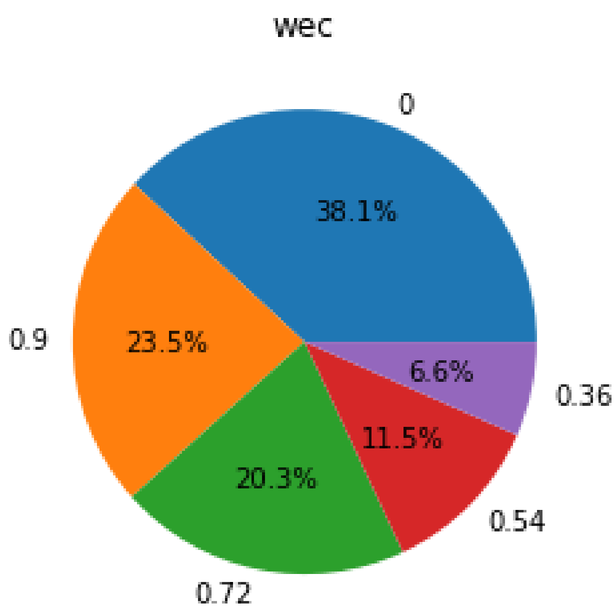
```
plt.pie(data.year.value_counts(),[0.1,0,0,0,0,0,0,0,0,0,0,0],labels=[2012,2
013,2014,2011,2010,2009,2008,2007,2005,2006,2003,2004 ],autopct='%1.1f%%')
plt.title('YEAR')
plt.show()
```



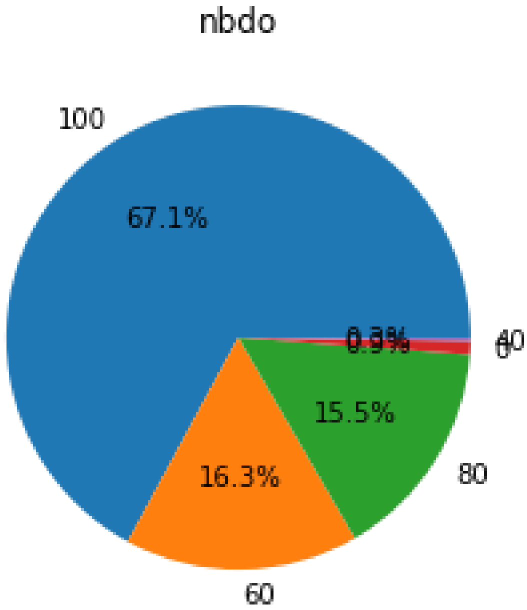

```
plt.pie(data.wph.value_counts(),[0,0.2,0,0,0],labels=[16.5,0.0,13.2,6.6,9.9
],autopct='%1.1f%%')
plt.title('wph')
plt.show()
```



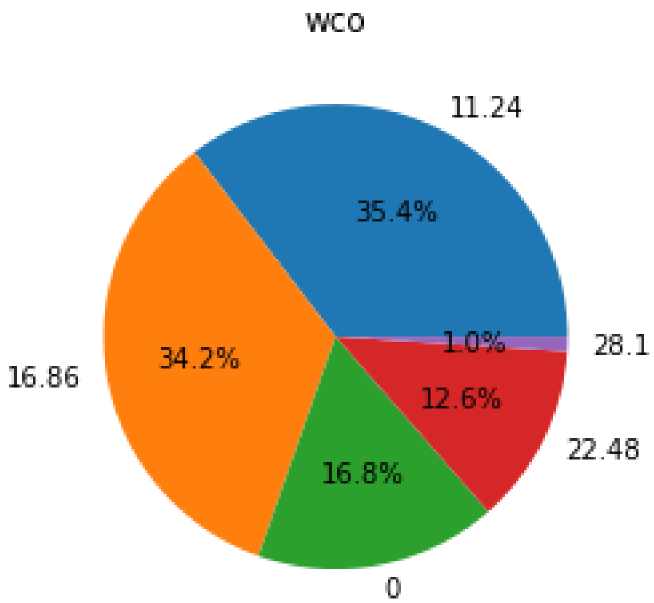

```
plt.pie(data.wec.value_counts(),labels=[0,0.90,0.72,0.54,0.36],autopct='%1.
1f%%')
plt.title('wec')
plt.show()
```




```
plt.pie(data.nbdo.value_counts(),labels=[100,60,80,0,40],autopct='%1.1f%%')
plt.title('nbdo')
plt.show()
```




```
plt.pie(data.wco.value_counts(),labels=[11.24,16.86,0,22.48,28.10],autopct=
'%1.1f%%')
plt.title('wco')
plt.show()
```

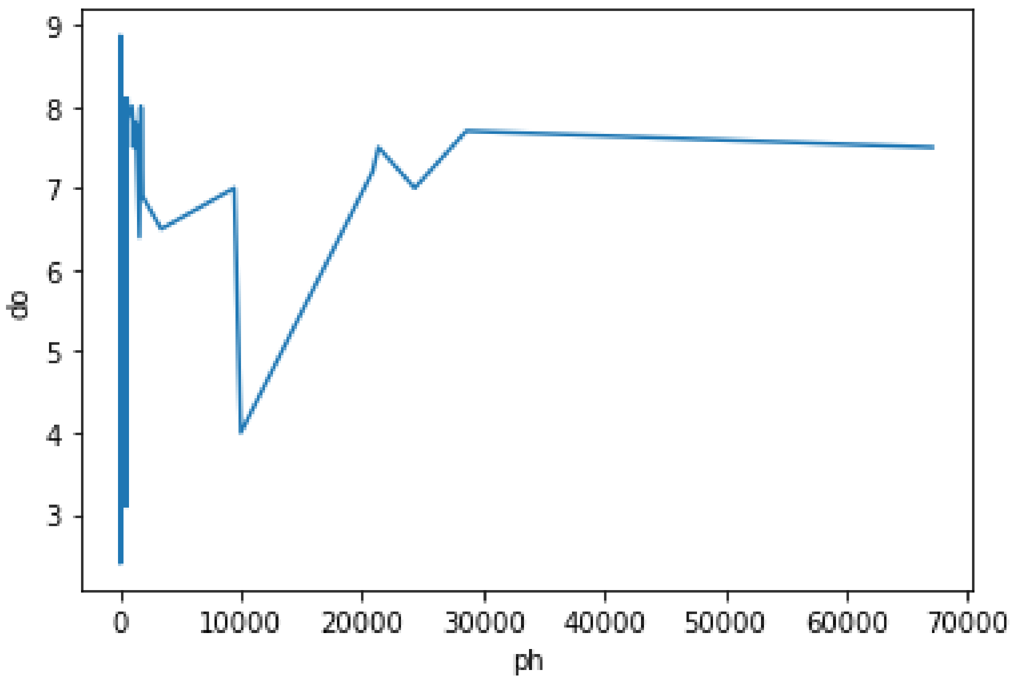


Bivariate analysis

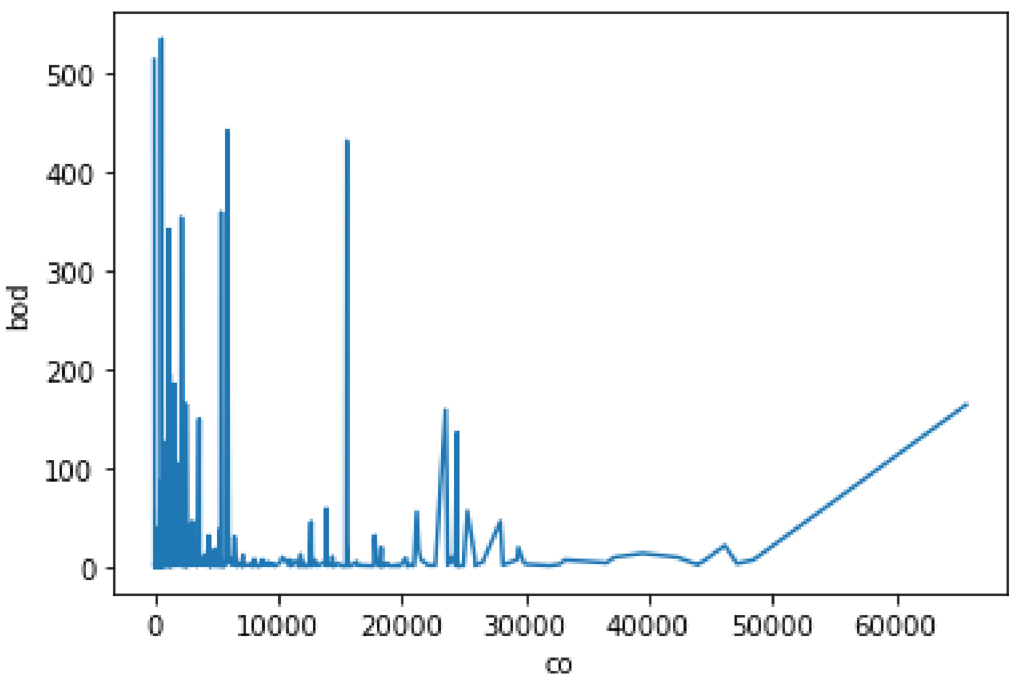
a)Line plot

In [40]:

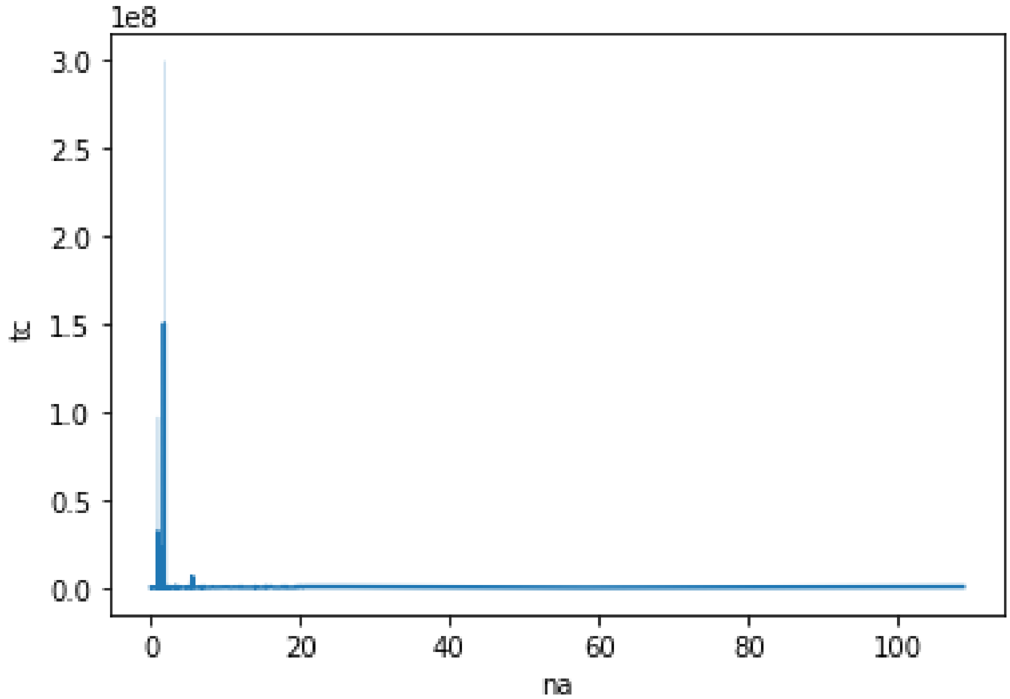
```
sns.lineplot(data.ph,data.do)
plt.show()
```



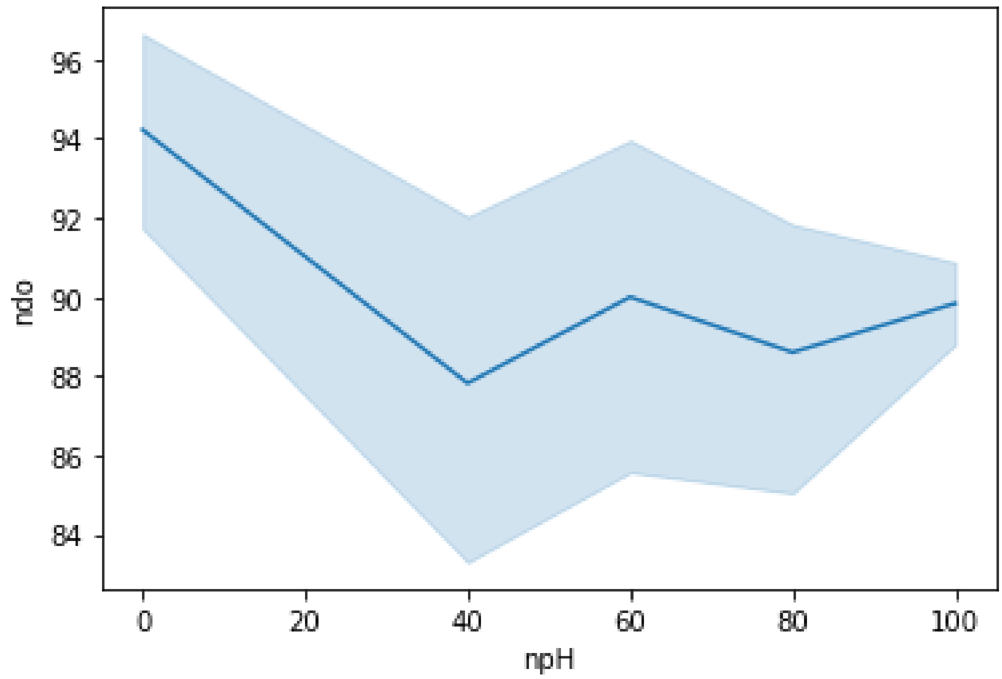

```
sns.lineplot(data.co,data.bod)
plt.show()
```



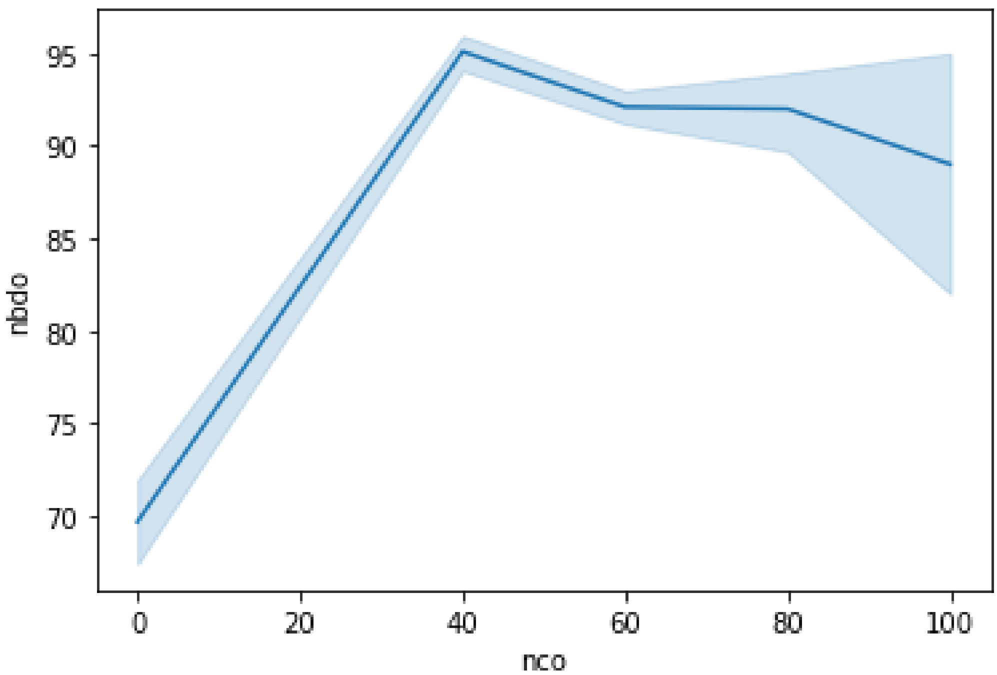

```
sns.lineplot(data.na,data.tc)
plt.show()
```



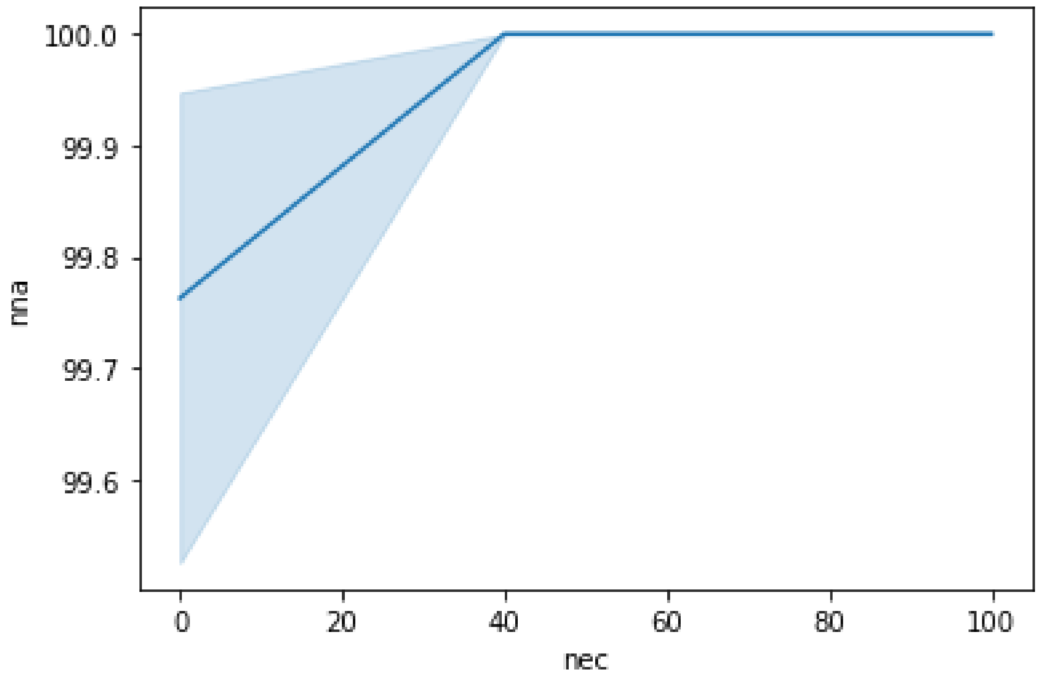

```
sns.lineplot(data.npH,data.ndo)
plt.show()
```



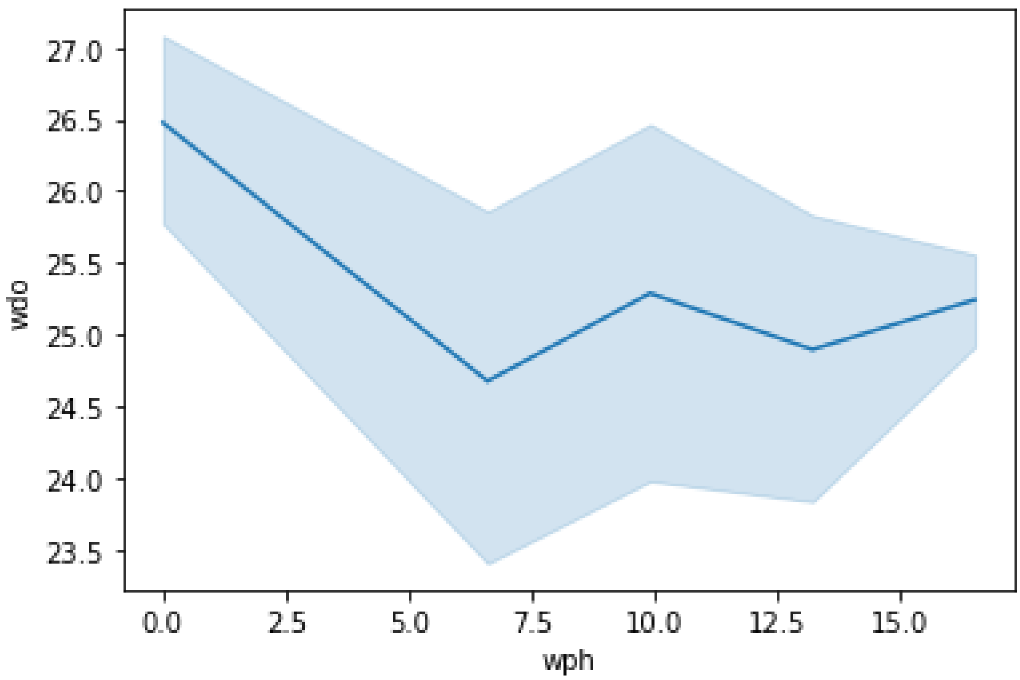

```
sns.lineplot(data.nco,data.nbdo)
plt.show()
```



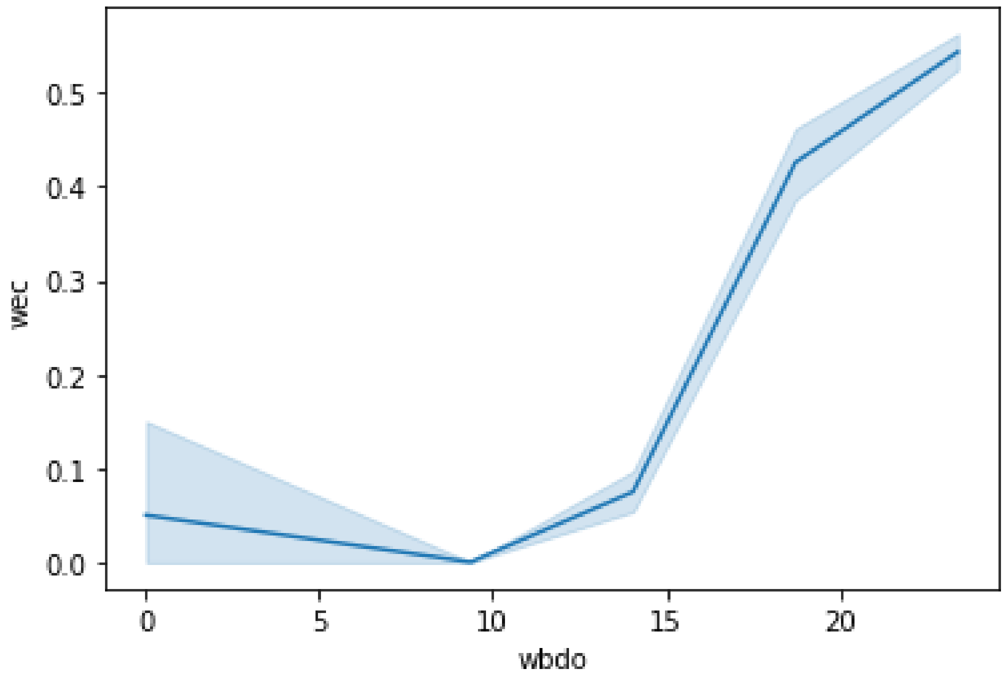

```
sns.lineplot(data.nec,data.nna)
plt.show()
```



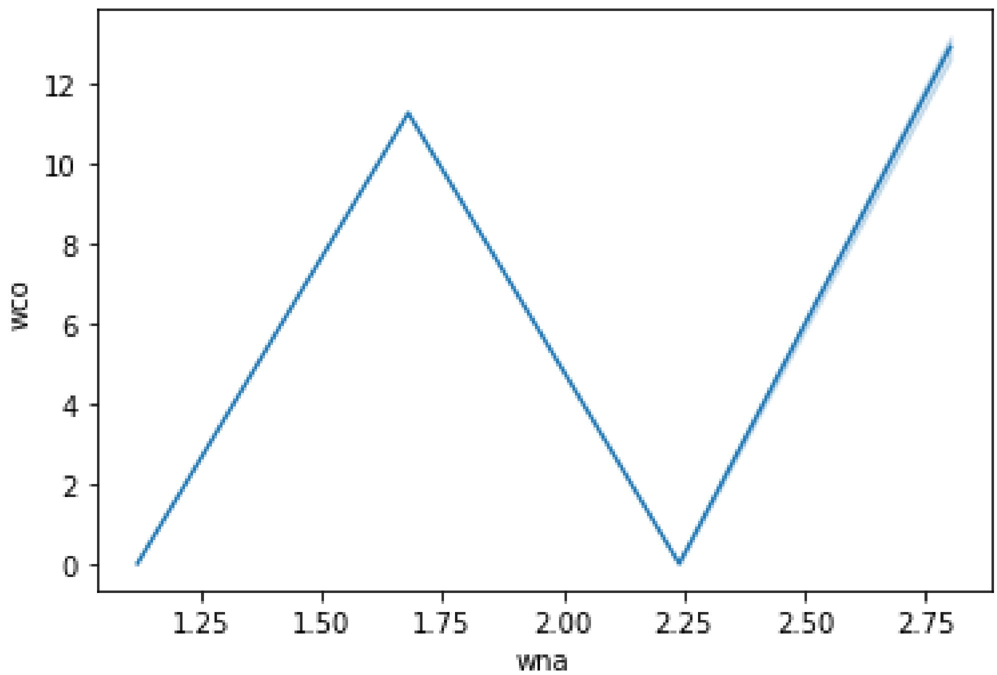

```
sns.lineplot(data.wph,data.wdo)
plt.show()
```




```
sns.lineplot(data.wbdo,data.wec)
plt.show()
```



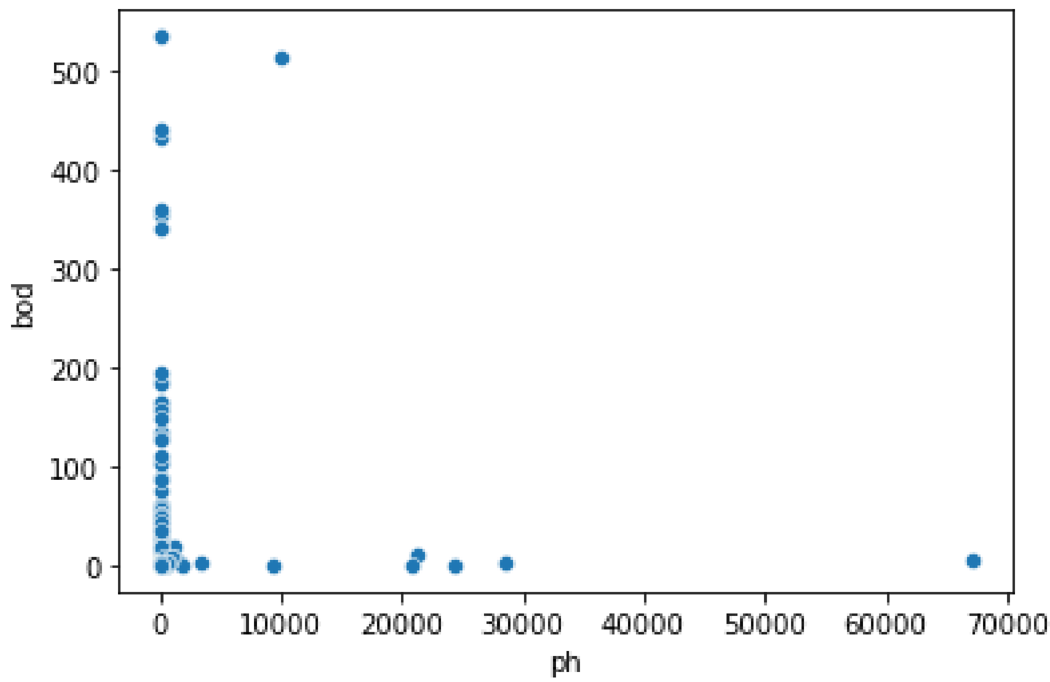

```
sns.lineplot(data.wna,data.wco)
plt.show()
```



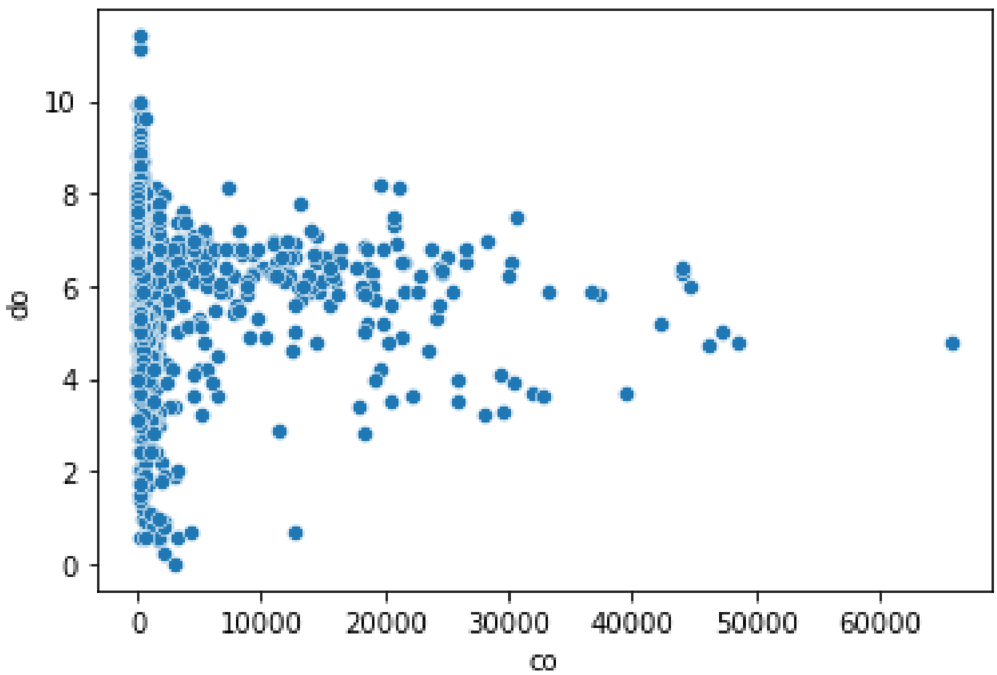
b)Scatter plot

In [49]:

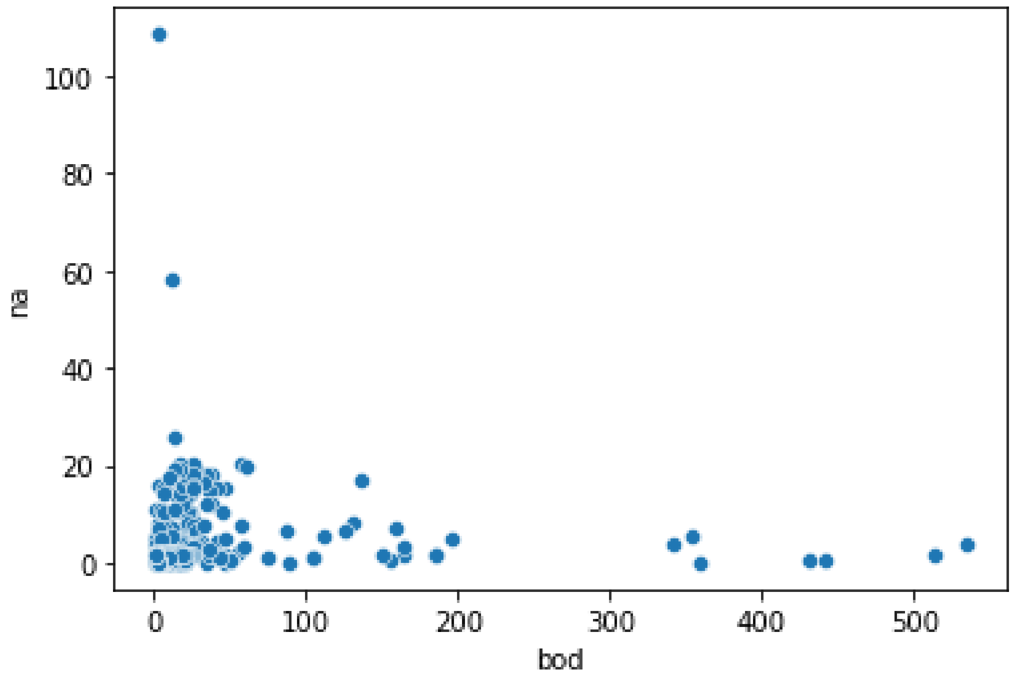
```
sns.scatterplot(data.ph,data.bod)
plt.show()
```



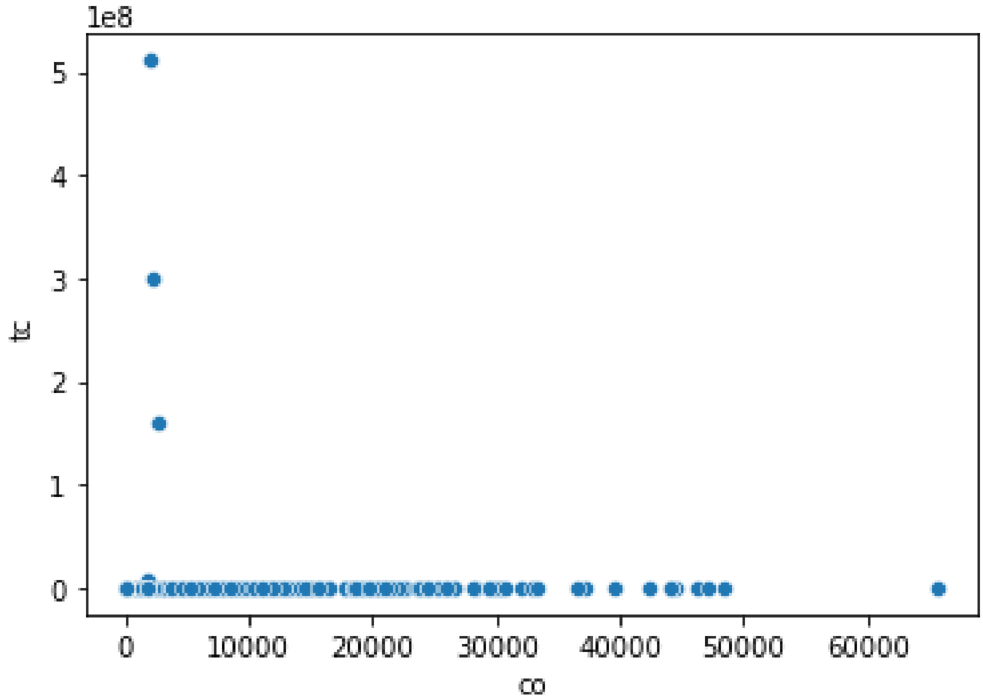

```
sns.scatterplot(data.co,data.do)
plt.show()
```



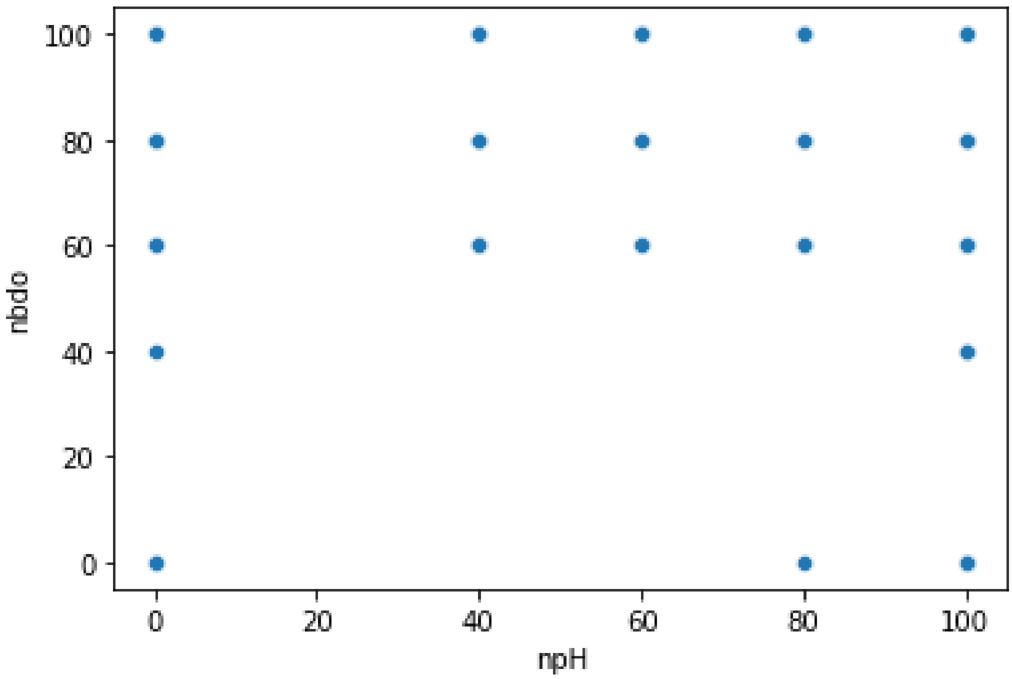

```
sns.scatterplot(data.bod,data.na)
plt.show()
```



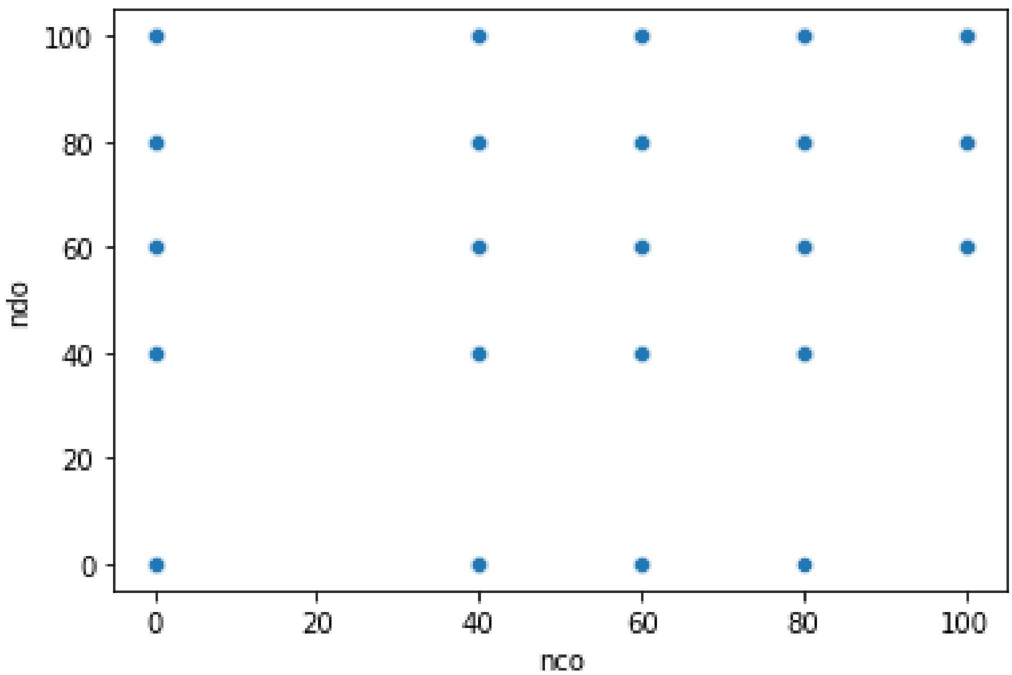

```
sns.scatterplot(data.co,data.tc)
plt.show()
```



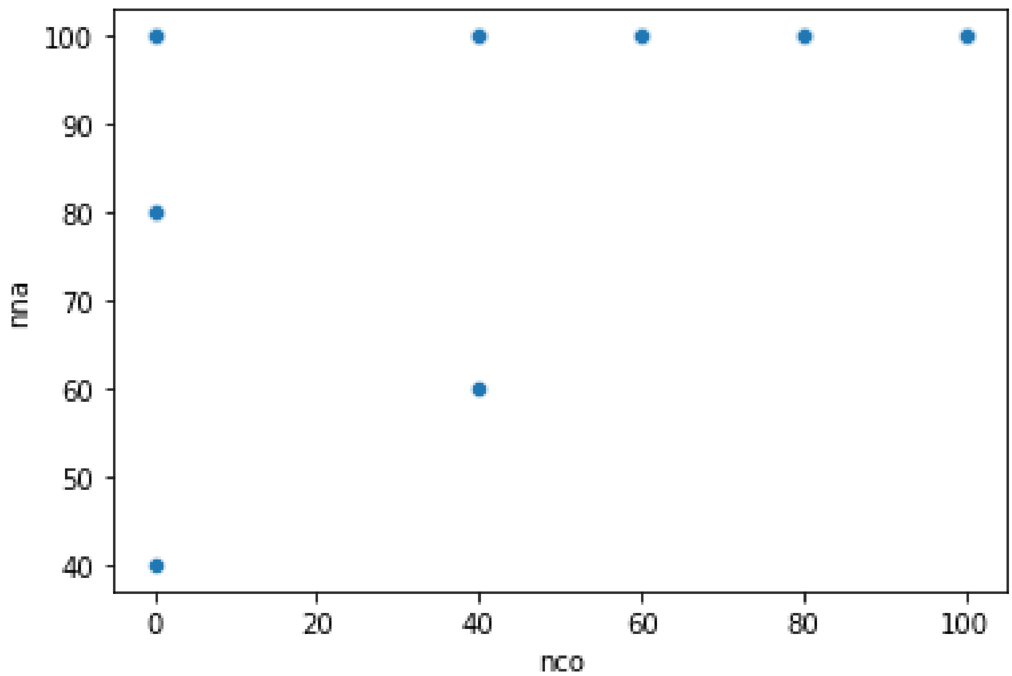

```
sns.scatterplot(data.npH,data.nbdo)
plt.show()
```



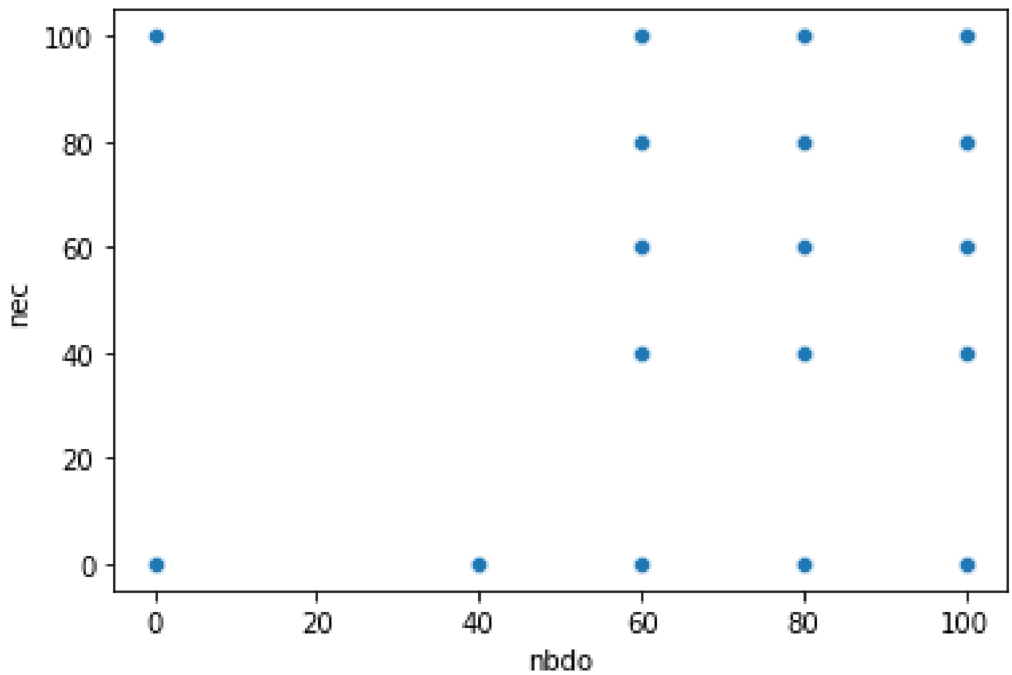

```
sns.scatterplot(data.nco,data.ndo)
plt.show()
```



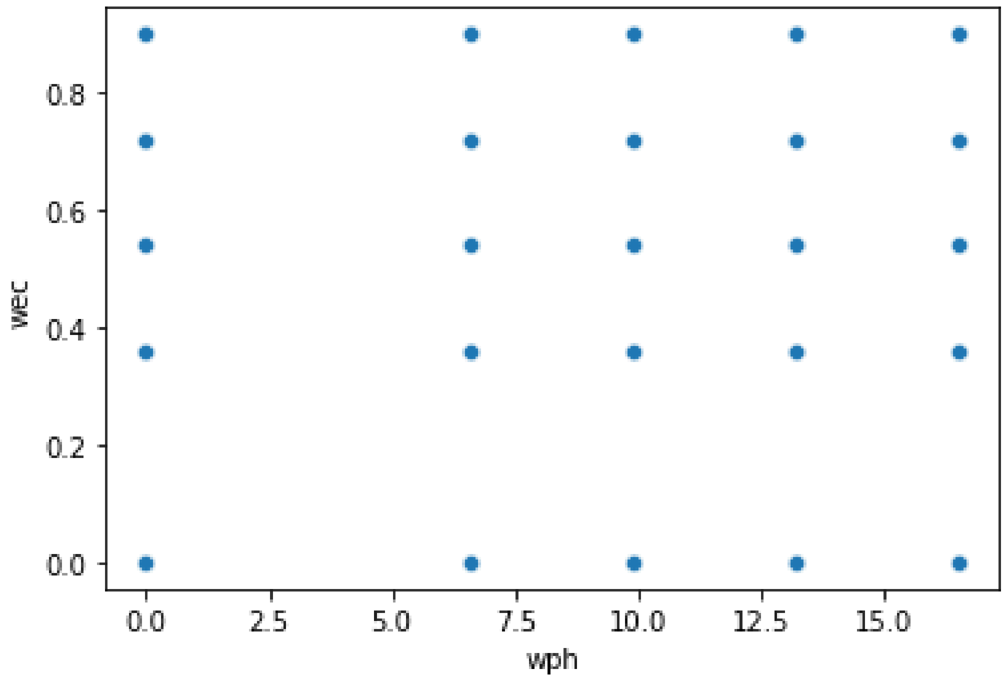

```
sns.scatterplot(data.nco,data.nna)
plt.show()
```



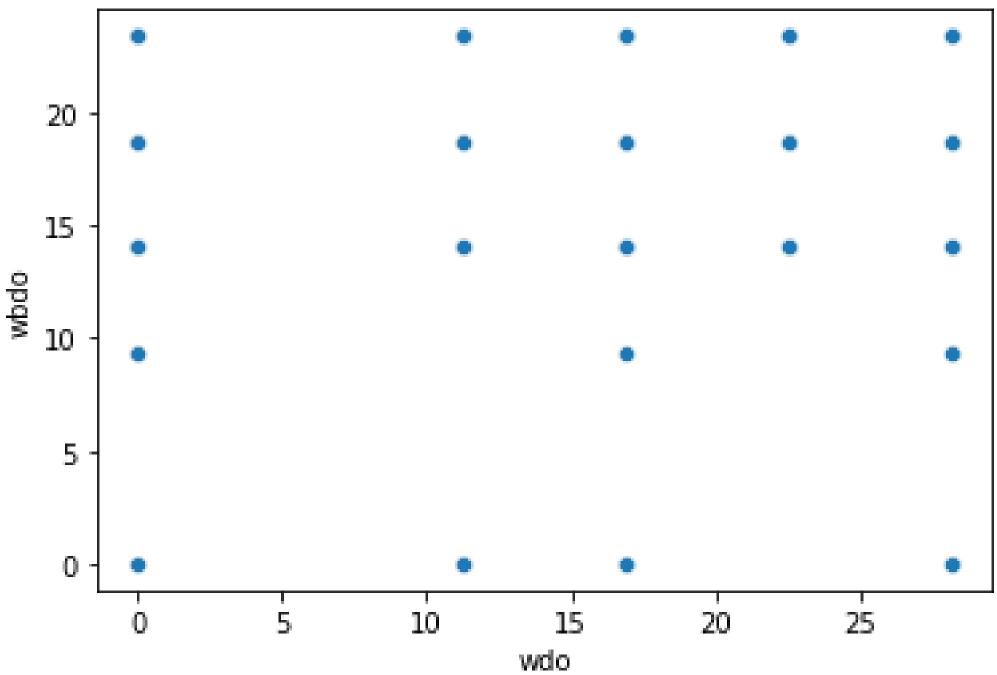

```
sns.scatterplot(data.nbdo,data.nec)
plt.show()
```



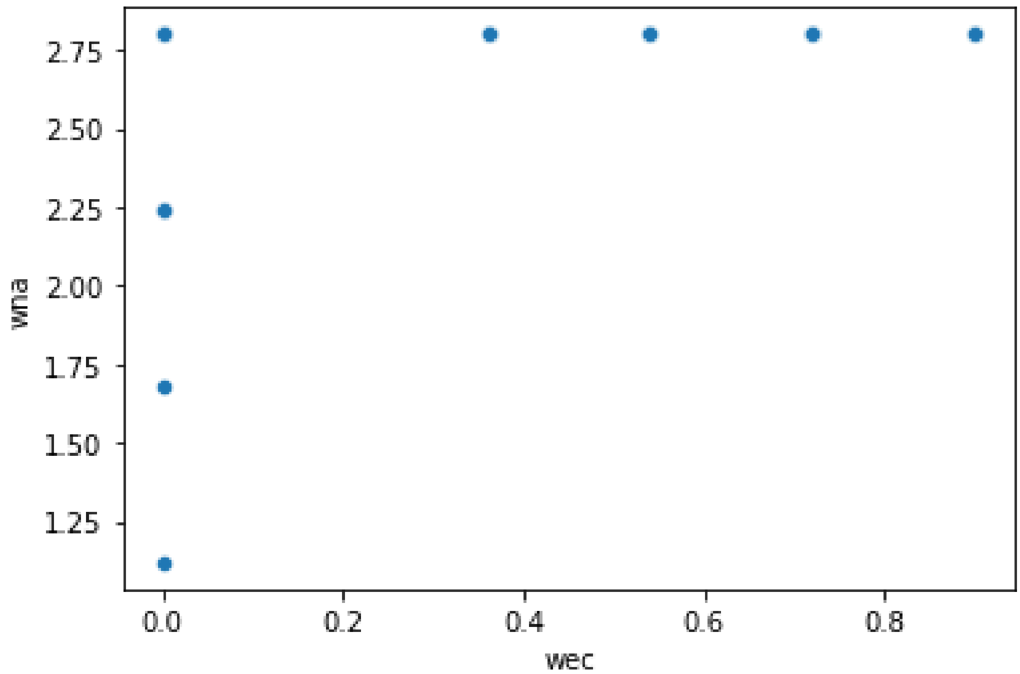

```
sns.scatterplot(data.wph,data.wec)
plt.show()
```




```
sns.scatterplot(data.wdo,data.wbdo)
plt.show()
```



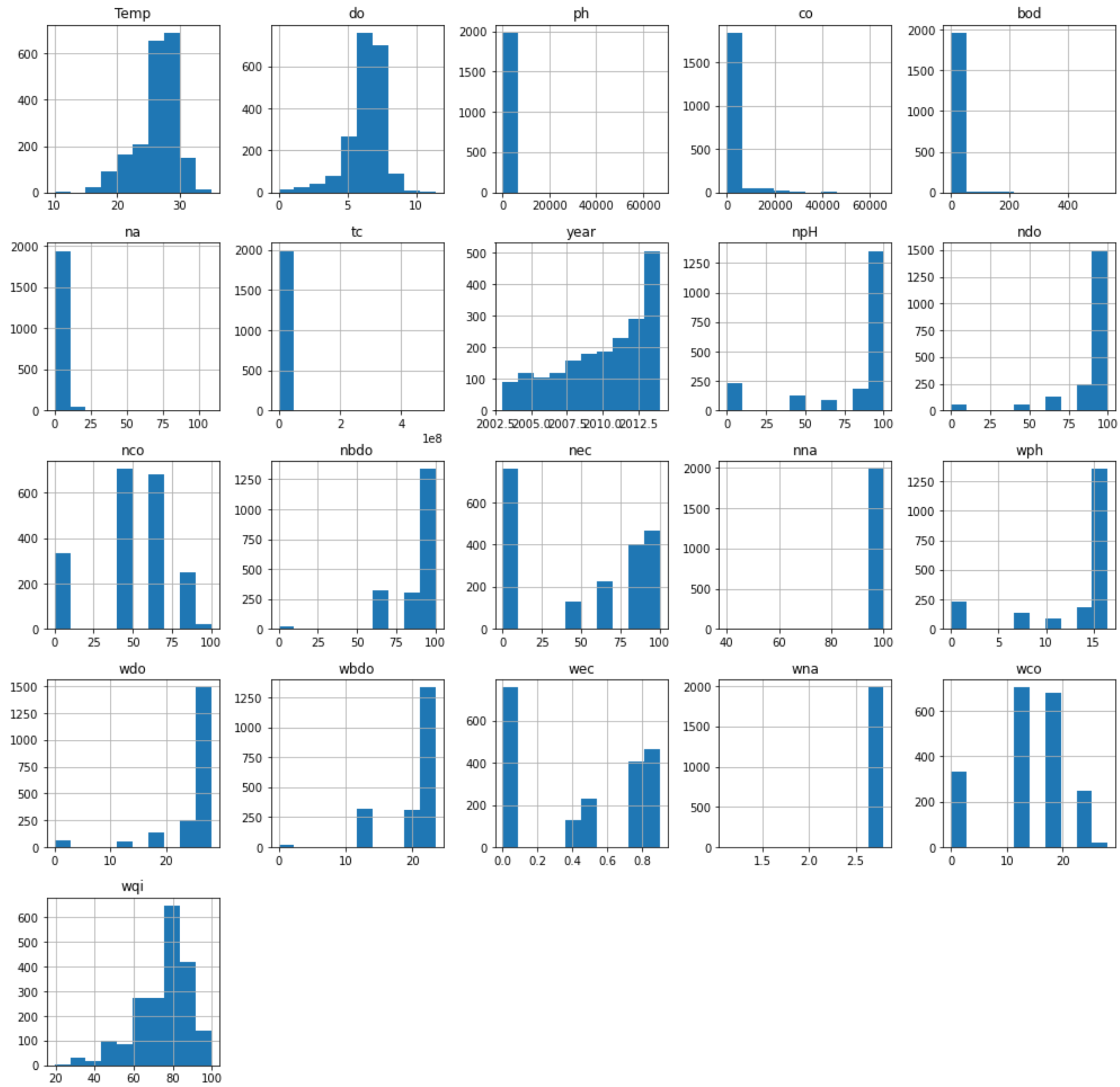

```
sns.scatterplot(data.wec,data.wna)
plt.show()
```



Multivariate analysis

In [61]:

```
data.hist(figsize=(17,17))
plt.show()
```



Label Encoding

In [62]:

```
from sklearn.preprocessing import LabelEncoder
```

In [63]:

```
le=LabelEncoder()
```

In [64]:

```
data.location=le.fit_transform(data.location)
data.state=le.fit_transform(data.state)
data.head()
```

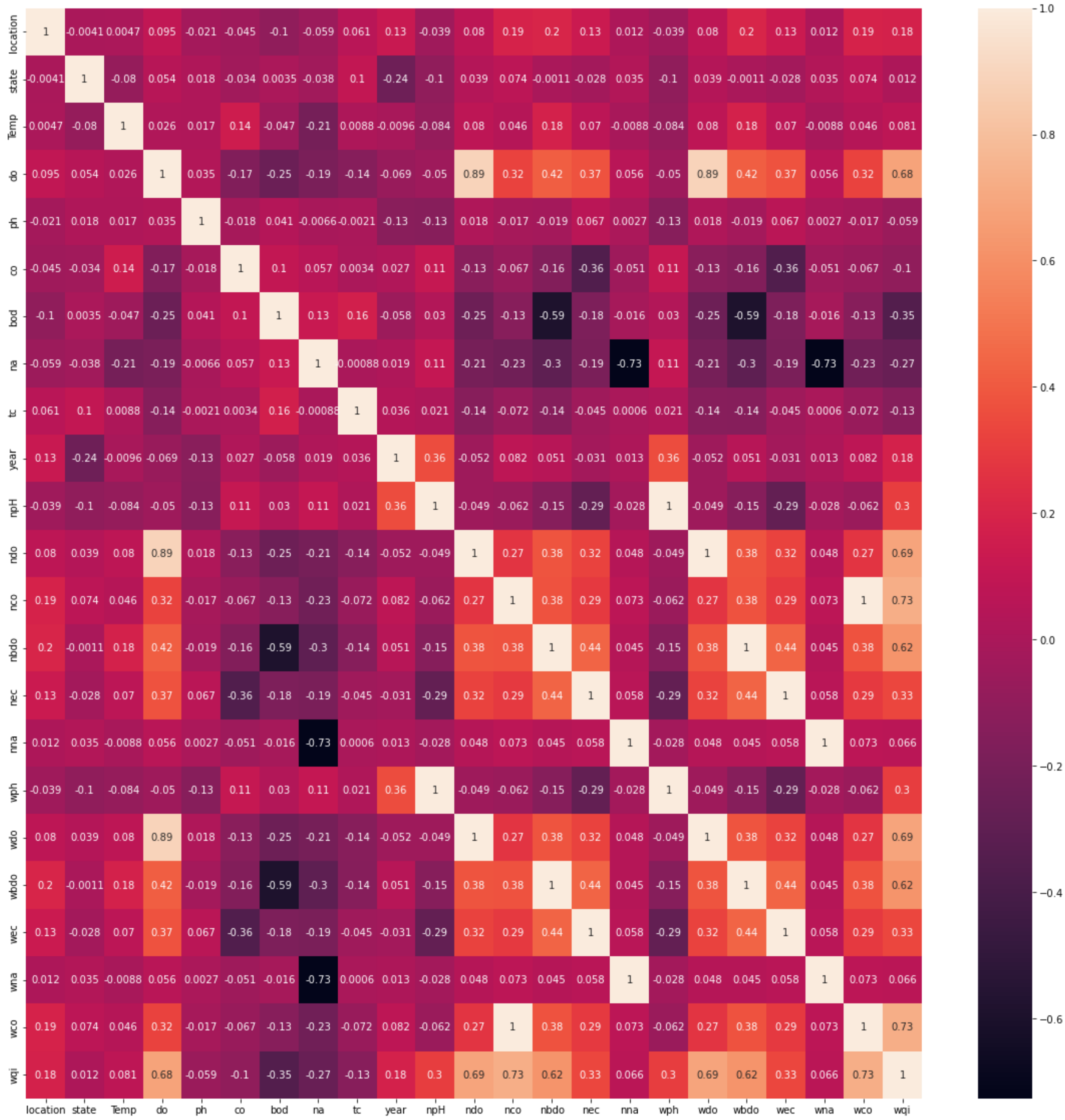
Out[64]:

	station	location	state	Temp	do	ph	co	bod	na	tc	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi
0	1393	83	21	30.6	6.7	7.5	203.0	6.940049	0.1	27.0	...	60	60	100	16.5	28.10	14.04	0.54	2.8	22.48	84.46
1	1399	664	51	29.8	5.7	7.2	189.0	2.000000	0.2	8391.0	...	100	60	100	16.5	22.48	23.40	0.54	2.8	11.24	76.96
2	1475	665	51	29.5	6.3	6.9	179.0	1.700000	0.1	5330.0	...	100	60	100	13.2	28.10	23.40	0.54	2.8	11.24	79.28
3	3181	495	51	29.7	5.8	6.9	64.0	3.800000	0.5	8443.0	...	80	100	100	13.2	22.48	18.72	0.90	2.8	11.24	69.34
4	3182	496	51	29.5	5.8	7.3	83.0	1.900000	0.4	5500.0	...	100	80	100	16.5	22.48	23.40	0.72	2.8	11.24	77.14

5 rows × 24 columns

Finding correlation matrix using Heatmap

```
plt.figure(figsize=(20,20))
sns.heatmap(data.corr(),annot=True)
plt.show()
```




```
df=data.drop(['nco','npH','ndo','nbdo','nec','nna','location','state','stat
ion','wph','wdo','wbdo','wec','wna','wco','Temp'],axis=1)
```

In [67]:

```
df
```

Out[67]:

	do	ph	co	bod	na	tc	year	wqi
0	6.7	7.5	203.0	6.940049	0.100000	27.0	2014	84.46
1	5.7	7.2	189.0	2.000000	0.200000	8391.0	2014	76.96
2	6.3	6.9	179.0	1.700000	0.100000	5330.0	2014	79.28

	do	ph	co	bod	na	tc	year	wqi
3	5.8	6.9	64.0	3.800000	0.500000	8443.0	2014	69.34
4	5.8	7.3	83.0	1.900000	0.400000	5500.0	2014	77.14
...	...	...	...	...	...	...	...	...
1986	7.9	738.0	7.2	2.700000	0.518000	202.0	2003	72.06
1987	7.5	585.0	6.3	2.600000	0.155000	315.0	2003	72.06
1988	7.6	98.0	6.2	1.200000	1.623079	570.0	2003	66.44
1989	7.7	91.0	6.5	1.300000	1.623079	562.0	2003	66.44
1990	7.6	110.0	5.7	1.100000	1.623079	546.0	2003	66.44

1991 rows × 8 columns

In [68]:

```
df.to_csv('df')
```

In [69]:

```
df.corr().wqi.sort_values(ascending=False)
```

Out[69]:

```
wqi     1.000000
do      0.678756
year    0.180629
ph     -0.059461
co     -0.104916
tc     -0.133946
na     -0.265051
bod    -0.349332
Name: wqi, dtype: float64
```

Splitting Dependent and Independent Columns

In [70]:

```
data.drop(['location','station','state'],axis =1,inplace=True)
```

In [71]:

```
data.head()
```

Out[71]:

	Temp	do	ph	co	bod	na	tc	year	npH	ndo	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi
0	30.6	6.7	7.5	203.0	6.940049	0.1	27.0	2014	100	100	...	60	60	100	16.5	28.10	14.04	0.54	2.8	22.48	84.46
1	29.8	5.7	7.2	189.0	2.000000	0.2	8391.0	2014	100	80	...	100	60	100	16.5	22.48	23.40	0.54	2.8	11.24	76.96
2	29.5	6.3	6.9	179.0	1.700000	0.1	5330.0	2014	80	100	...	100	60	100	13.2	28.10	23.40	0.54	2.8	11.24	79.28
3	29.7	5.8	6.9	64.0	3.800000	0.5	8443.0	2014	80	80	...	80	100	100	13.2	22.48	18.72	0.90	2.8	11.24	69.34
4	29.5	5.8	7.3	83.0	1.900000	0.4	5500.0	2014	100	80	...	100	80	100	16.5	22.48	23.40	0.72	2.8	11.24	77.14

5 rows × 21 columns

1991 rows × 8 columns

In [68]:

```
df.to_csv('df')
```

In [69]:

```
df.corr().wqi.sort_values(ascending=False)
```

Out[69]:

```
wqi      1.000000
do       0.678756
year     0.180629
ph      -0.059461
co      -0.104916
tc      -0.133946
na      -0.265051
bod     -0.349332
Name: wqi, dtype: float64
```

Splitting Dependent and Independent Columns

In [70]:

```
data.drop(['location','station','state'],axis =1,inplace=True)
```

In [71]:

```
data.head()
```

Out[71]:

Temp	do	ph	co	bod	na	tc	year	npH	ndo	...	nbdo	nec	nna	wph	wdo	wbdo	wec	wna	wco	wqi	
0	30.6	6.7	7.5	203.0	6.940049	0.1	27.0	2014	100	100	...	60	60	100	16.5	28.10	14.04	0.54	2.8	22.48	84.46
1	29.8	5.7	7.2	189.0	2.000000	0.2	8391.0	2014	100	80	...	100	60	100	16.5	22.48	23.40	0.54	2.8	11.24	76.96
2	29.5	6.3	6.9	179.0	1.700000	0.1	5330.0	2014	80	100	...	100	60	100	13.2	28.10	23.40	0.54	2.8	11.24	79.28
3	29.7	5.8	6.9	64.0	3.800000	0.5	8443.0	2014	80	80	...	80	100	100	13.2	22.48	18.72	0.90	2.8	11.24	69.34
4	29.5	5.8	7.3	83.0	1.900000	0.4	5500.0	2014	100	80	...	100	80	100	16.5	22.48	23.40	0.72	2.8	11.24	77.14

5 rows × 21 columns

```
x=df.iloc[:,0:7].values
```

In [73]:

```
x.shape
```

Out[73]:

```
(1991, 7)
```

In [74]:

```
y=df.iloc[:,-1:].values
```

In [75]:

```
y.shape
```

Out[75]:

```
(1991, 1)
```

In [76]:

```
print(x)
```

```
[[6.70000000e+00 7.50000000e+00 2.03000000e+02 ... 1.00000000e-01
  2.70000000e+01 2.01400000e+03]
 [5.70000000e+00 7.20000000e+00 1.89000000e+02 ... 2.00000000e-01
```

```
  8.39100000e+03 2.01400000e+03]
 [6.30000000e+00 6.90000000e+00 1.79000000e+02 ... 1.00000000e-01
  5.33000000e+03 2.01400000e+03]
 ...
 [7.60000000e+00 9.80000000e+01 6.20000000e+00 ... 1.62307871e+00
  5.70000000e+02 2.00300000e+03]
 [7.70000000e+00 9.10000000e+01 6.50000000e+00 ... 1.62307871e+00
  5.62000000e+02 2.00300000e+03]
 [7.60000000e+00 1.10000000e+02 5.70000000e+00 ... 1.62307871e+00
  5.46000000e+02 2.00300000e+03]]
print(y)
```

```
[[84.46]
 [76.96]
 [79.28]
 ...
 [66.44]
 [66.44]
 [66.44]]
```

Splitting the Data into Train and Test

In [80]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size =
0.2,random_state=10)
```

In [81]:

```
#Feature Scaling
#from sklearn.preprocessing import StandardScaler
#sc = StandardScaler()
#x_train = sc.fit_transform(x_train)
#x_test = sc.transform(x_test)
```

In [82]:

```
from sklearn.ensemble import RandomForestRegressor
regressor = RandomForestRegressor(n_estimators = 10, random_state = 0)
regressor.fit(x_train, y_train)
y_pred = regressor.predict(x_test)
```

Model Evaluation

```
from sklearn import metrics
print('MAE:',metrics.mean_absolute_error(y_test,y_pred))
print('MSE:',metrics.mean_squared_error(y_test,y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
MAE: 0.9425563909774494
MSE: 5.63627572932331
RMSE: 2.374084187497004
```

In [84]:

```
metrics.r2_score(y_test, y_pred)
```

Out[84]:

```
0.9692766700278257
```

In [85]:

```
import pickle
pickle.dump(regressor,open('wqi.pkl','wb'))
model=pickle.load(open('wqi.pkl','rb'))
```

In [86]:

```
regressor.predict([[5.7,7.2,189.0,2.000000,0.200000,8391.0,2014]])
```

Out[86]:

```
array([76.47])
```

In [87]:

```
regressor.predict([[6.7,7.5,203.0,6.940049,0.1,27.0,2014]])
```

Out[87]:

```
array([85.306])
```