Phase III- Water Quality Analysis

Introduction

Water quality is a crucial factor for human health and well-being, as well as for the environment and the economy. This project addresses the critical issue of water quality analysis, as it pertains to health, human rights, and broader public policy considerations. Access to safe drinking water is indispensable, with significant implications for health and economic well-being. This analysis focuses on a comprehensive water quality dataset comprising 3276 water bodies, encompassing various critical parameters.

Data Acquisition and Preprocessing

The initial phase of the project is dedicated to data preparation and exploratory data analysis (EDA). To initiate this process, we acquire the water quality dataset and preprocess it. This preprocessing encompasses the handling of missing values and outliers, ensuring data integrity and reliability.

Exploratory Data Analysis (EDA) is an approach to data analysis that aims to summarize the main characteristics of a dataset, often with the help of data visualization and summary statistics.

Subsequently, our EDA endeavours encompass the visualization of parameter distributions, correlation analyses, and the identification of potential deviations from established water quality standards. This stage serves as the foundation for a more in-depth and robust water quality assessment, enabling data-driven insights and informed policy decisions.

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Water Quality Analysis

In [ ]:
```
import pandas as pd
import numpy as np
```

In [3]:
```
df=pd.read_csv("water_potability.csv")
```

In [4]:
```
df.head(5)
```

Out[4]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_
0	NaN	204.890455	20791.318981	7.300212	368.516441	564.308654	10.
1	3.716080	129.422921	18630.057858	6.635246	NaN	592.885359	15.
2	8.099124	224.236259	19909.541732	9.275884	NaN	418.606213	16.
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	18.
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	11.

In [5]:
```
df.shape
```

Out[5]:
```
(3276, 10)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate', 'Conductivity',
       'Organic_carbon', 'Trihalomethanes', 'Turbidity', 'Potability'],
      dtype='object')
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
ph                491
Hardness            0
Solids              0
Chloramines         0
Sulfate           781
Conductivity        0
Organic_carbon      0
Trihalomethanes   162
Turbidity           0
Potability          0
dtype: int64
```

In [9]:
```
df.dropna(inplace=True)
```

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
ph                0
Hardness          0
Solids            0
Chloramines       0
Sulfate           0
Conductivity      0
Organic_carbon    0
Trihalomethanes   0
Turbidity         0
Potability        0
dtype: int64
```

In [12]:
```
df.describe()
```

Out[12]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity
count	2011.000000	2011.000000	2011.000000	2011.000000	2011.000000	2011.000000
mean	7.085990	195.968072	21917.441374	7.134338	333.224672	426.526409
std	1.573337	32.635085	8642.239815	1.584820	41.205172	80.712572
min	0.227499	73.492234	320.942611	1.390871	129.000000	201.619737
25%	6.089723	176.744938	15615.665390	6.138895	307.632511	366.680307
50%	7.027297	197.191839	20933.512750	7.143907	332.232177	423.455906
75%	8.052969	216.441070	27182.587067	8.109726	359.330555	482.373169
max	14.000000	317.338124	56488.672413	13.127000	481.030642	753.342620

In [14]:
```
df.nunique()
```

Out[14]:
```
ph                2011
Hardness          2011
Solids            2011
Chloramines       2011
Sulfate           2011
Conductivity      2011
Organic_carbon    2011
Trihalomethanes   2011
Turbidity         2011
Potability           2
dtype: int64
```

In [15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2011 entries, 3 to 3271
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   ph               2011 non-null   float64
 1   Hardness         2011 non-null   float64
 2   Solids           2011 non-null   float64
 3   Chloramines      2011 non-null   float64
 4   Sulfate          2011 non-null   float64
 5   Conductivity     2011 non-null   float64
 6   Organic_carbon   2011 non-null   float64
 7   Trihalomethanes  2011 non-null   float64
 8   Turbidity        2011 non-null   float64
 9   Potability       2011 non-null   int64  
dtypes: float64(9), int64(1)
memory usage: 172.8 KB
```

In [17]:
```
df.dtypes
```

Out[17]:
```
ph                 float64
Hardness           float64
Solids             float64
Chloramines        float64
Sulfate            float64
Conductivity       float64
Organic_carbon     float64
Trihalomethanes    float64
Turbidity          float64
Potability           int64
dtype: object
```

correlations

In [45]:
```
df.corr
```

Out[45]:
```
<bound method DataFrame.corr of             ph    Hardness        Solids  Chlor
amines     Sulfate  \
3      8.316766  214.373394  22018.417441     8.059332  356.886136
4      9.092223  181.101509  17978.986339     6.546600  310.135738
5      5.584087  188.313324  28748.687739     7.544869  326.678363
6     10.223862  248.071735  28749.716544     7.513408  393.663396
7      8.635849  203.361523  13672.091764     4.563009  303.309771
...         ...         ...           ...          ...         ...
3267   8.989900  215.047358  15921.412018     6.297312  312.931022
3268   6.702547  207.321086  17246.920347     7.708117  304.510230
3269  11.491011   94.812545  37188.826022     9.263166  258.930600
3270   6.069616  186.659040  26138.780191     7.747547  345.700257
3271   4.668102  193.681735  47580.991603     7.166639  359.948574

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity  Potability
3       363.266516       18.436524       100.341674   4.628771           0
4       398.410813       11.558279        31.997993   4.075075           0
5       280.467916        8.399735        54.917862   2.559708           0
6       283.651634       13.789695        84.603556   2.672989           0
7       474.607645       12.363817        62.798309   4.401425           0
...            ...             ...              ...        ...         ...
3267    390.410231        9.899115        55.069304   4.613843           1
3268    329.266002       16.217303        28.878601   3.442983           1
3269    439.893618       16.172755        41.558501   4.369264           1
3270    415.886955       12.067620        60.419921   3.669712           1
3271    526.424171       13.894419        66.687695   4.435821           1

[2011 rows x 10 columns]>
```

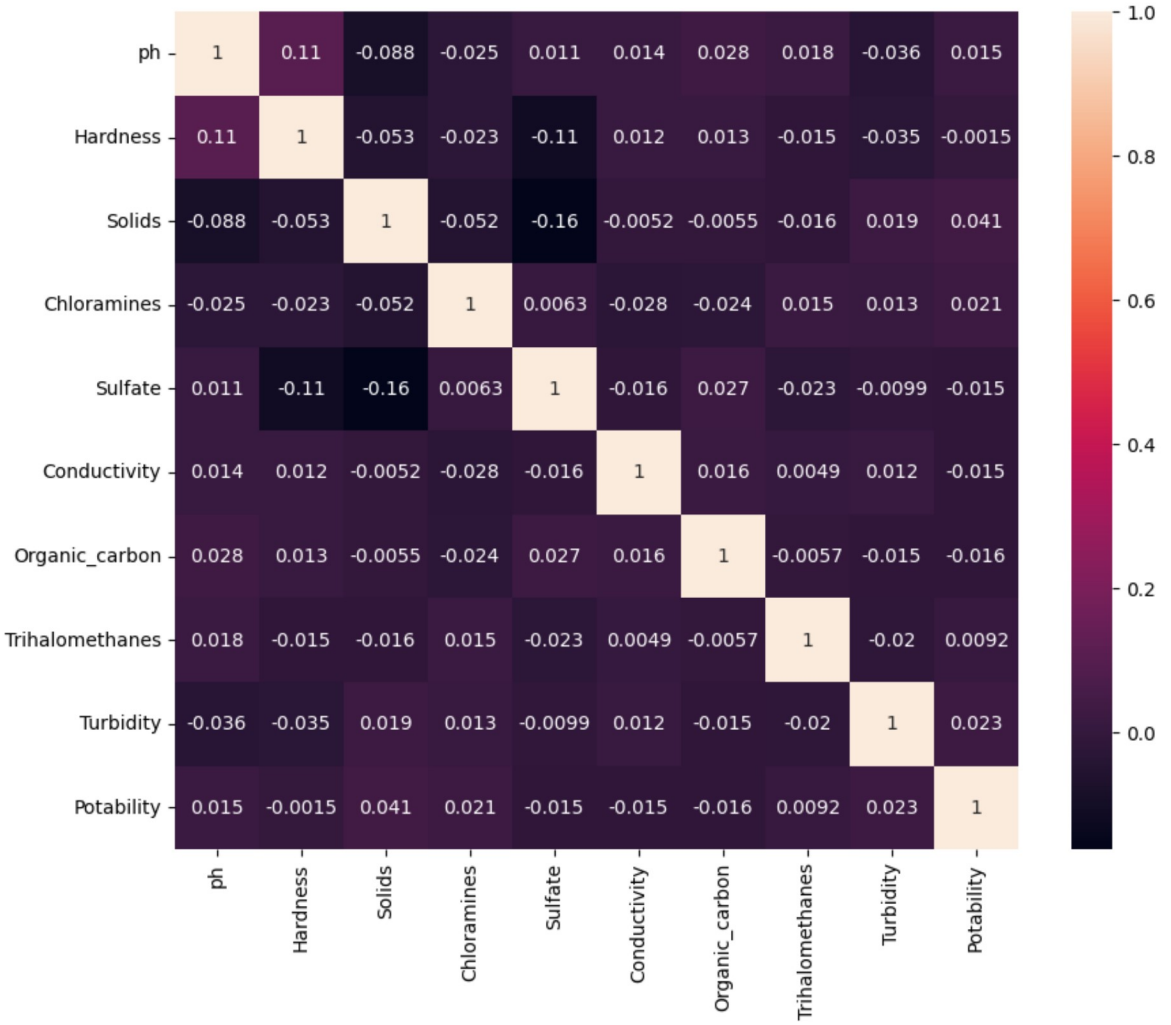
In [32]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [33]:
```
df['Potability'].value_counts()
```

Out[33]:
```
Potability
0    1200
1     811
Name: count, dtype: int64
```

In [35]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(),annot=True,cmap=None)
```

Out[35]:
```
<Axes: >
```

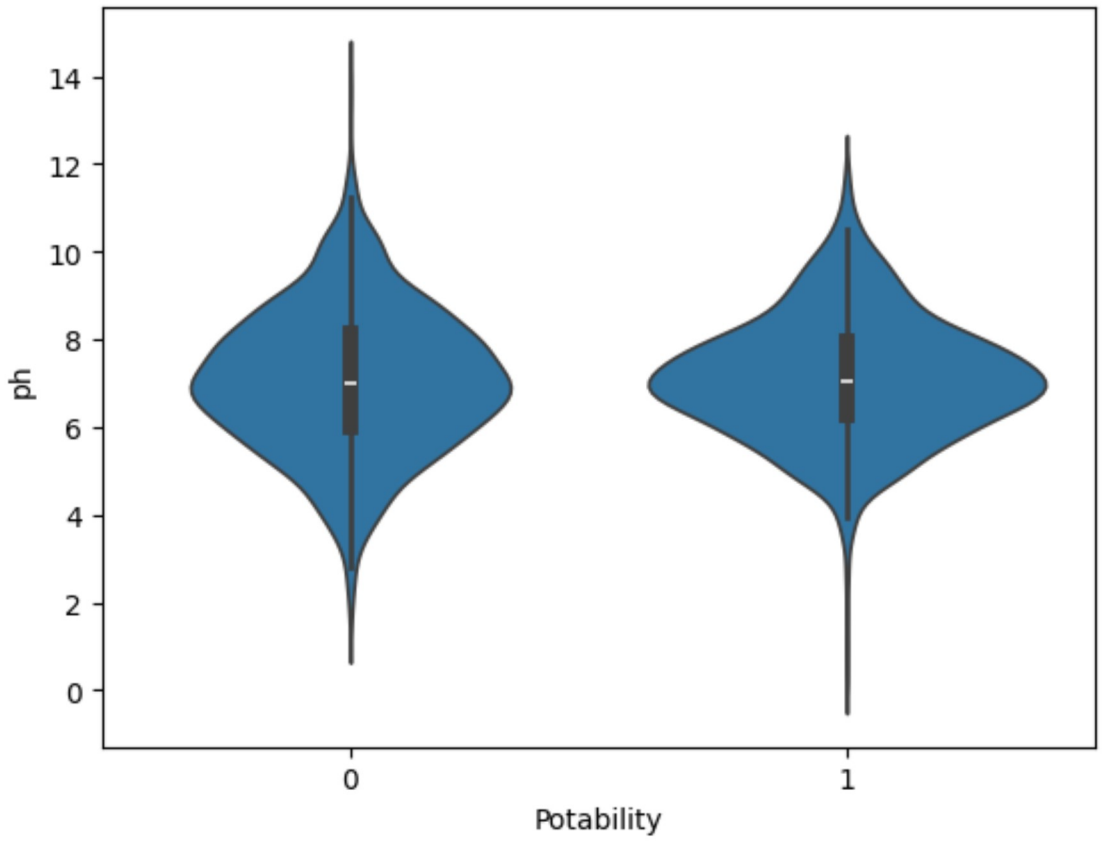


In [36]:
```
df['Potability'].value_counts()
```

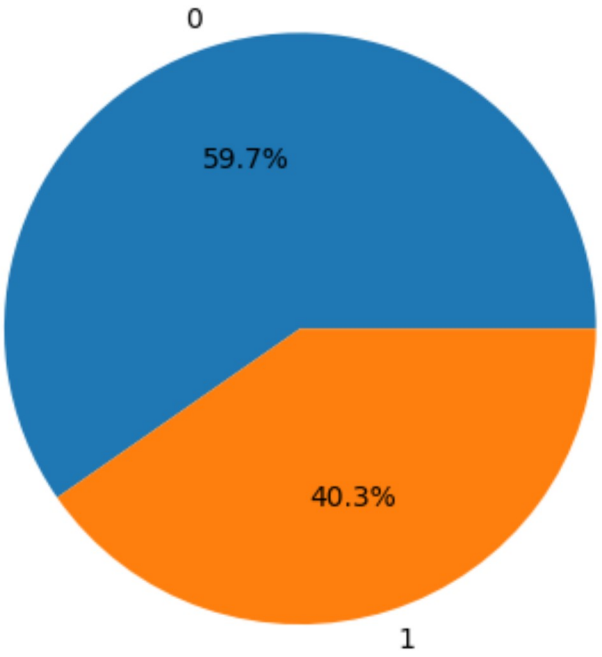
Out[36]:
```
Potability
0    1200
1     811
Name: count, dtype: int64
```

In [37]:
```
sns.violinplot(x='Potability',y='ph',data=df)
```

Out[37]:
```
<Axes: xlabel='Potability', ylabel='ph'>
```



In [38]:
```
plt.pie(df['Potability'].value_counts(),labels = list(df['Potability'].unique()))
plt.show()
```



In [39]:
```
df
```

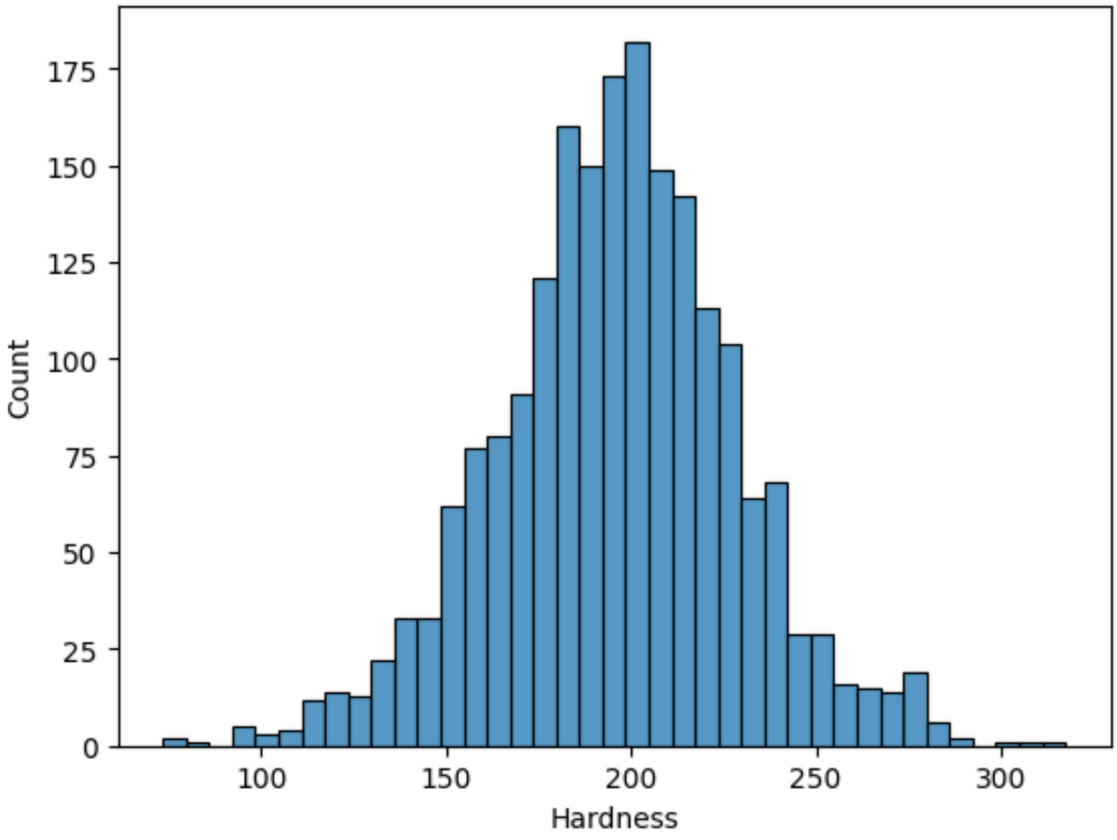
Out[39]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Orga
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	
6	10.223862	248.071735	28749.716544	7.513408	393.663396	283.651634	
7	8.635849	203.361523	13672.091764	4.563009	303.309771	474.607645	
...	...	...	...	...	...	...	
3267	8.989900	215.047358	15921.412018	6.297312	312.931022	390.410231	
3268	6.702547	207.321086	17246.920347	7.708117	304.510230	329.266002	
3269	11.491011	94.812545	37188.826022	9.263166	258.930600	439.893618	
3270	6.069616	186.659040	26138.780191	7.747547	345.700257	415.886955	
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	

2011 rows × 10 columns

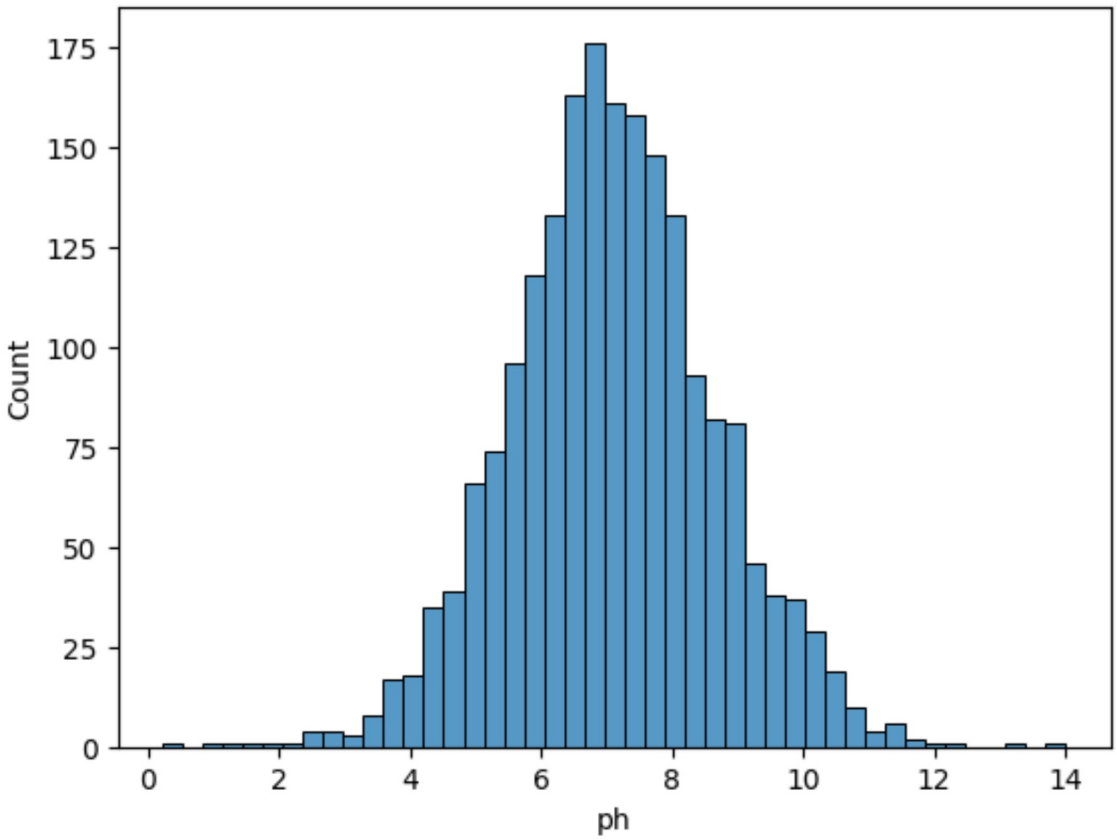
In [40]:
```
sns.histplot(df['Hardness'])
```

Out[40]:
```
<Axes: xlabel='Hardness', ylabel='Count'>
```

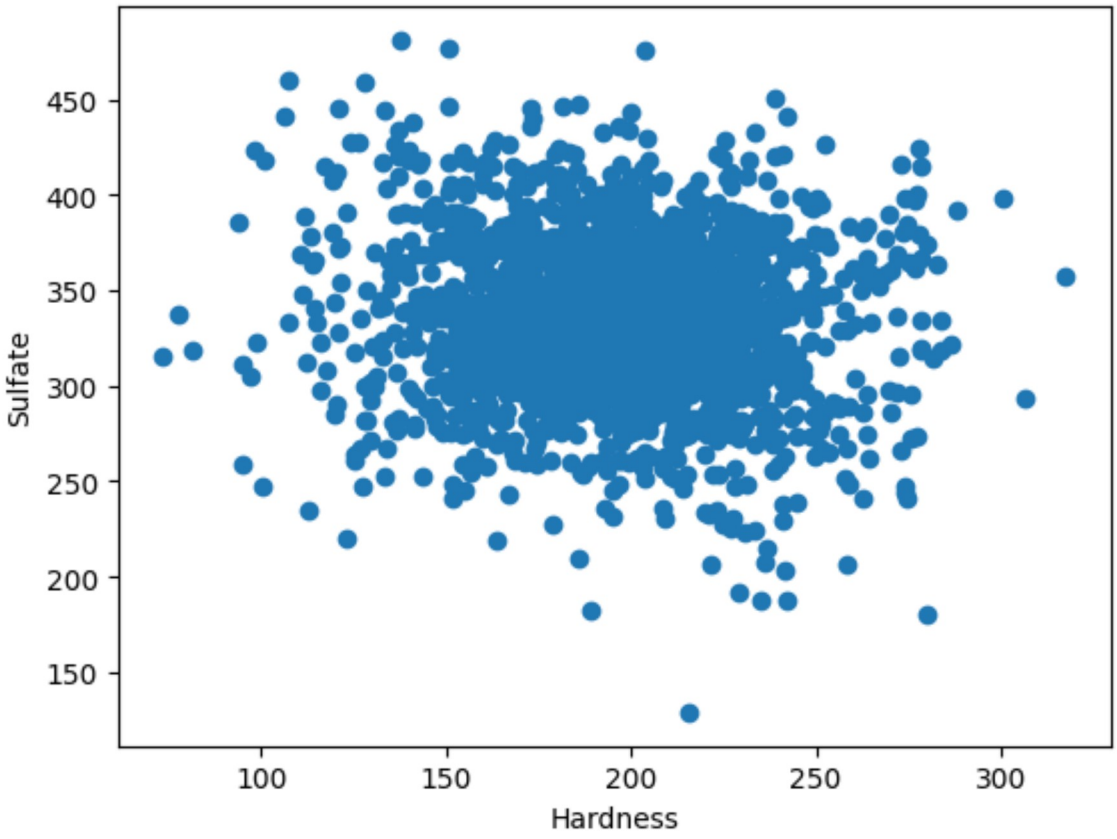


In [41]:
```
sns.histplot(df['ph'])
```

Out[41]:
```
<Axes: xlabel='ph', ylabel='Count'>
```

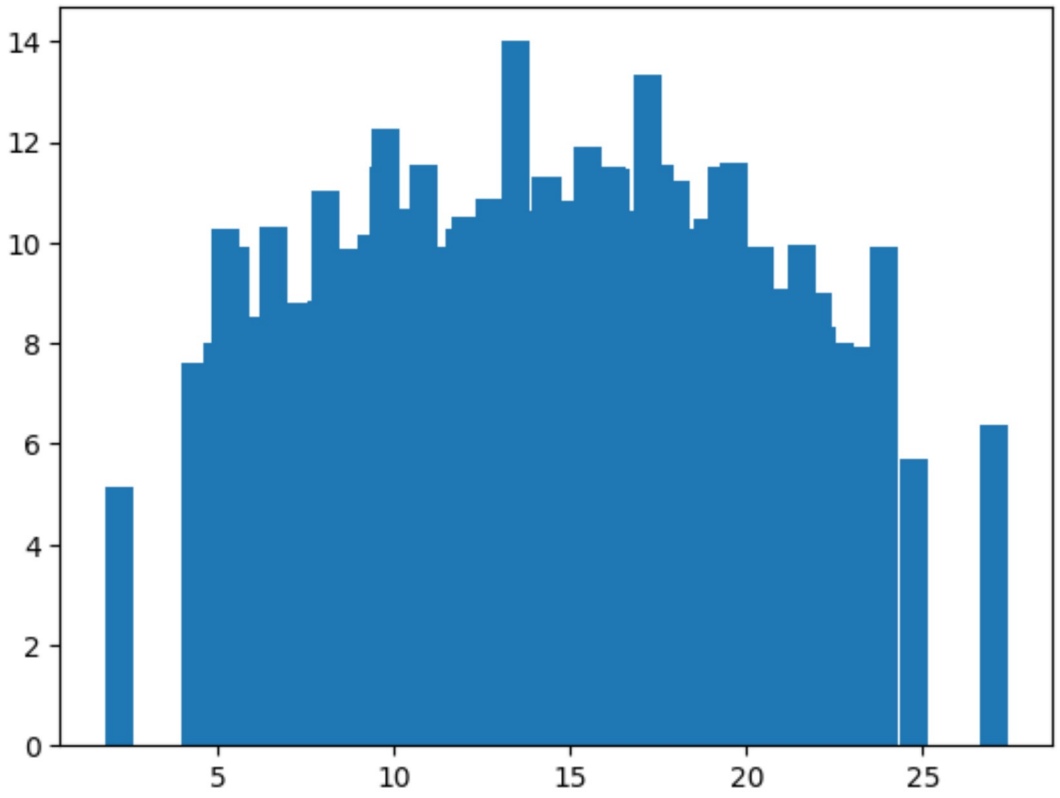


In [42]:
```
gp = plt.scatter(df['Hardness'],df['Sulfate'])
plt.xlabel('Hardness')
plt.ylabel('Sulfate')
plt.show(gp)
```



In [43]:
```
plt.bar(df['Organic_carbon'],df['ph'])
```

Out[43]: <BarContainer object of 2011 artists>



In [44]:
```
df
```

Out[44]:

	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Orga
3	8.316766	214.373394	22018.417441	8.059332	356.886136	363.266516	
4	9.092223	181.101509	17978.986339	6.546600	310.135738	398.410813	
5	5.584087	188.313324	28748.687739	7.544869	326.678363	280.467916	
6	10.223862	248.071735	28749.716544	7.513408	393.663396	283.651634	
7	8.635849	203.361523	13672.091764	4.563009	303.309771	474.607645	
...	...	...	...	...	...	...	
3267	8.989900	215.047358	15921.412018	6.297312	312.931022	390.410231	
3268	6.702547	207.321086	17246.920347	7.708117	304.510230	329.266002	
3269	11.491011	94.812545	37188.826022	9.263166	258.930600	439.893618	
3270	6.069616	186.659040	26138.780191	7.747547	345.700257	415.886955	
3271	4.668102	193.681735	47580.991603	7.166639	359.948574	526.424171	

2011 rows × 10 columns

In [ ]: