In [1]:
```
# Importing necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
# Reading the Excel file
AIQ = pd.read_excel("C:\\Users\\ROSHAN COMPUTERS\\Desktop\\Hyd.xlsx")

# Displaying the first few rows of the dataframe
AIQ.head()
```

Out[2]:

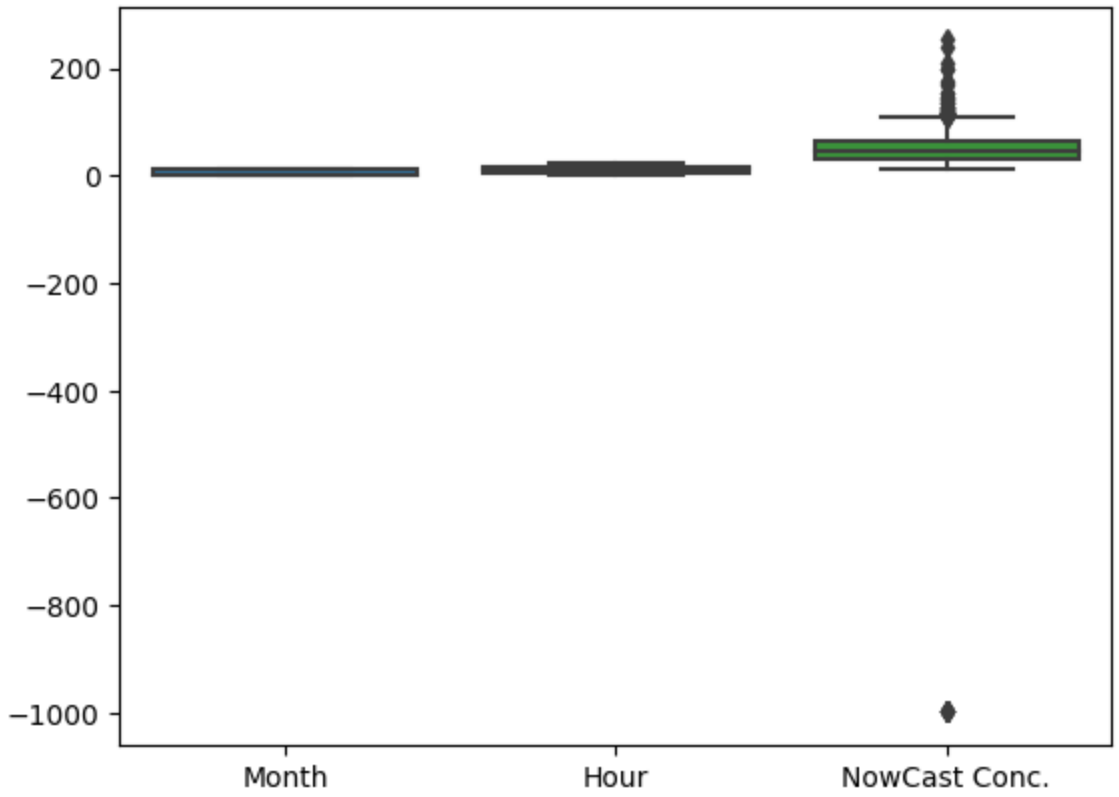
	Unnamed: 0	Site	Parameter	Date (LT)	Year	Month	Day	Hour	NowCast Conc.	Raw Conc.	Conc. Unit	Duration	QC Name	AQI	AQI Category
0	0	Hyderabad	PM2.5 - Principal	2019-12-01 01:00:00	2019	12	1	1	59.3	57	UG/M3	1 Hr	Valid	153	Unhealthy
1	1	Hyderabad	PM2.5 - Principal	2019-12-01 02:00:00	2019	12	1	2	70.1	81	UG/M3	1 Hr	Valid	159	Unhealthy
2	2	Hyderabad	PM2.5 - Principal	2019-12-01 03:00:00	2019	12	1	3	68.5	67	UG/M3	1 Hr	Valid	158	Unhealthy
3	3	Hyderabad	PM2.5 - Principal	2019-12-01 04:00:00	2019	12	1	4	62.0	53	UG/M3	1 Hr	Valid	154	Unhealthy
4	4	Hyderabad	PM2.5 - Principal	2019-12-01 05:00:00	2019	12	1	5	58.1	52	UG/M3	1 Hr	Valid	152	Unhealthy

In [3]:
```
# Displaying unique values in the 'Month' column
AIQ["Month"].unique()
```

Out[3]:
```
array([12,  1,  2,  3], dtype=int64)
```

In [4]:
```
sns.boxplot(AIQ[["Month","Hour","NowCast Conc."]])
```

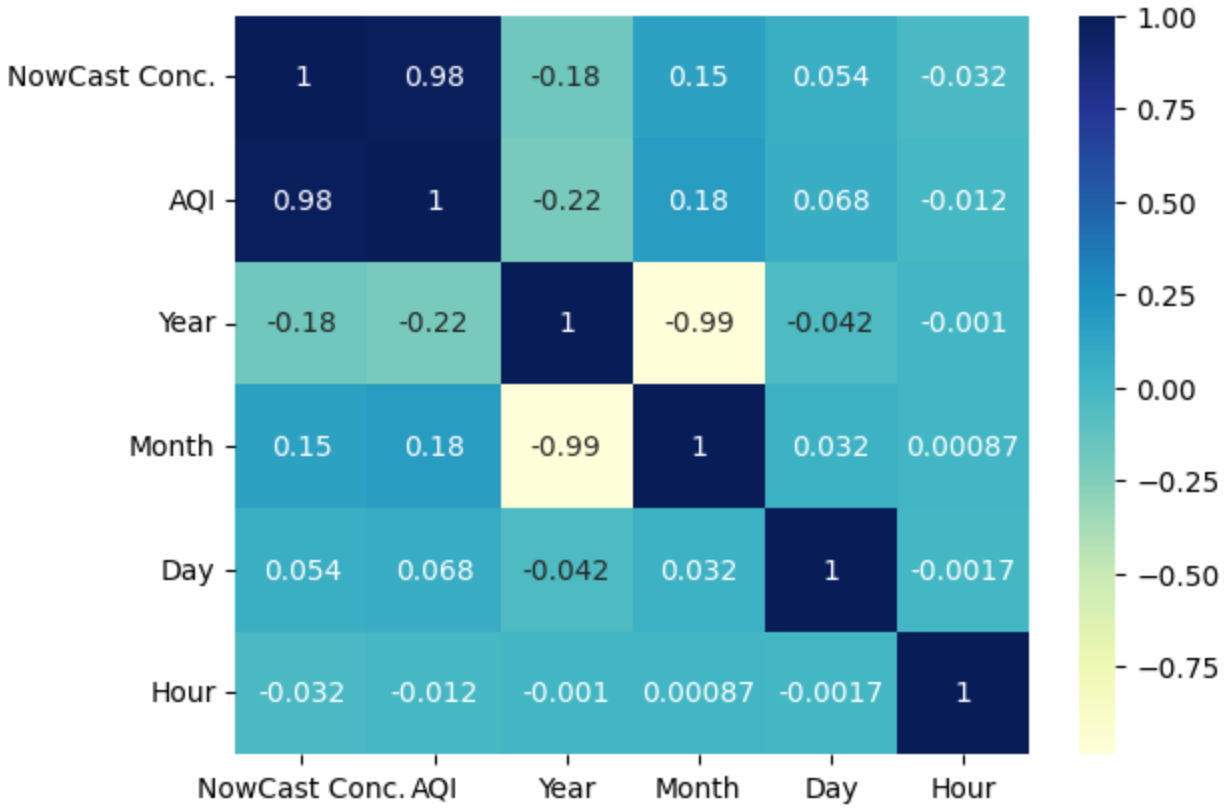
Out[4]: <AxesSubplot:>



In [5]:
```
# Displaying column names
AIQ.columns
```

Out[5]:
```
Index(['Unnamed: 0', 'Site', 'Parameter', 'Date (LT)', 'Year', 'Month', 'Day',
       'Hour', 'NowCast Conc.', 'Raw Conc.', 'Conc. Unit', 'Duration',
       'QC Name', 'AQI', 'AQI Category'],
      dtype='object')
```

In [6]:
```
# Correlation heatmap
corr_columns = ['NowCast Conc.', 'AQI', 'Year', 'Month', 'Day', 'Hour']
sns.heatmap(AIQ[corr_columns].corr(), annot=True,cmap="YlGnBu")
plt.savefig("Correlation", dpi=300)
```



In [7]:
```
# Profiling the data
from ydata_profiling import ProfileReport
Profile = ProfileReport(AIQ, title="Air Quality Index report", explorative=True)
#Profile.to_file("Air Quality Index report.html")
```

In [32]:
```
Profile
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

Overview

Dataset statistics

Number of variables	15
Number of observations	2853
Missing cells	7
Missing cells (%)	< 0.1%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	1.3 MiB
Average record size in memory	470.0 B

Variable types

Numeric	6
Categorical	8
DateTime	1

Alerts

`Site` has constant value ""	**Constant**
`Parameter` has constant value ""	**Constant**
`Conc. Unit` has constant value ""	**Constant**
`Duration` has constant value ""	**Constant**
`AQI` is highly overall correlated with `AQI Category` and 2 other fields (AQI Category, NowCast Conc., Raw Conc.)	**High correlation**

`AQI Category` is highly overall correlated with `AQI` **High correlation**

Out[32]:

In [8]:
```
# Data cleaning and outlier detection (NowCast Conc.)

Q1 = AIQ['NowCast Conc.'].quantile(0.25)
Q3 = AIQ['NowCast Conc.'].quantile(0.75)

IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

In [9]:
```
outliers = (AIQ["NowCast Conc."] < lower_bound) | (AIQ["NowCast Conc."] > upper_bound)
```

In [10]:
```
AIQ.loc[outliers, "NowCast Conc."] = np.mean(AIQ["NowCast Conc."])
```

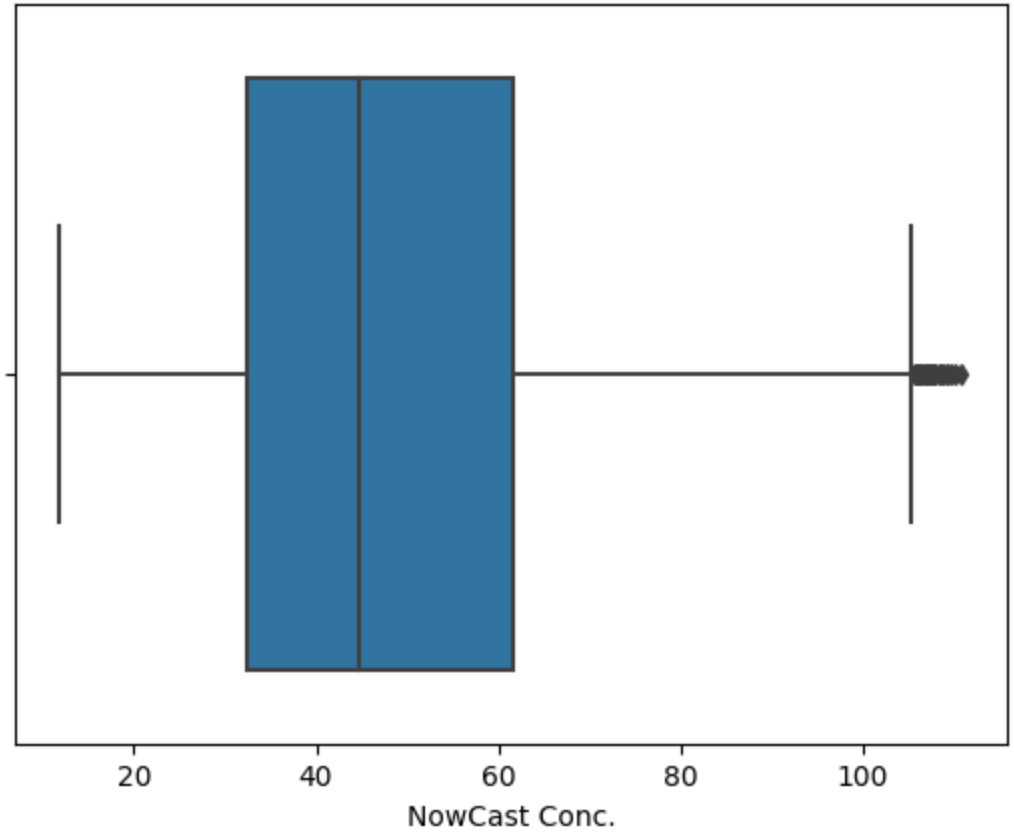
In [11]:
```
# Data cleaning and outlier detection (AQI)

Q1 = AIQ['AQI'].quantile(0.25)
Q3 = AIQ['AQI'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
```

In [12]:
```
outliers1 = (AIQ["AQI"] < lower_bound) | (AIQ["AQI"] > upper_bound)
```

In [13]:
```
AIQ.loc[outliers1, "AQI"] = np.mean(AIQ["AQI"])
```

In [14]:
```
# Boxplot visualization (NowCast Conc.)

sns.boxplot(data=AIQ, x='NowCast Conc.')
```

Out[14]:
```
<AxesSubplot:xlabel='NowCast Conc.'>
```



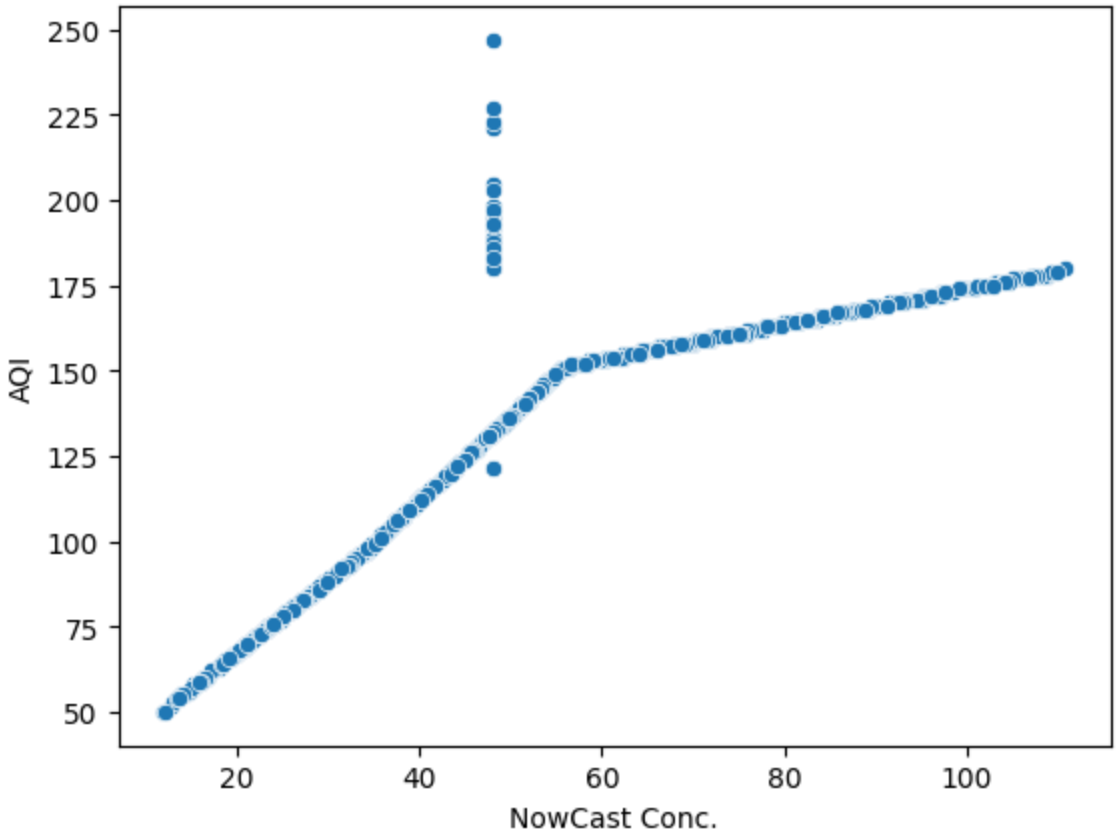
In [15]:
```
# Extracting relevant columns for further analysis
a = AIQ[['NowCast Conc.', 'AQI']]

# Descriptive statistics
a.describe()
```

Out[15]:

	NowCast Conc.	AQI
count	2853.000000	2853.000000
mean	49.020851	123.929322
std	21.314493	33.888271
min	11.900000	50.000000
25%	32.400000	94.000000
50%	44.800000	124.000000
75%	61.700000	155.000000
max	110.800000	247.000000

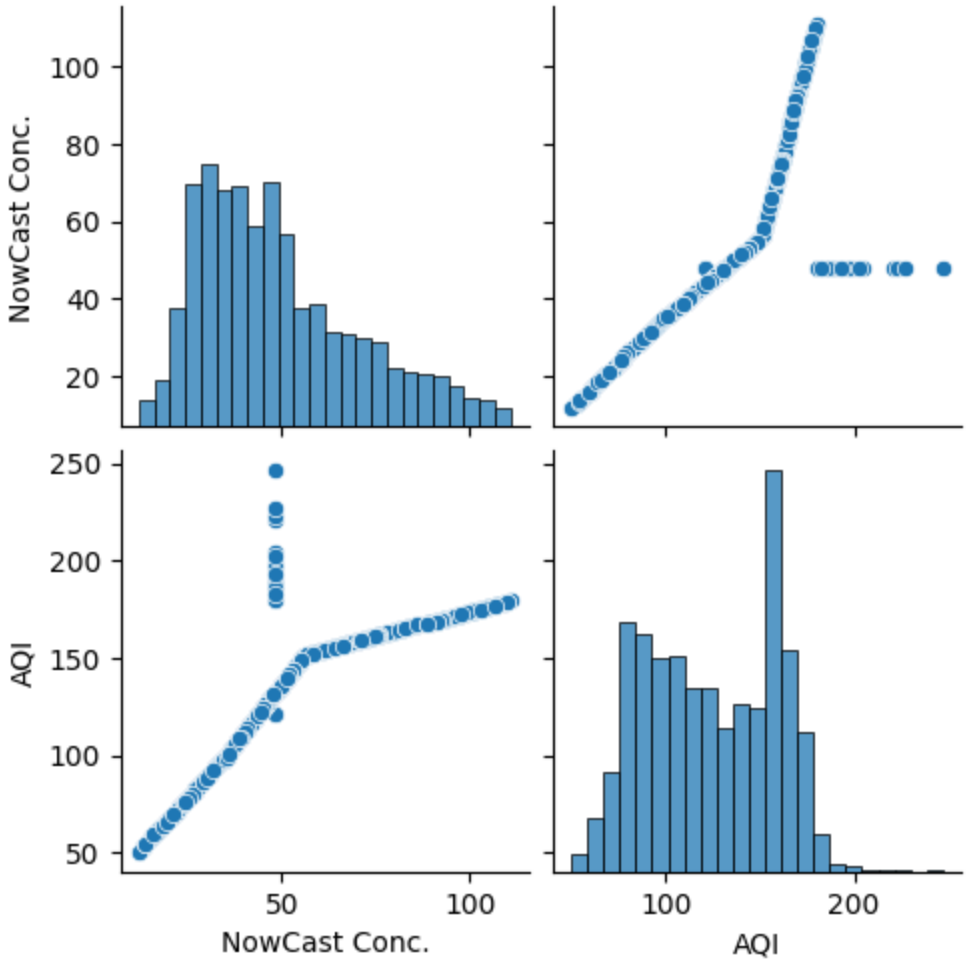
In [16]:
```
# Scatterplot
sns.scatterplot(x='NowCast Conc.', y='AQI', data=a)
```

Out[16]:
```
<AxesSubplot:xlabel='NowCast Conc.', ylabel='AQI'>
```



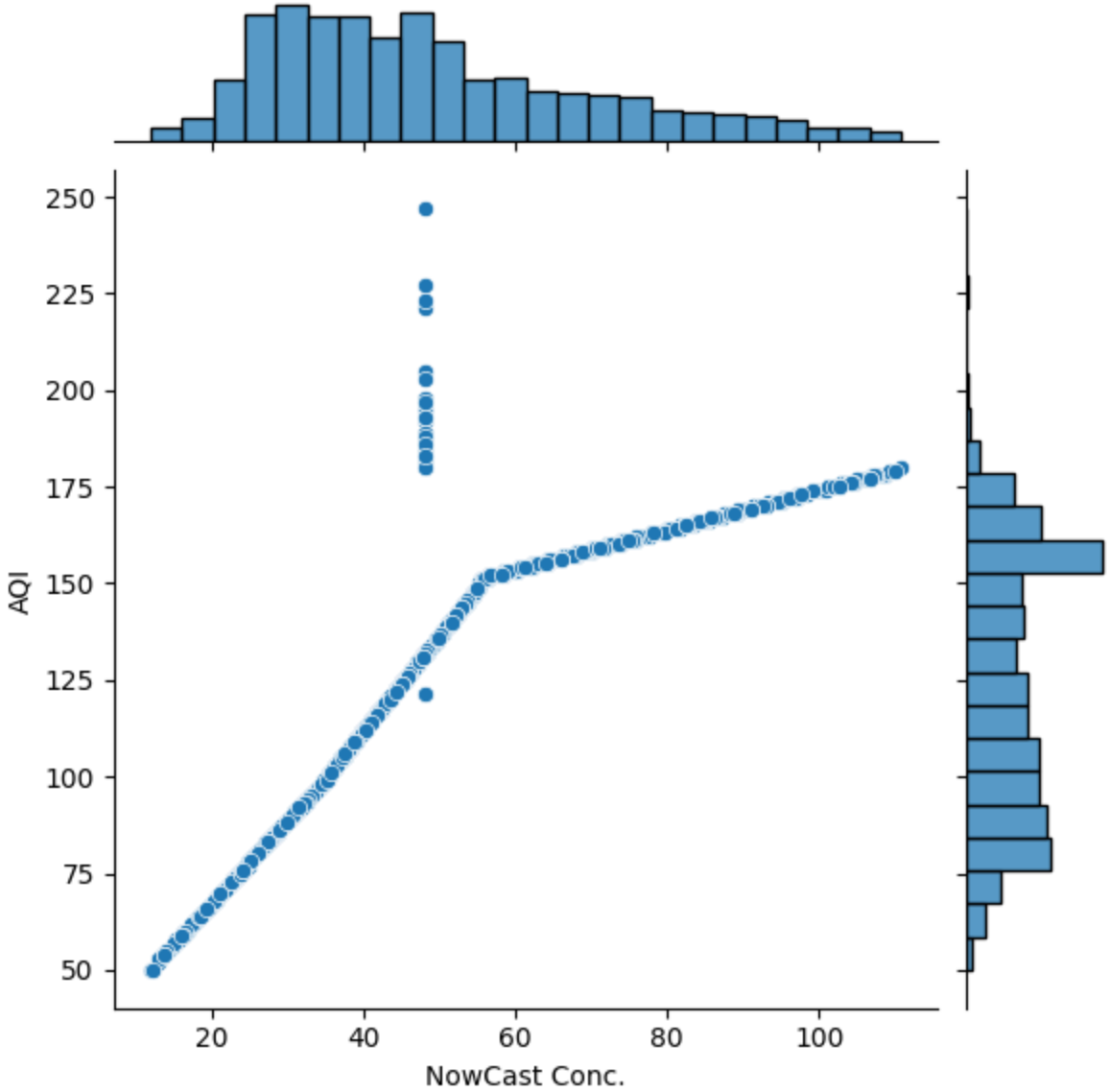
In [17]:
```
# Pairplot
sns.pairplot(a)
```

Out[17]:
```
<seaborn.axisgrid.PairGrid at 0x2b56e3245e0>
```



In [18]:
```
sns.jointplot(x='NowCast Conc.', y='AQI', data=a)
```

Out[18]:
```
<seaborn.axisgrid.JointGrid at 0x2b56e5648b0>
```



In [19]:
```
# Profiling the cleaned and processed data
Profile1 = ProfileReport(a, title="Air Quality Index report after cleaning", explorative=True)
#Profile1
```

Linear Regression Model

In [20]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
```

In [21]:
```
X = a[["NowCast Conc."]]
Y = a[["AQI"]]
```

In [22]:
```
# Splitting the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state=2)
```

In [23]:
```
# Training the linear regression model
lr = LinearRegression()
lr.fit(X_train, Y_train)
```

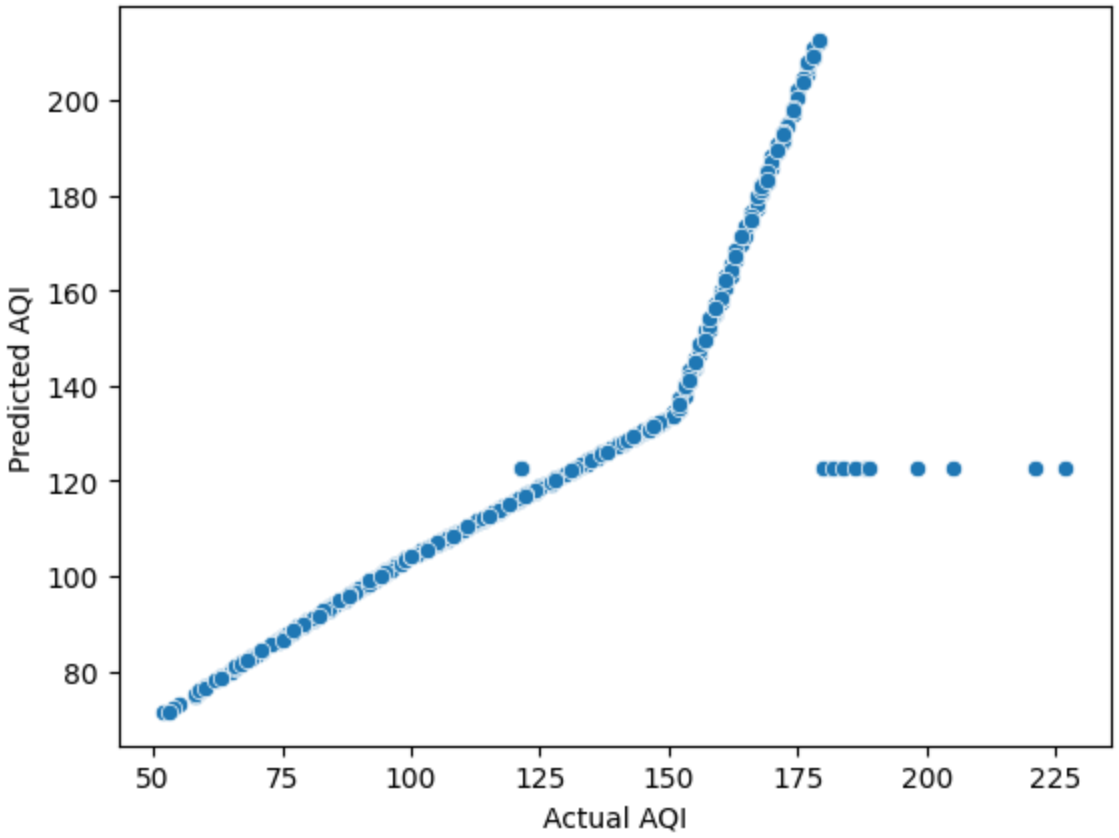
Out[23]:
```
▾ LinearRegression

LinearRegression()
```

In [24]:
```
# Making predictions on the test set
Y_train_pred=lr.predict(X_train)
Y_test_pred = lr.predict(X_test)
```

In [43]:
```
# Evaluating the model

r2_train=r2_score(Y_train,Y_train_pred)
r2_test = r2_score(Y_test, Y_test_pred)
print(f"R-squared on the train set: {r2_train}")
print(f"R-squared on the test set: {r2_test}")
```

```
R-squared on the train set: 0.8320181085388942
R-squared on the test set: 0.8302298731774278
```

In [26]:
```
# Scatterplot of predictions vs. actual values
sns.scatterplot(x=Y_test.values.flatten(), y=Y_test_pred.flatten())
plt.xlabel("Actual AQI")
plt.ylabel("Predicted AQI")
plt.show()
```

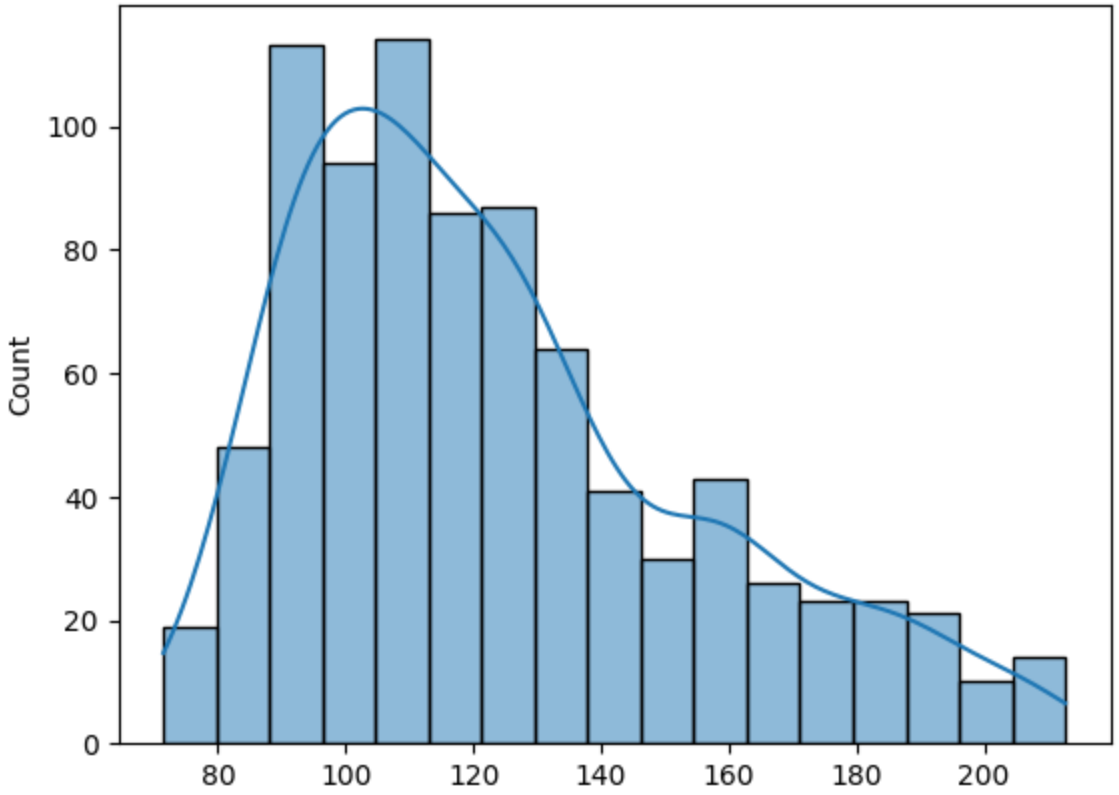


In [27]:
```
# Calculate evaluation metrics
from sklearn.metrics import mean_absolute_error,mean_squared_error

mae=mean_absolute_error(Y_test , Y_test_pred)
mse=mean_squared_error(Y_test,Y_test_pred)
rmse=np.sqrt(mse)

print(f" Mean Absolute Error :{mae}")

print(f" Mean Squared Error :{mae}")

print(f" Root Mean Squared Error :{mae}")
```

```
Mean Absolute Error :10.034468029125716
Mean Squared Error :10.034468029125716
Root Mean Squared Error :10.034468029125716
```

In [42]:
```
#Histogram Plot using Seaborn for predicted values:

x=Y_test.values.flatten()

y=Y_test_pred.flatten()

sns.histplot(y,kde=True)
```

Out[42]:
```
<AxesSubplot:ylabel='Count'>
```



In [44]:
```
#  D-Tale generates an interactive dashboard that allows users to explore their data visually.
#  The dashboard includes various tabs with information on statistics, charts, and other insights.


import dtale

#  AIQ is your DataFrame
dtale.show(AIQ)
```

```
D:\Python\lib\site-packages\dtale\views.py:793: FutureWarning:

['AQI Category'] did not aggregate successfully. If any error is raised this will raise in a future version of pandas.
Drop these columns/ops to avoid this warning.
```

Out[44]:

In [41]:
```
lr.predict([[62]])
```

```
D:\Python\lib\site-packages\sklearn\base.py:420: UserWarning:

X does not have valid feature names, but LinearRegression was fitted with feature names
```

Out[41]:
```
array([[142.95358847]])
```

In [ ]:
```

```