Assignment 1 INFO204 Yuki Yoshiyasu 5861229

Introduction

New Zealand has cultivated an image for itself as a "clean and green" country. However, we are increasingly aware of the fragility of our natural systems, and in particular the importance that our freshwater systems play on our fauna and flora. Maintaining good freshwater health has important environmental, economic, and political issues. In the analysis we will be investigating these issues using multiple data wrangling techniques.

```
#All the imports for the assignement
import pandas as pd
import numpy as np
import seaborn as sns

from matplotlib import pyplot as plt

from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor, plot_tree

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

Part 1: Data Wrangling and EDA

```
#Cleaning the data by removing irrelevant columns

sites = pd.read_csv('https://drive.google.com/uc?
export=download&id=1lx4k_ZhvtJLs1i65BiAop7b-86SeOqRN',
compression='gzip')
## remove irrelevant visit variables here
columns_to_remove = ["Altitude","Catchment area","Catchment height"]
sites.drop(columns = columns_to_remove, inplace = True)
sites.info()
sites.describe()
print(sites)


site_visits = pd.read_csv('https://drive.google.com/uc?
export=download&id=1tGBh4LD1UTlGfwGTS2-iMk_x6daRXPfA',
compression='gzip')
## remove irrelevant visit variables here
columns_to_remove = ["Scientist","Verified By","Day of Week"]
```

```
site_visits.drop(columns = columns_to_remove, inplace = True)
site_visits.info()
site_visits.describe()
print(site_visits)


long_measurements = pd.read_csv('https://drive.google.com/uc?
export=download&id=1Gl-BDg6gsJG25PgJkj7TFDxUkUPgyPgw',
compression='gzip')
long_measurements.info()
long_measurements.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 77 entries, 0 to 76
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   SiteID     77 non-null     object
 1   Region     77 non-null     object
 2   Name       77 non-null     object
 3   Longitude  77 non-null     float64
 4   Latitude   77 non-null     float64
dtypes: float64(2), object(3)
memory usage: 3.1+ KB
   SiteID      Region                       Name   Longitude   Latitude
0     AK1    Auckland            Hoteo at Gubbs  174.516776 -36.387085
1     AK2    Auckland   Rangitopuni at Walkers  174.617716 -36.746082
2     AX1   Alexandra    Clutha at Luggate Br.  169.279966 -44.730920
3     AX2   Alexandra      Kawarau at Chard Rd  168.868674 -45.007995
4     AX3   Alexandra  Shotover at Bowens Peak  168.714900 -44.991606
..    ...         ...                      ...         ...        ...
72    WN1  Wellington         Hutt at Boulcott  174.921966 -41.199706
73    WN2  Wellington          Hutt at Kaitoke  175.191361 -41.052600
74    WN3  Wellington   Ruamahanga at Waihenga  175.439426 -41.197160
75    WN4  Wellington   Ruamahanga at Wardells  175.671349 -41.004683
76    WN5  Wellington        Ruamahanga at SH2  175.604835 -40.763879

[77 rows x 5 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29601 entries, 0 to 29600
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Timestamp  29601 non-null  object
 1   SiteID     29601 non-null  object
 2   checksum   29601 non-null  object
dtypes: object(3)
memory usage: 693.9+ KB
```

```
                    Timestamp SiteID                          checksum
0      1989-02-01T10:30:00Z    AK1  deda7828c5ca8ae842d1d4c7dbaf8d7c
1      1989-03-15T11:45:00Z    AK1  5c47147d9c97ab9712106a520320c92b
2      1989-04-13T11:10:00Z    AK1  e6b793a64f5092a9ddc3fb850c92b150
3      1989-05-10T11:10:00Z    AK1  efe6310e08bbddf82bf35b713fd7bd94
4      1989-06-08T10:20:00Z    AK1  fc98017089311bfe513985c5e01393e7
...                     ...    ...                               ...
29596  2021-08-17T09:45:00Z    AX4  2d4fe85b2e25d08a45be0a1db9f6fdac
29597  2021-08-18T08:35:00Z    GY4  0d6cd16a677d4d0bf16601719ec21dbf
29598  2022-12-15T12:25:00Z    TU1  5d949a8ce724ad593491c7a0fd0008d3
29599  2022-12-15T08:30:00Z    TU2  a4378b7ff6be3e824664d24e94fdfa64
29600  2022-12-14T11:15:00Z    WA5  93663c6c9d9caf94a7b3ca8ba0fdbd1e

[29601 rows x 3 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 308555 entries, 0 to 308554
Data columns (total 3 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   checksum     308555 non-null  object
 1   Measurement  308555 non-null  object
 2   Value        308555 non-null  float64
dtypes: float64(1), object(2)
memory usage: 7.1+ MB

               Value
count  308555.000000
mean       92.092955
std       342.991958
min         0.000000
25%         7.000000
50%        14.600000
75%       100.300000
max     72700.000000
```

Each of the dataset has been obtained by using the link given for the assignemnt. Then I have dropped unwanted columns for each dataset and to obtain the desired dataframe, printing the descriptive statistics of each dataset have also helped to determine which columns to keep.

```
#Adding columns Year Hour and Season
site_visits
site_visits['Timestamp'] = pd.to_datetime(site_visits['Timestamp'])
site_visits['Year'] = site_visits['Timestamp'].dt.year
site_visits['Hour of day'] = site_visits['Timestamp'].dt.hour

def get_season(month):
    seasons = {0: 'Summer', 1: 'Autumn', 2: 'Winter', 3: 'Spring'}
    return seasons[(month % 12) // 3]
site_visits['Season'] =
```

```
site_visits['Timestamp'].dt.month.apply(get_season)

print(site_visits)

wide_measurements = long_measurements.pivot(index =
"checksum",columns='Measurement', values='Value')
wide_measurements["log(E Coli)"] = np.log10(wide_measurements["E
Coli"]+1)

display(wide_measurements)
```

```
                      Timestamp SiteID
checksum  \
0     1989-02-01 10:30:00+00:00    AK1
deda7828c5ca8ae842d1d4c7dbaf8d7c
1     1989-03-15 11:45:00+00:00    AK1
5c47147d9c97ab9712106a520320c92b
2     1989-04-13 11:10:00+00:00    AK1
e6b793a64f5092a9ddc3fb850c92b150
3     1989-05-10 11:10:00+00:00    AK1
efe6310e08bbddf82bf35b713fd7bd94
4     1989-06-08 10:20:00+00:00    AK1
fc98017089311bfe513985c5e01393e7
...                         ...    ...                               .
..
29596 2021-08-17 09:45:00+00:00    AX4
2d4fe85b2e25d08a45be0a1db9f6fdac
29597 2021-08-18 08:35:00+00:00    GY4
0d6cd16a677d4d0bf16601719ec21dbf
29598 2022-12-15 12:25:00+00:00    TU1
5d949a8ce724ad593491c7a0fd0008d3
29599 2022-12-15 08:30:00+00:00    TU2
a4378b7ff6be3e824664d24e94fdfa64
29600 2022-12-14 11:15:00+00:00    WA5
93663c6c9d9caf94a7b3ca8ba0fdbd1e

       Year  Hour of day  Season
0      1989           10  Summer
1      1989           11  Autumn
2      1989           11  Autumn
3      1989           11  Autumn
4      1989           10  Winter
...     ...          ...     ...
29596  2021            9  Winter
29597  2021            8  Winter
29598  2022           12  Summer
29599  2022            8  Summer
29600  2022           11  Summer
```

```
[29601 rows x 6 columns]
Measurement                       Ammonia  Dissolved Oxygen Saturation  \
checksum
000414253acc7df5faa656c94ca8e628      9.0                        100.3
0004f9dd58ee6cef1650fa225300f3ee      9.0                        100.0
0004fcf11172c3fcb74264fa36d33cbd     58.0                        112.7
000a014f09a691b27896d4731f985f47      4.0                        102.3
000fc049dbfa7b01334dbd0401992081      7.0                         99.8
...                                   ...                          ...
ffeae564043ba08ac2abd68299c12e92      8.0                         78.0
fff224af9c3d20e1b32645aadca78da8      8.0                         96.8
fff46cdd9d8d285af4e10467783b8d41     69.0                         98.7
fff51d3deea67e60c45d6a1cee40daef      4.0                        100.0
fff75fd36275ee970e9b3f566a092076     10.0                         95.0

Measurement                       Dissolved Reactive Phosphate  E Coli  \
checksum
000414253acc7df5faa656c94ca8e628                          31.5     NaN
0004f9dd58ee6cef1650fa225300f3ee                           6.0     NaN
0004fcf11172c3fcb74264fa36d33cbd                           2.0     NaN
000a014f09a691b27896d4731f985f47                           6.2     NaN
000fc049dbfa7b01334dbd0401992081                           7.4    77.1
...                                                        ...     ...
ffeae564043ba08ac2abd68299c12e92                           5.0     NaN
fff224af9c3d20e1b32645aadca78da8                           5.2   365.4
fff46cdd9d8d285af4e10467783b8d41                           5.0     NaN
```

```
fff51d3deea67e60c45d6a1cee40daef                          3.4     NaN

fff75fd36275ee970e9b3f566a092076                          5.1   697.0


Measurement                       Electrical Conductivity  Nitrate +
Nitrite  \
checksum

000414253acc7df5faa656c94ca8e628                     68.6
109.0
0004f9dd58ee6cef1650fa225300f3ee                    108.0
68.0
0004fcf11172c3fcb74264fa36d33cbd                    139.0
425.0
000a014f09a691b27896d4731f985f47                    121.0
11.0
000fc049dbfa7b01334dbd0401992081                     94.2
1228.0
...                                                   ...
...
ffeae564043ba08ac2abd68299c12e92                    209.0
1.0
fff224af9c3d20e1b32645aadca78da8                     90.0
325.0
fff46cdd9d8d285af4e10467783b8d41                     78.7
285.0
fff51d3deea67e60c45d6a1cee40daef                     94.8
246.0
fff75fd36275ee970e9b3f566a092076                    108.4
71.0

Measurement                        URS  Water Clarity  Water Kelvin  \
checksum
000414253acc7df5faa656c94ca8e628   5.8           0.45        292.95
0004f9dd58ee6cef1650fa225300f3ee  14.3           0.05        281.65
0004fcf11172c3fcb74264fa36d33cbd  10.9           3.17        286.35
000a014f09a691b27896d4731f985f47   5.8           3.05        281.05
000fc049dbfa7b01334dbd0401992081  13.4           2.31        286.35
...                                ...            ...           ...
ffeae564043ba08ac2abd68299c12e92   8.5           1.95        295.35
fff224af9c3d20e1b32645aadca78da8   8.4           2.42        288.15
fff46cdd9d8d285af4e10467783b8d41   9.9           0.03        287.85
fff51d3deea67e60c45d6a1cee40daef  21.5           1.69        280.55
fff75fd36275ee970e9b3f566a092076  15.6           0.36        287.25

Measurement                       Water Temp    pH  log(E Coli)
checksum
000414253acc7df5faa656c94ca8e628        19.8  7.53          NaN
0004f9dd58ee6cef1650fa225300f3ee         8.5  7.86          NaN
```

```
0004fcf11172c3fcb74264fa36d33cbd        13.2  8.49        NaN
000a014f09a691b27896d4731f985f47         7.9  7.76        NaN
000fc049dbfa7b01334dbd0401992081        13.2  7.78   1.892651
...                                      ...   ...        ...
ffeae564043ba08ac2abd68299c12e92        22.2  7.47        NaN
fff224af9c3d20e1b32645aadca78da8        15.0  7.45   2.563955
fff46cdd9d8d285af4e10467783b8d41        14.7  6.97        NaN
fff51d3deea67e60c45d6a1cee40daef         7.4  7.78        NaN
fff75fd36275ee970e9b3f566a092076        14.1  7.60   2.843855

[29599 rows x 12 columns]
```

In this step I have converted the 'site_visits' timestamp column into a datetime format, extracting year and hour information, and deriving a 'Season' column based on the month. Additionally for the other dataset the long measurements have been converted to a wide dataset. Also addding a new column for log(E Coli), which is calculated by the log10 function from numpy.

Combines the dataframes into a wide single master data frame

```
master_df = sites.merge(site_visits,how = "inner", on='SiteID')
#master_df.set_index('SiteID',inplace = True)
master_df = master_df.merge(wide_measurements,how = "inner", on =
"checksum")

master_df.drop(columns = "checksum", inplace = True)
#display(master_df)

master_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29599 entries, 0 to 29598
Data columns (total 21 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   SiteID                        29599 non-null  object
 1   Region                        29599 non-null  object
 2   Name                          29599 non-null  object
 3   Longitude                     29599 non-null  float64
 4   Latitude                      29599 non-null  float64
 5   Timestamp                     29599 non-null  datetime64[ns, UTC]
 6   Year                          29599 non-null  int32
 7   Hour of day                   29599 non-null  int32
 8   Season                        29599 non-null  object
 9   Ammonia                       28563 non-null  float64
 10  Dissolved Oxygen Saturation   29385 non-null  float64
 11  Dissolved Reactive Phosphate  29518 non-null  float64
 12  E Coli                        14529 non-null  float64
 13  Electrical Conductivity       29544 non-null  float64
 14  Nitrate + Nitrite             29518 non-null  float64
```

```
 15  URS                               29548 non-null  float64
 16  Water Clarity                     29414 non-null  float64
 17  Water Kelvin                      29548 non-null  float64
 18  Water Temp                        29548 non-null  float64
 19  pH                                29440 non-null  float64
 20  log(E Coli)                       14529 non-null  float64
dtypes: datetime64[ns, UTC](1), float64(14), int32(2), object(4)
memory usage: 4.5+ MB
```

In order to combine the dataset into a single master_df, I have using the merge function joining by the siteID, and dropping the non needed checksum column.

```
temp_selected = ["Longitude","Latitude","Year", "Hour of
day","Season","URS","Water Kelvin","Water Temp"]
temp_model_data = master_df[temp_selected]
temp_model_data = temp_model_data.dropna()
display(temp_model_data)
temp_model_data.info()

        Longitude   Latitude  Year  Hour of day  Season   URS  Water
Kelvin  \
0      174.516776 -36.387085  1989           10  Summer  13.9
292.25
1      174.516776 -36.387085  1989           11  Autumn   9.0
294.05
2      174.516776 -36.387085  1989           11  Autumn  12.5
288.05
3      174.516776 -36.387085  1989           11  Autumn   8.7
286.55
4      174.516776 -36.387085  1989           10  Winter   7.7
282.15
...           ...        ...   ...          ...     ...   ...
...
29594  175.604835 -40.763879  2022           13  Spring  18.8
285.45
29595  175.604835 -40.763879  2022           13  Spring  12.8
288.85
29596  175.604835 -40.763879  2022           13  Summer  11.0
292.05
29597  175.604835 -40.763879  2023           13  Summer   3.9
290.25
29598  175.604835 -40.763879  2004           14  Summer  26.8
288.65

       Water Temp
0            19.1
1            20.9
2            14.9
3            13.4
```

```
4               9.0
...             ...
29594          12.3
29595          15.7
29596          18.9
29597          17.1
29598          15.5

[29548 rows x 8 columns]

<class 'pandas.core.frame.DataFrame'>
Index: 29548 entries, 0 to 29598
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Longitude     29548 non-null  float64
 1   Latitude      29548 non-null  float64
 2   Year          29548 non-null  int32  
 3   Hour of day   29548 non-null  int32  
 4   Season        29548 non-null  object 
 5   URS           29548 non-null  float64
 6   Water Kelvin  29548 non-null  float64
 7   Water Temp    29548 non-null  float64
dtypes: float64(5), int32(2), object(1)
memory usage: 1.8+ MB
```

I have selected which variables to keep in the temp_model_data dataframe and dropped all na values.

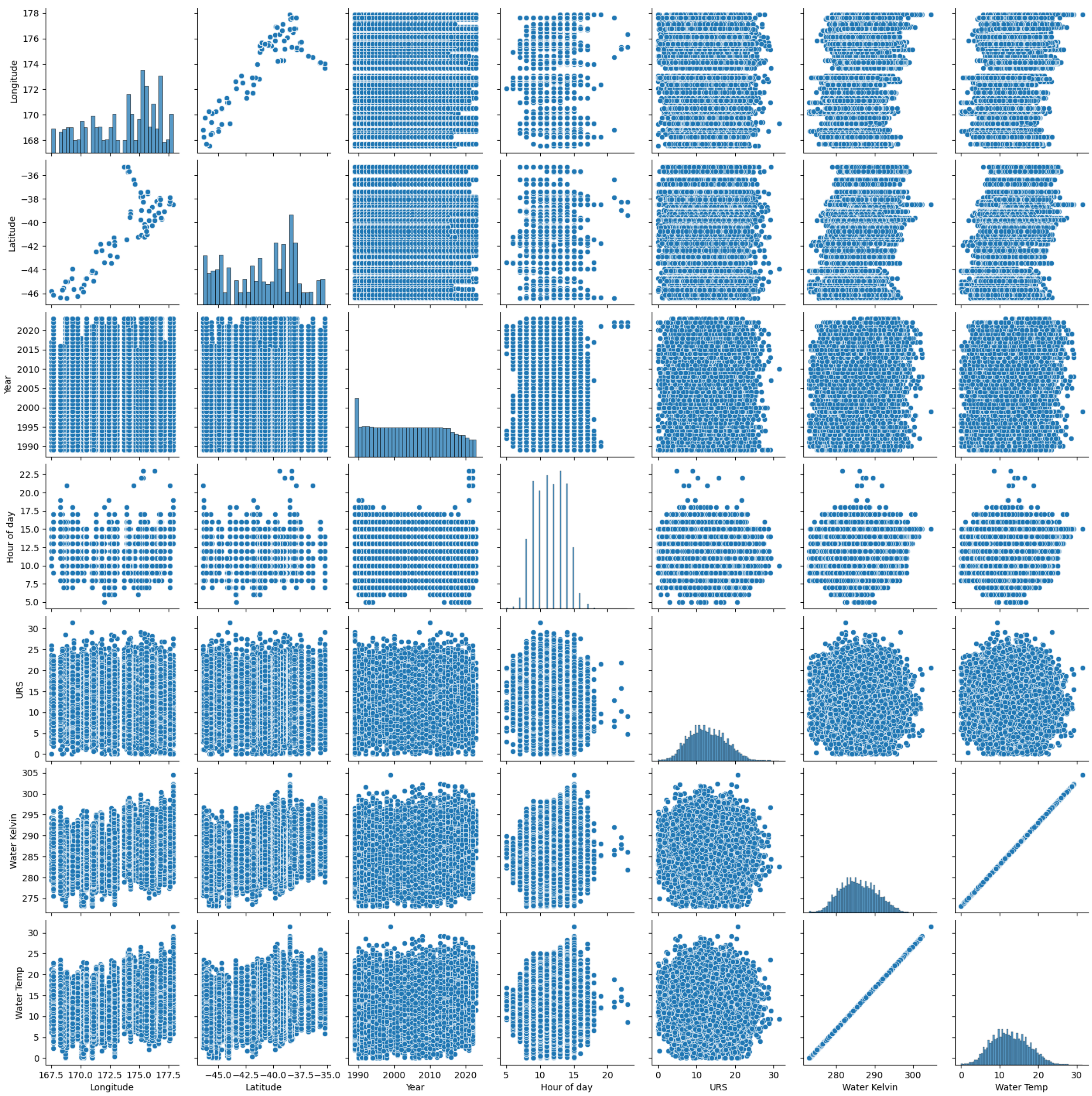
EDA for temp_model_data

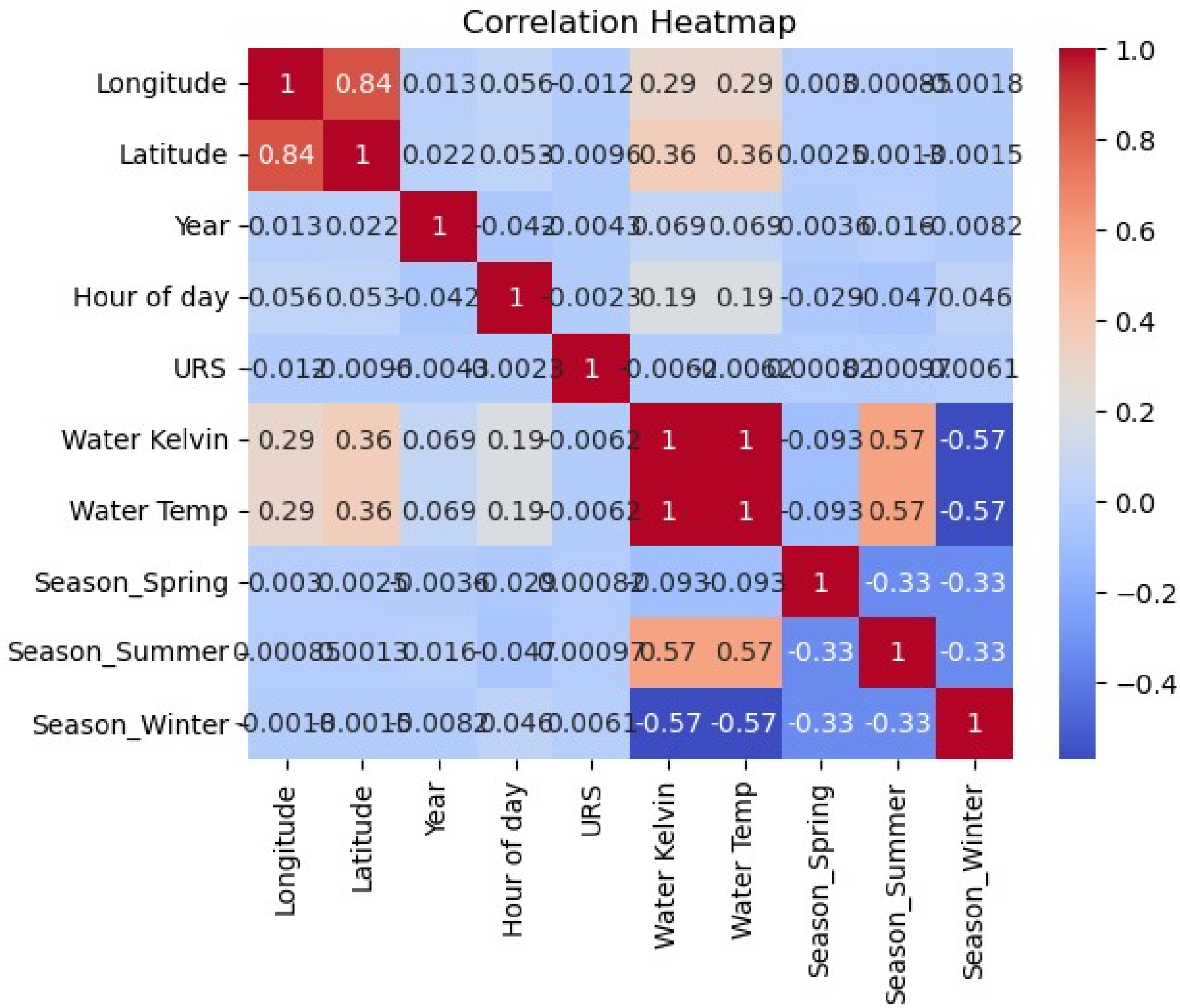
Upon observing the temp_model_data we can see it consists of 8 columns (Longitude,Latitude,Year, Hour of day,Season,URS,Water Kelvin and Water Temp). Majority of the datatypes are float64, int32's whereas the season column is an object. Floats and ints are both numerical values and differs if they have a decimal placing or not. We cannot observe any missing data in the temp_model_data dataframe. I beleive we can suggest to remove the Water Kelvin column since we already have the celsius readings which can be found by the Water Temp column. Hour of day and URS also seems irrelavent as those variables do not aid in investigating the temperature of the NZ water system, we will be investigating this further in the following steps.

```
sns.pairplot(temp_model_data[temp_selected])
plt.show()

#change season to categorical
temp_model_data['Season'] =
temp_model_data['Season'].astype('category')
```

```
#dummy variables for the categorical "season" column
temp_model_data_with_dummies =
pd.get_dummies(temp_model_data[temp_selected], columns=['Season'],
drop_first=True)

#correlation heatmap
sns.heatmap(temp_model_data_with_dummies.corr(), annot=True,
cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

```
/Users/yukiyoshiyasu/anaconda3/envs/INFO204/lib/python3.11/site-
packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has
changed to tight
  self._figure.tight_layout(*args, **kwargs)
```


Longitude
Latitude
Year
Hour of day
URS
Water Kelvin
Water Temp



The pairplot suggests there being some correlation between longitude, latitude and water temp. The plots for those variables show a slight linear trend, most likley since the warmer region of NZ would be in the northern part of the island. Water temp and water kelvin has a positive linear relationship, suggesting one of the variables can be removed, in this case the water kelvin should be dropped.

Observing the heat map for the temp_model_data we can see that season, latitude, longitude and water temp has some correlation which indicates those are the key columns that should stay in the dataset. The Year columns doesnt seem to have a correlation as the heat map reading is near 0, therefore suggests that it can be dropped. However keeping the year column will be beneficial to keep as a timestamp to keep track the trend of the results. URS also has readings near 0 suggesting it to be dropped from the dataset. The water temp for the summer season outputteda orange mark of 0.57 whereas with winter was -0.57 which is a significant correlation compared to the other variable, indicating the importance of the variables.

```
env_selected = ["Ammonia","Dissolved Oxygen Saturation","Dissolved
Reactive Phosphate","Electrical Conductivity","Nitrate +
Nitrite","Water Clarity","Water Temp","pH","log(E Coli)"]
```

```
env_model_data = master_df[env_selected]
env_model_data = env_model_data.dropna()
display(env_model_data)
```

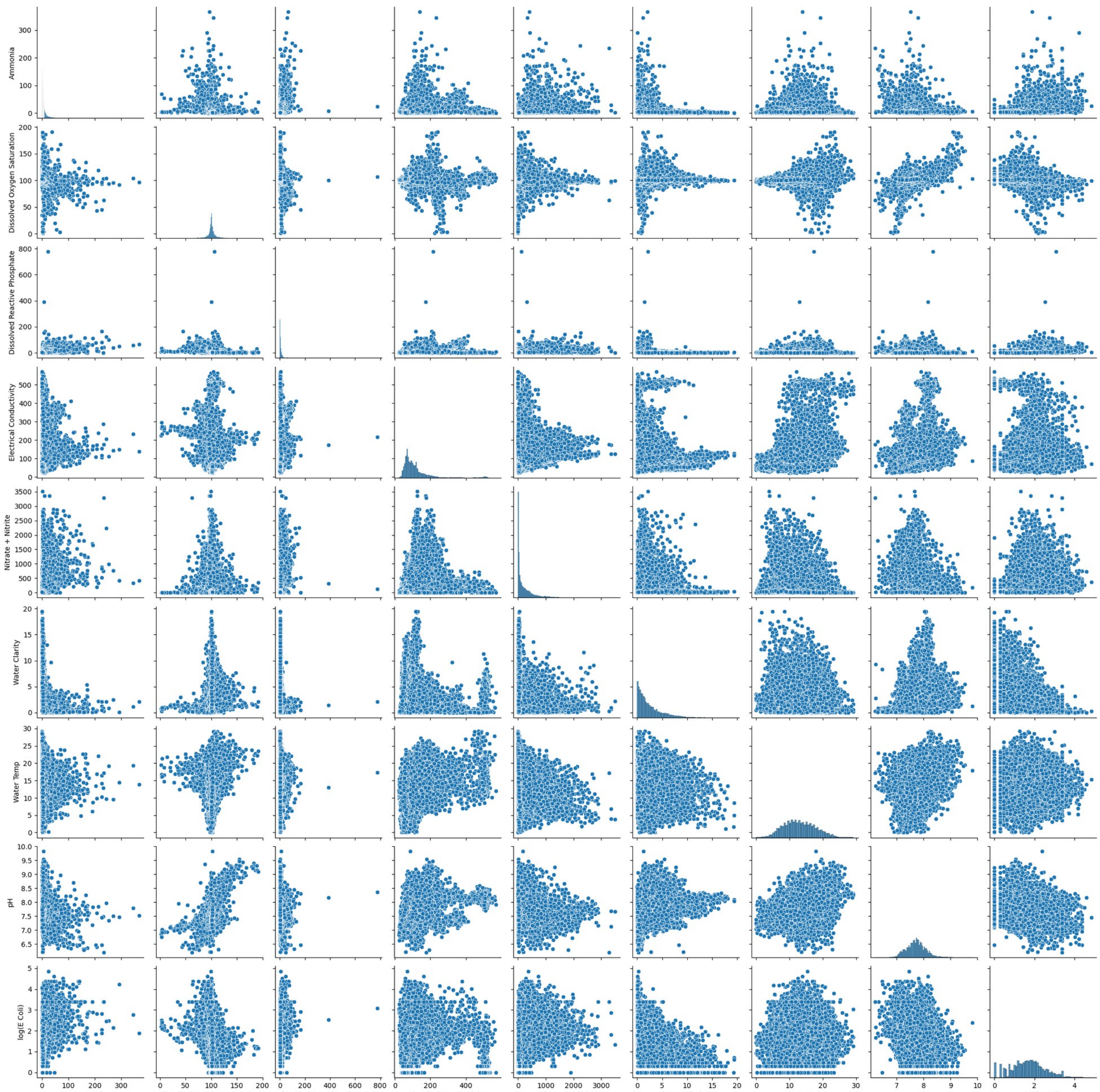
```
       Ammonia  Dissolved Oxygen Saturation  Dissolved Reactive
Phosphate  \
196        8.0                         88.9
21.4
197        6.0                         90.7
14.1
198        1.0                         89.6
17.7
199       28.0                         82.1
27.8
200       26.0                         88.5
28.0
...        ...                          ...
...
29593      2.0                        101.2
2.0
29594      3.0                        102.1
2.0
29595      3.0                        102.3
2.0
29596      4.0                        102.1
2.0
29597      1.0                        102.6
3.0

       Electrical Conductivity  Nitrate + Nitrite  Water Clarity
Water Temp  \
196                      190.0              155.0           0.68
20.1
197                      204.0                4.0           1.08
18.9
198                      227.0                6.0           1.26
14.3
199                      207.0              694.0           0.59
15.6
200                      198.0              637.0           0.53
10.5
...                        ...                ...            ...
...
29593                     51.9               29.0          10.00
10.3
29594                     48.8               22.0           6.80
12.3
29595                     53.6                5.0          10.48
15.7
29596                     55.9                8.0          11.47
```

```
18.9
29597                     58.0                  21.0          11.44
17.1

         pH  log(E Coli)
196    7.43     2.082785
197    7.62     1.623249
198    7.66     1.939519
199    7.22     2.309630
200    7.37     3.020046
...     ...          ...
29593  7.67     0.602060
29594  7.54     0.602060
29595  7.64     0.698970
29596  7.81     0.602060
29597  7.73     1.431364

[14250 rows x 9 columns]
```

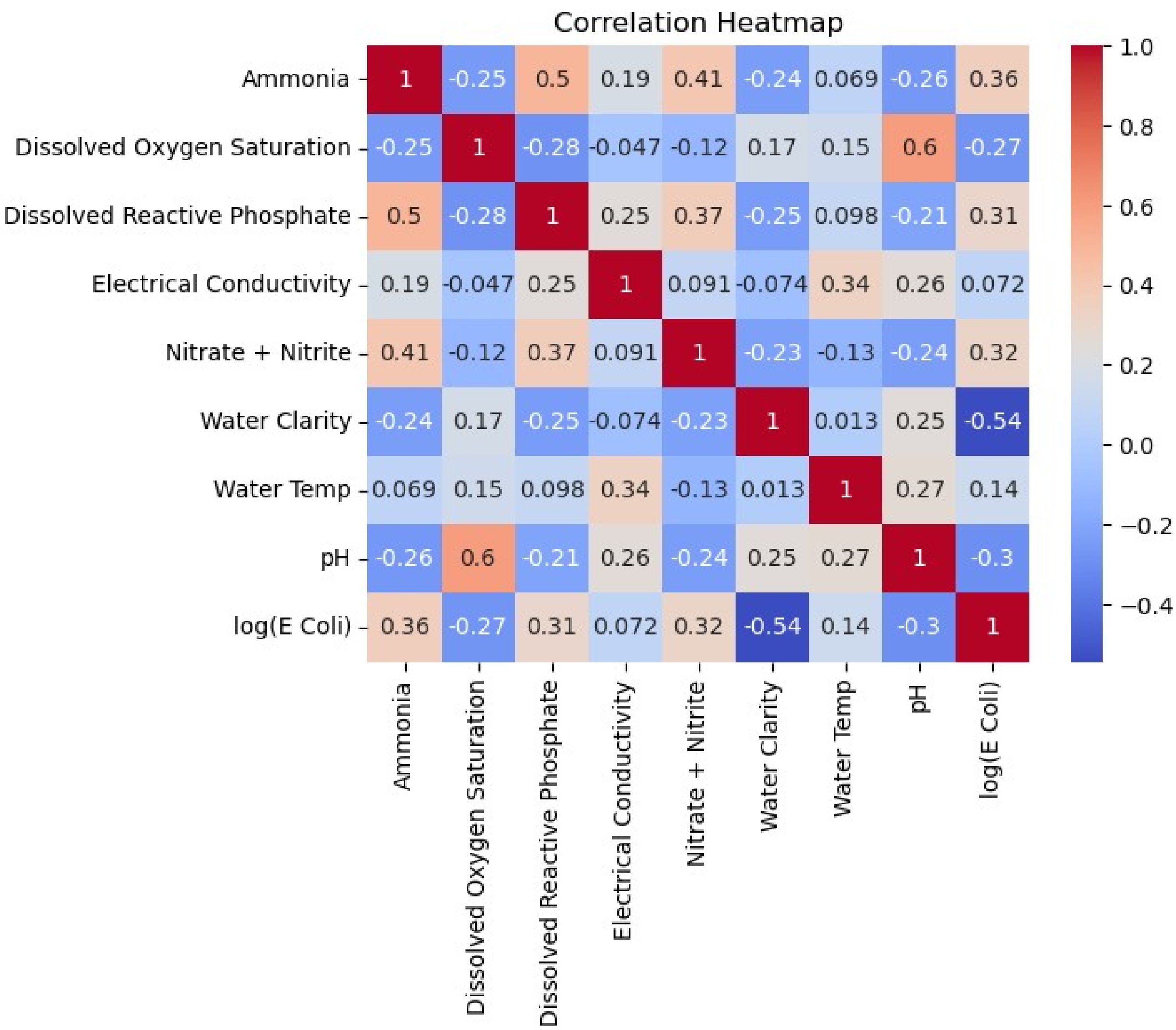
EDA for env_model_data

Upon observing the env_model_data dataframe we can see all of the columns types are float64 with 9 total columns. We can observe missing values in the log(E Coli) column where the first 5 readings has no presence of E Coli. This is as expected since that will be a disaster if most of the NZ water is contaminaited, therefore we will expect encountering into E Coli readings in this dataframe at a very low frequency. I would remove the Electrical conductivity variable from this data frame.

```
sns.pairplot(env_model_data[env_selected])
plt.show

/Users/yukiyoshiyasu/anaconda3/envs/INFO204/lib/python3.11/site-
packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has
changed to tight
  self._figure.tight_layout(*args, **kwargs)

<function matplotlib.pyplot.show(close=None, block=None)>
```




```
correlation_matrix = env_model_data[env_selected].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



From the pairplot, Log E Coli and water clarity could be investigated further as it shows a right skewed graph. Dissolved oxygen saturation and pH can be seen to have a correlation while interpreting the data with its similar trend to linear increase.

Observing the heat map for the temp_model_data we can see that Dissolved oxygen saturation and pH has a correlation which indicates those are the key columns that must stay in the dataset. Water clarity can be seen with a negative colleration with the log(C Coli readings) which was as expected since the clarity of water should decrease if bacteria E Coli is present. Wheareas Electrical conductivity has a correlation reading near 0.2 which is extremely low as a reading of 0 means that there is no colleration observed thus is suggested to be dropped.

Part 2: Data Querying / Exploration

```
# Group by 'SiteID' and find the maximum observed 'Timestamp'
last_visited_df = master_df.groupby('SiteID')
['Timestamp'].max().reset_index()
```

```python
# Rename the 'Timestamp' column to 'LastVisited'
last_visited_df.rename(columns={'Timestamp': 'Last Sampled'},
inplace=True)

# Merge the 'last_visited_df' with the 'sites' DataFrame on 'SiteID'
result_df = sites.merge(last_visited_df, on='SiteID')
display(result_df)

# Save the result to 'last_visited.csv'
result_df.to_csv('last_visited.csv', index=False)
```

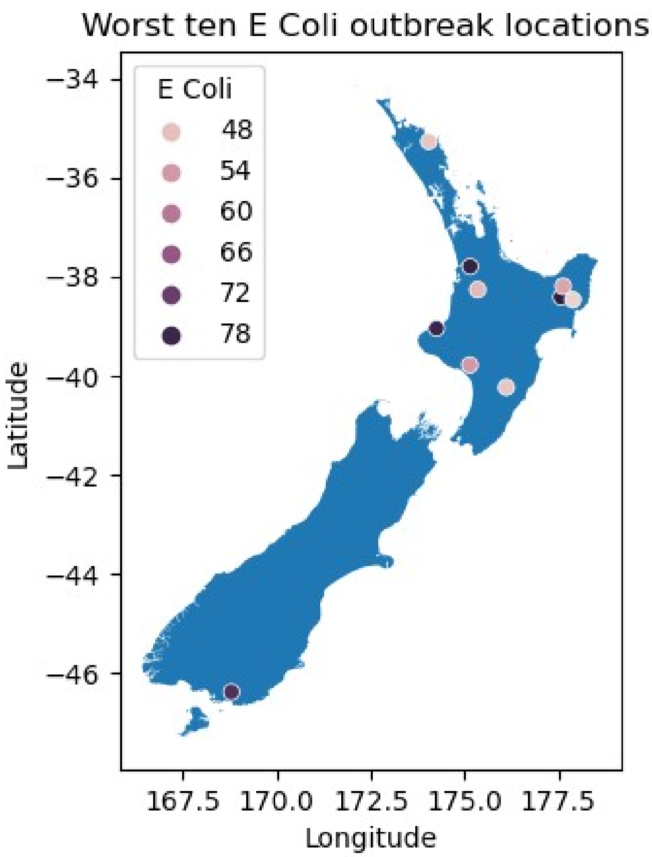
```
   SiteID      Region                       Name   Longitude   Latitude
\
0     AK1    Auckland             Hoteo at Gubbs  174.516776 -36.387085

1     AK2    Auckland   Rangitopuni at Walkers  174.617716 -36.746082

2     AX1  Alexandra     Clutha at Luggate Br.  169.279966 -44.730920

3     AX2  Alexandra      Kawarau at Chard Rd  168.868674 -45.007995

4     AX3  Alexandra  Shotover at Bowens Peak  168.714900 -44.991606

..    ...         ...                        ...         ...        ...

72    WN1  Wellington           Hutt at Boulcott  174.921966 -41.199706

73    WN2  Wellington            Hutt at Kaitoke  175.191361 -41.052600

74    WN3  Wellington   Ruamahanga at Waihenga  175.439426 -41.197160

75    WN4  Wellington   Ruamahanga at Wardells  175.671349 -41.004683

76    WN5  Wellington        Ruamahanga at SH2  175.604835 -40.763879


                 Last Sampled
0  2023-01-10 11:05:00+00:00
1  2021-07-06 11:26:00+00:00
2  2023-01-10 11:40:00+00:00
3  2022-01-11 14:10:00+00:00
4  2023-01-10 13:40:00+00:00
..                        ...
72 2015-09-16 14:10:00+00:00
73 2023-01-18 08:25:00+00:00
74 2017-06-26 14:40:00+00:00
75 2015-09-30 10:00:00+00:00
76 2023-01-18 13:15:00+00:00

[77 rows x 6 columns]
```

The key variables I have identified in this step is SiteID and Timestamp as these are required to sort the data by the SiteID order and timeStamp is needed to calculate the last sampled time. The operations I have used is the groupby function to sort the data in SiteID, used {:} to map the time stamp to be called last Sampled. Rename function was used to rename the time stamp to last Sampled. sites.merge was used to merge the sites dataframe to the last_visited dataframe using SiteID as a unique key. The last line of code .to_csv outputs the resulted dataframe to a csv named as "last_visited".

```
import fiona
# Fetchs the NZ shape
def fetch_nz_shape():
    import requests
    import fiona
    import geopandas as gpd

    nz_shape = "https://drive.google.com/uc?
export=download&id=1CsIBfAjOLJLrMoWSD5SN6x5ggUOYxKmP"
    request = requests.get(nz_shape)
    b = bytes(request.content)
    with fiona.BytesCollection(b) as f:
        crs = f.crs
        gdf = gpd.GeoDataFrame.from_features(f, crs=crs)
    return gdf

nz_shape = fetch_nz_shape()   ## A geopandas data frame that outlines
the coordinates of New Zealand

# Puts the E Coli readings from master_df exceeding 550 in a new data
frame
ecoli_unsafe_df = master_df[(master_df['E Coli'] > 550)]

# Group by 'SiteID' and count the number of unsafe samples, sorts
values
unsafe_counts =
ecoli_unsafe_df.groupby('SiteID').size().reset_index(name='UnsafeSampl
eCount')
unsafe_10 = unsafe_counts.sort_values(by='UnsafeSampleCount',
ascending=False).head(10)

unsafe_10_coords = unsafe_10.merge(master_df[['SiteID', 'Longitude',
'Latitude']], on='SiteID')
# removes duplicate readings
unique_unsafe_10_coords =
unsafe_10_coords.drop_duplicates(subset='SiteID')
# Displays the unique unsafe 10 coords dataframe
display(unique_unsafe_10_coords)
# plots the NZ boundary
nz_shape.plot()
# Plots the data, with hue as unsafe sample count
sns.scatterplot(data = unique_unsafe_10_coords, x = "Longitude", y =
```

```
"Latitude", color = "black" , hue = "UnsafeSampleCount")
# Adds the legend with title
plt.legend(title = "E Coli ")
# Adds the title of the graph
plt.title("Worst ten E Coli outbreak locations ")
# outputs the graph
plt.show()
```

	SiteID	UnsafeSampleCount	Longitude	Latitude
0	GS2	80	177.561462	-38.416776
411	HM2	79	175.151645	-37.800344
817	WA1	78	174.254867	-39.049664
1229	DN5	75	168.797037	-46.391100
1641	WA4	54	175.142311	-39.788644
2049	GS3	52	177.620792	-38.201502
2459	HM1	49	175.348059	-38.270489
2866	WA7	47	176.111484	-40.242260
3279	WH2	47	174.047358	-35.278154
3686	GS1	45	177.881610	-38.470312



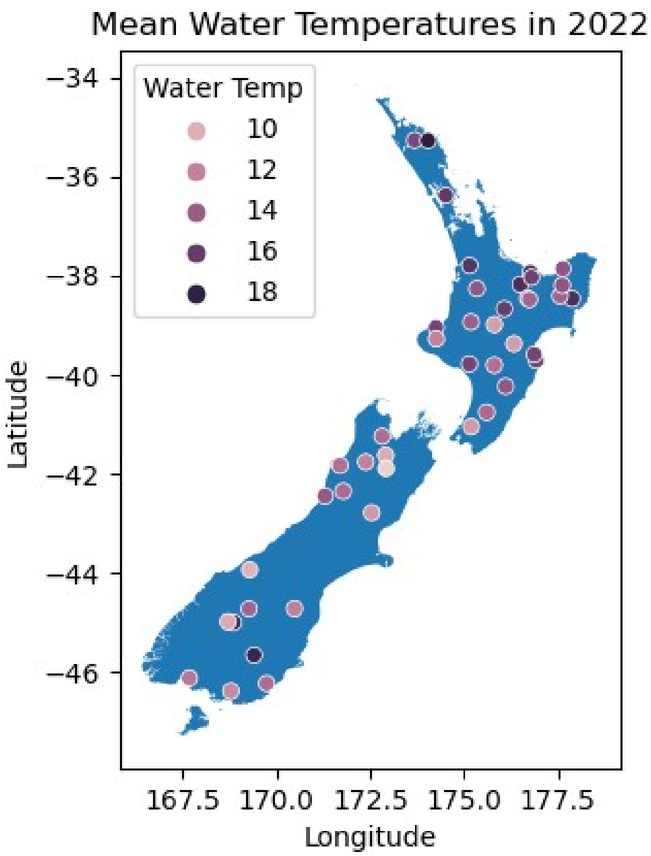
The key variables I have identified while acquiring the data for the worst ten E Coli out break locations were SiteID, E Coli, Latitude and Longitude. This is because to obtain the unsafe E Coli counts we first had to get readings that exceeded 550(cfu/100 mL) and then count how many unsafe readings were observed. SiteID was needed in order to use as groupby and as a unique key for merging the dataframes to obtain the latitude and the longitude of the readings. The merging operation occured between the 10 unsafe readings and the master_df. Latitdue and longitude was needed inorder to plot the readings on the correct location of the graph.

Operations I have utilized were a conditional operator to check the E Coli readings was above 550(cfu/100 mL), groupby function to order the data via the SiteID, sort_values was used to arange the order of the values by smallest to largest and size() function to count the number of readings. Drop_duplicates(subset='SiteID') was used to remove the duplicated siteID readings, as we dont want duplicated readings plotted on the graph. Finally the rest of the simple code was used to plot the graph using seaborns scatterplot function and matplotlibs functions.

Overall, viewing the graph allows us to identify 9 out of the 10 E Coli outbreaks have occured in the Northisland of New Zealand. Whereas one out break has occured in the South island.

```
# Fetches the nz shape

import fiona
def fetch_nz_shape():
    import requests
    import fiona
    import geopandas as gpd

    nz_shape = "https://drive.google.com/uc?
export=download&id=1CsIBfAjOLJLrMoWSD5SN6x5ggUOYxKmP"
    request = requests.get(nz_shape)
    b = bytes(request.content)
    with fiona.BytesCollection(b) as f:
        crs = f.crs
        gdf = gpd.GeoDataFrame.from_features(f, crs=crs)
    return gdf

nz_shape = fetch_nz_shape()   ## A geopandas data frame that outlines
the coordinates of New Zealand

# filters the data for only when year in 2022
year_2022 = master_df[master_df['Year'] == 2022]

# groups by siteID and calculates watertemp mean and resets index
meantemp = year_2022.groupby('SiteID')['Water
Temp'].mean().reset_index()

# mereges the dfs together to obtain coordinates to plot removing
dupes
meantemp_coords = meantemp.merge(year_2022[['SiteID', 'Longitude',
'Latitude']].drop_duplicates(subset='SiteID'),on='SiteID')

# plot the nz shape
nz_shape.plot()
```

```
# plot the mean temperature points on the map
sns.scatterplot(data = meantemp_coords, x = "Longitude",y =
"Latitude",hue = "Water Temp")
# adds legend
plt.legend(title = "Water Temp")
# xlabel
plt.xlabel('Longitude')
# ylabel
plt.ylabel('Latitude')
# adds title
plt.title('Mean Water Temperatures in 2022')
# outputs the graph
plt.show()
```

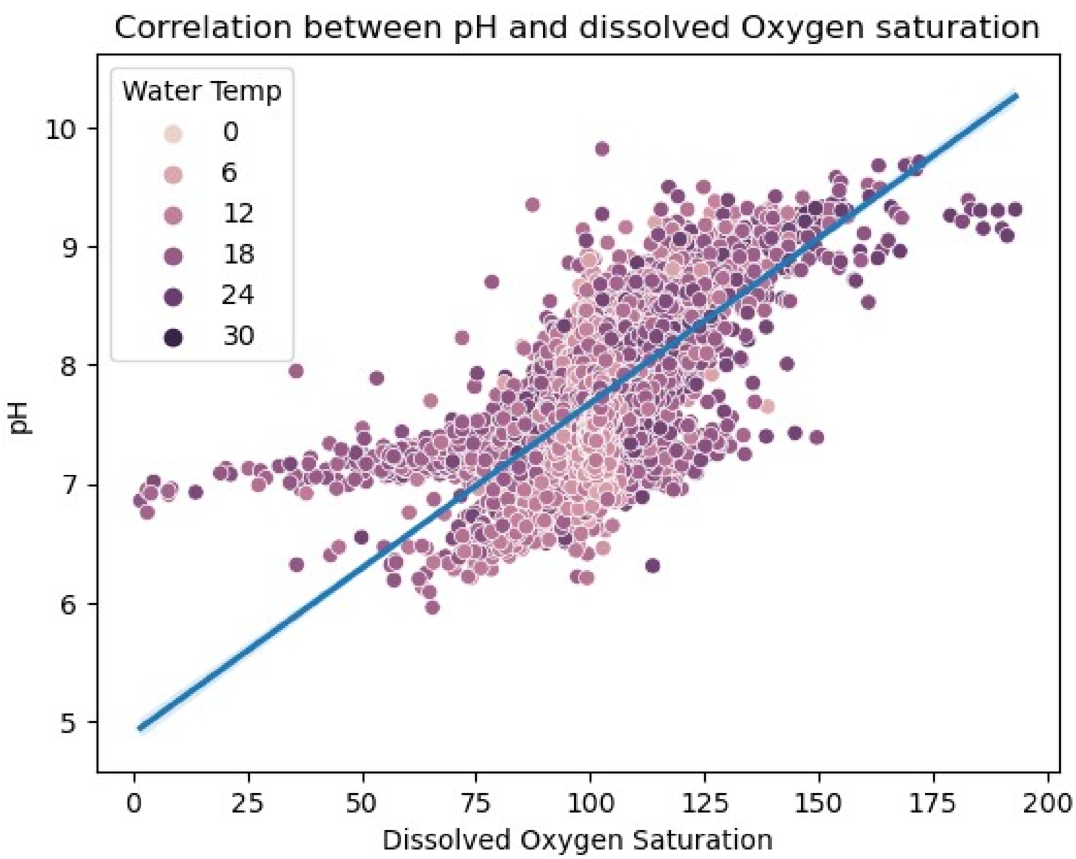


The key variables identified for the mean water temperatures were year, siteID, temperature, longitude and latitude. Firstly filtering the year to 2022 was needed to get the data in the desired year. To obtain the mean temperature the siteID was needed to group by the data to obtain the mean temperatures using basic python function (.mean()). Then to obtain the coordinates we had to merge the dataframes dropping the duplicate values. Finally, plotting the data on the NZ map was generated by seaborn and plotting.

Overall, viewing the mean water temperature graph has readings spread out evenly in the country however, majority of the high water temps recorded are located in the north island.

```
sns.scatterplot(data = master_df, x = "Dissolved Oxygen Saturation",y
= "pH",hue = "Water Temp")
sns.regplot(data=master_df, x="Dissolved Oxygen Saturation", y="pH",
scatter=False)
plt.title("Correlation between pH and dissolved Oxygen saturation")
```

```
Text(0.5, 1.0, 'Correlation between pH and dissolved Oxygen
saturation')
```

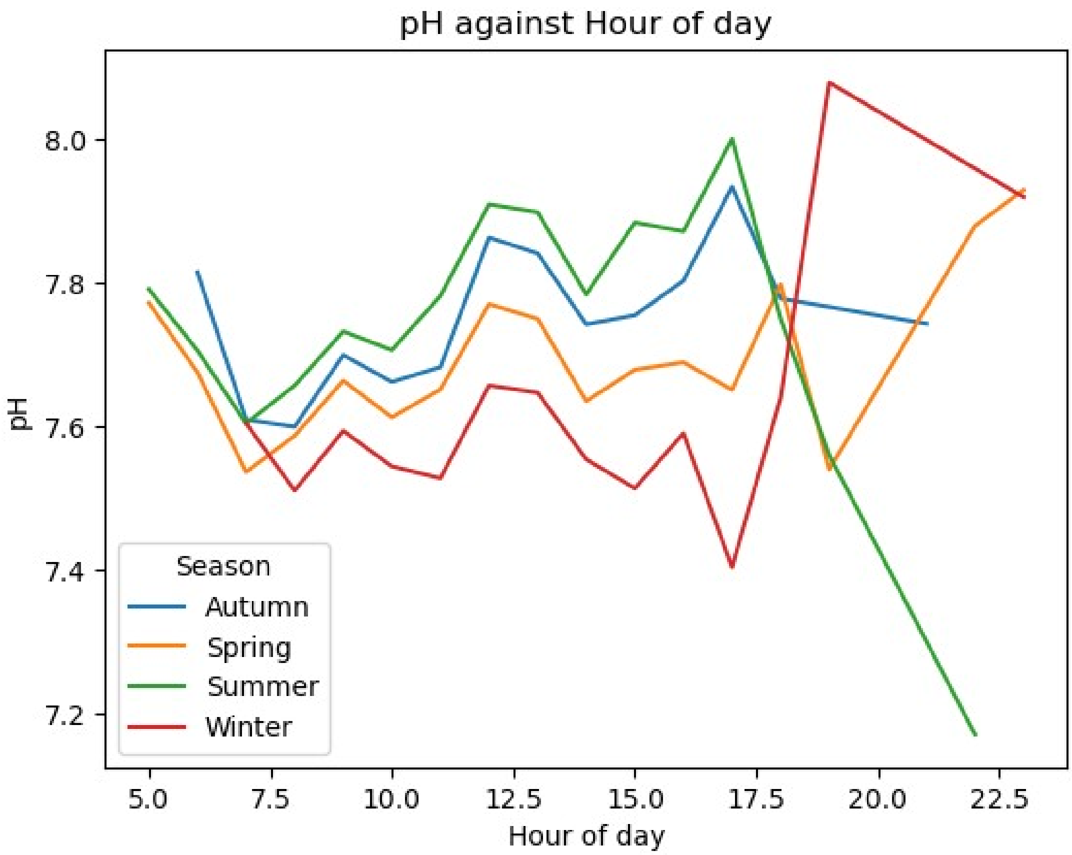


Seaborns scatterplot were used in order to generate the water temp scatterplot. Whereas the regplot function from seaborn outputs the trend line. The trend line shows a positive linear trend between the two varaibles (pH and dissolved oxygen saturation). The key variables identified in the process were the dissolved oxygen saturation, pH, Water Temp for the x and y axis and the points itself (hue as water temp).

Three line plots that show the mean pH, dissolved oxygen and water temperature for each hour of the day, grouped by season.

```
mean_pH = master_df.groupby(["Season", "Hour of day"])
["pH"].mean().reset_index()
#add title
plt.title("pH against Hour of day")

sns.lineplot(mean_pH, x="Hour of day", y="pH", hue="Season")
```

```
<Axes: title={'center': 'pH against Hour of day'}, xlabel='Hour of
day', ylabel='pH'>
```

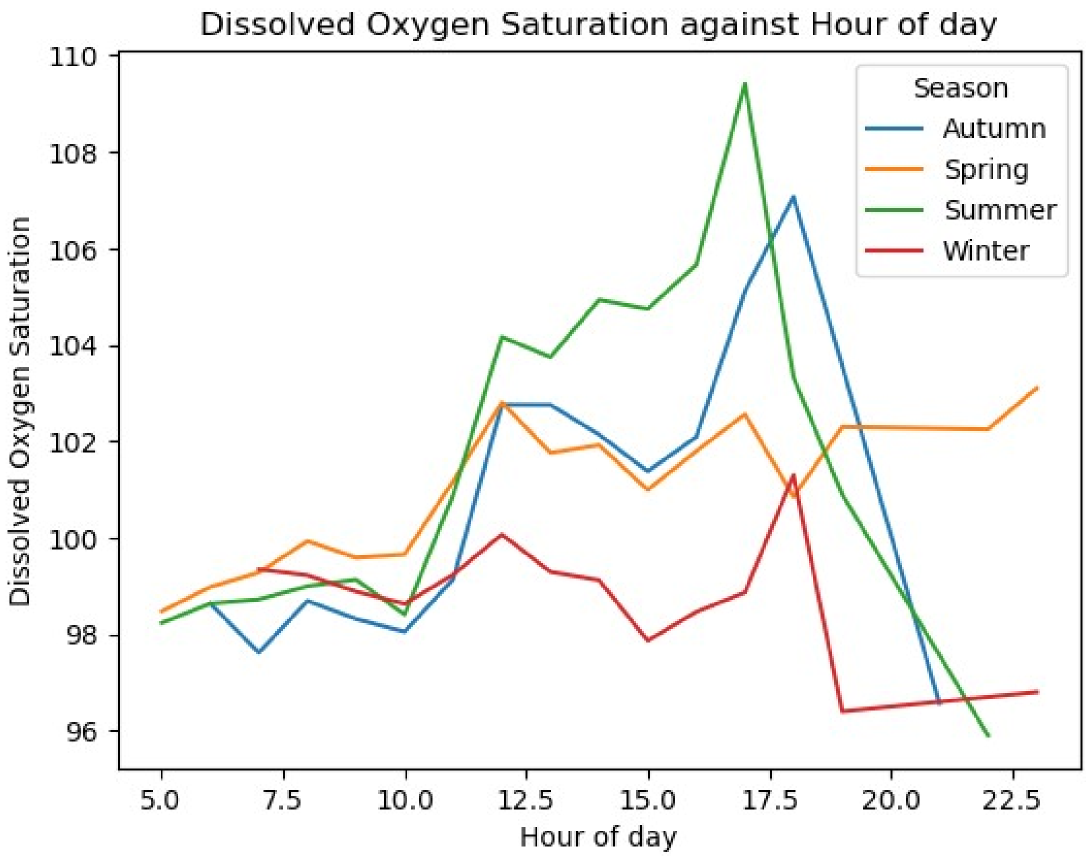


The key variables identified here are the season, hour of day and pH. In order to plot the line plot, the mean pH per hour of day had to be calculated, which is done by the groupby and mean functions. Seaborns lineplot function is used to plot each of the lines via different seasons. Hour of day is represented as the xlab and the pH for the ylab. By viewing the line plots we can observe that summer and winter had the greatest flutuations (steepest gradients) of pH depending on the hour of day.

```
mean_dissolved_oxygen = master_df.groupby(["Season","Hour of day"])
["Dissolved Oxygen Saturation"].mean().reset_index()
#add title
plt.title("Dissolved Oxygen Saturation against Hour of day")
```

```
sns.lineplot(mean_dissolved_oxygen, x="Hour of day", y ="Dissolved Oxygen Saturation", hue = "Season" )
```

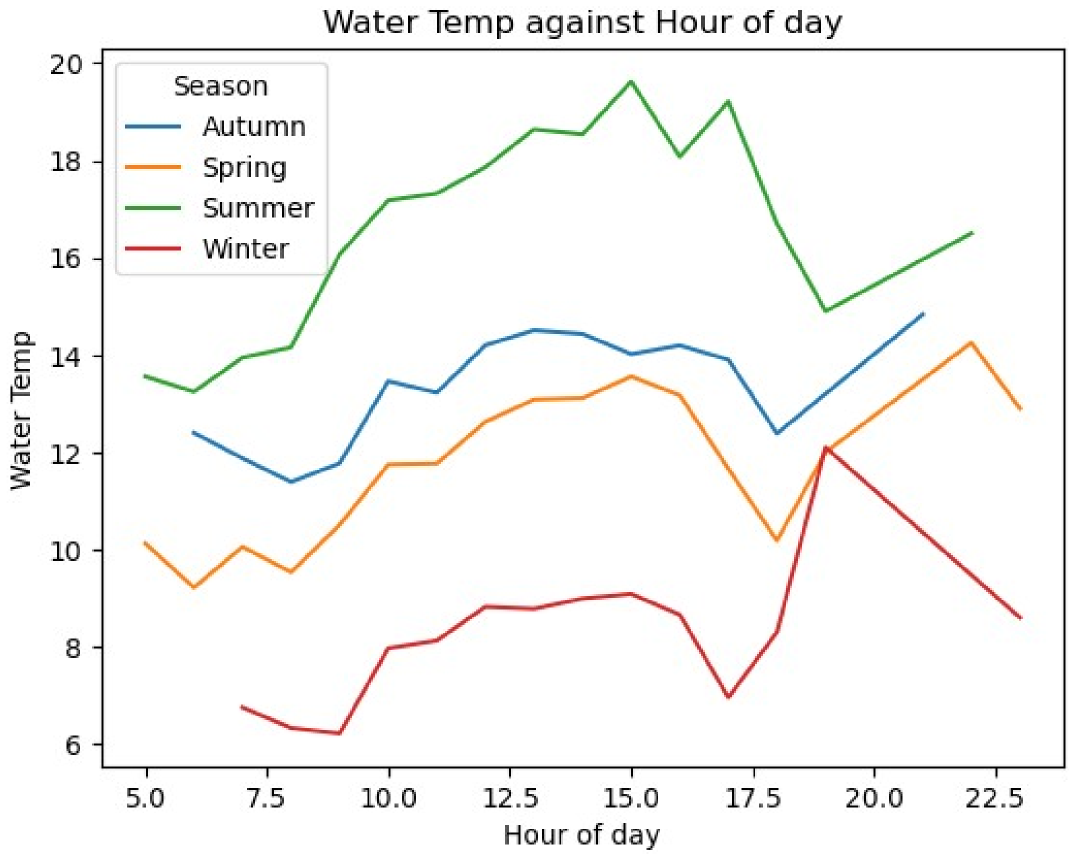
```
<Axes: title={'center': 'Dissolved Oxygen Saturation against Hour of day'}, xlabel='Hour of day', ylabel='Dissolved Oxygen Saturation'>
```



The key variables identified here are the season, hour of day and dissolved oxygen saturation. To obtain the data to plot, the mean dissolved oxygen saturation was calculated using the groupby and mean functions. Once again the seabrons lineplot function is used to plot the values with hour of day on the xlab and dissolved oxygen saturation on the ylab. Each line represents each of the seasons mean dissolved oxygen. By viewing the line plots we can observe that summer and autumn had the greatest flutuations (highest peaks) of dissolved oxygen saturation depending on the hour of day.

```
mean_wtemp = master_df.groupby(["Season","Hour of day"])["Water Temp"].mean().reset_index()
#add title
plt.title("Water Temp against Hour of day")
sns.lineplot(mean_wtemp, x="Hour of day", y = "Water Temp", hue = "Season")
```

```
<Axes: title={'center': 'Water Temp against Hour of day'}, xlabel='Hour of day', ylabel='Water Temp'>
```



The key variables identified here are season, hour of day and water temp. The mean water temp used to plot the data was calculated by using the groupby and mean functions. The lineplot function from seaborn is used to output the plots of mean water temps on different hours of the day, with each line representing each season. The xlab shows the hour of day whereas ylab shows the water temperature. By viewing the line plots we can observe the obvious results as the warmer seasons will have a higher average temperature agains the hour of day. The order of the line plots go from Summer, Autumn, Spring, Winter (highest temp to lowest).

Part 3 : NIWA Suitability Analysis

https://niwa.co.nz/sites/niwa.co.nz/files/import/attachments/Suitability-of-NZ-rivers-for-contact-recreation.pdf E Coli and Water Clarity

```
#Create median visibility and median E Coli




filtered_df_2008 = master_df[(master_df['Year'] >= 2005) &
(master_df['Year'] <= 2008)]
```

```
median_visibility_df_2008 = filtered_df_2008.groupby('SiteID')['Water Clarity'].median()
median_ecoli_df_2008 = filtered_df_2008.groupby('SiteID')['E Coli'].median()

name_series_2008 = filtered_df_2008.groupby('SiteID')['Name'].first()

# Create a new DataFrame with median values and "Name" column
suitability_df_2008 = pd.DataFrame({
     "Name": name_series_2008,
    "Visibility (m)_2008": median_visibility_df_2008,
    "E Coli (cfu/100 mL)_2008": median_ecoli_df_2008
}).reset_index()

print(suitability_df_2008)
```

```
   SiteID                     Name  Visibility (m)_2008  \
0     AK1           Hoteo at Gubbs               0.6600
1     AK2    Rangitopuni at Walkers               0.6800
2     AX1     Clutha at Luggate Br.               5.7000
3     AX2       Kawarau at Chard Rd               2.0550
4     AX3   Shotover at Bowens Peak               0.6250
..    ...                      ...                  ...
72    WN1          Hutt at Boulcott               2.7450
73    WN2           Hutt at Kaitoke               4.9250
74    WN3    Ruamahanga at Waihenga               1.4450
75    WN4    Ruamahanga at Wardells               1.8650
76    WN5         Ruamahanga at SH2               4.3475

    E Coli (cfu/100 mL)_2008
0                      125.9
1                      235.9
2                        2.0
3                        3.1
4                        2.0
..                       ...
72                     121.0
73                       4.1
74                      96.0
75                      75.4
76                      13.1

[77 rows x 4 columns]
```

The first process was to filter the data for the years 2005 to 2008 using the year column. Then I have calculated the median visibility and E. coli values using the groupby and median function by siteID on water clarity and E Coli readings. Thirdly to get the names of the siteID groupby was used, then each of those filtered data were all combined as suitability_df_2008 using the dictionary stored as key value pairs.

```python
#Create median visibility and median E Coli



filtered_df_2022 = master_df[(master_df['Year'] >= 2019) &
(master_df['Year'] <= 2022)]

median_visibility_df_2022 = filtered_df_2022.groupby('SiteID')['Water
Clarity'].median()
median_ecoli_df_2022 = filtered_df_2022.groupby('SiteID')['E
Coli'].median()
name_series_2022 = filtered_df_2022.groupby('SiteID')['Name'].first()

# Create a new DataFrame with median values and "Name" column
suitability_df_2022 = pd.DataFrame({
    "Name": name_series_2022,
    "Visibility (m)_2022": median_visibility_df_2022,
    "E Coli (cfu/100 mL)_2022": median_ecoli_df_2022
}).reset_index()

print(suitability_df_2022)
```

```
   SiteID                          Name  Visibility (m)_2022  \
0     AK1               Hoteo at Gubbs               1.5000
1     AK2        Rangitopuni at Walkers               1.3700
2     AX1          Clutha at Luggate Br.               4.8200
3     AX2            Kawarau at Chard Rd               1.0500
4     AX3        Shotover at Bowens Peak               0.3700
5     AX4         Clutha at Millers Flat               1.9000
6     CH1            Hurunui at Mandamus               1.7500
7     CH2             Hurunui at SH1 Br.               0.7400
8     CH3          Waimakariri at Gorge               0.4400
9     CH4  Waimakariri above old HW Br.               0.3725
10    DN4            Clutha at Balclutha               1.6300
11    DN5        Mataura at Seaward Down               1.0000
12    DN9             Waiau at Tuatapere               1.6300
13    GS1          Waipaoa at Kanakanaia               0.0725
14    GS2           Waikohu at No. 1 Br.               1.1650
15    GS3            Motu at Waitangirua               1.3000
16    GS4                Motu at Houpoto               2.2900
17    GY1              Buller at Te Kuha               1.2000
18    GY2                Grey at Dobson               1.6000
19    GY3               Grey at Waipuna               3.2500
20    GY4         Haast at Roaring Billy               2.4000
21    HM1                Waipa at Otewa               1.4100
22    HM2            Waipa at Whatawhata               0.5300
23    HM6        Ohinemuri at Karangahake               3.4000
24    HV2            Tukituki at Red Br.               2.6500
25    HV3        Ngaruroro at Chesterhope               1.7500
26    HV4        Ngaruroro at Kuripapango               6.4500
```

27	NN1	Motueka at Woodstock	4.5500
28	NN2	Motueka at Gorge	10.5000
29	NN3	Wairau at Dip Flat	3.3200
30	NN5	Buller at Longford	3.3700
31	RO1	Tarawera at Lake outlet	4.7300
32	RO2	Tarawera at Awakaponga	1.0425
33	RO3	Rangitaiki at Murupara	1.9400
34	RO4	Whirinaki at Galatea	1.0850
35	RO5	Rangitaiki at Te Teko	1.5525
36	RO6	Waikato at Reids Farm	7.3000
37	TK1	Opihi at Grassy Banks	5.8000
38	TK2	Opihi at Rockwood	5.0400
39	TK3	Opuha at Skipton Br.	2.6700
40	TK4	Waitaki at Kurow	4.0200
41	TK5	Hakataramea above MH Br.	6.9900
42	TK6	Waitaki at SH1 Br.	1.0250
43	TU1	Whanganui at Te Maire	1.1000
44	TU2	Tongariro at Turangi	3.0750
45	WA1	Waitara at Bertrand Rd	0.4850
46	WA2	Manganui at SH3	3.4400
47	WA4	Whanganui at Paetawa	0.4950
48	WA5	Rangitikei at Mangaweka	0.9000
49	WA7	Manawatu at Weber Rd	2.3500
50	WH1	Waipapa at Forest Ranger	3.4650
51	WH2	Waitangi at Wakelins	1.3500
52	WH3	Mangakahia at Titoki Br.	1.7000
53	WH4	Wairu at Purua	1.3500
54	WN2	Hutt at Kaitoke	5.7300
55	WN5	Ruamahanga at SH2	6.8000

	E Coli (cfu/100 mL)_2022
0	125.15
1	193.00
2	4.10
3	4.10
4	6.30
5	12.20
6	16.10
7	95.90
8	83.00
9	74.00
10	40.00
11	435.20
12	63.80
13	168.00
14	547.50
15	203.00
16	11.50
17	24.30

```
18                       52.10
19                       17.70
20                        5.20
21                      223.35
22                      365.00
23                       33.50
24                       31.30
25                       30.45
26                        6.00
27                       27.00
28                        5.20
29                        4.10
30                       29.90
31                        1.00
32                       79.35
33                       36.40
34                       63.10
35                       28.75
36                        6.30
37                       38.40
38                       70.80
39                       75.40
40                        5.20
41                       14.50
42                       86.00
43                      178.50
44                       26.00
45                      173.80
46                       87.25
47                      188.40
48                       53.00
49                       86.95
50                       60.70
51                      191.80
52                      137.60
53                       79.80
54                        6.20
55                       12.70
```

The first step of the process was to filter the data using the year column from 2019 to 2022. Then the groupby function using the SiteID to calculate median water clarity, median E Coli and siteID's name. Once again the dictionary is created with the name suitability_df_2022 which stores each of the key value pairs.

```
#Merge based on site ID then take league table indexing, get the 2022
and normalise against 2008.
leagueTable = suitability_df_2008.merge(suitability_df_2022,
on="SiteID")
```

```
#Using the two datasets compute a relative index for water clarity
(2022-2008)/2008
leagueTable["WaterClarity_RelativeIndex"] = (leagueTable["Visibility
(m)_2022"] - leagueTable["Visibility (m)_2008"]) /
leagueTable["Visibility (m)_2008"]
#Using the two datasets compute a relative index for E Coli (2008-
2022)/2008
leagueTable["E Coli_RelativeIndex"] = (leagueTable["E Coli (cfu/100
mL)_2008"] - leagueTable["E Coli (cfu/100 mL)_2022"]) / leagueTable["E
Coli (cfu/100 mL)_2008"]

#Create a scatter plot of the two indicies with an optional trend line
sns.scatterplot(data = leagueTable, x = "WaterClarity_RelativeIndex",
y = "E Coli_RelativeIndex")
plt.title("Water clarity index against E Coli Index")
plt.xlabel("Water Clarity Index")
plt.ylabel("E Coli Index")
sns.regplot(data=leagueTable, x="WaterClarity_RelativeIndex", y="E
Coli_RelativeIndex", scatter=False)


display(leagueTable)
```

	SiteID	Name_x	Visibility (m)_2008 \
0	AK1	Hoteo at Gubbs	0.6600
1	AK2	Rangitopuni at Walkers	0.6800
2	AX1	Clutha at Luggate Br.	5.7000
3	AX2	Kawarau at Chard Rd	2.0550
4	AX3	Shotover at Bowens Peak	0.6250
5	AX4	Clutha at Millers Flat	2.7250
6	CH1	Hurunui at Mandamus	2.1750
7	CH2	Hurunui at SH1 Br.	1.8750
8	CH3	Waimakariri at Gorge	0.6000
9	CH4	Waimakariri above old HW Br.	0.2900
10	DN4	Clutha at Balclutha	1.4550
11	DN5	Mataura at Seaward Down	0.8950
12	DN9	Waiau at Tuatapere	1.8650
13	GS1	Waipaoa at Kanakanaia	0.1100
14	GS2	Waikohu at No. 1 Br.	1.6950
15	GS3	Motu at Waitangirua	1.6900
16	GS4	Motu at Houpoto	0.8500
17	GY1	Buller at Te Kuha	1.6750
18	GY2	Grey at Dobson	2.1150
19	GY3	Grey at Waipuna	3.6200
20	GY4	Haast at Roaring Billy	2.4150
21	HM1	Waipa at Otewa	1.4900
22	HM2	Waipa at Whatawhata	0.5000
23	HM6	Ohinemuri at Karangahake	2.5925
24	HV2	Tukituki at Red Br.	1.6800
25	HV3	Ngaruroro at Chesterhope	1.3000

26	HV4	Ngaruroro at Kuripapango	6.6450
27	NN1	Motueka at Woodstock	4.3675
28	NN2	Motueka at Gorge	11.4925
29	NN3	Wairau at Dip Flat	2.8400
30	NN5	Buller at Longford	5.5850
31	RO1	Tarawera at Lake outlet	5.3450
32	RO2	Tarawera at Awakaponga	0.8100
33	RO3	Rangitaiki at Murupara	2.0050
34	RO4	Whirinaki at Galatea	1.7600
35	RO5	Rangitaiki at Te Teko	1.2000
36	RO6	Waikato at Reids Farm	7.5100
37	TK1	Opihi at Grassy Banks	4.0350
38	TK2	Opihi at Rockwood	2.1750
39	TK3	Opuha at Skipton Br.	2.4075
40	TK4	Waitaki at Kurow	3.4400
41	TK5	Hakataramea above MH Br.	4.0950
42	TK6	Waitaki at SH1 Br.	2.0900
43	TU1	Whanganui at Te Maire	1.3100
44	TU2	Tongariro at Turangi	3.1400
45	WA1	Waitara at Bertrand Rd	0.5850
46	WA2	Manganui at SH3	3.8250
47	WA4	Whanganui at Paetawa	0.9650
48	WA5	Rangitikei at Mangaweka	1.4100
49	WA7	Manawatu at Weber Rd	1.1000
50	WH1	Waipapa at Forest Ranger	2.2550
51	WH2	Waitangi at Wakelins	1.4550
52	WH3	Mangakahia at Titoki Br.	0.6500
53	WH4	Wairu at Purua	0.6550
54	WN2	Hutt at Kaitoke	4.9250
55	WN5	Ruamahanga at SH2	4.3475

	E Coli (cfu/100 mL)_2008	Name_y \
0	125.90	Hoteo at Gubbs
1	235.90	Rangitopuni at Walkers
2	2.00	Clutha at Luggate Br.
3	3.10	Kawarau at Chard Rd
4	2.00	Shotover at Bowens Peak
5	10.80	Clutha at Millers Flat
6	8.55	Hurunui at Mandamus
7	64.55	Hurunui at SH1 Br.
8	66.90	Waimakariri at Gorge
9	36.15	Waimakariri above old HW Br.
10	41.70	Clutha at Balclutha
11	488.40	Mataura at Seaward Down
12	88.10	Waiau at Tuatapere
13	125.90	Waipaoa at Kanakanaia
14	224.70	Waikohu at No. 1 Br.
15	157.60	Motu at Waitangirua
16	20.60	Motu at Houpoto

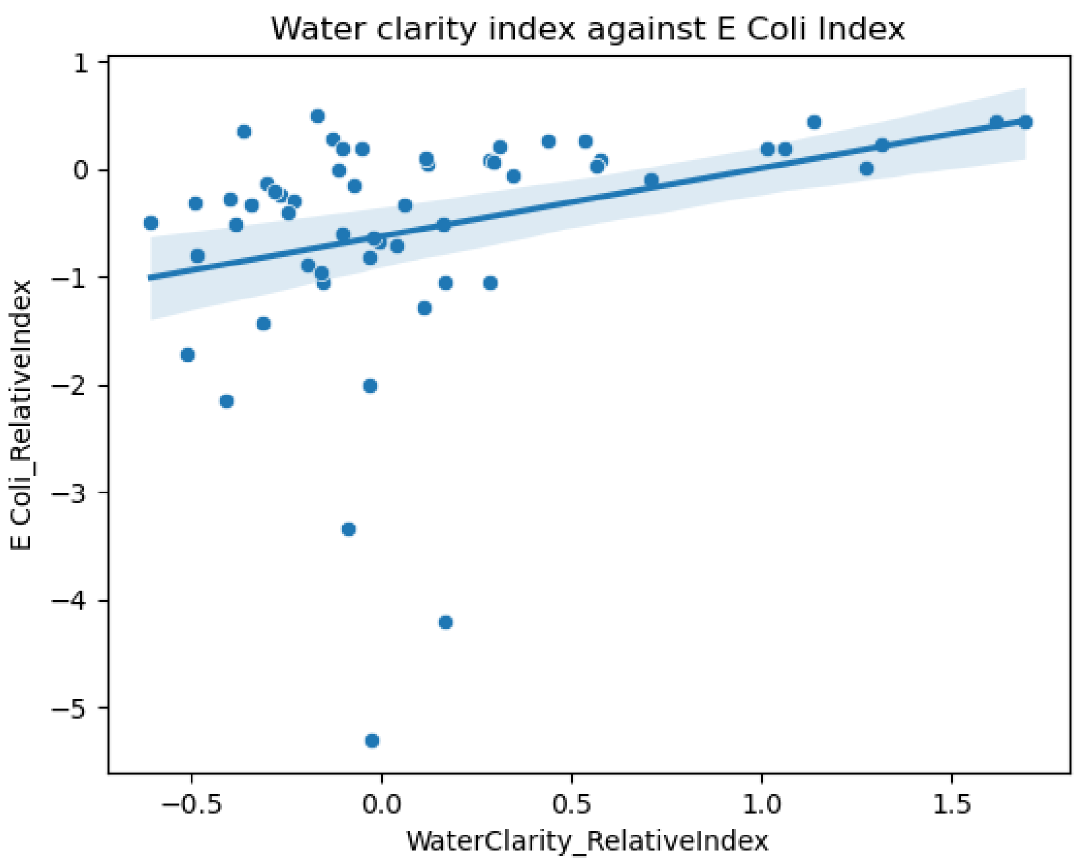
```
17                       20.10            Buller at Te Kuha
18                       36.90               Grey at Dobson
19                       11.00              Grey at Waipuna
20                        3.10       Haast at Roaring Billy
21                      275.50              Waipa at Otewa
22                      272.80          Waipa at Whatawhata
23                       42.60     Ohinemuri at Karangahake
24                       33.90           Tukituki at Red Br.
25                       28.60     Ngaruroro at Chesterhope
26                        2.00     Ngaruroro at Kuripapango
27                       15.80         Motueka at Woodstock
28                        1.20             Motueka at Gorge
29                        2.00            Wairau at Dip Flat
30                       23.30            Buller at Longford
31                        1.00      Tarawera at Lake outlet
32                       86.20       Tarawera at Awakaponga
33                       20.10       Rangitaiki at Murupara
34                       41.90         Whirinaki at Galatea
35                       30.90        Rangitaiki at Te Teko
36                        1.00        Waikato at Reids Farm
37                       52.00        Opihi at Grassy Banks
38                       90.90            Opihi at Rockwood
39                       33.10         Opuha at Skipton Br.
40                        1.00             Waitaki at Kurow
41                       13.10     Hakataramea above MH Br.
42                       31.70            Waitaki at SH1 Br.
43                       90.60        Whanganui at Te Maire
44                       15.80         Tongariro at Turangi
45                      344.10       Waitara at Bertrand Rd
46                      108.00              Manganui at SH3
47                      104.60         Whanganui at Paetawa
48                       81.60      Rangitikei at Mangaweka
49                      155.00         Manawatu at Weber Rd
50                       81.60     Waipapa at Forest Ranger
51                      166.90         Waitangi at Wakelins
52                      248.90     Mangakahia at Titoki Br.
53                       98.50              Wairu at Purua
54                        4.10             Hutt at Kaitoke
55                       13.10            Ruamahanga at SH2

    Visibility (m)_2022  E Coli (cfu/100 mL)_2022  
WaterClarity_RelativeIndex  \
0                1.5000                    125.15  
1.272727
1                1.3700                    193.00  
1.014706
2                4.8200                      4.10                    -
0.154386
3                1.0500                      4.10                    -
```

```
0.489051
4                0.3700                    6.30                   -
0.408000
5                1.9000                   12.20                   -
0.302752
6                1.7500                   16.10                   -
0.195402
7                0.7400                   95.90                   -
0.605333
8                0.4400                   83.00                   -
0.266667
9                0.3725                   74.00
0.284483
10               1.6300                   40.00
0.120275
11               1.0000                  435.20
0.117318
12               1.6300                   63.80                   -
0.126005
13               0.0725                  168.00                   -
0.340909
14               1.1650                  547.50                   -
0.312684
15               1.3000                  203.00                   -
0.230769
16               2.2900                   11.50
1.694118
17               1.2000                   24.30                   -
0.283582
18               1.6000                   52.10                   -
0.243499
19               3.2500                   17.70                   -
0.102210
20               2.4000                    5.20                   -
0.006211
21               1.4100                  223.35                   -
0.053691
22               0.5300                  365.00
0.060000
23               3.4000                   33.50
0.311475
24               2.6500                   31.30
0.577381
25               1.7500                   30.45
0.346154
26               6.4500                    6.00                   -
0.029345
27               4.5500                   27.00
0.041786
```

28	10.5000	5.20	-0.086361
29	3.3200	4.10	0.169014
30	3.3700	29.90	-0.396598
31	4.7300	1.00	-0.115061
32	1.0425	79.35	0.287037
33	1.9400	36.40	-0.032419
34	1.0850	63.10	-0.383523
35	1.5525	28.75	0.293750
36	7.3000	6.30	-0.027963
37	5.8000	38.40	0.437423
38	5.0400	70.80	1.317241
39	2.6700	75.40	0.109034
40	4.0200	5.20	0.168605
41	6.9900	14.50	0.706960
42	1.0250	86.00	-0.509569
43	1.1000	178.50	-0.160305
44	3.0750	26.00	-0.020701
45	0.4850	173.80	-0.170940
46	3.4400	87.25	-0.100654
47	0.4950	188.40	-0.487047
48	0.9000	53.00	-0.361702
49	2.3500	86.95	1.136364
50	3.4650	60.70	0.536585
51	1.3500	191.80	-0.072165
52	1.7000	137.60	

```
1.615385
53                1.3500                      79.80
1.061069
54                5.7300                       6.20
0.163452
55                6.8000                      12.70
0.564117

    E Coli_RelativeIndex
0               0.005957
1               0.181857
2              -1.050000
3              -0.322581
4              -2.150000
5              -0.129630
6              -0.883041
7              -0.485670
8              -0.240658
9              -1.047026
10              0.040767
11              0.108927
12              0.275823
13             -0.334392
14             -1.436582
15             -0.288071
16              0.441748
17             -0.208955
18             -0.411924
19             -0.609091
20             -0.677419
21              0.189292
22             -0.337977
23              0.213615
24              0.076696
25             -0.064685
26             -2.000000
27             -0.708861
28             -3.333333
29             -1.050000
30             -0.283262
31              0.000000
32              0.079466
33             -0.810945
34             -0.505967
35              0.069579
36             -5.300000
37              0.261538
38              0.221122
39             -1.277946
```

```
40    -4.200000
41    -0.106870
42    -1.712934
43    -0.970199
44    -0.645570
45     0.494914
46     0.192130
47    -0.801147
48     0.350490
49     0.439032
50     0.256127
51    -0.149191
52     0.447168
53     0.189848
54    -0.512195
55     0.030534
```



To create the league table I have merged the suitability data frames for 2005-2008 and 2019-2022 using the siteID as the unique key. The formula given in the assignemnt specification has been used to calculate the relative indexes for water clarity and E Coli. Then those relative indexes has been created as new columns in the league table. A scatter plot has been created using the seaborn package to visualise the correlation of water clarity index against E Coli index. The extra trend line via the regplot function allows us to see a positive correlation between the two variables. Therefore as E Coli's relative increase, the water clairty relative index will also increase. Even though some outliers can be observed, near the 0.0 of water clairty index and -5 of E Coli index it will not affect the overall trend.

```
# Assuming leagueTable is the merged and normalized DataFrame

# Create logical tests for improvement
leagueTable["EColi_Improved"] = leagueTable["E Coli_RelativeIndex"] >
0
leagueTable["WaterClarity_Improved"] =
leagueTable["WaterClarity_RelativeIndex"] > 0

# Create a crosstab to display counts
subset_cols = ["WaterClarity_RelativeIndex", "E Coli_RelativeIndex"]
leagueTable.dropna(subset=subset_cols, inplace=True)

crosstab_counts = pd.crosstab(leagueTable["WaterClarity_Improved"],
leagueTable["EColi_Improved"])

# Swap the counts in rows and columns
crosstab_counts = crosstab_counts.iloc[::-1, ::-1]

# Rename the index and columns for clarity
crosstab_counts.columns = ["E Coli Improved", "E Coli Not Improved"]
crosstab_counts.index = ["Water Clarity Improved", "Water Clarity Not
Improved"]

# Display the crosstab
print(crosstab_counts)
```

```
                            E Coli Improved  E Coli Not Improved
Water Clarity Improved                   16                    9
Water Clarity Not Improved                5                   26
```

Firstly I have created the improved column for E Coli and water clarity when their index values are greater than 0. Secondly the data undergoes the crossstab function from the pandas package to create the crossstab and some manual index switches had to be made as the results position were inversed.

Upon observing the matrix, it suggests that there are increasing cases of contaminated water in the time frame from 2008 to 2022. As there are 26 total counts of E Coli and water clarity not improved and 16 total counts of improved in both E Coli and water clarity. This is not the result we wished for, as it suggests the water quality to decrease in the following years. We can also observe 5 cases where the E Coli improved however the water clarity uninproved, 9 cases of water clarity improved and E Coli not improved.

Part 4: Linear Regression

*The processes for coding the linear regressions and crossvalidation has been breifly explained in the code comments below

Water temp against Year, Season, Time of day, and Longitude / Latitude

```
temp_model_data
# removing unwanted columns
columns_to_remove = ["URS","Water Kelvin"]
# dropping the columns
temp_model_data.drop(columns=columns_to_remove, inplace=True)

# One-hot encode categorical features
temp_model_data = pd.get_dummies(temp_model_data, columns=["Season"])


# create target name
target_name = 'Water Temp' ## identify the name of the column that we
are interested in modelling (the response)
# create feature columns list
feature_names = [
"Year","Season_Autumn","Season_Spring","Season_Summer","Season_Winter"
,"Hour of day","Longitude","Latitude" ]

# create training data
X = temp_model_data[feature_names].to_numpy()
t = temp_model_data[target_name].to_numpy()
X_train, X_test, t_train, t_test = train_test_split(X, t,
train_size=0.7, random_state=1234)

from sklearn.model_selection import KFold, cross_validate
#state the model (linearmodel)
mdl = LinearRegression()
mdl.fit(X_train, t_train)
print(f"Intercept value:",mdl.intercept_)


# Predict values for the test set
y_test = mdl.predict(X_test)

# Calculate mean squared error using mean_squared_error function
mse = mean_squared_error(t_test, y_test)
print("Mean Squared Error (MSE):", mse)

# Calculate the score (coefficient of determination) using the model's
score() function
score = mdl.score(X_test, t_test)
```

```
print("Model Score (R^2):", score)
#stating the number of k folds and undergoes the cross validation
process
kf = KFold(n_splits=10, shuffle=True, random_state=1234)
cv_res = cross_validate(LinearRegression(), X, t, cv=kf)

print(f"Cross validation R-Squared performance of linear regression is
{np.mean(cv_res['test_score']):.3}")
#Create the model for better visuals
model = pd.DataFrame({"feature" :
feature_names,"coefficient":mdl.coef_})
display(model)
```

```
Intercept value: -7.583429531509925
Mean Squared Error (MSE): 6.998095443781172
Model Score (R^2): 0.6736459142560385
Cross validation R-Squared performance of linear regression is 0.677
```

	feature	coefficient
0	Year	0.029284
1	Season_Autumn	0.719611
2	Season_Spring	-0.722356
3	Season_Summer	4.679087
4	Season_Winter	-4.676341
5	Hour of day	0.444699
6	Longitude	-0.109157
7	Latitude	0.599151

Upon viewing each of the coefficient values (the effect of each predictor variable on the response variable (Water temp)) we can suggest the following. Overall we can see a large change in water temperature during varying times such as seasonal patterns especially Summer and Winter which is expected, as the outside temperature will be affected greatly with cooler times in the winter and warmer in the summer. For the summer season we expect a 4.68 degree increase and a 4.68 degree decrease in winter. Year is expected to have a severe effect against water temperature as it is expected to increase by 0.029 degrees per year. In 100 years time it's a 2.9 degree increase which is a durastic increase endangering life for some aquatic organisms. Water temperature seems to be somewhat affected by the space as well, as we can read from the coefficient for each unit increase in latitude with 0.6 degrees increase. Whereas for each unit increase in longitude with -0.1 degrees change doesnt show much of a correlation between the water temperature.

The linear models R^2 value is approximately 0.67 which indicates that approximately 67% of the proportion of varaince is explained by the model. Which leaves the 33% of the varaince model is unexplained. Therefore, predictor variables included in the model explain a significant portion of the observed temperature changes.

```
display(env_model_data)
```

```
       Ammonia  Dissolved Oxygen Saturation  Dissolved Reactive
Phosphate  \
```

```
196        8.0                            88.9
21.4
197        6.0                            90.7
14.1
198        1.0                            89.6
17.7
199       28.0                            82.1
27.8
200       26.0                            88.5
28.0
...        ...                             ...
...
29593      2.0                           101.2
2.0
29594      3.0                           102.1
2.0
29595      3.0                           102.3
2.0
29596      4.0                           102.1
2.0
29597      1.0                           102.6
3.0

       Electrical Conductivity  Nitrate + Nitrite  Water Clarity
Water Temp  \
196                      190.0              155.0           0.68
20.1
197                      204.0                4.0           1.08
18.9
198                      227.0                6.0           1.26
14.3
199                      207.0              694.0           0.59
15.6
200                      198.0              637.0           0.53
10.5
...                        ...                ...            ...
...
29593                     51.9               29.0          10.00
10.3
29594                     48.8               22.0           6.80
12.3
29595                     53.6                5.0          10.48
15.7
29596                     55.9                8.0          11.47
18.9
29597                     58.0               21.0          11.44
17.1

         pH  log(E Coli)
```

```
196    7.43     2.082785
197    7.62     1.623249
198    7.66     1.939519
199    7.22     2.309630
200    7.37     3.020046
...     ...          ...
29593  7.67     0.602060
29594  7.54     0.602060
29595  7.64     0.698970
29596  7.81     0.602060
29597  7.73     1.431364

[14250 rows x 9 columns]
```

Water temp against Measurement features

```
env_model_data
target_name = 'Water Temp' ## identify the name of the column that we
are interested in modelling (the response)
feature_names = [ "Ammonia", "Dissolved Oxygen Saturation", "Dissolved
Reactive Phosphate", "Electrical Conductivity", "Nitrate + Nitrite",
"Water Clarity", "pH","log(E Coli)" ]

X = env_model_data[feature_names].to_numpy()
t = env_model_data[target_name].to_numpy()
X_train, X_test, t_train, t_test = train_test_split(X, t,
train_size=0.7, random_state=1234)

from sklearn.model_selection import KFold, cross_validate

#state the model (linearmodel)
mdl = LinearRegression()
mdl.fit(X_train, t_train)
print(f"Intercept value:",mdl.intercept_)


# Predict values for the test set
y_test = mdl.predict(X_test)

# Calculate mean squared error using mean_squared_error function
mse = mean_squared_error(t_test, y_test)
print("Mean Squared Error (MSE):", mse)

# Calculate the score (coefficient of determination) using the model's
score() function
score = mdl.score(X_test, t_test)
print("Model Score (R^2):", score)
#stating the number of k folds and undergoes the cross validation
process
kf = KFold(n_splits=10, shuffle=True, random_state=1234)
```

```
cv_res = cross_validate(LinearRegression(), X, t, cv=kf)

print(f"Cross validation R-Squared performance of linear regression is
{np.mean(cv_res['test_score']):.3}")
#Create the model for better visuals
model = pd.DataFrame({"feature" :
feature_names,"coefficient":mdl.coef_})
display(model)
```

```
Intercept value: -14.630178379576538
Mean Squared Error (MSE): 16.37374887166536
Model Score (R^2): 0.24567701939360176
Cross validation R-Squared performance of linear regression is 0.238
```

	feature	coefficient
0	Ammonia	0.016849
1	Dissolved Oxygen Saturation	0.081157
2	Dissolved Reactive Phosphate	0.030752
3	Electrical Conductivity	0.014717
4	Nitrate + Nitrite	-0.002794
5	Water Clarity	0.220015
6	pH	1.892582
7	log(E Coli)	1.677189

Upon observing the coefficient values (the effect of each predictor variable on the response variable (water temp)) we can suggest the following. The features that had the most effect with the changing environment would be pH, log(E Coli) and potentially water clarity. The linear regression model suggests that for a unit of pH the water temperature increased by 1.89 degrees, which makes it evident that water temperature changes against the environmental factors (pH). For example, the pH of the water will differ in regions with varying pH in the soil of the water source affecting the water temperature. For a unit increase of log(E Coli) value, the water temperature approximately increased by 1.68 degrees. Which is interesting and will need further investigation to find how E Coli acts on water temperature. Water clarity most likely has a small effect on water temperature as the coefficient is 0.22 degrees. This small value seems negligible however we do not have enough evidence to rule out the option.

The R^2 value with the linear regression performance was approximatley 0.24. This is likely a poor fit as it only explains approximately 23.8% of the proportion of variances leaving the majority (approximately 76.2%) of the variance from the predictor variables unexplained.

pH against the Measurement features

```
target_name = 'pH' ## identify the name of the column that we are
interested in modelling (the response)
feature_names = [ "Ammonia", "Dissolved Oxygen Saturation", "Dissolved
Reactive Phosphate", "Electrical Conductivity", "Nitrate + Nitrite",
"Water Clarity", "Water Temp","log(E Coli)" ]

X = env_model_data[feature_names].to_numpy()
t = env_model_data[target_name].to_numpy()
```

```
X_train, X_test, t_train, t_test = train_test_split(X, t,
train_size=0.7, random_state=1234)

from sklearn.model_selection import KFold, cross_validate

mdl = LinearRegression()
mdl.fit(X_train, t_train)
print(f"Intercept value:",mdl.intercept_)


# Predict values for the test set
y_test = mdl.predict(X_test)

# Calculate mean squared error using mean_squared_error function
mse = mean_squared_error(t_test, y_test)
print("Mean Squared Error (MSE):", mse)

# Calculate the score (coefficient of determination) using the model's
score() function
score = mdl.score(X_test, t_test)
print("Model Score (R^2):", score)

#stating the number of k folds and undergoes the cross validation
process
kf = KFold(n_splits=10, shuffle=True, random_state=1234)
cv_res = cross_validate(LinearRegression(), X, t, cv=kf)

print(f"Cross validation R-Squared performance of linear regression is
{np.mean(cv_res['test_score']):.3}")
#Create the model for better visuals
model = pd.DataFrame({"feature" :
feature_names,"coefficient":mdl.coef_})
display(model)
```

```
Intercept value: 5.272879733514568
Mean Squared Error (MSE): 0.06907385654076616
Model Score (R^2): 0.5216025109483045
Cross validation R-Squared performance of linear regression is 0.507
```

	feature	coefficient
0	Ammonia	-0.001868
1	Dissolved Oxygen Saturation	0.022584
2	Dissolved Reactive Phosphate	-0.000409
3	Electrical Conductivity	0.001290
4	Nitrate + Nitrite	-0.000104
5	Water Clarity	0.013164
6	Water Temp	0.008178
7	log(E Coli)	-0.037927

Upon observing the coefficient values (the effect of each predictor variable (measurements) on the response variable (pH)) we can suggest the following). We can observe that the increase of dissolved oxygen saturation of the environment increases the levels of the pH by 0.022. This is as expected since the increased presence of oxygen will increase the pH making the water basic/alkaline and vice versa. The environmental factor with changing Log(E Coli) approximately decreases the pH by 0.038. This is most likely due to the growth of E Coli which maintains a certain pH level and contaminates the water sources. Electrical conductivity, water clarity and water temp could have potential of varying the pH levels however will need further analysis as the coefficients are currently negligible.

The R^2 score of linear regression is approximately 0.51, thus the model shows approximately 51% of the proportion of variances, leaving the rest of the variance of predictor variables unexplained.

Conclusion

In the course of this report we embarked on a comprehensive exploration of the suitability of New Zealand waterways, utilizing many data science techniques such as: data wrangling, exploratory data analysis, linear regression analysis and various visual representations of the data. These techniques help us to understand the New Zealand water ways in depth allowing us to find methods to prevent the water quality from declining.

Key findings

Data Wrangling: The critical initial step of data wrangling allowed us to ensure the dataset's cleanliness and completeness for further analysis techniques. Without this step, EDA and visualisations will be troublesome due to the missing data or the extra disposable columns in the datasets.

Exploratory Data Analysis (EDA): Using EDA, we investigated the relationships and distributions that the data contained. We gained a deep understanding of the behaviours and prospective trends of the variables via the visual representations.

Data querying / exploration: Manipulating the datasets into subsetted dataframes to obtain relationships which will be used in visualisation of the data.

We sought to identify any potential linear correlations between the variables by doing a linear regression analysis. With the help of this analytical technique, we were able to quantify the effects of particular variables and get insights into the characteristics that affect the suitability of New Zealand waterways.

Utilising different visual representations, such as scatter plots, lineplots, heatmaps, pair plots and crosstabs allowed a concise understanding of the findings for viewers of the analysis.