In [199…

```
import pandas as pd
import numpy as np
import seaborn as sns
```

Specify the headers of the dataframes and load the csv into tow seperate data frames

In [200…

```
# Correcting the headers lists: each column name should be a separate string within the list.
df1_headers = [
    "Station_ID", "Date_Time", "altimeter_set_1", "air_temp_set_1", "relative_humidity_set_1",
    "wind_speed_set_1", "wind_direction_set_1", "wind_gust_set_1", "solar_radiation_set_1",
    "precip_accum_24_hour_set_1", "precip_accum_since_local_midnight_set_1",
    "wind_chill_set_1d", "wind_cardinal_direction_set_1d", "heat_index_set_1d",
    "dew_point_temperature_set_1d", "pressure_set_1d", "sea_level_pressure_set_1d"
    # Make sure all headers are included and separated correctly
]

df2_headers = [
    "Station_ID", "Date_Time", "altimeter_set_1", "air_temp_set_1", "dew_point_temperature_set_1",
    "relative_humidity_set_1", "wind_speed_set_1", "wind_direction_set_1", "wind_gust_set_1",
    "sea_level_pressure_set_1", "weather_cond_code_set_1", "cloud_layer_3_code_set_1",
    "pressure_tendency_set_1", "precip_accum_one_hour_set_1", "precip_accum_three_hour_set_1",
    "cloud_layer_1_code_set_1", "cloud_layer_2_code_set_1", "precip_accum_six_hour_set_1",
    "precip_accum_24_hour_set_1", "visibility_set_1", "metar_remark_set_1", "metar_set_1",
    "air_temp_high_6_hour_set_1", "air_temp_low_6_hour_set_1", "peak_wind_speed_set_1",
    "ceiling_set_1", "pressure_change_code_set_1", "air_temp_high_24_hour_set_1",
    "air_temp_low_24_hour_set_1", "peak_wind_direction_set_1", "wind_chill_set_1d",
    "wind_cardinal_direction_set_1d", "heat_index_set_1d", "weather_condition_set_1d",
    "weather_summary_set_1d", "cloud_layer_1_set_1d", "cloud_layer_2_set_1d",
    "cloud_layer_3_set_1d", "dew_point_temperature_set_1d", "pressure_set_1d",
    "sea_level_pressure_set_1d"
    # Again, ensure all headers are separated correctly
]

# Read the CSV files with the corrected header alignment
df1 = pd.read_csv("G3425.csv", names=df1_headers, skiprows=8, index_col=False)
df2 = pd.read_csv("KHYI.csv", names=df2_headers, skiprows=8, index_col=False)
# Inspect the first few rows of the 'Date_Time' column
print(df1['Date_Time'].head())
print(df2['Date_Time'].head())

import pandas as pd

# Define a function to remove timezone information
def remove_timezone(dt_str):
    return dt_str[:-4]  # Adjust slicing based on your data format

# Apply this function to your 'Date_Time' columns
df1['Date_Time'] = df1['Date_Time'].apply(remove_timezone)
df2['Date_Time'] = df2['Date_Time'].apply(remove_timezone)
```

```python
# Specify the format of your date-time strings
date_format = "%m/%d/%Y %H:%M"  # Adjust this format to match your data

# Convert 'Date_Time' to datetime
df1['Date_Time'] = pd.to_datetime(df1['Date_Time'], format=date_format, errors='coerce')
df2['Date_Time'] = pd.to_datetime(df2['Date_Time'], format=date_format, errors='coerce')

# Optional: Localize to a specific timezone if needed
# df1['Date_Time'] = df1['Date_Time'].dt.tz_localize('America/Chicago')
# df2['Date_Time'] = df2['Date_Time'].dt.tz_localize('UTC')

# Rename columns
df1.rename(columns={'Date_Time': 'timestamp'}, inplace=True)
df2.rename(columns={'Date_Time': 'timestamp'}, inplace=True)
df3 = pd.read_csv("Meadow Center Sensor Data Test.csv")
df3 = df3.drop(columns=['Month','Day','Year','Date'])
df3.rename(columns={'Taken At': 'timestamp'}, inplace=True)
df4 = pd.read_csv('usgs.waterservices.csv',skiprows=1)
df4.rename(columns={'20d': 'timestamp'}, inplace=True)
date_range = pd.date_range(start= '2022-06-11', end = '2023-06-11', freq='15S')
df3.rename(columns={'Temperature': 'Water Temperature'}, inplace=True)

final_df = pd.DataFrame(date_range, columns=['timestamp'])
```

```
0    05/03/2023 13:37 CDT
1    05/03/2023 13:47 CDT
2    05/03/2023 14:07 CDT
3    05/03/2023 14:47 CDT
4    05/03/2023 15:07 CDT
Name: Date_Time, dtype: object
0    06/11/2022 23:00 UTC
1    06/11/2022 23:05 UTC
2    06/11/2022 23:10 UTC
3    06/11/2022 23:15 UTC
4    06/11/2022 23:20 UTC
Name: Date_Time, dtype: object
```

This function is used to reset the timezones in the dataset because the usgs and Sensor Data use UTC time zone

In [201…

```
import pytz
dfs = [df1, df2, df3, df4]
# Function to parse datetime with different formats and timezones
def parse_datetime(dt):
    try:
        # Try parsing as is (if no timezone info, etc.)
        return pd.to_datetime(dt)
    except ValueError:
        # Handle entries with 'CDT' and 'UTC' separately
        if 'CDT' in dt:
            dt = dt.replace(' CDT', '')  # Remove 'CDT'
            parsed_dt = pd.to_datetime(dt, format='%m/%d/%Y %H:%M')  # Parse the datetime
            central = pytz.timezone('America/Chicago')
            return parsed_dt.tz_localize(central).tz_convert(pytz.utc).tz_localize(None)  # Convert to UTC
        elif 'UTC' in dt:
            dt = dt.replace(' UTC', '')  # Remove 'UTC'
            return pd.to_datetime(dt, format='%m/%d/%Y %H:%M')  # Parse the datetime
        else:
            # Custom parsing for other formats can be added here
            return pd.to_datetime(dt)  # Or a default return, if it's a format pandas can parse by default

# Iterate over all DataFrames
for dataframe in dfs:
    # Apply the conversion function to the 'Date_Time' column
    dataframe['timestamp'] = dataframe['timestamp'].apply(parse_datetime)

    # If you want to rename 'Date_Time' to 'timestamp', uncomment the following line
    # dataframe.rename(columns={'Date_Time': 'timestamp'}, inplace=True)

# Now, all your 'Date_Time' columns should have a unified format, and you can proceed with combining your
# Iterate over all DataFrames
for dataframe in dfs:
    # Apply the conversion function to the 'Date_Time' column
    dataframe['timestamp'] = dataframe['timestamp'].apply(parse_datetime)

    # If you want to rename 'Date_Time' to 'timestamp', uncomment the following line
    #dataframe.rename(columns={'Date_Time': 'timestamp'}, inplace=True)

# Now, all your 'Date_Time' columns should have a unified format, and you can proceed with combining your
```

In [202…
```
df1['timestamp'] = df1['timestamp'].dt.tz_localize(None)
df2['timestamp'] = df2['timestamp'].dt.tz_localize(None)
df3['timestamp'] = df3['timestamp'].dt.tz_localize(None)
df4['timestamp'] = df4['timestamp'].dt.tz_localize(None)
df1.set_index('timestamp', inplace=True)
df2.set_index('timestamp', inplace=True)
df3.set_index('timestamp', inplace=True)
df4.set_index('timestamp', inplace=True)
dfs = [df1,df2]
merged_df = pd.concat(dfs, axis=0)
merged_df = pd.merge(merged_df, df3, on='timestamp', how='outer')
merged_df = pd.merge(merged_df, df4, on='timestamp', how='outer')
merged_df.reset_index(inplace=True)
final_df = merged_df
final_df = merged_df.drop(columns=['5s','15s','6s','10s'])
```

This cell adds a feature column to the dataframe by dividing the lake into 2 sections, upstream and down stream. The dividing line is around Deep Hole and the Weather Station onsite.

In [203…
```
#Divide into two clusters {Upstream and Downstream}
# a lat line between 29.89303 and 29.89310
# Dividing line coordinates
dividing_line = np.array([[29.89303, -97.932837], [29.89310, -97.932837]])

# Since the dividing line has the same longitude, we can cluster based on latitude.
# Points with latitude less than 29.89303 will be 'Downstream', greater will be 'Upstream'.
final_df['Cluster'] = np.where(final_df['Lat'] < dividing_line[0, 0], 'Downstream', 'Upstream')
```

In [204…
```
final_df.set_index('timestamp', inplace=True)
final_df = final_df[~final_df.index.duplicated(keep='last')]
all_timestamps = pd.date_range(start='2022-06-11 00:00:00', end='2023-06-11 00:00:00', freq='15S')
final_df = final_df.reindex(all_timestamps, fill_value=pd.NA)
final_df.rename(columns={'index': 'timestamp'}, inplace=True)
final_df = final_df.rename(columns={'14n': 'Discharge Rate'})
```

In [205…

```
#Current shape of Dataset
final_df.shape
```

Out[205]:

```
(2102401, 48)
```

Data Preprocessing

This cell is the first part for our linear interpolation. We take the mean of each column and have it as the first and last entry in each column

In [206…

```
import pandas as pd
import numpy as np

# Assuming you have a DataFrame 'final_df'

# Iterating over each column in the DataFrame
for col_name in final_df.columns:
    # We're only interested in columns with numeric data
    if pd.api.types.is_numeric_dtype(final_df[col_name]):
        col_mean = final_df[col_name].mean()

        # If col_mean is not NaN, this means that there's at least one non-NaN value in the column
        if not np.isnan(col_mean):
            # Finding the first and last NaN indices in the column
            # We're specifically looking for NaN entries, not just any entry
            first_nan_index = final_df[col_name].index[final_df[col_name].isna()].min()
            last_nan_index = final_df[col_name].index[final_df[col_name].isna()].max()

            # Filling these specific NaN positions with the column mean, if they exist
            if first_nan_index is not np.nan:
                final_df.at[first_nan_index, col_name] = col_mean
            if last_nan_index is not np.nan:
                final_df.at[last_nan_index, col_name] = col_mean

# You can now check your DataFrame to see if the first and last NaNs were replaced appropriately.
final_df.head()
```

Out[206]:

	Station_ID	altimeter_set_1	air_temp_set_1	relative_humidity_set_1	wind_speed_set_1	wind_direction_set_1	wind_gust_set
2022-06-11 00:00:00	NaN	30.012548	73.204991	68.73463	8.306313	153.281394	12.0774
2022-06-11 00:00:15	<NA>	NaN	NaN	NaN	NaN	NaN	Na
2022-06-11 00:00:30	<NA>	NaN	NaN	NaN	NaN	NaN	Na
2022-06-11 00:00:45	<NA>	NaN	NaN	NaN	NaN	NaN	Na
2022-06-11 00:01:00	<NA>	NaN	NaN	NaN	NaN	NaN	Na

5 rows × 48 columns

This cell does forward linear interpolation for the dataset on numeric columns

In [207…

```
# Linear interpolation for the numeric columns.
final_df.interpolate(method='linear', limit_direction='forward', inplace=True)
```

```
C:\Users\garre\AppData\Local\Temp\ipykernel_2780\2070673214.py:2: FutureWarning:

DataFrame.interpolate with object dtype is deprecated and will raise in a future version. Call obj.infer_o
bjects(copy=False) before interpolating instead.
```

This cell is for the non-numeric columns, we do forward and backward filling for these columns

In [208…

```
non_numeric_columns = final_df.select_dtypes(exclude='number').columns
final_df[non_numeric_columns] = final_df[non_numeric_columns].fillna(method='ffill')
final_df[non_numeric_columns] = final_df[non_numeric_columns].fillna(method='bfill')
```

```
C:\Users\garre\AppData\Local\Temp\ipykernel_2780\2580860926.py:2: FutureWarning:

DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bf
ill() instead.

C:\Users\garre\AppData\Local\Temp\ipykernel_2780\2580860926.py:3: FutureWarning:

DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bf
ill() instead.
```

In [209…

```
final_df.head()
```

Out[209]:

	Station_ID	altimeter_set_1	air_temp_set_1	relative_humidity_set_1	wind_speed_set_1	wind_direction_set_1	wind_gust_set
2022-06-11 00:00:00	KHYI	30.012548	73.204991	68.734630	8.306313	153.281394	12.0774
2022-06-11 00:00:15	KHYI	30.012504	73.209917	68.728196	8.306894	153.282611	12.0782
2022-06-11 00:00:30	KHYI	30.012460	73.214844	68.721762	8.307474	153.283828	12.0790
2022-06-11 00:00:45	KHYI	30.012416	73.219771	68.715328	8.308055	153.285045	12.0798
2022-06-11 00:01:00	KHYI	30.012373	73.224697	68.708894	8.308635	153.286262	12.0807

5 rows × 48 columns

This cell checks if there are any more NaN values. And based on the output, this is probaly due to a bad merge on combining the dataframes into one large data frame. We drop these columns.

In [210…

```
# Checking if there are any NaN values left in the DataFrame
nan_check = final_df.isna().sum().sum()

if nan_check == 0:
    print("There are no NaN values in the DataFrame.")
else:
    print(f"There are {nan_check} NaN values in the DataFrame.")
    # Optionally, to see the count of NaNs in each column:
    print("\nCount of NaN values in each column:")
    print(final_df.isna().sum())
```

```
There are 8409604 NaN values in the DataFrame.

Count of NaN values in each column:
Station_ID                                        0
altimeter_set_1                                   0
air_temp_set_1                                    0
relative_humidity_set_1                           0
wind_speed_set_1                                  0
wind_direction_set_1                              0
wind_gust_set_1                                   0
solar_radiation_set_1                             0
precip_accum_24_hour_set_1                        0
precip_accum_since_local_midnight_set_1           0
wind_chill_set_1d                                 0
wind_cardinal_direction_set_1d                    0
heat_index_set_1d                                 0
dew_point_temperature_set_1d                      0
pressure_set_1d                                   0
sea_level_pressure_set_1d                         0
dew_point_temperature_set_1                       0
sea_level_pressure_set_1                          0
weather_cond_code_set_1                           0
cloud_layer_3_code_set_1                          0
pressure_tendency_set_1                           0
precip_accum_one_hour_set_1                       0
precip_accum_three_hour_set_1                     0
cloud_layer_1_code_set_1                          0
cloud_layer_2_code_set_1                          0
precip_accum_six_hour_set_1                       0
visibility_set_1                                  0
metar_remark_set_1                          2102401
metar_set_1                                       0
air_temp_high_6_hour_set_1                        0
air_temp_low_6_hour_set_1                         0
peak_wind_speed_set_1                             0
ceiling_set_1                                     0
pressure_change_code_set_1                        0
air_temp_high_24_hour_set_1                       0
air_temp_low_24_hour_set_1                        0
peak_wind_direction_set_1                         0
weather_condition_set_1d                          0
weather_summary_set_1d                            0
cloud_layer_1_set_1d                        2102401
cloud_layer_2_set_1d                        2102401
```

```
cloud_layer_3_set_1d                      2102401
Lat                                             0
Long                                            0
TDS                                             0
Water Temperature                               0
Discharge Rate                                  0
Cluster                                         0
dtype: int64
```

In [211…

```
# This drops any column containing at least one NaN.
final_df = final_df.dropna(axis=1, how='any')
final_df.head()
```

Out[211]:

	Station_ID	altimeter_set_1	air_temp_set_1	relative_humidity_set_1	wind_speed_set_1	wind_direction_set_1	wind_gust_set
2022-06-11 00:00:00	KHYI	30.012548	73.204991	68.734630	8.306313	153.281394	12.0774
2022-06-11 00:00:15	KHYI	30.012504	73.209917	68.728196	8.306894	153.282611	12.0782
2022-06-11 00:00:30	KHYI	30.012460	73.214844	68.721762	8.307474	153.283828	12.0790
2022-06-11 00:00:45	KHYI	30.012416	73.219771	68.715328	8.308055	153.285045	12.0798
2022-06-11 00:01:00	KHYI	30.012373	73.224697	68.708894	8.308635	153.286262	12.0807

5 rows × 44 columns

Due to the inaccuracies with the sensor, these are the upper and lower bounds of what would be acceptable as TDS values in Spring Lake. We drop these rows that are out-of-bounds. We also print out the mean of TDS to check to make sure it's acceptable to what the average TDS yearly value is for lakes connected to the Edwards Quifier

In [212…

```
final_df = final_df[(final_df['TDS'] >= 200) & (final_df['TDS'] <= 1000)]
print(final_df['TDS'].mean())
```

```
414.45872334768944
```

Due to the limited power of the computer we have and how large our dataset is, we are doing sampling to run our models

In [213…

```
final_df_copy = final_df
final_df = final_df.sample(frac=0.005)
final_df.shape
```

Out[213]:

```
(9454, 44)
```

Dataset Stats

1. Heatmaps of the two variables we are interested in, TDS and Water Temperature
2. Histogram
3. Scatter plots, to see any trends and to identify noise

In [214…

```
import plotly.express as px

# Assuming 'final_df' is your final dataframe
numeric_df = final_df.select_dtypes(include='number')
tds_corr = numeric_df.corr().loc[['TDS'], :]

# Create an interactive heatmap using Plotly
fig = px.imshow(tds_corr,
                text_auto=True, # Automatically annotate cells
                aspect='auto',   # Flexible cell size
                color_continuous_scale='RdBu') # Red Blue colormap

# Update layout for side-scrolling
fig.update_layout(
    title='Interactive Heatmap of TDS Correlation',
    autosize=False,
    width=1000,  # Set a suitable width
    height=300,  # Set a suitable height
    xaxis_nticks=36,  # Adjust based on your dataset
    margin=dict(l=10, r=10, t=50, b=10)
)

# Update xaxis properties if needed
fig.update_xaxes(side="bottom")

# Display the heatmap
fig.show()
```

In [215…

```
import plotly.express as px

# Assuming 'final_df' is your final dataframe
numeric_df = final_df.select_dtypes(include='number')
watertemp_corr = numeric_df.corr().loc[['Water Temperature'], :]

# Create an interactive heatmap using Plotly
fig = px.imshow(watertemp_corr,
                text_auto=True, # Automatically annotate cells
                aspect='auto',   # Flexible cell size
                color_continuous_scale='RdBu') # Red Blue colormap

# Update layout for side-scrolling
fig.update_layout(
    title='Interactive Heatmap of TDS Correlation',
    autosize=False,
    width=1000,  # Set a suitable width
    height=300,  # Set a suitable height
    xaxis_nticks=36,  # Adjust based on your dataset
    margin=dict(l=10, r=10, t=50, b=10)
)

# Update xaxis properties if needed
fig.update_xaxes(side="bottom")

# Display the heatmap
fig.show()
```

Models - All features, no hyperparameter tunining or cross validation

1. Decison Tree - Baseline
2. Random Forest - main model
3. FNN - Experiment
4. Gradient Boosting - Experiment
5. SVR - Experiment
6. Performance Graphs
7. Importance Features

In [216…

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
# Step 1: Select numeric columns
numeric_columns = final_df.select_dtypes(include=['number']).columns.tolist()

# Step 2: Remove 'TDS' and 'Water Temperature' if they are in numeric_columns
features_to_exclude = ['TDS', 'Water Temperature']
numeric_features = [col for col in numeric_columns if col not in features_to_exclude]

# Step 3: Use LabelEncoder to encode string columns
le = LabelEncoder()
encoded_columns = final_df.select_dtypes(include=['object']).apply(le.fit_transform)

# Step 4: Concatenate the encoded string columns back to the numeric DataFrame
X = pd.concat([final_df[numeric_features], encoded_columns], axis=1)
y = final_df[features_to_exclude]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the DecisionTreeRegressor
dt_regressor = DecisionTreeRegressor(random_state=42)

# Training the model
dt_regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_dt = dt_regressor.predict(X_test)

# Computing the Mean Squared Error (MSE) for both outputs
mse_dt_tds = mean_squared_error(y_test['TDS'], y_pred_dt[:, 0])
mse_dt_temp = mean_squared_error(y_test['Water Temperature'], y_pred_dt[:, 1])

print(f"Decision Tree - Mean Squared Error for TDS: {mse_dt_tds}")
print(f"Decision Tree - Mean Squared Error for Water Temperature: {mse_dt_temp}")

# Compute the R^2 score for both outputs
r2_dt_tds = r2_score(y_test['TDS'], y_pred_dt[:, 0])
r2_dt_temp = r2_score(y_test['Water Temperature'], y_pred_dt[:, 1])

print(f"Decision Tree - R^2 Score for TDS: {r2_dt_tds}")
```

```
print(f"Decision Tree - R^2 Score for Water Temperature: {r2_dt_temp}")

# Compute the Mean Absolute Error (MAE) for both outputs
mae_dt_tds = mean_absolute_error(y_test['TDS'], y_pred_dt[:, 0])
mae_dt_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_dt[:, 1])

print(f"Decision Tree - Mean Absolute Error for TDS: {mae_dt_tds}")
print(f"Decision Tree - Mean Absolute Error for Water Temperature: {mae_dt_temp}")

# Compute the Root Mean Squared Error (RMSE) for both outputs
rmse_dt_tds = mean_squared_error(y_test['TDS'], y_pred_dt[:, 0], squared=False)
rmse_dt_temp = mean_squared_error(y_test['Water Temperature'], y_pred_dt[:, 1], squared=False)

print(f"Decision Tree - Root Mean Squared Error for TDS: {rmse_dt_tds}")
print(f"Decision Tree - Root Mean Squared Error for Water Temperature: {rmse_dt_temp}")
```

```
Decision Tree - Mean Squared Error for TDS: 9.071655087596147
Decision Tree - Mean Squared Error for Water Temperature: 0.09323823955629205
Decision Tree - R^2 Score for TDS: 0.9961608882477865
Decision Tree - R^2 Score for Water Temperature: 0.9874407592315082
Decision Tree - Mean Absolute Error for TDS: 0.7520232276310884
Decision Tree - Mean Absolute Error for Water Temperature: 0.11833921057445455
Decision Tree - Root Mean Squared Error for TDS: 3.0119188381488877
Decision Tree - Root Mean Squared Error for Water Temperature: 0.30534937294235937
```

In [217…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.preprocessing import LabelEncoder

# Assuming final_df is defined
# We'll simulate it here with random data for demonstration purposes

# Step 1: Select numeric columns
numeric_columns = final_df.select_dtypes(include=['number']).columns.tolist()

# Step 2: Remove 'TDS' and 'Water Temperature' if they are in numeric_columns
features_to_exclude = ['TDS', 'Water Temperature']
numeric_features = [col for col in numeric_columns if col not in features_to_exclude]

# Step 3: Use LabelEncoder to encode string columns
le = LabelEncoder()
encoded_columns = final_df.select_dtypes(include=['object']).apply(le.fit_transform)

# Step 4: Concatenate the encoded string columns back to the numeric DataFrame
X = pd.concat([final_df[numeric_features], encoded_columns], axis=1)
y = final_df[features_to_exclude]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the RandomForestRegressor
regressor = RandomForestRegressor(random_state=42)

# Training the model
regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf = regressor.predict(X_test)

# Computing the Mean Squared Error (MSE) for both outputs
mse_rf_tds = mean_squared_error(y_test['TDS'], y_pred_rf[:, 0])
mse_rf_temp = mean_squared_error(y_test['Water Temperature'], y_pred_rf[:, 1])

print(f"Mean Squared Error for TDS: {mse_rf_tds}")
print(f"Mean Squared Error for Water Temperature: {mse_rf_temp}")
```

```python
# Compute the R^2 score for both outputs
r2_rf_tds = r2_score(y_test['TDS'], y_pred_rf[:, 0])
r2_rf_temp = r2_score(y_test['Water Temperature'], y_pred_rf[:, 1])

print(f"R^2 Score for TDS: {r2_rf_tds}")
print(f"R^2 Score for Water Temperature: {r2_rf_temp}")
# Compute the Mean Absolute Error (MAE) for both outputs
mae_rf_tds = mean_absolute_error(y_test['TDS'], y_pred_rf[:, 0])
mae_rf_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_rf[:, 1])

print(f"Mean Absolute Error for TDS: {mae_rf_tds}")
print(f"Mean Absolute Error for Water Temperature: {mae_rf_temp}")

# Compute the Root Mean Squared Error (RMSE) for both outputs
rmse_rf_tds = mean_squared_error(y_test['TDS'], y_pred_rf[:, 0], squared=False)
rmse_rf_temp = mean_squared_error(y_test['Water Temperature'], y_pred_rf[:, 1], squared=False)

print(f"Root Mean Squared Error for TDS: {rmse_rf_tds}")
print(f"Root Mean Squared Error for Water Temperature: {rmse_rf_temp}")
```

```
Mean Squared Error for TDS: 3.891120469374974
Mean Squared Error for Water Temperature: 0.047147688039776564
R^2 Score for TDS: 0.9983532832565822
R^2 Score for Water Temperature: 0.9936491811880276
Mean Absolute Error for TDS: 0.6382615690644924
Mean Absolute Error for Water Temperature: 0.09844764240660724
Root Mean Squared Error for TDS: 1.9725923221423565
Root Mean Squared Error for Water Temperature: 0.2171351837905975
```

In [218…

```python
!pip3 install tensorflow
```

```
Requirement already satisfied: tensorflow in c:\users\garre\appdata\local\programs\python\python311\lib\si
te-packages (2.15.0)
Requirement already satisfied: tensorflow-intel==2.15.0 in c:\users\garre\appdata\local\programs\python\py
thon311\lib\site-packages (from tensorflow) (2.15.0)
Requirement already satisfied: absl-py>=1.0.0 in c:\users\garre\appdata\local\programs\python\python311\li
b\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.0.0)
Requirement already satisfied: astunparse>=1.6.0 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in c:\users\garre\appdata\local\programs\python\python
311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (23.5.26)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in c:\users\garre\appdata\local\program
s\python\python311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.5.4)
Requirement already satisfied: google-pasta>=0.1.1 in c:\users\garre\appdata\local\programs\python\python3
11\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.2.0)
Requirement already satisfied: h5py>=2.9.0 in c:\users\garre\appdata\local\programs\python\python311\lib\s
ite-packages (from tensorflow-intel==2.15.0->tensorflow) (3.10.0)
Requirement already satisfied: libclang>=13.0.0 in c:\users\garre\appdata\local\programs\python\python311\
lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (16.0.6)
Requirement already satisfied: ml-dtypes~=0.2.0 in c:\users\garre\appdata\local\programs\python\python311\
lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.2.0)
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in c:\users\garre\appdata\local\programs\python\python
311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.26.2)
Requirement already satisfied: opt-einsum>=2.3.2 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (3.3.0)
Requirement already satisfied: packaging in c:\users\garre\appdata\roaming\python\python311\site-packages
(from tensorflow-intel==2.15.0->tensorflow) (23.2)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=
3.20.3 in c:\users\garre\appdata\local\programs\python\python311\lib\site-packages (from tensorflow-intel=
=2.15.0->tensorflow) (4.23.4)
Requirement already satisfied: setuptools in c:\users\garre\appdata\local\programs\python\python311\lib\si
te-packages (from tensorflow-intel==2.15.0->tensorflow) (65.5.0)
Requirement already satisfied: six>=1.12.0 in c:\users\garre\appdata\local\programs\python\python311\lib\s
ite-packages (from tensorflow-intel==2.15.0->tensorflow) (1.16.0)
Requirement already satisfied: termcolor>=1.1.0 in c:\users\garre\appdata\local\programs\python\python311\
lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in c:\users\garre\appdata\local\programs\python\py
thon311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (4.8.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in c:\users\garre\appdata\local\programs\python\python3
11\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in c:\users\garre\appdata\local\progra
ms\python\python311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (0.31.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\garre\appdata\local\programs\python\python3
11\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (1.60.0)
Requirement already satisfied: tensorboard<2.16,>=2.15 in c:\users\garre\appdata\local\programs\python\pyt
```

```
hon311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.15.1)
Requirement already satisfied: tensorflow-estimator<2.16,>=2.15.0 in c:\users\garre\appdata\local\program
s\python\python311\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.15.0)
Requirement already satisfied: keras<2.16,>=2.15.0 in c:\users\garre\appdata\local\programs\python\python3
11\lib\site-packages (from tensorflow-intel==2.15.0->tensorflow) (2.15.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from astunparse>=1.6.0->tensorflow-intel==2.15.0->tensorflow) (0.42.0)
Requirement already satisfied: google-auth<3,>=1.6.3 in c:\users\garre\appdata\local\programs\python\pytho
n311\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (2.25.1)
Requirement already satisfied: google-auth-oauthlib<2,>=0.5 in c:\users\garre\appdata\local\programs\pytho
n\python311\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (1.1.0)
Requirement already satisfied: markdown>=2.6.8 in c:\users\garre\appdata\local\programs\python\python311\l
ib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (3.5.1)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\garre\appdata\local\programs\python\python3
11\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (2.31.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in c:\users\garre\appdata\local\progr
ams\python\python311\lib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflo
w) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in c:\users\garre\appdata\local\programs\python\python311\l
ib\site-packages (from tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow) (3.0.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in c:\users\garre\appdata\local\programs\python\pyth
on311\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->te
nsorflow) (5.3.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\users\garre\appdata\local\programs\python\pytho
n311\lib\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->ten
sorflow) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in c:\users\garre\appdata\local\programs\python\python311\li
b\site-packages (from google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflo
w) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in c:\users\garre\appdata\local\programs\python\py
thon311\lib\site-packages (from google-auth-oauthlib<2,>=0.5->tensorboard<2.16,>=2.15->tensorflow-intel==
2.15.0->tensorflow) (1.3.1)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\garre\appdata\local\programs\python\py
thon311\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->te
nsorflow) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in c:\users\garre\appdata\local\programs\python\python311\lib\
site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow)
(3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorfl
ow) (2.1.0)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from requests<3,>=2.21.0->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorfl
ow) (2023.11.17)
```

```
Requirement already satisfied: MarkupSafe>=2.1.1 in c:\users\garre\appdata\local\programs\python\python31
1\lib\site-packages (from werkzeug>=1.0.1->tensorboard<2.16,>=2.15->tensorflow-intel==2.15.0->tensorflow)
(2.1.3)
Requirement already satisfied: pyasn1<0.6.0,>=0.4.6 in c:\users\garre\appdata\local\programs\python\python
311\lib\site-packages (from pyasn1-modules>=0.2.1->google-auth<3,>=1.6.3->tensorboard<2.16,>=2.15->tensorf
low-intel==2.15.0->tensorflow) (0.5.1)
Requirement already satisfied: oauthlib>=3.0.0 in c:\users\garre\appdata\local\programs\python\python311\l
ib\site-packages (from requests-oauthlib>=0.7.0->google-auth-oauthlib<2,>=0.5->tensorboard<2.16,>=2.15->te
nsorflow-intel==2.15.0->tensorflow) (3.2.2)

[notice] A new release of pip is available: 23.2.1 -> 23.3.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [219…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Assuming final_df is defined
# We'll simulate it here with random data for demonstration purposes

# Step 1: Select numeric columns
numeric_columns = final_df.select_dtypes(include=['number']).columns.tolist()

# Step 2: Remove 'TDS' and 'Water Temperature' if they are in numeric_columns
features_to_exclude = ['TDS', 'Water Temperature']
numeric_features = [col for col in numeric_columns if col not in features_to_exclude]

# Step 3: Use LabelEncoder to encode string columns
le = LabelEncoder()
encoded_columns = final_df.select_dtypes(include=['object']).apply(le.fit_transform)

# Step 4: Concatenate the encoded string columns back to the numeric DataFrame
X = pd.concat([final_df[numeric_features], encoded_columns], axis=1)
y = final_df[features_to_exclude]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Neural network architecture
model = Sequential()
model.add(Dense(128, activation='relu', input_shape=(X_train.shape[1],)))
model.add(Dense(64, activation='relu'))
model.add(Dense(2))  # Two output neurons for TDS and Water Temperature

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train, y_train, epochs=100, batch_size=32, verbose=1)

# Predicting on the test set
y_pred_fnn = model.predict(X_test)
```

```
# Computing the Mean Squared Error (MSE) for both outputs
mse_fnn_tds = mean_squared_error(y_test['TDS'], y_pred_fnn[:, 0])
mse_fnn_temp = mean_squared_error(y_test['Water Temperature'], y_pred_fnn[:, 1])

print(f"Mean Squared Error for TDS: {mse_fnn_tds}")
print(f"Mean Squared Error for Water Temperature: {mse_fnn_temp}")

# Compute the R^2 score for both outputs
r2_fnn_tds = r2_score(y_test['TDS'], y_pred_fnn[:, 0])
r2_fnn_temp = r2_score(y_test['Water Temperature'], y_pred_fnn[:, 1])

print(f"R^2 Score for TDS: {r2_fnn_tds}")
print(f"R^2 Score for Water Temperature: {r2_fnn_temp}")

# Compute the Mean Absolute Error (MAE) for both outputs
mae_fnn_tds = mean_absolute_error(y_test['TDS'], y_pred_fnn[:, 0])
mae_fnn_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_fnn[:, 1])

print(f"Mean Absolute Error for TDS: {mae_fnn_tds}")
print(f"Mean Absolute Error for Water Temperature: {mae_fnn_temp}")

# Compute the Root Mean Squared Error (RMSE) for both outputs
rmse_fnn_tds = mean_squared_error(y_test['TDS'], y_pred_fnn[:, 0], squared=False)
rmse_fnn_temp = mean_squared_error(y_test['Water Temperature'], y_pred_fnn[:, 1], squared=False)

print(f"Root Mean Squared Error for TDS: {rmse_fnn_tds}")
print(f"Root Mean Squared Error for Water Temperature: {rmse_fnn_temp}")
```

```
Epoch 1/100
207/207 [==============================] - 1s 2ms/step - loss: 35384.1445
Epoch 2/100
207/207 [==============================] - 0s 2ms/step - loss: 3034.9458
Epoch 3/100
207/207 [==============================] - 0s 2ms/step - loss: 2095.7729
Epoch 4/100
207/207 [==============================] - 0s 2ms/step - loss: 1883.6213
Epoch 5/100
207/207 [==============================] - 0s 2ms/step - loss: 1678.9712
Epoch 6/100
207/207 [==============================] - 0s 2ms/step - loss: 1467.2106
Epoch 7/100
207/207 [==============================] - 0s 2ms/step - loss: 1365.7531
Epoch 8/100
```

```
207/207 [==============================] - 0s 2ms/step - loss: 1230.3900
Epoch 9/100
207/207 [==============================] - 0s 2ms/step - loss: 1163.0511
Epoch 10/100
207/207 [==============================] - 0s 2ms/step - loss: 1077.4747
Epoch 11/100
207/207 [==============================] - 0s 2ms/step - loss: 1049.3544
Epoch 12/100
207/207 [==============================] - 0s 2ms/step - loss: 1163.4706
Epoch 13/100
207/207 [==============================] - 0s 2ms/step - loss: 930.9797
Epoch 14/100
207/207 [==============================] - 0s 2ms/step - loss: 974.2123
Epoch 15/100
207/207 [==============================] - 0s 2ms/step - loss: 870.3370
Epoch 16/100
207/207 [==============================] - 0s 2ms/step - loss: 1020.6346
Epoch 17/100
207/207 [==============================] - 0s 2ms/step - loss: 891.2598
Epoch 18/100
207/207 [==============================] - 0s 2ms/step - loss: 945.1652
Epoch 19/100
207/207 [==============================] - 0s 2ms/step - loss: 833.3882
Epoch 20/100
207/207 [==============================] - 0s 2ms/step - loss: 907.5218
Epoch 21/100
207/207 [==============================] - 0s 2ms/step - loss: 876.4801
Epoch 22/100
207/207 [==============================] - 0s 2ms/step - loss: 879.0033
Epoch 23/100
207/207 [==============================] - 0s 2ms/step - loss: 845.8460
Epoch 24/100
207/207 [==============================] - 0s 2ms/step - loss: 720.5051
Epoch 25/100
207/207 [==============================] - 0s 2ms/step - loss: 771.9529
Epoch 26/100
207/207 [==============================] - 0s 2ms/step - loss: 859.0952
Epoch 27/100
207/207 [==============================] - 0s 2ms/step - loss: 797.9520
Epoch 28/100
207/207 [==============================] - 0s 2ms/step - loss: 777.1867
Epoch 29/100
207/207 [==============================] - 0s 2ms/step - loss: 719.2070
Epoch 30/100
```

```
207/207 [==============================] - 1s 3ms/step - loss: 784.5101
Epoch 31/100
207/207 [==============================] - 0s 2ms/step - loss: 740.4086
Epoch 32/100
207/207 [==============================] - 1s 2ms/step - loss: 679.6040
Epoch 33/100
207/207 [==============================] - 0s 2ms/step - loss: 732.0250
Epoch 34/100
207/207 [==============================] - 0s 2ms/step - loss: 653.9208
Epoch 35/100
207/207 [==============================] - 0s 2ms/step - loss: 662.6386
Epoch 36/100
207/207 [==============================] - 0s 2ms/step - loss: 669.4089
Epoch 37/100
207/207 [==============================] - 0s 2ms/step - loss: 618.2332
Epoch 38/100
207/207 [==============================] - 1s 3ms/step - loss: 641.9571
Epoch 39/100
207/207 [==============================] - 0s 2ms/step - loss: 687.1234
Epoch 40/100
207/207 [==============================] - 0s 2ms/step - loss: 587.1140
Epoch 41/100
207/207 [==============================] - 0s 2ms/step - loss: 674.0953
Epoch 42/100
207/207 [==============================] - 0s 2ms/step - loss: 665.5754
Epoch 43/100
207/207 [==============================] - 0s 2ms/step - loss: 614.5387
Epoch 44/100
207/207 [==============================] - 0s 2ms/step - loss: 588.8399
Epoch 45/100
207/207 [==============================] - 0s 2ms/step - loss: 527.6152
Epoch 46/100
207/207 [==============================] - 0s 2ms/step - loss: 625.1907
Epoch 47/100
207/207 [==============================] - 0s 2ms/step - loss: 551.3329
Epoch 48/100
207/207 [==============================] - 1s 3ms/step - loss: 574.7208
Epoch 49/100
207/207 [==============================] - 0s 2ms/step - loss: 502.9691
Epoch 50/100
207/207 [==============================] - 0s 2ms/step - loss: 519.0423
Epoch 51/100
207/207 [==============================] - 0s 2ms/step - loss: 525.6318
Epoch 52/100
```

```
207/207 [==============================] - 0s 2ms/step - loss: 560.1821
Epoch 53/100
207/207 [==============================] - 1s 3ms/step - loss: 473.9650
Epoch 54/100
207/207 [==============================] - 0s 2ms/step - loss: 476.2396
Epoch 55/100
207/207 [==============================] - 0s 2ms/step - loss: 523.6508
Epoch 56/100
207/207 [==============================] - 0s 2ms/step - loss: 452.9756
Epoch 57/100
207/207 [==============================] - 0s 2ms/step - loss: 454.6203
Epoch 58/100
207/207 [==============================] - 0s 2ms/step - loss: 528.3415
Epoch 59/100
207/207 [==============================] - 0s 2ms/step - loss: 421.5878
Epoch 60/100
207/207 [==============================] - 0s 2ms/step - loss: 447.4997
Epoch 61/100
207/207 [==============================] - 0s 2ms/step - loss: 443.5658
Epoch 62/100
207/207 [==============================] - 0s 2ms/step - loss: 471.7131
Epoch 63/100
207/207 [==============================] - 0s 2ms/step - loss: 462.3701
Epoch 64/100
207/207 [==============================] - 0s 2ms/step - loss: 376.7401
Epoch 65/100
207/207 [==============================] - 0s 2ms/step - loss: 453.2094
Epoch 66/100
207/207 [==============================] - 0s 2ms/step - loss: 389.4216
Epoch 67/100
207/207 [==============================] - 0s 2ms/step - loss: 372.1000
Epoch 68/100
207/207 [==============================] - 1s 3ms/step - loss: 383.9114
Epoch 69/100
207/207 [==============================] - 0s 2ms/step - loss: 348.7758
Epoch 70/100
207/207 [==============================] - 0s 2ms/step - loss: 350.7368
Epoch 71/100
207/207 [==============================] - 0s 2ms/step - loss: 390.2962
Epoch 72/100
207/207 [==============================] - 0s 2ms/step - loss: 357.8492
Epoch 73/100
207/207 [==============================] - 0s 2ms/step - loss: 316.8531
Epoch 74/100
```

```
207/207 [==============================] - 1s 3ms/step - loss: 339.6685
Epoch 75/100
207/207 [==============================] - 0s 2ms/step - loss: 341.1899
Epoch 76/100
207/207 [==============================] - 0s 2ms/step - loss: 321.4549
Epoch 77/100
207/207 [==============================] - 0s 2ms/step - loss: 337.5688
Epoch 78/100
207/207 [==============================] - 0s 2ms/step - loss: 321.0665
Epoch 79/100
207/207 [==============================] - 0s 2ms/step - loss: 279.0584
Epoch 80/100
207/207 [==============================] - 0s 2ms/step - loss: 313.7420
Epoch 81/100
207/207 [==============================] - 1s 3ms/step - loss: 298.5030
Epoch 82/100
207/207 [==============================] - 0s 2ms/step - loss: 282.4916
Epoch 83/100
207/207 [==============================] - 0s 2ms/step - loss: 263.1433
Epoch 84/100
207/207 [==============================] - 0s 2ms/step - loss: 237.5447
Epoch 85/100
207/207 [==============================] - 0s 2ms/step - loss: 206.0233
Epoch 86/100
207/207 [==============================] - 0s 2ms/step - loss: 376.6208
Epoch 87/100
207/207 [==============================] - 0s 2ms/step - loss: 287.7973
Epoch 88/100
207/207 [==============================] - 0s 2ms/step - loss: 256.2764
Epoch 89/100
207/207 [==============================] - 0s 2ms/step - loss: 212.0907
Epoch 90/100
207/207 [==============================] - 0s 2ms/step - loss: 199.4911
Epoch 91/100
207/207 [==============================] - 0s 2ms/step - loss: 216.5326
Epoch 92/100
207/207 [==============================] - 0s 2ms/step - loss: 254.9792
Epoch 93/100
207/207 [==============================] - 0s 2ms/step - loss: 279.1051
Epoch 94/100
207/207 [==============================] - 0s 2ms/step - loss: 196.4071
Epoch 95/100
207/207 [==============================] - 0s 2ms/step - loss: 213.3995
Epoch 96/100
```

```
207/207 [==============================] - 0s 2ms/step - loss: 181.9137
Epoch 97/100
207/207 [==============================] - 0s 2ms/step - loss: 196.3370
Epoch 98/100
207/207 [==============================] - 0s 2ms/step - loss: 206.9362
Epoch 99/100
207/207 [==============================] - 0s 2ms/step - loss: 197.3644
Epoch 100/100
207/207 [==============================] - 0s 2ms/step - loss: 180.5293
89/89 [==============================] - 0s 1ms/step
Mean Squared Error for TDS: 294.7846265235038
Mean Squared Error for Water Temperature: 6.6828233417121545
R^2 Score for TDS: 0.8752475581213777
R^2 Score for Water Temperature: 0.09982011928499712
Mean Absolute Error for TDS: 10.384389848621929
Mean Absolute Error for Water Temperature: 1.8946835293075437
Root Mean Squared Error for TDS: 17.16929312824217
Root Mean Squared Error for Water Temperature: 2.585115730815964
```

In [220…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
from sklearn.ensemble import GradientBoostingRegressor

# Step 1: Select numeric columns
numeric_columns = final_df.select_dtypes(include=['number']).columns.tolist()

# Step 2: Remove 'TDS' and 'Water Temperature' if they are in numeric_columns
features_to_exclude = ['TDS', 'Water Temperature']
numeric_features = [col for col in numeric_columns if col not in features_to_exclude]

# Step 3: Use LabelEncoder to encode string columns
le = LabelEncoder()
encoded_columns = final_df.select_dtypes(include=['object']).apply(le.fit_transform)

X = pd.concat([final_df[numeric_features], encoded_columns], axis=1)
y = final_df[features_to_exclude]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Gradient Boosting for 'TDS' prediction
gb_model_tds = GradientBoostingRegressor()
y_train_tds = y_train['TDS']  # Select 'TDS' as the target variable
gb_model_tds.fit(X_train, y_train_tds)
y_pred_gb_tds = gb_model_tds.predict(X_test)

# Gradient Boosting for 'Water Temperature' prediction
gb_model_temp = GradientBoostingRegressor()
y_train_temp = y_train['Water Temperature']  # Select 'Water Temperature' as the target variable
gb_model_temp.fit(X_train, y_train_temp)
y_pred_gb_temp = gb_model_temp.predict(X_test)

# Computing the Mean Squared Error (MSE) for both outputs
mse_gb_tds = mean_squared_error(y_test['TDS'], y_pred_gb_tds)
mse_gb_temp = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp)

print(f"Mean Squared Error for TDS: {mse_gb_tds}")
print(f"Mean Squared Error for Water Temperature: {mse_gb_temp}")
```

```python
# Compute the R^2 score for both outputs
r2_gb_tds = r2_score(y_test['TDS'], y_pred_gb_tds)
r2_gb_temp = r2_score(y_test['Water Temperature'], y_pred_gb_temp)

print(f"R^2 Score for TDS: {r2_gb_tds}")
print(f"R^2 Score for Water Temperature: {r2_gb_temp}")

# Compute the Mean Absolute Error (MAE) for both outputs
mae_gb_tds = mean_absolute_error(y_test['TDS'], y_pred_gb_tds)
mae_gb_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_gb_temp)

print(f"Mean Absolute Error for TDS: {mae_dt_tds}")
print(f"Mean Absolute Error for Water Temperature: {mae_dt_temp}")

# Compute the Root Mean Squared Error (RMSE) for both outputs
rmse_gb_tds = mean_squared_error(y_test['TDS'], y_pred_gb_tds, squared=False)
rmse_gb_temp = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp, squared=False)

print(f"Root Mean Squared Error for TDS: {rmse_gb_tds}")
print(f"Root Mean Squared Error for Water Temperature: {rmse_gb_temp}")
```

```
Mean Squared Error for TDS: 15.628113685105518
Mean Squared Error for Water Temperature: 0.19326334046676424
R^2 Score for TDS: 0.9933862041342981
R^2 Score for Water Temperature: 0.9739673246063418
Mean Absolute Error for TDS: 0.7520232276310884
Mean Absolute Error for Water Temperature: 0.11833921057445455
Root Mean Squared Error for TDS: 3.953240909065057
Root Mean Squared Error for Water Temperature: 0.4396172658879133
```

In [221…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Step 1: Select numeric columns
numeric_columns = final_df.select_dtypes(include=['number']).columns.tolist()

# Step 2: Remove 'TDS' and 'Water Temperature' if they are in numeric_columns
features_to_exclude = ['TDS', 'Water Temperature']
numeric_features = [col for col in numeric_columns if col not in features_to_exclude]

# Step 3: Use LabelEncoder to encode string columns
le = LabelEncoder()
encoded_columns = final_df.select_dtypes(include=['object']).apply(le.fit_transform)

# Step 4: Concatenate the encoded string columns back to the numeric DataFrame
X = pd.concat([final_df[numeric_features], encoded_columns], axis=1)
y = final_df[features_to_exclude]



# Assuming 'TDS' and 'Water Temperature' are your target variables
target_columns = ['TDS', 'Water Temperature']
# Initialize two lists to store predictions for each target variable
y_pred_svr_tds = []
y_pred_svr_water_temp = []

# Initialize and train the SVR model for each target variable
for target_column in target_columns:
    # Reshape the target variable to a 1-dimensional array
    y_train_single = y_train[target_column].values
    y_test_single = y_test[target_column].values

    # Initialize the SVR model
    svr_model = SVR()

    # Train the SVR model
    svr_model.fit(X_train, y_train_single)

    # Predict using the SVR model
    y_pred_svr = svr_model.predict(X_test)
```

```
    if target_column == 'TDS':
        y_pred_svr_tds = y_pred_svr
    elif target_column == 'Water Temperature':
        y_pred_svr_water_temp = y_pred_svr

    # Computing the Mean Squared Error (MSE) and R^2 score for each output
    mse_svr = mean_squared_error(y_test_single, y_pred_svr)
    r2_svr = r2_score(y_test_single, y_pred_svr)
    mae_svr = mean_absolute_error(y_test_single, y_pred_svr)
    rmse_svr = mean_squared_error(y_test_single, y_pred_svr, squared=False)

    print(f"SVR - Mean Squared Error for {target_column}: {mse_svr}")
    print(f"SVR - R^2 Score for {target_column}: {r2_svr}")
    print(f"SVR - Mean Absolute Error for {target_column}: {mae_svr}")
    print(f"SVR - Root Mean Squared Error for {target_column}: {rmse_svr}")
```

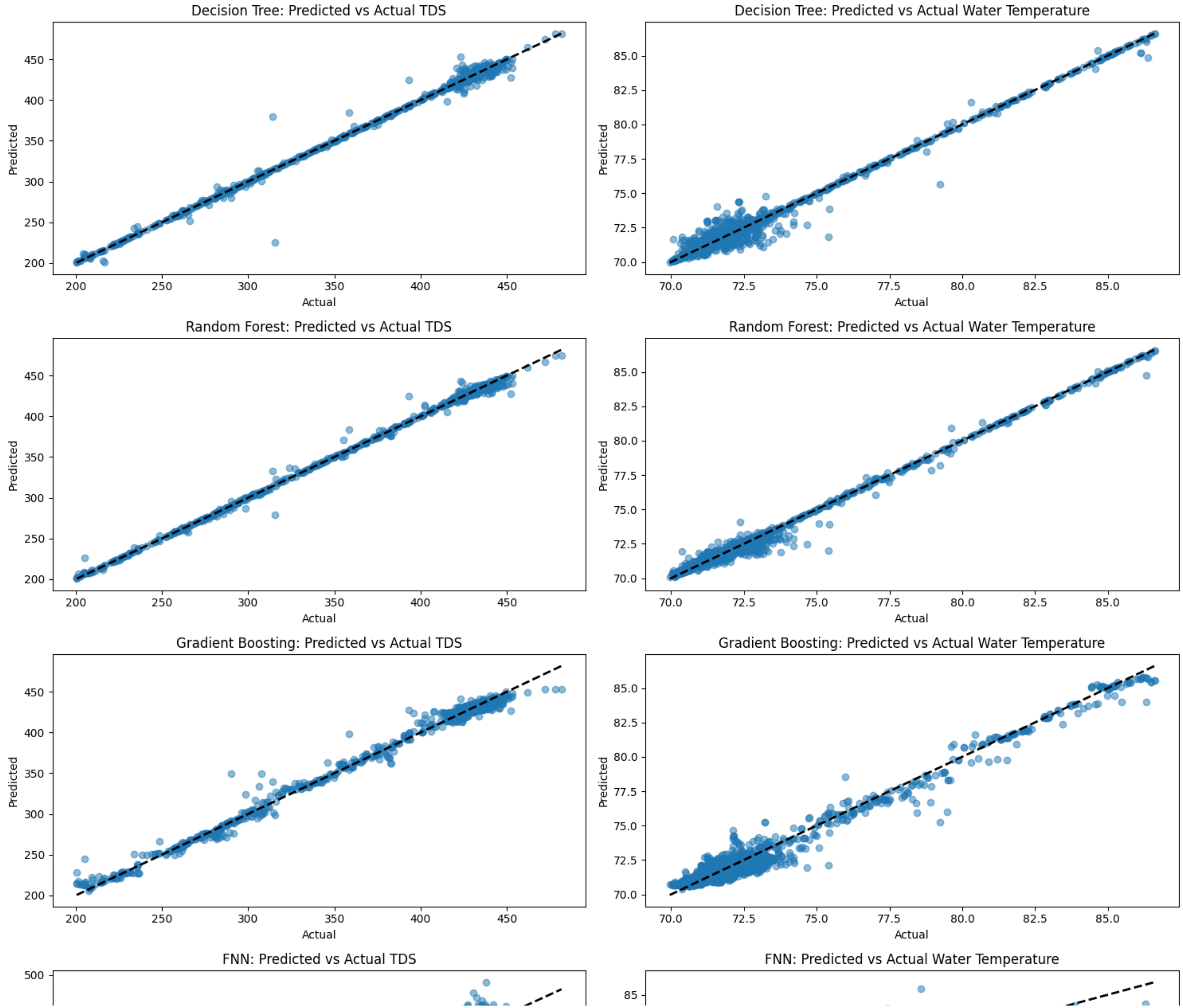
```
SVR - Mean Squared Error for TDS: 2599.3587885989373
SVR - R^2 Score for TDS: -0.1000450058087401
SVR - Mean Absolute Error for TDS: 21.004773175937263
SVR - Root Mean Squared Error for TDS: 50.98390715312958
SVR - Mean Squared Error for Water Temperature: 7.6802539738753355
SVR - R^2 Score for Water Temperature: -0.03453432068320139
SVR - Mean Absolute Error for Water Temperature: 1.1486484076007644
SVR - Root Mean Squared Error for Water Temperature: 2.771327114195532
```

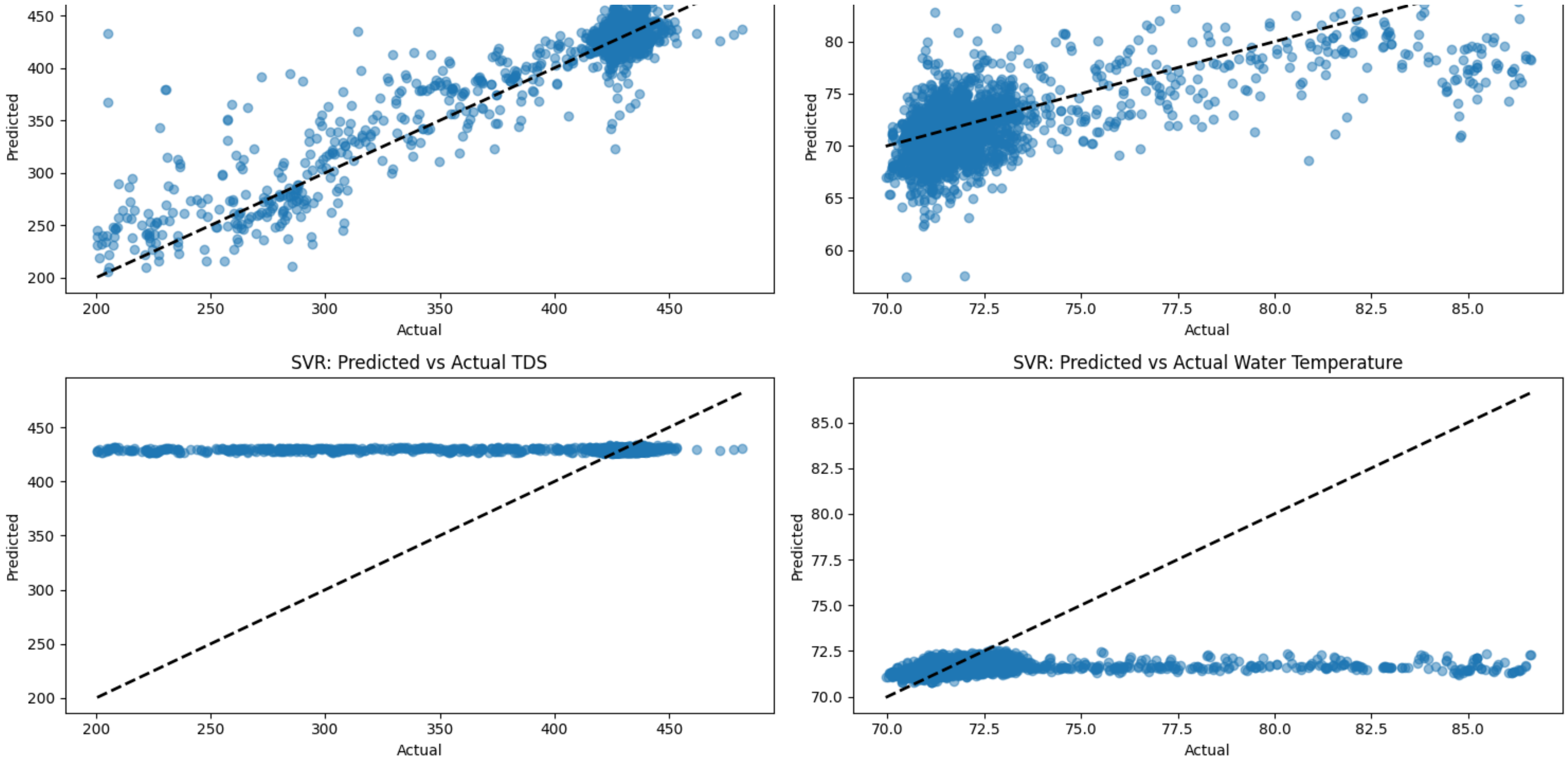
Performance Graphs - All features, no hyperparameter tuning, no validation, no scaling

In [222…

```
import matplotlib.pyplot as plt

# Make sure you have predictions for each model
# Example: y_pred_dt, y_pred_rf, y_pred_fnn, y_pred_gb, y_pred_svr

plt.figure(figsize=(15, 20))  # Adjust the figure size as needed

# Decision Tree
plt.subplot(5, 2, 1)
plt.scatter(y_test['TDS'], y_pred_dt[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Decision Tree: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_dt[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Decision Tree: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Random Forest
plt.subplot(5, 2, 3)
plt.scatter(y_test['TDS'], y_pred_rf[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Random Forest: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_rf[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Random Forest: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')


# Feedforward Neural Network (FNN)
plt.subplot(5, 2, 7)
plt.scatter(y_test['TDS'], y_pred_fnn[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('FNN: Predicted vs Actual TDS')
```

```
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 8)
plt.scatter(y_test['Water Temperature'], y_pred_fnn[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('FNN: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')


# Gradient Boosting
plt.subplot(5, 2, 5)
plt.scatter(y_test['TDS'], y_pred_gb_tds, alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Gradient Boosting: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 6)
plt.scatter(y_test['Water Temperature'], y_pred_gb_temp, alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Gradient Boosting: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Support Vector Regression (SVR) for TDS
plt.subplot(5, 2, 9)
plt.scatter(y_test['TDS'], y_pred_svr_tds, alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('SVR: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Support Vector Regression (SVR) for Water Temperature
plt.subplot(5, 2, 10)
plt.scatter(y_test['Water Temperature'], y_pred_svr_water_temp, alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('SVR: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.tight_layout()
plt.show()
```


Decision Tree: Predicted vs Actual TDS
Predicted
Actual
Decision Tree: Predicted vs Actual Water Temperature
Predicted
Actual
Random Forest: Predicted vs Actual TDS
Predicted
Actual
Random Forest: Predicted vs Actual Water Temperature
Predicted
Actual
Gradient Boosting: Predicted vs Actual TDS
Predicted
Actual
Gradient Boosting: Predicted vs Actual Water Temperature
Predicted
Actual
FNN: Predicted vs Actual TDS
FNN: Predicted vs Actual Water Temperature



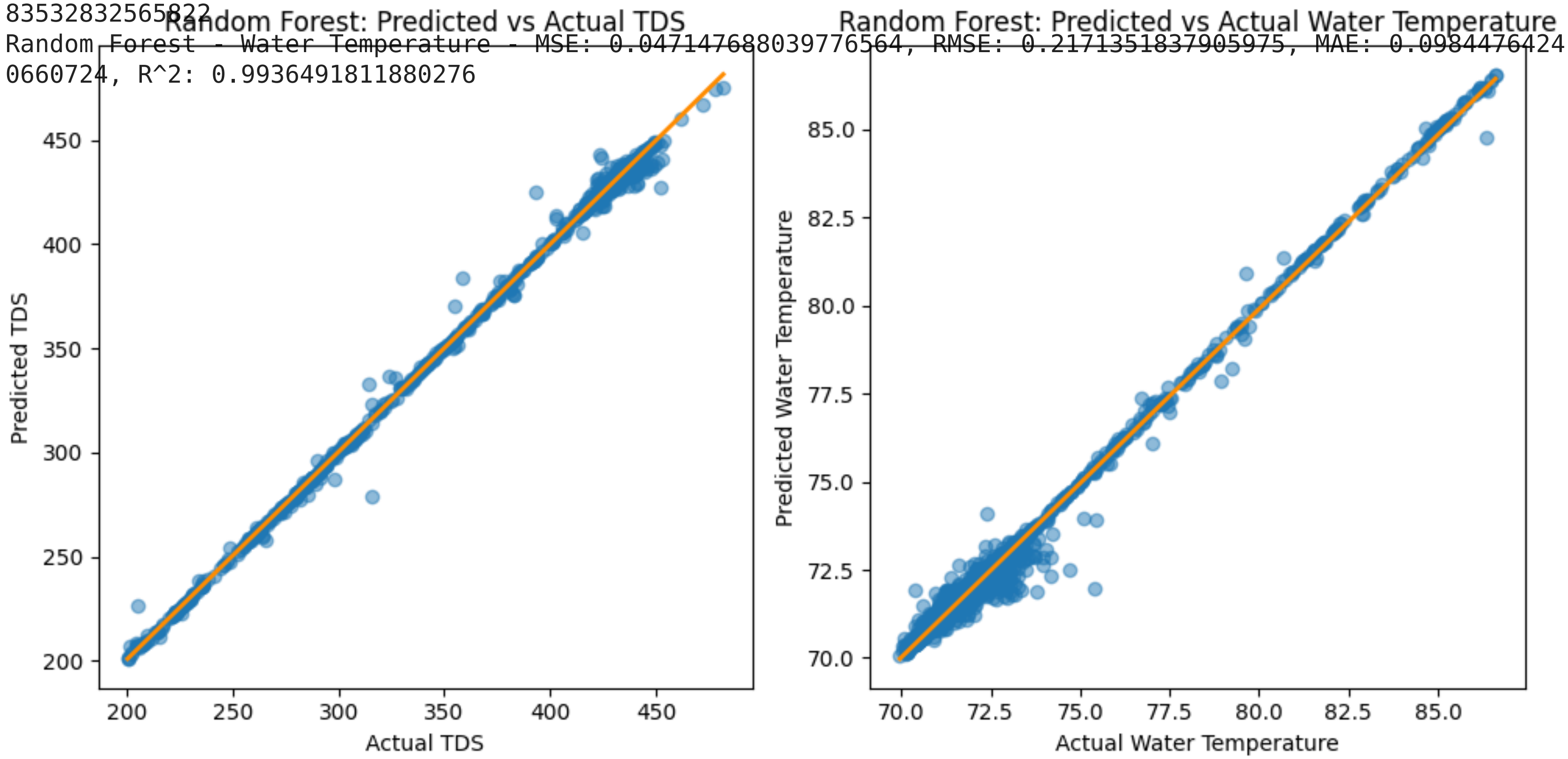
In [223…

```
#Random Forest vs Decision Tree
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import numpy as np

# Assuming y_test['TDS'] and y_test['Water Temperature'] are the actual values
# Assuming y_pred_dt and y_pred_rf are the predicted values from Decision Tree and Random Forest respectiv

# Calculate metrics for Decision Tree
mse_dt_tds = mean_squared_error(y_test['TDS'], y_pred_dt[:, 0])
rmse_dt_tds = mean_squared_error(y_test['TDS'], y_pred_dt[:, 0], squared=False)
mae_dt_tds = mean_absolute_error(y_test['TDS'], y_pred_dt[:, 0])
r2_dt_tds = r2_score(y_test['TDS'], y_pred_dt[:, 0])

mse_dt_temp = mean_squared_error(y_test['Water Temperature'], y_pred_dt[:, 1])
rmse_dt_temp = mean_squared_error(y_test['Water Temperature'], y_pred_dt[:, 1], squared=False)
mae_dt_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_dt[:, 1])
r2_dt_temp = r2_score(y_test['Water Temperature'], y_pred_dt[:, 1])
```

```
# Calculate metrics for Random Forest
mse_rf_tds = mean_squared_error(y_test['TDS'], y_pred_rf[:, 0])
rmse_rf_tds = mean_squared_error(y_test['TDS'], y_pred_rf[:, 0], squared=False)
mae_rf_tds = mean_absolute_error(y_test['TDS'], y_pred_rf[:, 0])
r2_rf_tds = r2_score(y_test['TDS'], y_pred_rf[:, 0])

mse_rf_temp = mean_squared_error(y_test['Water Temperature'], y_pred_rf[:, 1])
rmse_rf_temp = mean_squared_error(y_test['Water Temperature'], y_pred_rf[:, 1], squared=False)
mae_rf_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_rf[:, 1])
r2_rf_temp = r2_score(y_test['Water Temperature'], y_pred_rf[:, 1])

# Plotting the predicted vs actual values for Decision Tree and Random Forest
plt.figure(figsize=(10, 10))  # Adjust the figure size as needed

# Decision Tree
plt.subplot(2, 2, 1)
plt.scatter(y_test['TDS'], y_pred_dt[:, 0], alpha=0.5)
plt.plot(np.unique(y_test['TDS']), np.poly1d(np.polyfit(y_test['TDS'], y_pred_dt[:, 0], 1))(np.unique(y_te
plt.title('Decision Tree: Predicted vs Actual TDS')
plt.xlabel('Actual TDS')
plt.ylabel('Predicted TDS')

plt.subplot(2, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_dt[:, 1], alpha=0.5)
plt.plot(np.unique(y_test['Water Temperature']), np.poly1d(np.polyfit(y_test['Water Temperature'], y_pred_
plt.title('Decision Tree: Predicted vs Actual Water Temperature')
plt.xlabel('Actual Water Temperature')
plt.ylabel('Predicted Water Temperature')

# Random Forest
plt.subplot(2, 2, 3)
plt.scatter(y_test['TDS'], y_pred_rf[:, 0], alpha=0.5)
plt.plot(np.unique(y_test['TDS']), np.poly1d(np.polyfit(y_test['TDS'], y_pred_rf[:, 0], 1))(np.unique(y_te
plt.title('Random Forest: Predicted vs Actual TDS')
plt.xlabel('Actual TDS')
plt.ylabel('Predicted TDS')

plt.subplot(2, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_rf[:, 1], alpha=0.5)
plt.plot(np.unique(y_test['Water Temperature']), np.poly1d(np.polyfit(y_test['Water Temperature'], y_pred_
plt.title('Random Forest: Predicted vs Actual Water Temperature')
plt.xlabel('Actual Water Temperature')
plt.ylabel('Predicted Water Temperature')
```

```
plt.tight_layout()
plt.show()

# Print metrics for Decision Tree
print(f"Decision Tree - TDS - MSE: {mse_dt_tds}, RMSE: {rmse_dt_tds}, MAE: {mae_dt_tds}, R^2: {r2_dt_tds}"
print(f"Decision Tree - Water Temperature - MSE: {mse_dt_temp}, RMSE: {rmse_dt_temp}, MAE: {mae_dt_temp},

# Print metrics for Random Forest
print(f"Random Forest - TDS - MSE: {mse_rf_tds}, RMSE: {rmse_rf_tds}, MAE: {mae_rf_tds}, R^2: {r2_rf_tds}"
print(f"Random Forest - Water Temperature - MSE: {mse_rf_temp}, RMSE: {rmse_rf_temp}, MAE: {mae_rf_temp},
```

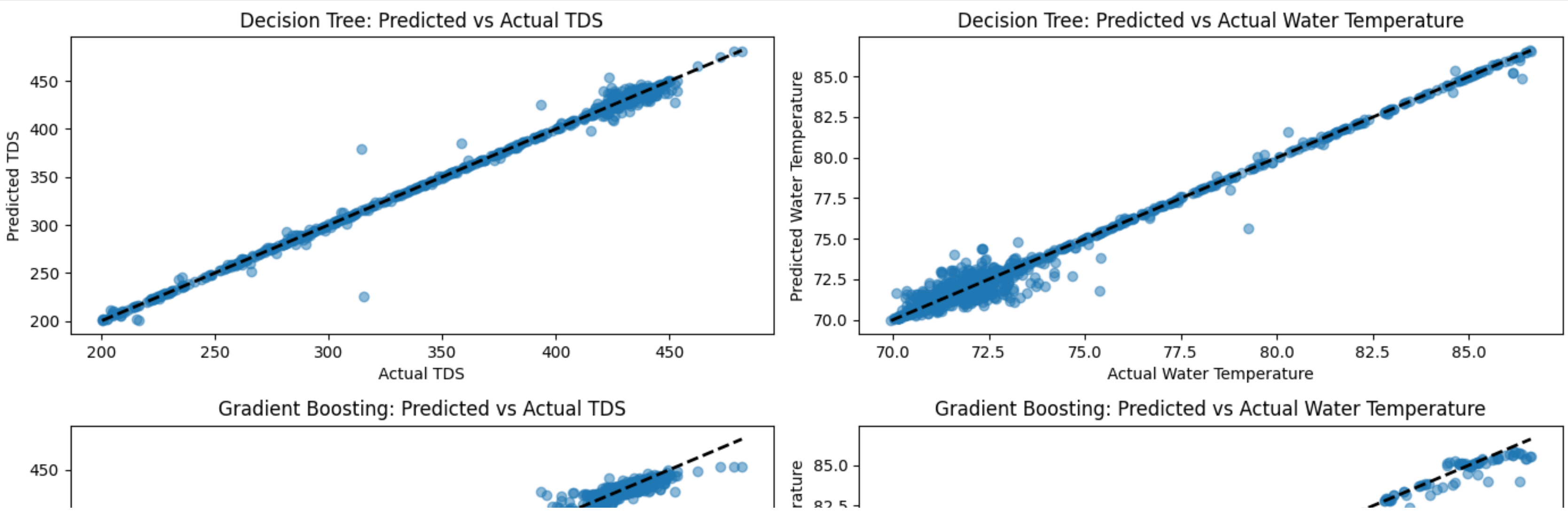
```
Random Forest - TDS - MSE: 3.891120469374974, RMSE: 1.9725923221423565, MAE: 0.6382615690644924, R^2: 0.99
83532832565822
Random Forest - Water Temperature - MSE: 0.047147688039776564, RMSE: 0.2171351837905975, MAE: 0.0984476424
0660724, R^2: 0.9936491811880276
```

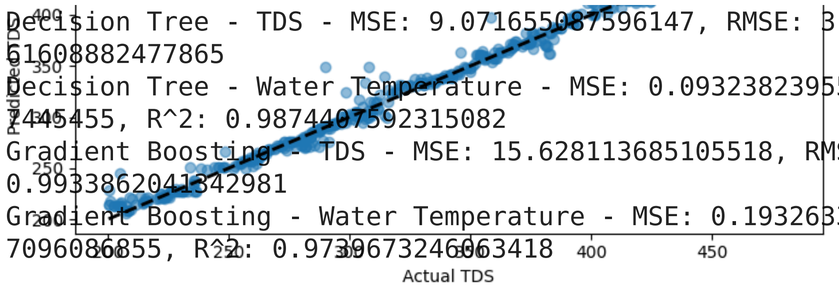


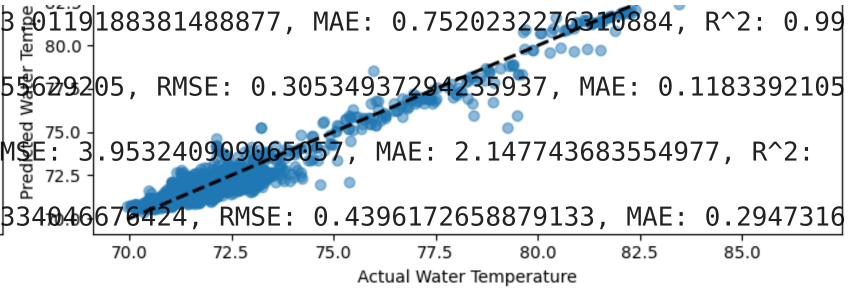
In [224…

```
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import numpy as np

# Make sure you have predictions for each model
# Example: y_pred_dt_tds, y_pred_dt_temp for Decision Tree
# Example: y_pred_gb_tds, y_pred_gb_temp for Gradient Boosting

# Corrected indexing for predictions
mse_dt_tds = mean_squared_error(y_test['TDS'], y_pred_dt[:, 0])
mse_dt_temp = mean_squared_error(y_test['Water Temperature'], y_pred_dt[:, 1])
rmse_dt_tds = np.sqrt(mse_dt_tds)
rmse_dt_temp = np.sqrt(mse_dt_temp)
mae_dt_tds = mean_absolute_error(y_test['TDS'], y_pred_dt[:, 0])
mae_dt_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_dt[:, 1])
r2_dt_tds = r2_score(y_test['TDS'], y_pred_dt[:, 0])
r2_dt_temp = r2_score(y_test['Water Temperature'], y_pred_dt[:, 1])

# Calculate metrics for Gradient Boosting
mse_gb_tds = mean_squared_error(y_test['TDS'], y_pred_gb_tds)
mse_gb_temp = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp)
rmse_gb_tds = np.sqrt(mse_gb_tds)
rmse_gb_temp = np.sqrt(mse_gb_temp)
mae_gb_tds = mean_absolute_error(y_test['TDS'], y_pred_gb_tds)
mae_gb_temp = mean_absolute_error(y_test['Water Temperature'], y_pred_gb_temp)
r2_gb_tds = r2_score(y_test['TDS'], y_pred_gb_tds)
r2_gb_temp = r2_score(y_test['Water Temperature'], y_pred_gb_temp)

# Plotting the predicted vs actual values for Decision Tree
plt.figure(figsize=(14, 7))

plt.subplot(2, 2, 1)
plt.scatter(y_test['TDS'], y_pred_dt[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Decision Tree: Predicted vs Actual TDS')
plt.xlabel('Actual TDS')
plt.ylabel('Predicted TDS')

plt.subplot(2, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_dt[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Decision Tree: Predicted vs Actual Water Temperature')
plt.xlabel('Actual Water Temperature')
```

```
plt.ylabel('Predicted Water Temperature')

# Plotting the predicted vs actual values for Gradient Boosting
plt.subplot(2, 2, 3)
plt.scatter(y_test['TDS'], y_pred_gb_tds, alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Gradient Boosting: Predicted vs Actual TDS')
plt.xlabel('Actual TDS')
plt.ylabel('Predicted TDS')

plt.subplot(2, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_gb_temp, alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Gradient Boosting: Predicted vs Actual Water Temperature')
plt.xlabel('Actual Water Temperature')
plt.ylabel('Predicted Water Temperature')

plt.tight_layout()
plt.show()

# Print metrics for Decision Tree
print(f"Decision Tree - TDS - MSE: {mse_dt_tds}, RMSE: {rmse_dt_tds}, MAE: {mae_dt_tds}, R^2: {r2_dt_tds}"
print(f"Decision Tree - Water Temperature - MSE: {mse_dt_temp}, RMSE: {rmse_dt_temp}, MAE: {mae_dt_temp},

#Print metrics for Gradient Boosting
print(f"Gradient Boosting - TDS - MSE: {mse_gb_tds}, RMSE: {rmse_gb_tds}, MAE: {mae_gb_tds}, R^2: {r2_gb_t
print(f"Gradient Boosting - Water Temperature - MSE: {mse_gb_temp}, RMSE: {rmse_gb_temp}, MAE: {mae_gb_tem
```








```
Decision Tree - TDS - MSE: 9.071655087596147, RMSE: 3.0119188381488877, MAE: 0.7520232276310884, R^2: 0.9961608882477865
Decision Tree - Water Temperature - MSE: 0.09323823955629205, RMSE: 0.30534937294235937, MAE: 0.11833921057445455, R^2: 0.9874407592315082
Gradient Boosting - TDS - MSE: 15.628113685105518, RMSE: 3.953240909065057, MAE: 2.147743683554977, R^2: 0.9933862041342981
Gradient Boosting - Water Temperature - MSE: 0.19326334046676424, RMSE: 0.4396172658879133, MAE: 0.29473167096086855, R^2: 0.9739673246063418
```

Issues.

1. The dataset is imbalance
2. It's taking too long because of how many features
3. There is noise in the dataset

We are dropping FNN and SVR because they didn't perform anywhere close to the other models. The next thing we are doing is MinMax Scaling and we are doing feature selection. One of the feature selection will be the correlations we have from the heatmaps. The other, we think, should be related to the tradional formual for TDS : TDS = k * EC.

We think that the correlations for the dataset may be incorrect to what acutually affects TDS. We were told that the things that affect TDS is Electric Conductivity (which we don't have) and water input (this is percipation, rain, discharge from aquifier, etc); That feature selection is manual

Data Processing

1. MinMax Scaling
2. Normalization

In [225…

```
final_df = final_df_copy
final_df = final_df.sample(frac=0.01)
```

In [226…

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, normalize

# Assuming final_df is your DataFrame

# Initialize the LabelEncoder
le = LabelEncoder()

# Separate numeric and non-numeric columns
numeric_columns = final_df.select_dtypes(include=['number'])
non_numeric_columns = final_df.select_dtypes(exclude=['number'])

# Apply LabelEncoder to each non-numeric column and store in a new DataFrame
encoded_columns = non_numeric_columns.apply(lambda col: le.fit_transform(col.astype(str)))

# Concatenate the numeric columns and encoded columns
final_df_processed = pd.concat([numeric_columns, encoded_columns], axis=1)

# Apply MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(final_df_processed)

# Convert scaled data back to a DataFrame
scaled_df = pd.DataFrame(scaled_data, columns=final_df_processed.columns)
# Step 2: Apply Normalization
# Normalize the scaled data
normalized_df = normalize(scaled_df, axis=0)

# Convert normalized data back to a DataFrame
normalized_df = pd.DataFrame(normalized_df, columns=final_df.columns)

# Now 'normalized_df' is your MinMax scaled and normalized DataFrame
```

In [227…

```
final_df = normalized_df
```

The next part is feature selection. There will be two features, one from the correlation charts, the other from manual feature selection.

In [228…

```
# Convert to Series if watertemp_corr and tds_corr are DataFrames
if isinstance(watertemp_corr, pd.DataFrame):
    watertemp_corr_series = watertemp_corr.iloc[0]
else:
    watertemp_corr_series = watertemp_corr

if isinstance(tds_corr, pd.DataFrame):
    tds_corr_series = tds_corr.iloc[0]
else:
    tds_corr_series = tds_corr

# Drop 'TDS' and 'Water Temperature' from the correlation Series
watertemp_corr_series = watertemp_corr_series.drop(labels=['TDS', 'Water Temperature'], errors='ignore')
tds_corr_series = tds_corr_series.drop(labels=['TDS', 'Water Temperature'], errors='ignore')

# Now sort and get the top 10 features excluding 'TDS' and 'Water Temperature'
top10_watertemp_features = watertemp_corr_series.abs().sort_values(ascending=False).head(10)
print("Top 10 Features for Water Temperature Correlation:")
print(top10_watertemp_features)

top10_tds_features = tds_corr_series.abs().sort_values(ascending=False).head(10)
print("\nTop 10 Features for TDS Correlation:")
print(top10_tds_features)
```

```
Top 10 Features for Water Temperature Correlation:
air_temp_high_24_hour_set_1     0.631003
air_temp_low_24_hour_set_1      0.544564
heat_index_set_1d               0.476116
air_temp_high_6_hour_set_1      0.466329
air_temp_set_1                  0.462303
air_temp_low_6_hour_set_1       0.443846
Lat                             0.443629
dew_point_temperature_set_1d    0.390484
dew_point_temperature_set_1     0.389924
Long                            0.373344
Name: Water Temperature, dtype: float64

Top 10 Features for TDS Correlation:
air_temp_high_24_hour_set_1     0.627974
air_temp_low_24_hour_set_1      0.529529
heat_index_set_1d               0.454768
air_temp_high_6_hour_set_1      0.433467
air_temp_low_6_hour_set_1       0.417796
air_temp_set_1                  0.393269
Discharge Rate                  0.374901
precip_accum_24_hour_set_1      0.344013
precip_accum_six_hour_set_1     0.334546
dew_point_temperature_set_1d    0.317050
Name: TDS, dtype: float64
```

In [229…

```
import pandas as pd
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

# Assuming final_df is your DataFrame
# Assuming top10_watertemp_features and top10_tds_features are your Series with top features

# Combine top 10 features from both watertemp_corr and tds_corr, removing duplicates
top10_features = list(set(top10_watertemp_features.index.tolist() + top10_tds_features.index.tolist()))

# Select only the top 10 features from your DataFrame
X = final_df[top10_features]

# If any of the top 10 features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the DecisionTreeRegressor
dt_regressor = DecisionTreeRegressor(random_state=42)

# Training the model
dt_regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_dt_top10 = dt_regressor.predict(X_test)

# Computing the performance metrics
mse_dt_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_dt_top10[:, 0])
mse_dt_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_dt_top10[:, 1])
r2_dt_tds_top10 = r2_score(y_test['TDS'], y_pred_dt_top10[:, 0])
r2_dt_temp_top10 = r2_score(y_test['Water Temperature'], y_pred_dt_top10[:, 1])
mae_dt_tds_top10 = mean_absolute_error(y_test['TDS'], y_pred_dt_top10[:, 0])
mae_dt_temp_top10 = mean_absolute_error(y_test['Water Temperature'], y_pred_dt_top10[:, 1])
rmse_dt_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_dt_top10[:, 0], squared=False)
```

```
rmse_dt_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_dt_top10[:, 1], squared=False)

# Print the performance metrics
print(f"Decision Tree - Mean Squared Error for TDS: {mse_dt_tds_top10}")
print(f"Decision Tree - Mean Squared Error for Water Temperature: {mse_dt_temp_top10}")
print(f"Decision Tree - R^2 Score for TDS: {r2_dt_tds_top10}")
print(f"Decision Tree - R^2 Score for Water Temperature: {r2_dt_temp_top10}")
print(f"Decision Tree - Mean Absolute Error for TDS: {mae_dt_tds_top10}")
print(f"Decision Tree - Mean Absolute Error for Water Temperature: {mae_dt_temp_top10}")
print(f"Decision Tree - Root Mean Squared Error for TDS: {rmse_dt_tds_top10}")
print(f"Decision Tree - Root Mean Squared Error for Water Temperature: {rmse_dt_temp_top10}")
```

```
Decision Tree - Mean Squared Error for TDS: 6.730824759314669e-06
Decision Tree - Mean Squared Error for Water Temperature: 8.546030278766147e-07
Decision Tree - R^2 Score for TDS: 0.49650067860555525
Decision Tree - R^2 Score for Water Temperature: 0.9208631554091119
Decision Tree - Mean Absolute Error for TDS: 0.0008969040561687503
Decision Tree - Mean Absolute Error for Water Temperature: 0.0001357987756125978
Decision Tree - Root Mean Squared Error for TDS: 0.002594383310020836
Decision Tree - Root Mean Squared Error for Water Temperature: 0.0009244474175833987
```

In [230…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.preprocessing import LabelEncoder

# Assuming final_df is your DataFrame
# Assuming top10_watertemp_features and top10_tds_features are your Series with top features

# Combine top 10 features from both watertemp_corr and tds_corr, removing duplicates
top10_features = list(set(top10_watertemp_features.index.tolist() + top10_tds_features.index.tolist()))

# Select only the top 10 features from your DataFrame
X = final_df[top10_features]

# If any of the top 10 features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the RandomForestRegressor
regressor = RandomForestRegressor(random_state=42)

# Training the model
regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf_top10 = regressor.predict(X_test)

# Computing the performance metrics
mse_rf_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_rf_top10[:, 0])
mse_rf_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_rf_top10[:, 1])
r2_rf_tds_top10 = r2_score(y_test['TDS'], y_pred_rf_top10[:, 0])
r2_rf_temp_top10 = r2_score(y_test['Water Temperature'], y_pred_rf_top10[:, 1])
mae_rf_tds_top10 = mean_absolute_error(y_test['TDS'], y_pred_rf_top10[:, 0])
mae_rf_temp_top10 = mean_absolute_error(y_test['Water Temperature'], y_pred_rf_top10[:, 1])
rmse_rf_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_rf_top10[:, 0], squared=False)
```

```
rmse_rf_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_rf_top10[:, 1], squared=False)

# Print the performance metrics
print(f"Random Forest - Mean Squared Error for TDS: {mse_rf_tds_top10}")
print(f"Random Forest - Mean Squared Error for Water Temperature: {mse_rf_temp_top10}")
print(f"Random Forest - R^2 Score for TDS: {r2_rf_tds_top10}")
print(f"Random Forest - R^2 Score for Water Temperature: {r2_rf_temp_top10}")
print(f"Random Forest - Mean Absolute Error for TDS: {mae_rf_tds_top10}")
print(f"Random Forest - Mean Absolute Error for Water Temperature: {mae_rf_temp_top10}")
print(f"Random Forest - Root Mean Squared Error for TDS: {rmse_rf_tds_top10}")
print(f"Random Forest - Root Mean Squared Error for Water Temperature: {rmse_rf_temp_top10}")
```

```
Random Forest - Mean Squared Error for TDS: 4.1119079515526485e-06
Random Forest - Mean Squared Error for Water Temperature: 4.0345200717596406e-07
Random Forest - R^2 Score for TDS: 0.692408740789445
Random Forest - R^2 Score for Water Temperature: 0.9626400588924946
Random Forest - Mean Absolute Error for TDS: 0.0008935029305746907
Random Forest - Mean Absolute Error for Water Temperature: 0.00018490323565529575
Random Forest - Root Mean Squared Error for TDS: 0.002027784000221091
Random Forest - Root Mean Squared Error for Water Temperature: 0.0006351787206573942
```

In [231…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.ensemble import GradientBoostingRegressor

# Assuming final_df is your DataFrame
# Assuming top10_watertemp_features and top10_tds_features are your Series with top features

# Combine top 10 features from both watertemp_corr and tds_corr, removing duplicates
top10_features = list(set(top10_watertemp_features.index.tolist() + top10_tds_features.index.tolist()))

# Select only the top 10 features from your DataFrame
X = final_df[top10_features]

# If any of the top 10 features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Gradient Boosting for 'TDS' prediction
gb_model_tds = GradientBoostingRegressor()
y_train_tds = y_train['TDS']  # Select 'TDS' as the target variable
gb_model_tds.fit(X_train, y_train_tds)
y_pred_gb_tds_top10 = gb_model_tds.predict(X_test)

# Gradient Boosting for 'Water Temperature' prediction
gb_model_temp = GradientBoostingRegressor()
y_train_temp= y_train['Water Temperature']  # Select 'Water Temperature' as the target variable
gb_model_temp.fit(X_train, y_train_temp)
y_pred_gb_temp_top10 = gb_model_temp.predict(X_test)

# Computing the performance metrics
mse_gb_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_gb_tds_top10)
mse_gb_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_top10)
r2_gb_tds_top10 = r2_score(y_test['TDS'], y_pred_gb_tds_top10)
r2_gb_temp_top10 = r2_score(y_test['Water Temperature'], y_pred_gb_temp_top10)
```

```
mae_gb_tds_top10 = mean_absolute_error(y_test['TDS'], y_pred_gb_tds_top10)
mae_gb_temp_top10 = mean_absolute_error(y_test['Water Temperature'], y_pred_gb_temp_top10)
rmse_gb_tds_top10 = mean_squared_error(y_test['TDS'], y_pred_gb_tds_top10, squared=False)
rmse_gb_temp_top10 = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_top10, squared=False)

# Print the performance metrics
print(f"Gradient Boosting - Mean Squared Error for TDS: {mse_gb_tds_top10}")
print(f"Gradient Boosting - Mean Squared Error for Water Temperature: {mse_gb_temp_top10}")
print(f"Gradient Boosting - R^2 Score for TDS: {r2_gb_tds_top10}")
print(f"Gradient Boosting - R^2 Score for Water Temperature: {r2_gb_temp_top10}")
print(f"Gradient Boosting - Mean Absolute Error for TDS: {mae_gb_tds_top10}")
print(f"Gradient Boosting - Mean Absolute Error for Water Temperature: {mae_gb_temp_top10}")
print(f"Gradient Boosting - Root Mean Squared Error for TDS: {rmse_gb_tds_top10}")
print(f"Gradient Boosting - Root Mean Squared Error for Water Temperature: {rmse_gb_temp_top10}")
```

```
Gradient Boosting - Mean Squared Error for TDS: 5.626286709966643e-06
Gradient Boosting - Mean Squared Error for Water Temperature: 2.60455904142036e-06
Gradient Boosting - R^2 Score for TDS: 0.5791256433294475
Gradient Boosting - R^2 Score for Water Temperature: 0.7588159913254671
Gradient Boosting - Mean Absolute Error for TDS: 0.0017099628133661164
Gradient Boosting - Mean Absolute Error for Water Temperature: 0.0010842606595140713
Gradient Boosting - Root Mean Squared Error for TDS: 0.002371979491894195
Gradient Boosting - Root Mean Squared Error for Water Temperature: 0.00161386462921162
```

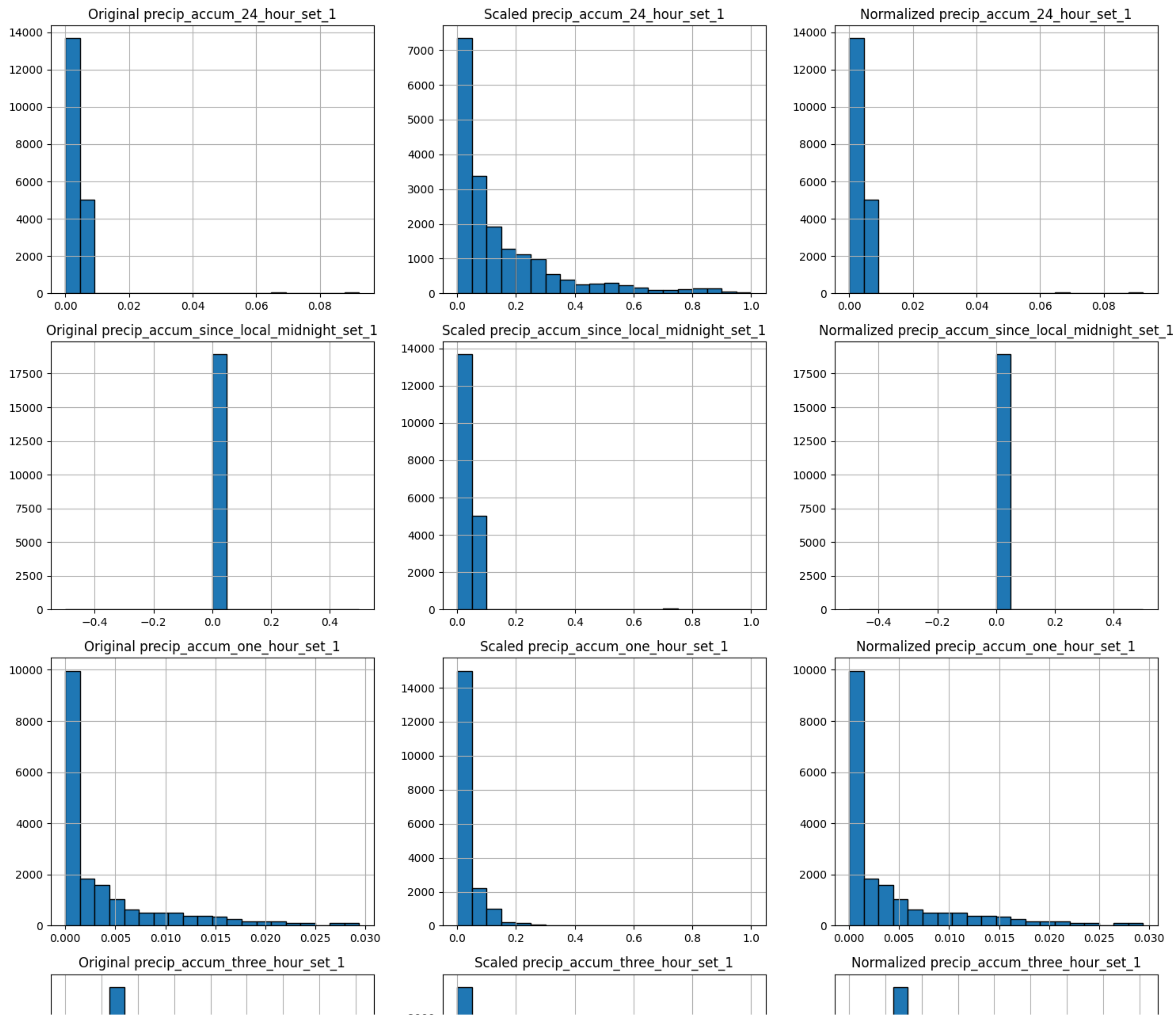
We are now going to only select features related to percipitation, discharge rate, and wind. We are selecting wind because usually, if the weather station has higher wind or cloud cover, this relates to it raining.

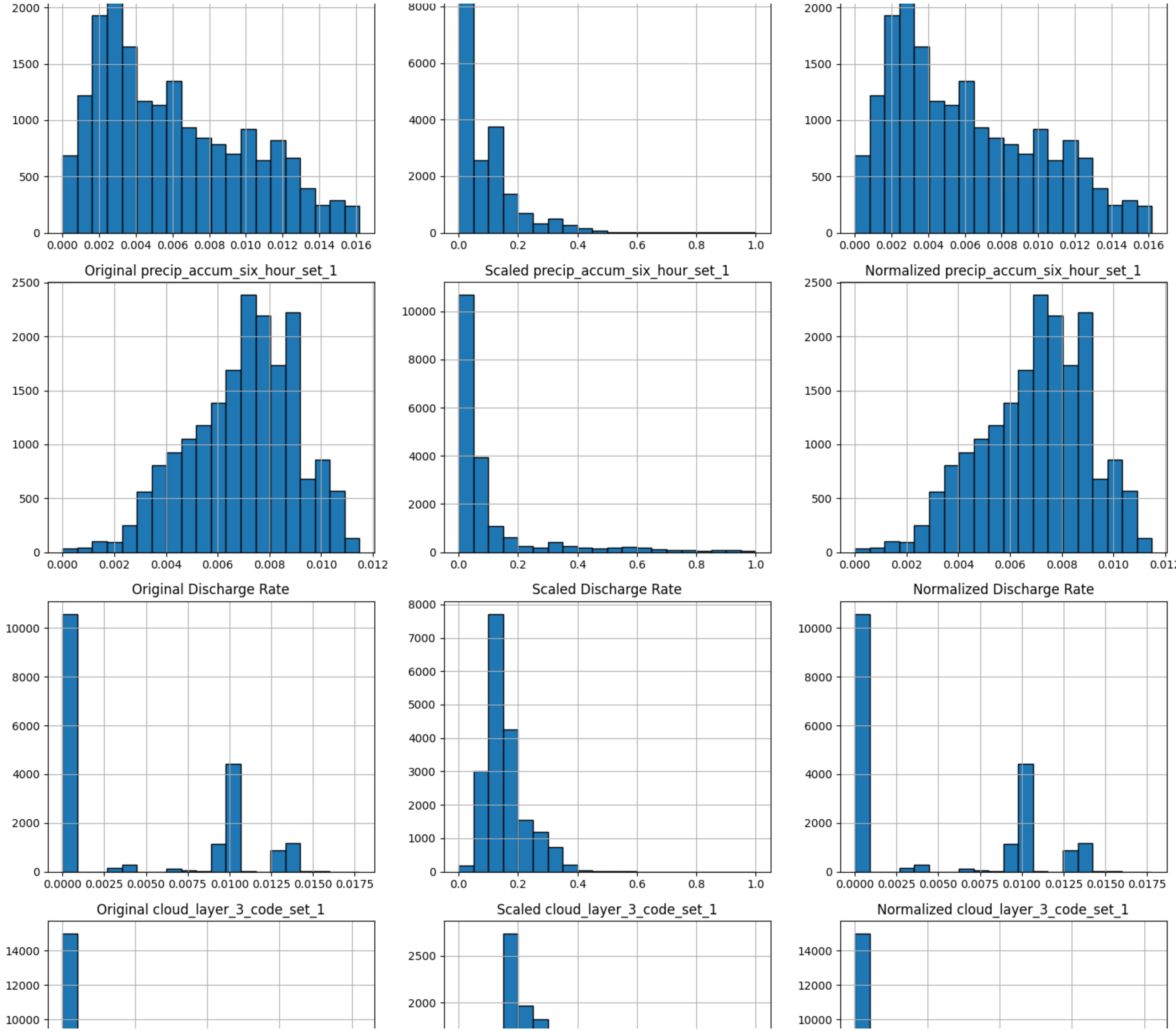
In [232…

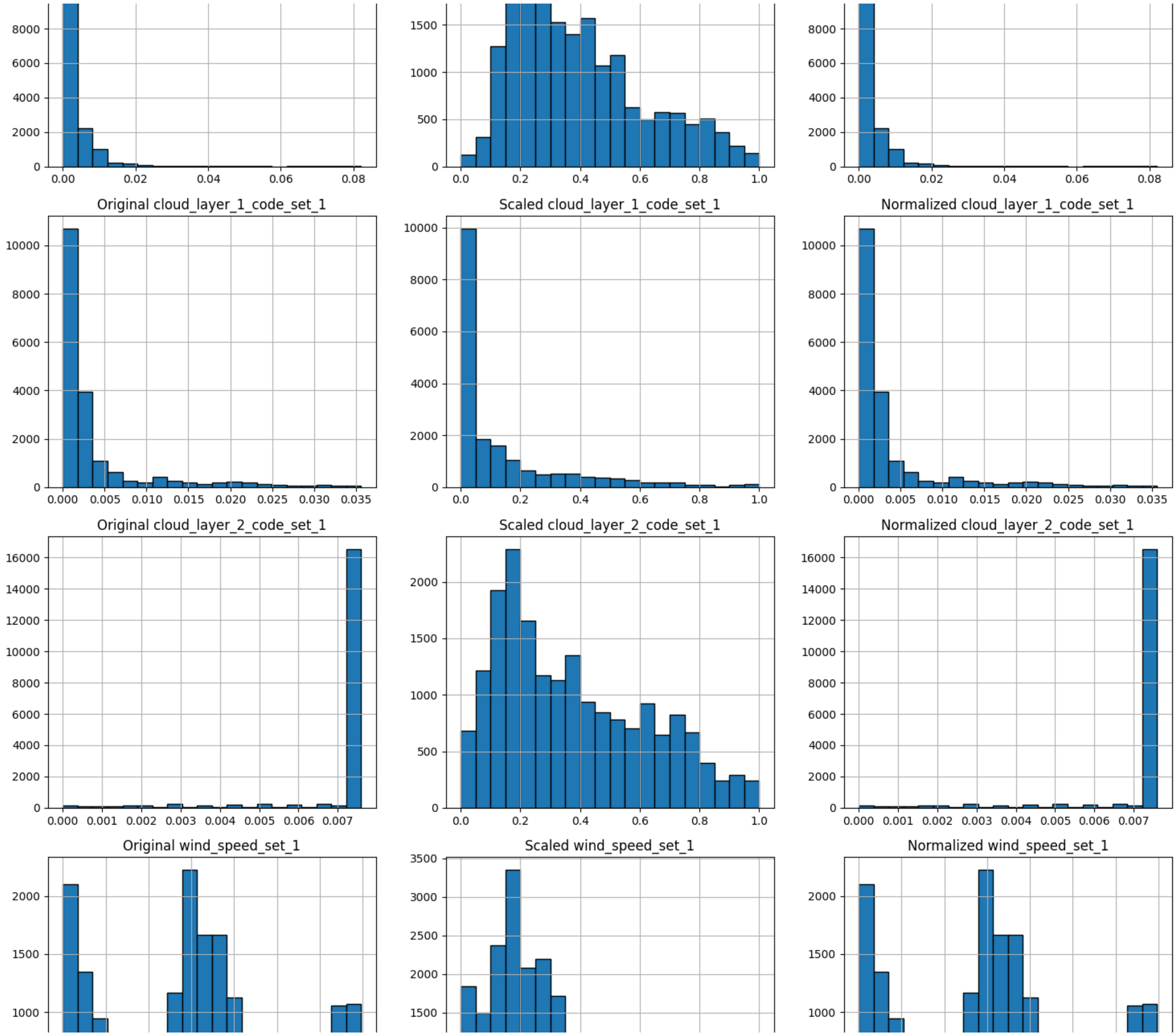
```
weather_related_features = [
    'precip_accum_24_hour_set_1',
    'precip_accum_since_local_midnight_set_1',
    'precip_accum_one_hour_set_1',
    'precip_accum_three_hour_set_1',
    'precip_accum_six_hour_set_1',
    'Discharge Rate',
    'cloud_layer_3_code_set_1',
    'cloud_layer_1_code_set_1',
    'cloud_layer_2_code_set_1',
    'wind_speed_set_1',
    'wind_direction_set_1',
    'wind_gust_set_1',
    'wind_chill_set_1d',
    'wind_cardinal_direction_set_1d',
    'peak_wind_speed_set_1',
    'peak_wind_direction_set_1'
]
```

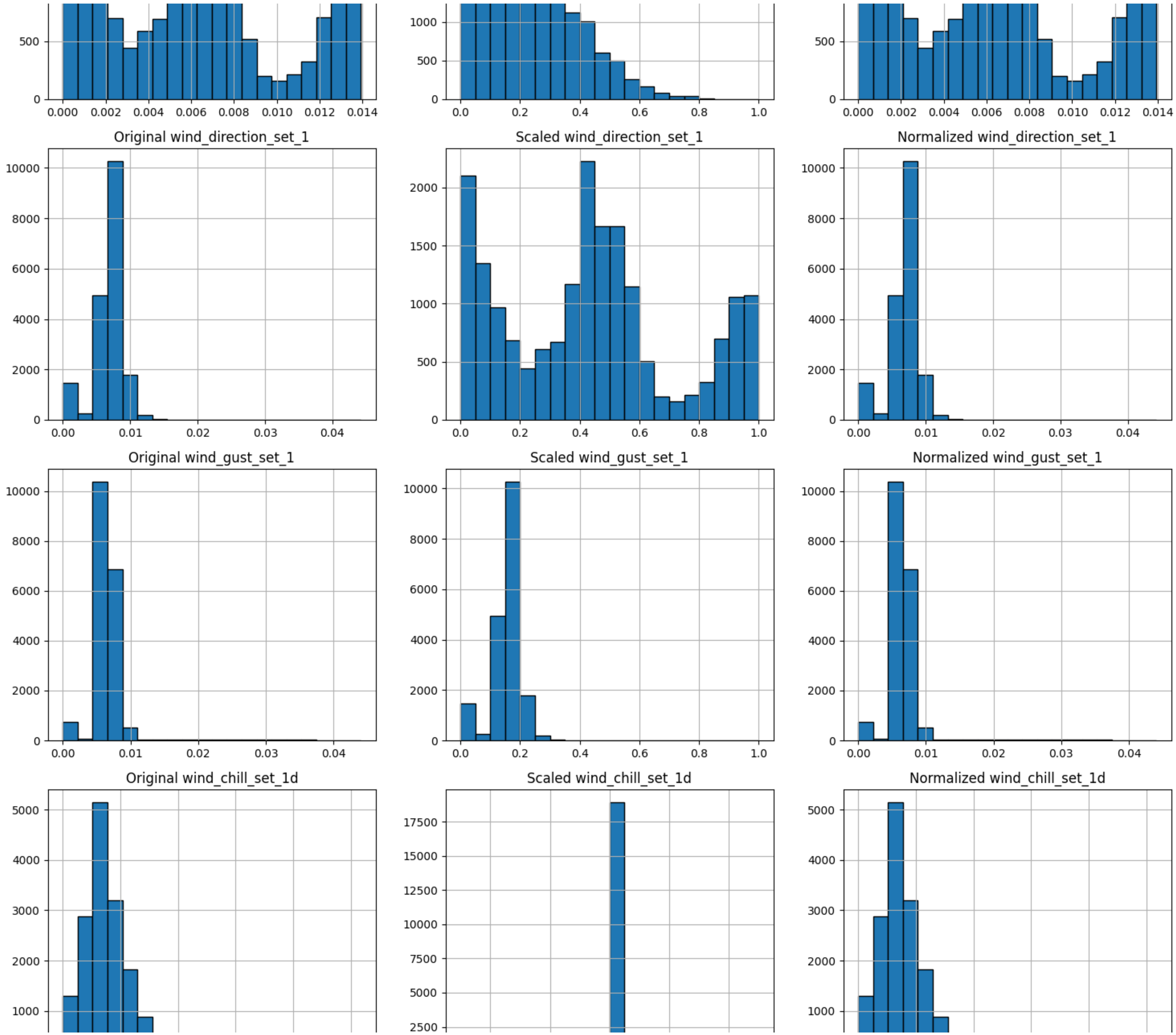
In [233…

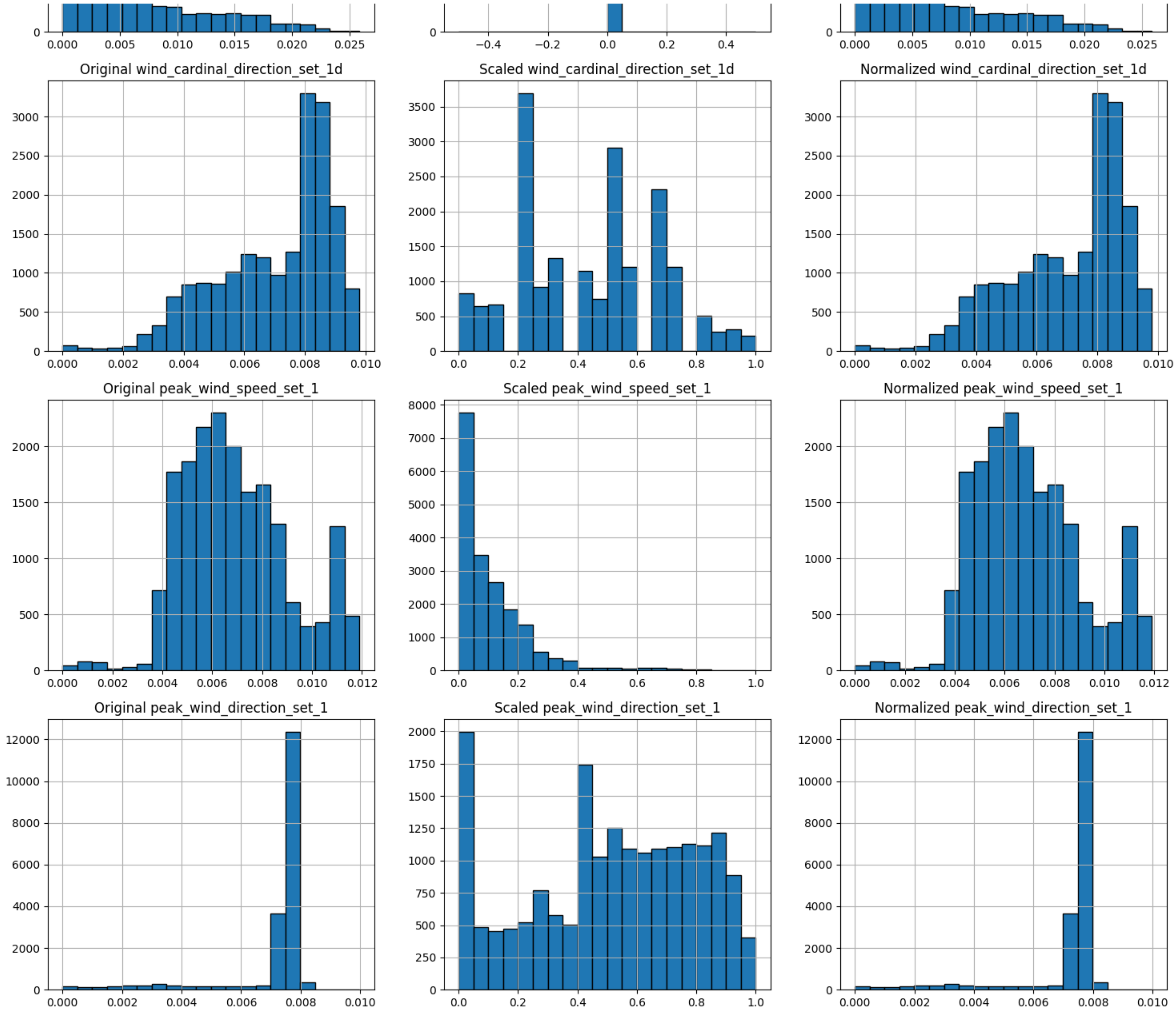
```
import matplotlib.pyplot as plt

# Assuming weather_related_features is your list of features related to weather
num_cols = len(weather_related_features)

# Set up the matplotlib figure (adjust figsize as needed)
plt.figure(figsize=(15, 4 * num_cols))

# Iterate over each weather-related feature to create histograms
for i, column in enumerate(weather_related_features):
    if column in final_df.columns:
        # Original data histogram
        plt.subplot(num_cols, 3, 3*i + 1)
        final_df[column].hist(bins=20, edgecolor='black')
        plt.title(f'Original {column}')

        # Scaled data histogram
        plt.subplot(num_cols, 3, 3*i + 2)
        scaled_df[column].hist(bins=20, edgecolor='black')
        plt.title(f'Scaled {column}')

        # Normalized data histogram
        plt.subplot(num_cols, 3, 3*i + 3)
        normalized_df[column].hist(bins=20, edgecolor='black')
        plt.title(f'Normalized {column}')

plt.tight_layout()
plt.show()
```


Original precip_accum_24_hour_set_1
Scaled precip_accum_24_hour_set_1
Normalized precip_accum_24_hour_set_1
Original precip_accum_since_local_midnight_set_1
Scaled precip_accum_since_local_midnight_set_1
Normalized precip_accum_since_local_midnight_set_1
Original precip_accum_one_hour_set_1
Scaled precip_accum_one_hour_set_1
Normalized precip_accum_one_hour_set_1
Original precip_accum_three_hour_set_1
Scaled precip_accum_three_hour_set_1
Normalized precip_accum_three_hour_set_1


Original precip_accum_six_hour_set_1
Scaled precip_accum_six_hour_set_1
Normalized precip_accum_six_hour_set_1
Original Discharge Rate
Scaled Discharge Rate
Normalized Discharge Rate
Original cloud_layer_3_code_set_1
Scaled cloud_layer_3_code_set_1
Normalized cloud_layer_3_code_set_1


Original cloud_layer_1_code_set_1
Scaled cloud_layer_1_code_set_1
Normalized cloud_layer_1_code_set_1
Original cloud_layer_2_code_set_1
Scaled cloud_layer_2_code_set_1
Normalized cloud_layer_2_code_set_1
Original wind_speed_set_1
Scaled wind_speed_set_1
Normalized wind_speed_set_1


Original wind_direction_set_1
Scaled wind_direction_set_1
Normalized wind_direction_set_1
Original wind_gust_set_1
Scaled wind_gust_set_1
Normalized wind_gust_set_1
Original wind_chill_set_1d
Scaled wind_chill_set_1d
Normalized wind_chill_set_1d


Original wind_cardinal_direction_set_1d
Scaled wind_cardinal_direction_set_1d
Normalized wind_cardinal_direction_set_1d
Original peak_wind_speed_set_1
Scaled peak_wind_speed_set_1
Normalized peak_wind_speed_set_1
Original peak_wind_direction_set_1
Scaled peak_wind_direction_set_1
Normalized peak_wind_direction_set_1

In [234…

```
import pandas as pd
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

# Assuming final_df is your DataFrame
# Assuming weather_related_features is your list of features related to weather

# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the DecisionTreeRegressor
dt_regressor = DecisionTreeRegressor(random_state=42)

# Training the model
dt_regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_dt_precip = dt_regressor.predict(X_test)

# Computing the performance metrics
mse_dt_tds_precip = mean_squared_error(y_test['TDS'], y_pred_dt_precip[:, 0])
mse_dt_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_dt_precip[:, 1])
r2_dt_tds_precip = r2_score(y_test['TDS'], y_pred_dt_precip[:, 0])
r2_dt_temp_precip = r2_score(y_test['Water Temperature'], y_pred_dt_precip[:, 1])
mae_dt_tds_precip = mean_absolute_error(y_test['TDS'], y_pred_dt_precip[:, 0])
mae_dt_temp_precip = mean_absolute_error(y_test['Water Temperature'], y_pred_dt_precip[:, 1])
rmse_dt_tds_precip = mean_squared_error(y_test['TDS'], y_pred_dt_precip[:, 0], squared=False)
rmse_dt_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_dt_precip[:, 1], squared=Fals

# Print the performance metrics
```

```
print(f"Decision Tree - Mean Squared Error for TDS: {mse_dt_tds_precip}")
print(f"Decision Tree - Mean Squared Error for Water Temperature: {mse_dt_temp_precip}")
print(f"Decision Tree - R^2 Score for TDS: {r2_dt_tds_precip}")
print(f"Decision Tree - R^2 Score for Water Temperature: {r2_dt_temp_precip}")
print(f"Decision Tree - Mean Absolute Error for TDS: {mae_dt_tds_precip}")
print(f"Decision Tree - Mean Absolute Error for Water Temperature: {mae_dt_temp_precip}")
print(f"Decision Tree - Root Mean Squared Error for TDS: {rmse_dt_tds_precip}")
print(f"Decision Tree - Root Mean Squared Error for Water Temperature: {rmse_dt_temp_precip}")
```

```
Decision Tree - Mean Squared Error for TDS: 5.746510341151657e-06
Decision Tree - Mean Squared Error for Water Temperature: 7.764022260473017e-07
Decision Tree - R^2 Score for TDS: 0.5701323150403013
Decision Tree - R^2 Score for Water Temperature: 0.9281046049469465
Decision Tree - Mean Absolute Error for TDS: 0.0007410065671251002
Decision Tree - Mean Absolute Error for Water Temperature: 0.00011568043848480554
Decision Tree - Root Mean Squared Error for TDS: 0.002397188007051524
Decision Tree - Root Mean Squared Error for Water Temperature: 0.0008811368940450183
```

In [235…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.preprocessing import LabelEncoder

# Assuming final_df is your DataFrame
# Assuming weather_related_features is your list of features related to weather

# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the RandomForestRegressor
regressor = RandomForestRegressor(random_state=42)

# Training the model
regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf_precip = regressor.predict(X_test)

# Computing the performance metrics
mse_rf_tds_precip = mean_squared_error(y_test['TDS'], y_pred_rf_precip[:, 0])
mse_rf_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
r2_rf_tds_precip = r2_score(y_test['TDS'], y_pred_rf_precip[:, 0])
r2_rf_temp_precip = r2_score(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
mae_rf_tds_precip = mean_absolute_error(y_test['TDS'], y_pred_rf_precip[:, 0])
mae_rf_temp_precip = mean_absolute_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
rmse_rf_tds_precip = mean_squared_error(y_test['TDS'], y_pred_rf_precip[:, 0], squared=False)
rmse_rf_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1], squared=Fals

# Print the performance metrics
```

```
print(f"Random Forest - Mean Squared Error for TDS: {mse_rf_tds}")
print(f"Random Forest - Mean Squared Error for Water Temperature: {mse_rf_temp}")
print(f"Random Forest - R^2 Score for TDS: {r2_rf_tds}")
print(f"Random Forest - R^2 Score for Water Temperature: {r2_rf_temp}")
print(f"Random Forest - Mean Absolute Error for TDS: {mae_rf_tds}")
print(f"Random Forest - Mean Absolute Error for Water Temperature: {mae_rf_temp}")
print(f"Random Forest - Root Mean Squared Error for TDS: {rmse_rf_tds}")
print(f"Random Forest - Root Mean Squared Error for Water Temperature: {rmse_rf_temp}")
```

```
Random Forest - Mean Squared Error for TDS: 3.891120469374974
Random Forest - Mean Squared Error for Water Temperature: 0.047147688039776564
Random Forest - R^2 Score for TDS: 0.9983532832565822
Random Forest - R^2 Score for Water Temperature: 0.9936491811880276
Random Forest - Mean Absolute Error for TDS: 0.6382615690644924
Random Forest - Mean Absolute Error for Water Temperature: 0.09844764240660724
Random Forest - Root Mean Squared Error for TDS: 1.9725923221423565
Random Forest - Root Mean Squared Error for Water Temperature: 0.2171351837905975
```

In [236…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.ensemble import GradientBoostingRegressor

# Assuming final_df is your DataFrame
# Assuming weather_related_features is your list of features related to weather

# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Gradient Boosting for 'TDS' prediction
gb_model_tds = GradientBoostingRegressor()
y_train_tds = y_train['TDS']  # Select 'TDS' as the target variable
gb_model_tds.fit(X_train, y_train_tds)
y_pred_gb_tds_precip = gb_model_tds.predict(X_test)

# Gradient Boosting for 'Water Temperature' prediction
gb_model_temp = GradientBoostingRegressor()
y_train_temp = y_train['Water Temperature']  # Select 'Water Temperature' as the target variable
gb_model_temp.fit(X_train, y_train_temp)
y_pred_gb_temp_precip = gb_model_temp.predict(X_test)

# Computing the performance metrics
mse_gb_tds_precip = mean_squared_error(y_test['TDS'], y_pred_gb_tds_precip)
mse_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_precip)
r2_gb_tds_precip = r2_score(y_test['TDS'], y_pred_gb_tds_precip)
r2_gb_temp_precip = r2_score(y_test['Water Temperature'], y_pred_gb_temp_precip)
mae_gb_tds_precip = mean_absolute_error(y_test['TDS'], y_pred_gb_tds_precip)
mae_gb_temp_precip = mean_absolute_error(y_test['Water Temperature'], y_pred_gb_temp_precip)
rmse_gb_tds_precip = mean_squared_error(y_test['TDS'], y_pred_gb_tds_precip, squared=False)
```

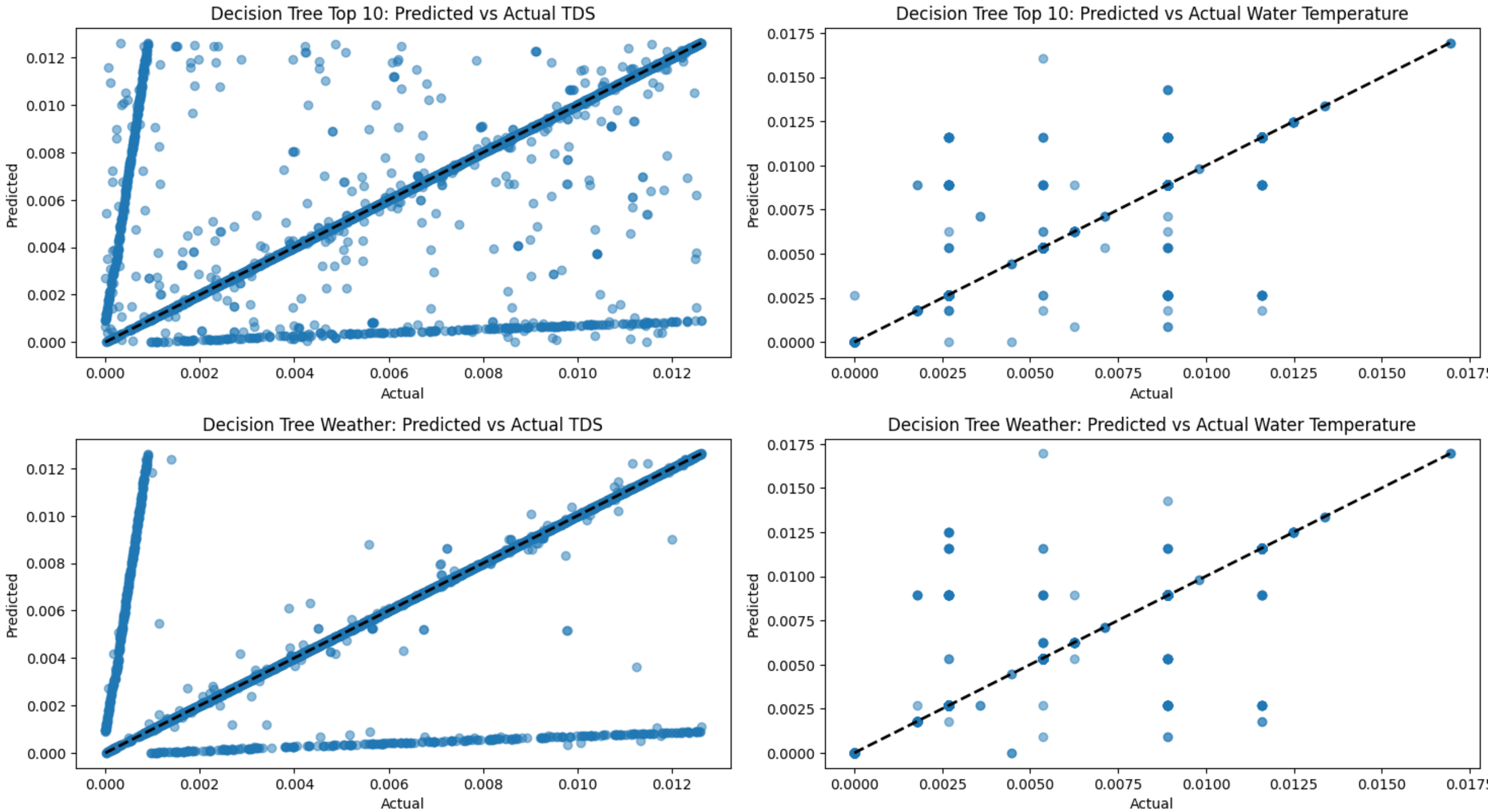
```
rmse_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_precip, squared=False

# Print the performance metrics
print(f"Gradient Boosting - Mean Squared Error for TDS: {mse_gb_tds_precip}")
print(f"Gradient Boosting - Mean Squared Error for Water Temperature: {mse_gb_temp_precip}")
print(f"Gradient Boosting - R^2 Score for TDS: {r2_gb_tds_precip}")
print(f"Gradient Boosting - R^2 Score for Water Temperature: {r2_gb_temp_precip}")
print(f"Gradient Boosting - Mean Absolute Error for TDS: {mae_gb_tds_precip}")
print(f"Gradient Boosting - Mean Absolute Error for Water Temperature: {mae_gb_temp_precip}")
print(f"Gradient Boosting - Root Mean Squared Error for TDS: {rmse_gb_tds_precip}")
print(f"Gradient Boosting - Root Mean Squared Error for Water Temperature: {rmse_gb_temp_precip}")
```

```
Gradient Boosting - Mean Squared Error for TDS: 4.844306200979698e-06
Gradient Boosting - Mean Squared Error for Water Temperature: 3.457297437714935e-06
Gradient Boosting - R^2 Score for TDS: 0.6376216924315636
Gradient Boosting - R^2 Score for Water Temperature: 0.6798518129373816
Gradient Boosting - Mean Absolute Error for TDS: 0.0015373832838891884
Gradient Boosting - Mean Absolute Error for Water Temperature: 0.0014873154791622129
Gradient Boosting - Root Mean Squared Error for TDS: 0.002200978464451594
Gradient Boosting - Root Mean Squared Error for Water Temperature: 0.0018593809286197745
```

Here are the performance graphs to compare the models that chose the top10 features and the ones that used precip features

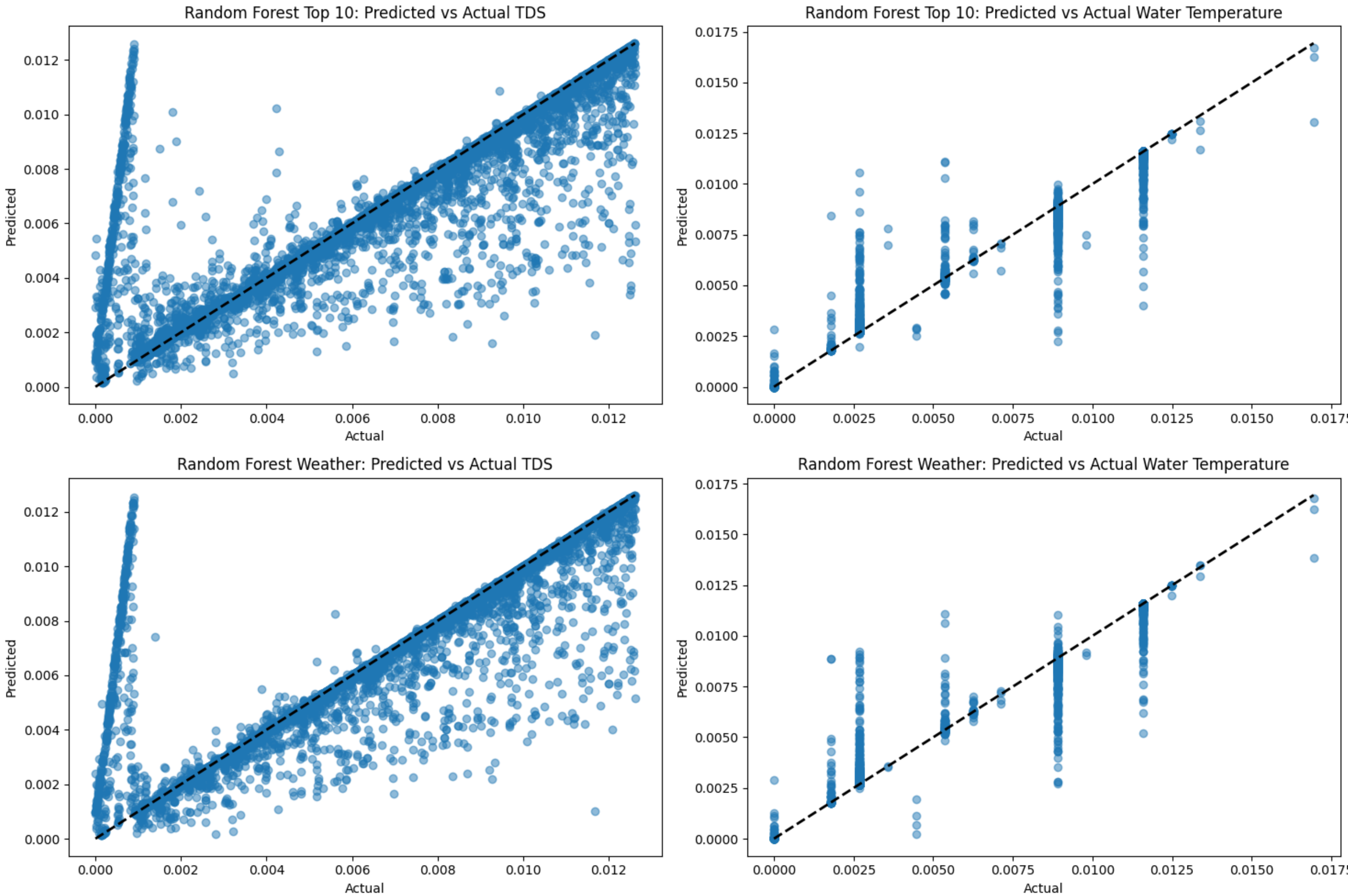
In [237…

```
import matplotlib.pyplot as plt

# Assuming you have predictions as y_pred_dt_top10, y_pred_dt_weather, etc.

plt.figure(figsize=(15, 20))  # Adjust the figure size as needed

# Decision Tree using Top 10 Features
plt.subplot(5, 2, 1)
plt.scatter(y_test['TDS'], y_pred_dt_top10[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Decision Tree Top 10: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_dt_top10[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Decision Tree Top 10: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Decision Tree using Weather-Related Features
plt.subplot(5, 2, 3)
plt.scatter(y_test['TDS'], y_pred_dt_precip[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Decision Tree Weather: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(5, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_dt_precip[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Decision Tree Weather: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Add similar subplots for Random Forest, Gradient Boosting, etc., using both feature sets

plt.tight_layout()
plt.show()
```


Decision Tree Top 10: Predicted vs Actual TDS
Decision Tree Top 10: Predicted vs Actual Water Temperature
Decision Tree Weather: Predicted vs Actual TDS
Decision Tree Weather: Predicted vs Actual Water Temperature
Predicted
Actual
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.0000
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175

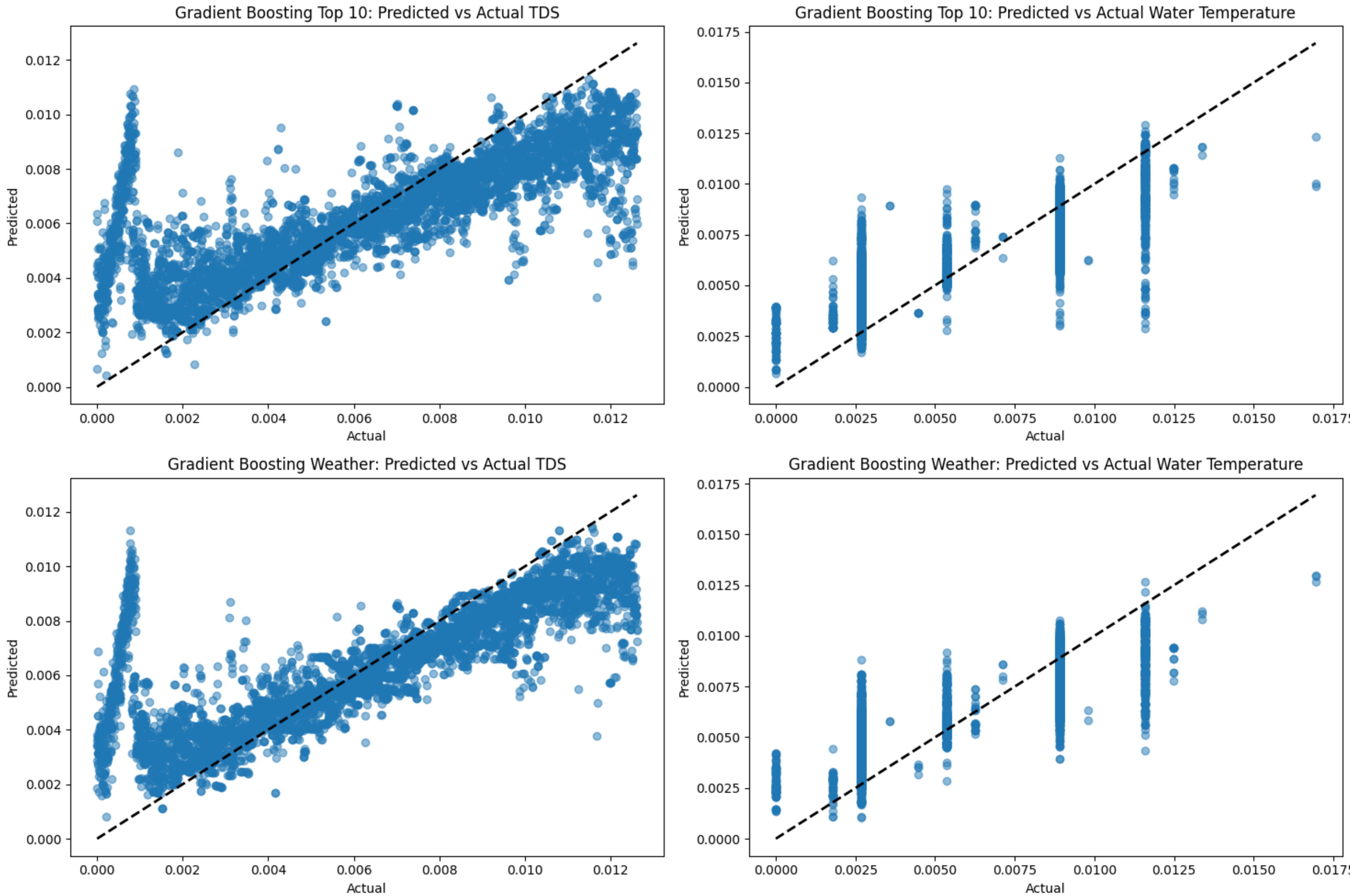
In [238…

```
import matplotlib.pyplot as plt

# Assuming you have predictions as y_pred_rf_top10, y_pred_rf_weather, etc. for Random Forest

plt.figure(figsize=(15, 10))  # Adjust the figure size as needed

# Random Forest using Top 10 Features
plt.subplot(2, 2, 1)
plt.scatter(y_test['TDS'], y_pred_rf_top10[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Random Forest Top 10: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(2, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_rf_top10[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Random Forest Top 10: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Random Forest using Weather-Related Features
plt.subplot(2, 2, 3)
plt.scatter(y_test['TDS'], y_pred_rf_precip[:, 0], alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Random Forest Weather: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(2, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_rf_precip[:, 1], alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Random Forest Weather: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.tight_layout()
plt.show()
```


Random Forest Top 10: Predicted vs Actual TDS
Predicted
Actual
0.000 0.002 0.004 0.006 0.008 0.010 0.012
Random Forest Top 10: Predicted vs Actual Water Temperature
Predicted
Actual
0.0000 0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175
Random Forest Weather: Predicted vs Actual TDS
Predicted
Actual
0.000 0.002 0.004 0.006 0.008 0.010 0.012
Random Forest Weather: Predicted vs Actual Water Temperature
Predicted
Actual
0.0000 0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175

In [239…

```
import matplotlib.pyplot as plt

# Assuming you have predictions as y_pred_gb_top10, y_pred_gb_weather, etc. for Gradient Boosting

plt.figure(figsize=(15, 10))  # Adjust the figure size as needed

# Gradient Boosting using Top 10 Features
plt.subplot(2, 2, 1)
plt.scatter(y_test['TDS'], y_pred_gb_tds_top10, alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Gradient Boosting Top 10: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(2, 2, 2)
plt.scatter(y_test['Water Temperature'], y_pred_gb_temp_top10, alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Gradient Boosting Top 10: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

# Gradient Boosting using Weather-Related Features
plt.subplot(2, 2, 3)
plt.scatter(y_test['TDS'], y_pred_gb_tds_precip, alpha=0.5)
plt.plot([min(y_test['TDS']), max(y_test['TDS'])], [min(y_test['TDS']), max(y_test['TDS'])], 'k--', lw=2)
plt.title('Gradient Boosting Weather: Predicted vs Actual TDS')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.subplot(2, 2, 4)
plt.scatter(y_test['Water Temperature'], y_pred_gb_temp_precip, alpha=0.5)
plt.plot([min(y_test['Water Temperature']), max(y_test['Water Temperature'])], [min(y_test['Water Temperat
plt.title('Gradient Boosting Weather: Predicted vs Actual Water Temperature')
plt.xlabel('Actual')
plt.ylabel('Predicted')

plt.tight_layout()
plt.show()
```



There is a data preprocessing issue so before doing validation and hyperparameter tuning, rerun the whole data preprocessing with scaling and normalization. We will be dropping DT and focus on RF and GB for our models

In [240…

```
final_df = final_df_copy
final_df.shape
```

Out[240]:

```
(1890836, 44)
```

In [241…

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, normalize

def scale_and_normalize(df):
    """
    Scales and normalizes a given DataFrame.

    Parameters:
    df (DataFrame): The DataFrame to be scaled and normalized.

    Returns:
    DataFrame: A new DataFrame that is scaled and normalized.
    """

    # Initialize the LabelEncoder
    le = LabelEncoder()

    # Separate numeric and non-numeric columns
    numeric_columns = df.select_dtypes(include=['number'])
    non_numeric_columns = df.select_dtypes(exclude=['number'])

    # Apply LabelEncoder to each non-numeric column and store in a new DataFrame
    encoded_columns = non_numeric_columns.apply(lambda col: le.fit_transform(col.astype(str)))

    # Concatenate the numeric columns and encoded columns
    df_processed = pd.concat([numeric_columns, encoded_columns], axis=1)

    # Apply MinMaxScaler
    scaler = MinMaxScaler(feature_range=(0, 1))
    scaled_data = scaler.fit_transform(df_processed)

    # Convert scaled data back to a DataFrame
    scaled_df = pd.DataFrame(scaled_data, columns=df_processed.columns)

    # Normalize the scaled data
    normalized_data = normalize(scaled_df, axis=0)

    # Convert normalized data back to a DataFrame
    normalized_df = pd.DataFrame(normalized_data, columns=scaled_df.columns)

    return normalized_df

# Usage:
```

```
# Assuming final_df is your original DataFrame
final_df = scale_and_normalize(final_df)
```

This is a function to handle the outliers to hopefully get rid of the diagonal offset line

In [242…

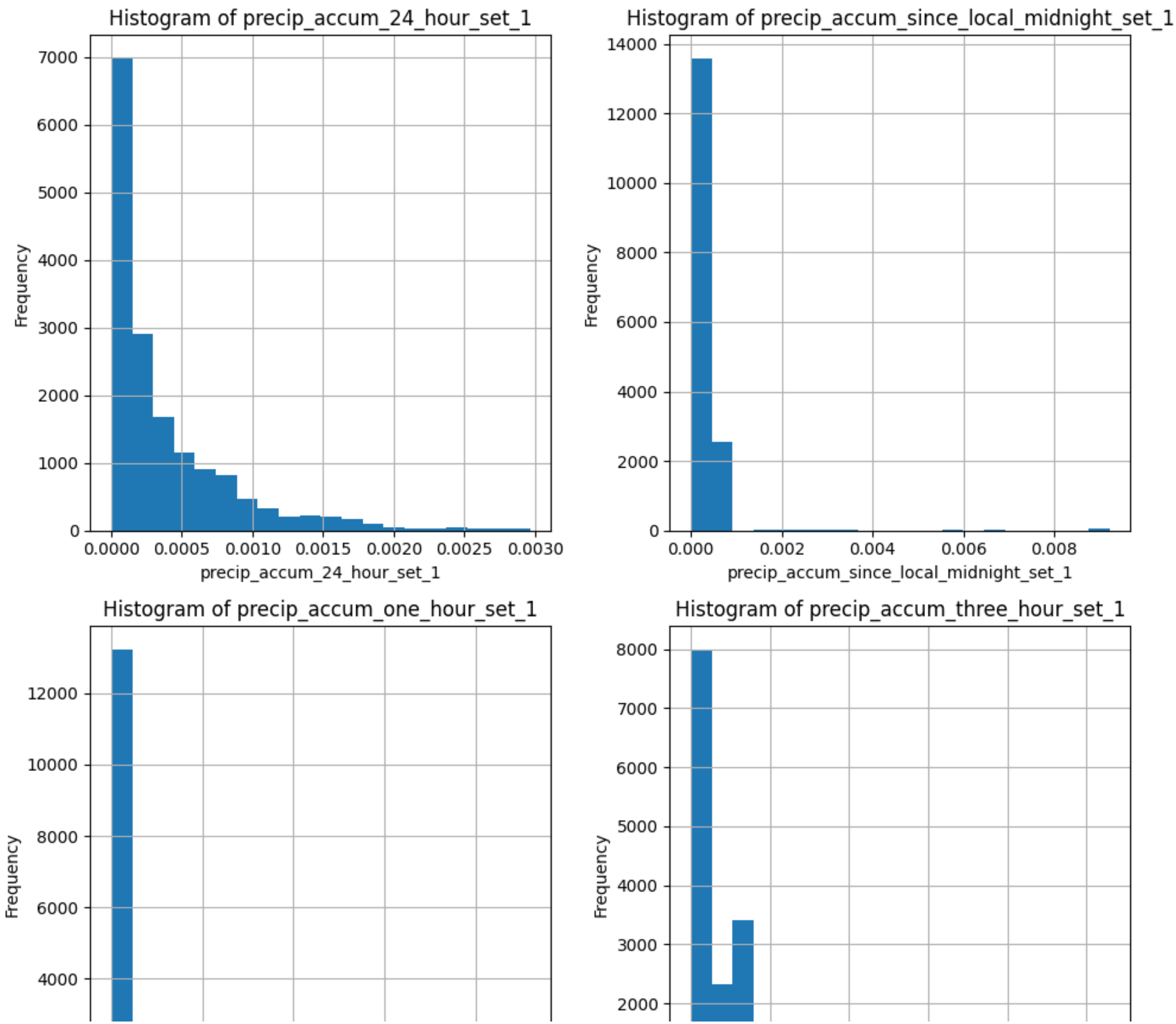
```
def handle_outliers(df, column, method='IQR'):
    if method == 'IQR':
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
    elif method == 'std':
        mean = df[column].mean()
        std = df[column].std()
        lower_bound = mean - 3 * std
        upper_bound = mean + 3 * std
        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
    return df

# Apply to your DataFrame
final_df = handle_outliers(final_df, 'TDS', method='IQR')
```

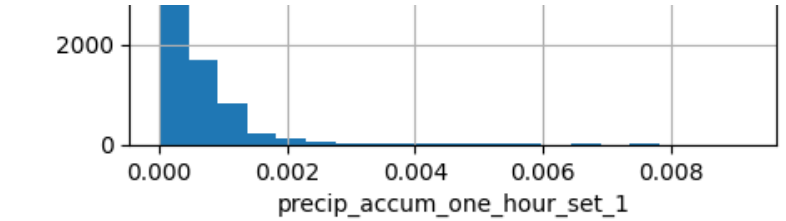
In [243…

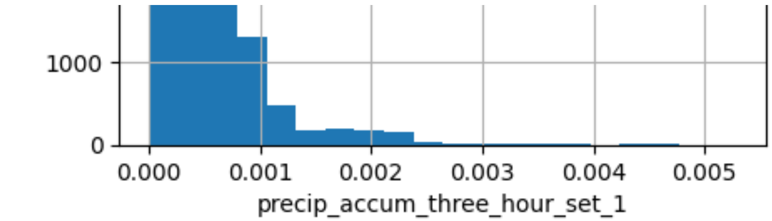
```
final_df = final_df.sample(frac=0.01)
```

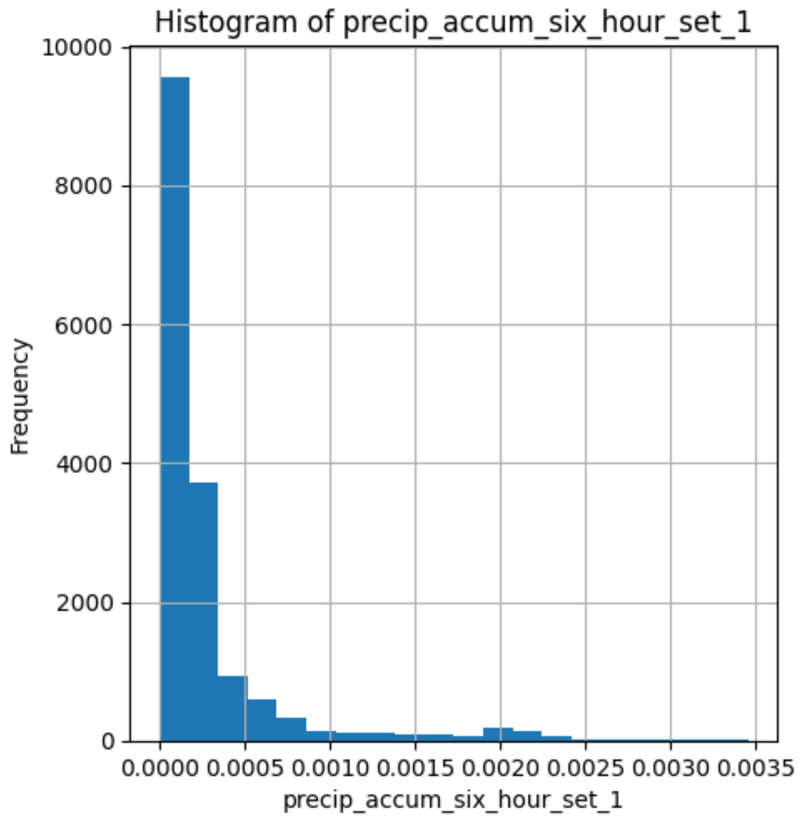
In [244…

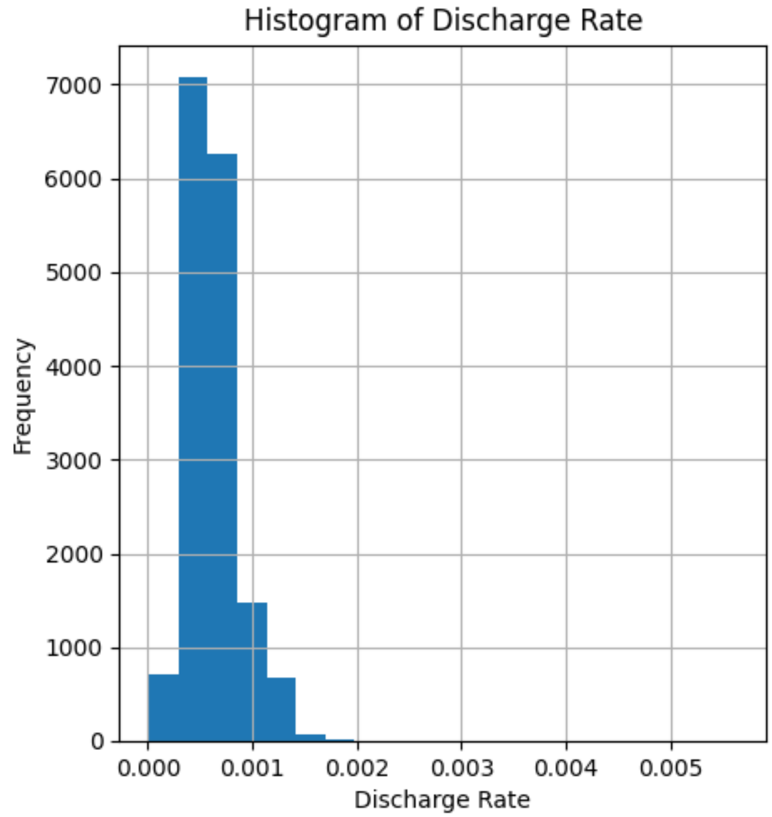
```
import matplotlib.pyplot as plt

# Assuming weather_related_features is your list of features related to weather
num_features = len(weather_related_features)

# Determine the number of rows required for subplots
rows = int(num_features / 2) if num_features % 2 == 0 else int(num_features / 2) + 1

# Create a figure and axes for subplots
fig, axes = plt.subplots(nrows=rows, ncols=2, figsize=(10, 5 * rows))

for i, column in enumerate(weather_related_features):
    if column in final_df.columns and final_df[column].dtype.kind in 'biufc':  # Check if the column is nu
        ax = axes[i // 2, i % 2]  # Determine the position of the subplot
        final_df[column].hist(bins=20, ax=ax)  # Plot the histogram on the designated subplot
        ax.set_title(f'Histogram of {column}')
        ax.set_xlabel(column)
        ax.set_ylabel('Frequency')

# Adjust layout for better fit
plt.tight_layout()
plt.show()
```

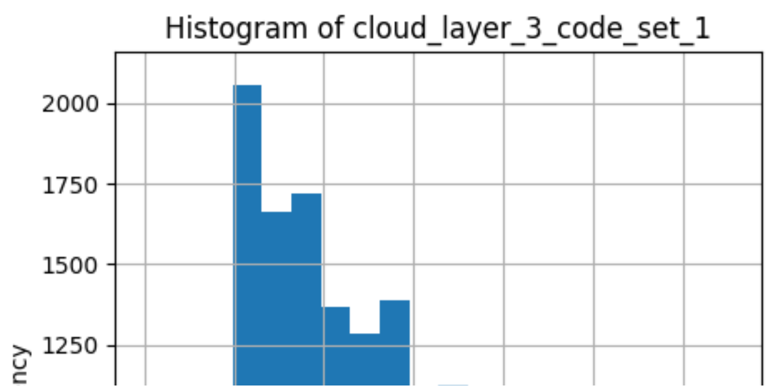

Histogram of precip_accum_24_hour_set_1
Frequency
0
1000
2000
3000
4000
5000
6000
7000
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030
precip_accum_24_hour_set_1
Histogram of precip_accum_since_local_midnight_set_1
Frequency
0
2000
4000
6000
8000
10000
12000
14000
0.000
0.002
0.004
0.006
0.008
precip_accum_since_local_midnight_set_1
Histogram of precip_accum_one_hour_set_1
Frequency
4000
6000
8000
10000
12000
Histogram of precip_accum_three_hour_set_1
Frequency
2000
3000
4000
5000
6000
7000
8000

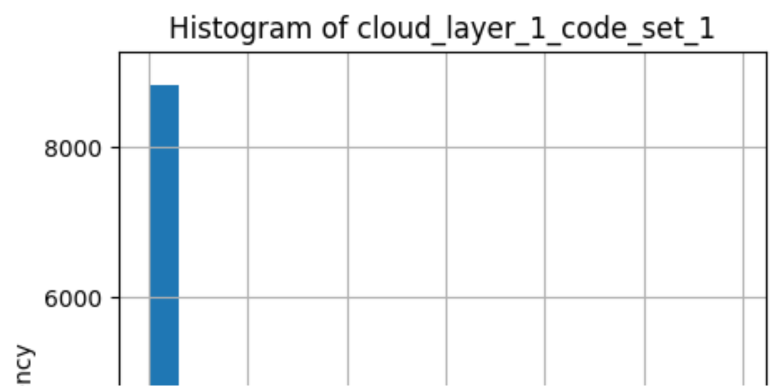

2000
0
0.000
0.002
0.004
0.006
0.008
precip_accum_one_hour_set_1

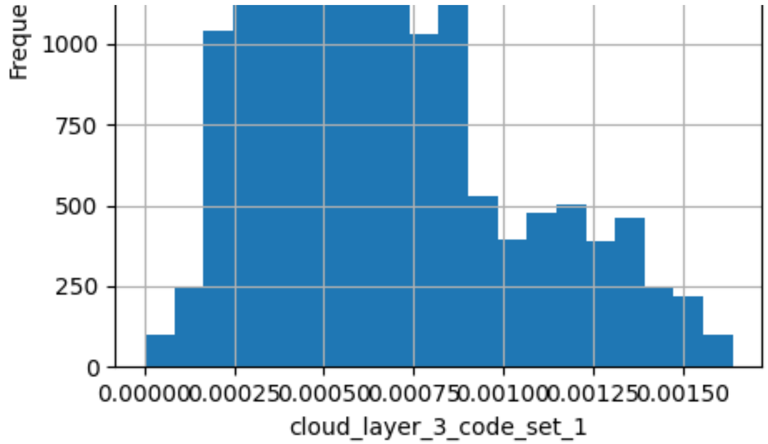

1000
0
0.000
0.001
0.002
0.003
0.004
0.005
precip_accum_three_hour_set_1

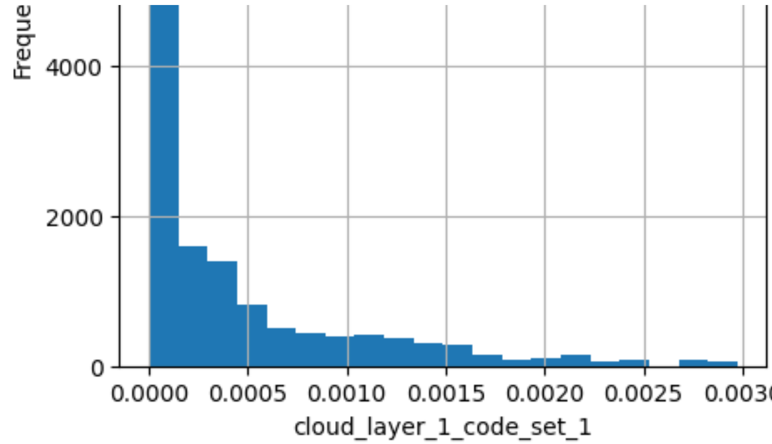

Histogram of precip_accum_six_hour_set_1
Frequency
10000
8000
6000
4000
2000
0
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030 0.0035
precip_accum_six_hour_set_1


Histogram of Discharge Rate
Frequency
7000
6000
5000
4000
3000
2000
1000
0
0.000 0.001 0.002 0.003 0.004 0.005
Discharge Rate

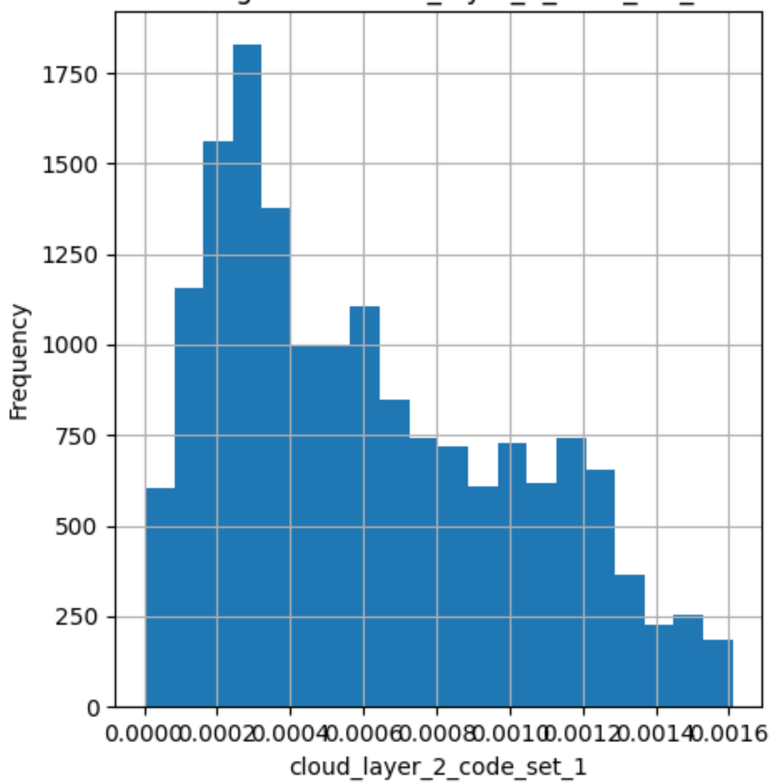

Histogram of cloud_layer_3_code_set_1
2000
1750
1500
1250


Histogram of cloud_layer_1_code_set_1
8000
6000

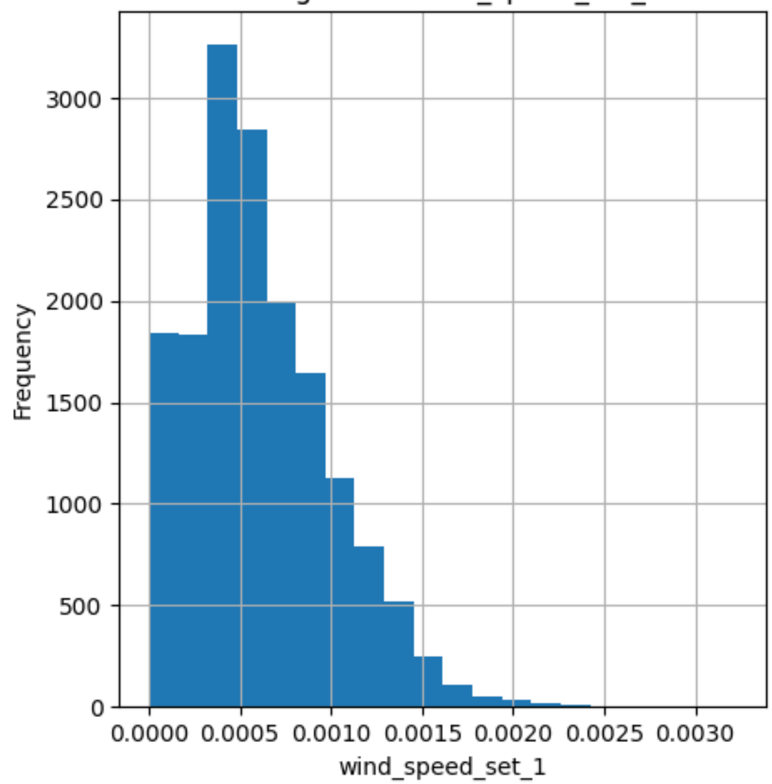




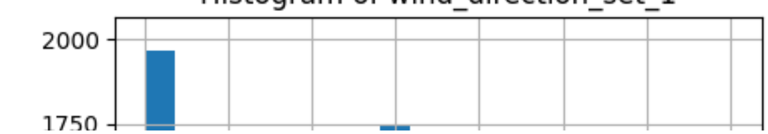
Histogram of cloud_layer_2_code_set_1



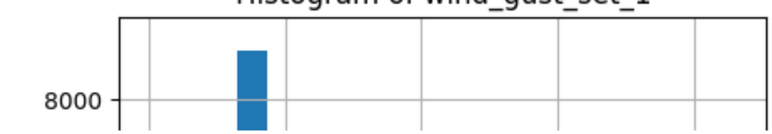
Histogram of wind_speed_set_1

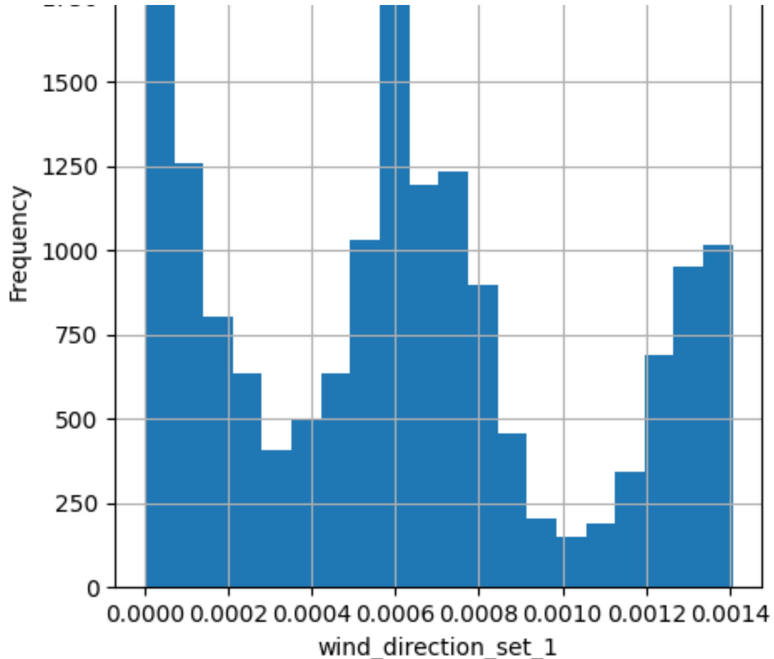


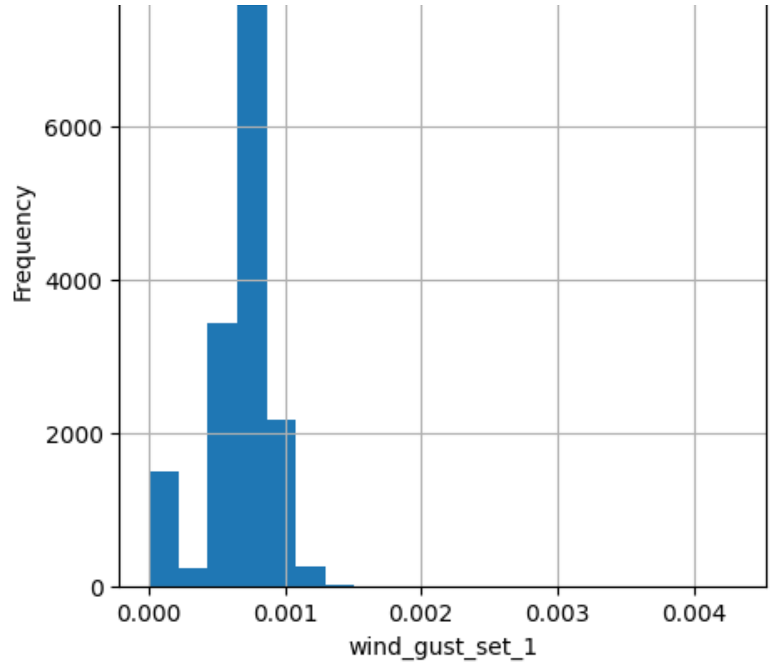
Histogram of wind_direction_set_1



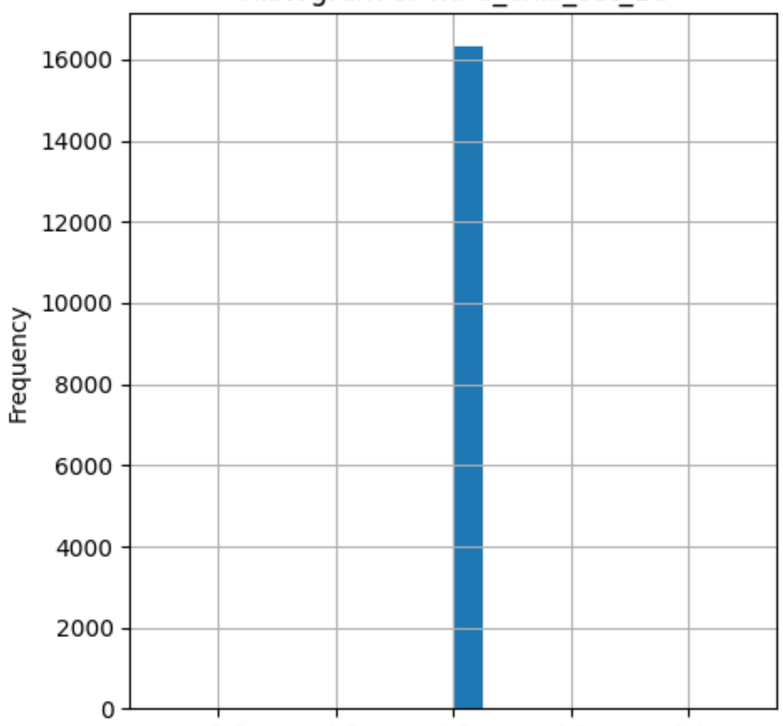
Histogram of wind_gust_set_1



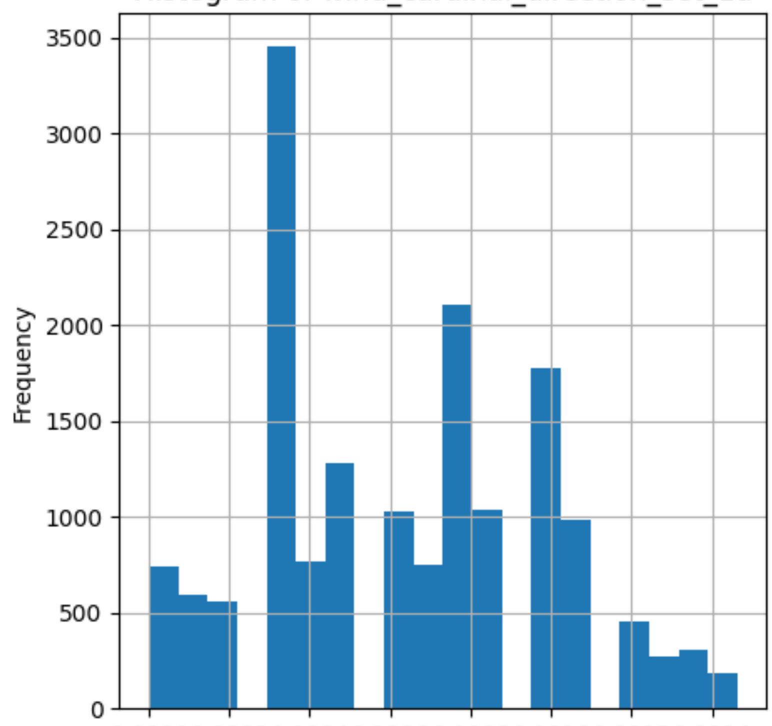


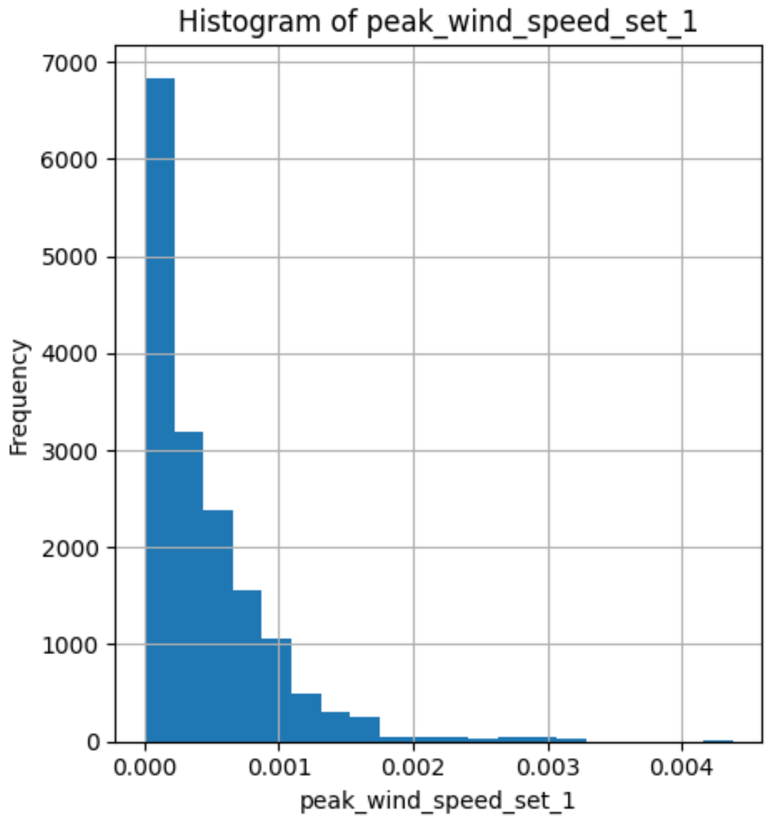


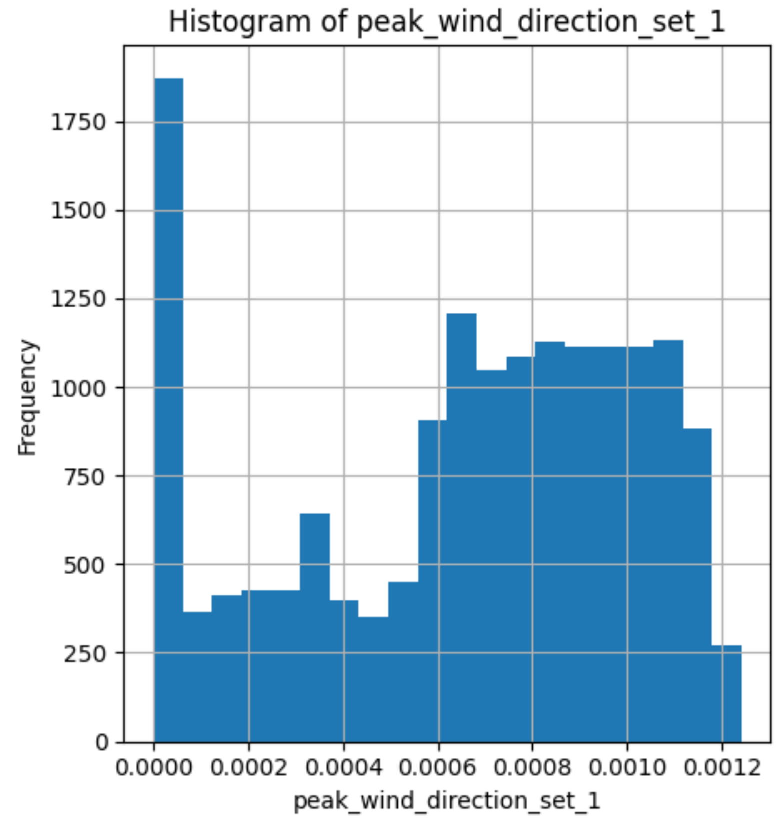
Histogram of wind_chill_set_1d



Histogram of wind_cardinal_direction_set_1d







This dataset is still unbalanced either because of the highly localized data, the bad data from the TDS sensor, and not properly merging the dataset into one dataframe

We will still be using RF and GB models but only for the top10 features because those models performed better than the precip feature selection. (The model is losing MSE becuase of taking away features, scaling data, and normalization).

We will be using RandomizedSearchCV and GridSearchCV

After that, run the models again with the best parameters for the top10 features

Base models with precip features after dataset is normailized and scaled

In [245…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.preprocessing import LabelEncoder

# Assuming final_df is your DataFrame
# Assuming weather_related_features is your list of features related to weather

# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing the RandomForestRegressor
regressor = RandomForestRegressor(random_state=42)

# Training the model
regressor.fit(X_train, y_train)

# Predicting on the test set
y_pred_rf_precip = regressor.predict(X_test)

# Computing the performance metrics
mse_rf_tds_precip = mean_squared_error(y_test['TDS'], y_pred_rf_precip[:, 0])
mse_rf_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
r2_rf_tds_precip = r2_score(y_test['TDS'], y_pred_rf_precip[:, 0])
r2_rf_temp_precip = r2_score(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
mae_rf_tds_precip = mean_absolute_error(y_test['TDS'], y_pred_rf_precip[:, 0])
mae_rf_temp_precip = mean_absolute_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1])
rmse_rf_tds_precip = mean_squared_error(y_test['TDS'], y_pred_rf_precip[:, 0], squared=False)
rmse_rf_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_rf_precip[:, 1], squared=Fals

# Print the performance metrics
```

```
print(f"Random Forest - Mean Squared Error for TDS: {mse_rf_tds_precip}")
print(f"Random Forest - Mean Squared Error for Water Temperature: {mse_rf_temp_precip}")
print(f"Random Forest - R^2 Score for TDS: {r2_rf_tds_precip}")
print(f"Random Forest - R^2 Score for Water Temperature: {r2_rf_temp_precip}")
print(f"Random Forest - Mean Absolute Error for TDS: {mae_rf_tds_precip}")
print(f"Random Forest - Mean Absolute Error for Water Temperature: {mae_rf_temp_precip}")
print(f"Random Forest - Root Mean Squared Error for TDS: {rmse_rf_tds_precip}")
print(f"Random Forest - Root Mean Squared Error for Water Temperature: {rmse_rf_temp_precip}")
```

```
Random Forest - Mean Squared Error for TDS: 3.9604285955557524e-11
Random Forest - Mean Squared Error for Water Temperature: 2.5655313300434408e-12
Random Forest - R^2 Score for TDS: 0.8889249870655435
Random Forest - R^2 Score for Water Temperature: 0.9409586475629059
Random Forest - Mean Absolute Error for TDS: 1.9918988064788977e-06
Random Forest - Mean Absolute Error for Water Temperature: 6.670123272464302e-07
Random Forest - Root Mean Squared Error for TDS: 6.293193621332116e-06
Random Forest - Root Mean Squared Error for Water Temperature: 1.60172760794195e-06
```

In [246…

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.ensemble import GradientBoostingRegressor

# Assuming final_df is your DataFrame
# Assuming weather_related_features is your list of features related to weather

# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y = final_df[['TDS', 'Water Temperature']]

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Gradient Boosting for 'TDS' prediction
gb_model_tds = GradientBoostingRegressor()
y_train_tds = y_train['TDS']  # Select 'TDS' as the target variable
gb_model_tds.fit(X_train, y_train_tds)
y_pred_gb_tds_precip = gb_model_tds.predict(X_test)

# Gradient Boosting for 'Water Temperature' prediction
gb_model_temp = GradientBoostingRegressor()
y_train_temp = y_train['Water Temperature']  # Select 'Water Temperature' as the target variable
gb_model_temp.fit(X_train, y_train_temp)
y_pred_gb_temp_precip = gb_model_temp.predict(X_test)

# Computing the performance metrics
mse_gb_tds_precip = mean_squared_error(y_test['TDS'], y_pred_gb_tds_precip)
mse_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_precip)
r2_gb_tds_precip = r2_score(y_test['TDS'], y_pred_gb_tds_precip)
r2_gb_temp_precip = r2_score(y_test['Water Temperature'], y_pred_gb_temp_precip)
mae_gb_tds_precip = mean_absolute_error(y_test['TDS'], y_pred_gb_tds_precip)
mae_gb_temp_precip = mean_absolute_error(y_test['Water Temperature'], y_pred_gb_temp_precip)
rmse_gb_tds_precip = mean_squared_error(y_test['TDS'], y_pred_gb_tds_precip, squared=False)
```

```
rmse_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], y_pred_gb_temp_precip, squared=False

# Print the performance metrics
print(f"Gradient Boosting - Mean Squared Error for TDS: {mse_gb_tds_precip}")
print(f"Gradient Boosting - Mean Squared Error for Water Temperature: {mse_gb_temp_precip}")
print(f"Gradient Boosting - R^2 Score for TDS: {r2_gb_tds_precip}")
print(f"Gradient Boosting - R^2 Score for Water Temperature: {r2_gb_temp_precip}")
print(f"Gradient Boosting - Mean Absolute Error for TDS: {mae_gb_tds_precip}")
print(f"Gradient Boosting - Mean Absolute Error for Water Temperature: {mae_gb_temp_precip}")
print(f"Gradient Boosting - Root Mean Squared Error for TDS: {rmse_gb_tds_precip}")
print(f"Gradient Boosting - Root Mean Squared Error for Water Temperature: {rmse_gb_temp_precip}")
```

```
Gradient Boosting - Mean Squared Error for TDS: 7.861537645930804e-11
Gradient Boosting - Mean Squared Error for Water Temperature: 1.3228483302054574e-11
Gradient Boosting - R^2 Score for TDS: 0.7795136625652117
Gradient Boosting - R^2 Score for Water Temperature: 0.6955688922217945
Gradient Boosting - Mean Absolute Error for TDS: 5.188939552729347e-06
Gradient Boosting - Mean Absolute Error for Water Temperature: 2.544817722836688e-06
Gradient Boosting - Root Mean Squared Error for TDS: 8.866531252936971e-06
Gradient Boosting - Root Mean Squared Error for Water Temperature: 3.637098198021958e-06
```

In [247…

```
# Select only the weather-related features from your DataFrame
X = final_df[weather_related_features]

# If any of the weather-related features are non-numeric, encode them
le = LabelEncoder()
for col in X.select_dtypes(include=['object']).columns:
    X[col] = le.fit_transform(X[col])

# Define the target variables
y_tds = final_df['TDS']
y_temp = final_df['Water Temperature']

# Splitting the data
X_train_tds, X_test_tds, y_train_tds, y_test_tds = train_test_split(X, y_tds, test_size=0.3, random_state=
X_train_temp, X_test_temp, y_train_temp, y_test_temp = train_test_split(X, y_temp, test_size=0.3, random_s
```

In [248…

```
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.ensemble import RandomForestRegressor

# Define the parameter grid for GridSearchCV
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt']  # Changed 'auto' to 'sqrt'
}

# K-Fold Cross-Validation setup
k_fold = KFold(n_splits=5, shuffle=True, random_state=42)

# GridSearchCV setup
grid_search = GridSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_grid=param_grid,
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1,
    error_score='raise'  # Raises an error on fit failures
)

# Fit GridSearchCV
grid_search.fit(X_train, y_train)

# Save the best model from GridSearchCV
best_rf_grid = grid_search.best_estimator_
```

```
Fitting 5 folds for each of 81 candidates, totalling 405 fits
```

In [249…

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint

# Define the parameter distribution for RandomizedSearchCV
param_dist = {
    'n_estimators': sp_randint(100, 400),
    'max_depth': sp_randint(10, 50),
    'min_samples_split': sp_randint(2, 11),
    'min_samples_leaf': sp_randint(1, 5),
    'max_features': ['sqrt']
    # Add other parameters if needed
}

# RandomizedSearchCV setup
random_search = RandomizedSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_distributions=param_dist,
    n_iter=10,  # Number of iterations
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1,
    random_state=42
)

# Fit RandomizedSearchCV
random_search.fit(X_train, y_train)

# Save the best model from RandomizedSearchCV
best_rf_random = random_search.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

We now need to edit the hyperparameter tuning methods to do a K-fold cross validation, after that our main model (RF) should be close or better than our previous models and the GB model

In [250…

```
X_train_tds, X_test_tds, y_train_tds, y_test_tds = train_test_split(X, y['TDS'], test_size=0.3, random_sta
X_train_temp, X_test_temp, y_train_temp, y_test_temp = train_test_split(X, y['Water Temperature'], test_si
```

In [251…

```
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.ensemble import GradientBoostingRegressor

# Define the parameter grid for GridSearchCV
gb_param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    # Add other parameters as needed
}

# K-Fold Cross-Validation setup
k_fold = KFold(n_splits=5, shuffle=True, random_state=42)

# GridSearchCV setup for TDS
gb_grid_search_tds = GridSearchCV(
    estimator=GradientBoostingRegressor(random_state=42),
    param_grid=gb_param_grid,
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1
)

# Fit GridSearchCV for TDS
gb_grid_search_tds.fit(X_train_tds, y_train_tds)  # Use y_train_tds
best_gb_grid_tds = gb_grid_search_tds.best_estimator_
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

In [252…

```
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.ensemble import GradientBoostingRegressor

# Define the parameter grid for GridSearchCV
gb_param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4, 5],
    # Add other parameters as needed
}

# K-Fold Cross-Validation setup
k_fold = KFold(n_splits=5, shuffle=True, random_state=42)

# GridSearchCV setup for TDS
gb_grid_search_temp = GridSearchCV(
    estimator=GradientBoostingRegressor(random_state=42),
    param_grid=gb_param_grid,
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1
)

# Fit GridSearchCV for TDS
gb_grid_search_temp.fit(X_train_temp, y_train_temp)  # Use y_train_tds
best_gb_grid_temp = gb_grid_search_temp.best_estimator_
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

In [253…

```
# Computing the performance metrics
mse_best_gb_tds_precip = mean_squared_error(y_test['TDS'], best_gb_grid_tds.predict(X_test_tds))
mse_best_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], best_gb_grid_temp.predict(X_test
r2_best_gb_tds_precip = r2_score(y_test['TDS'], best_gb_grid_tds.predict(X_test_tds))
r2_best_gb_temp_precip = r2_score(y_test['Water Temperature'], best_gb_grid_temp.predict(X_test_temp))
mae_best_gb_tds_precip = mean_absolute_error(y_test['TDS'], best_gb_grid_tds.predict(X_test_tds))
mae_best_gb_temp_precip = mean_absolute_error(y_test['Water Temperature'], best_gb_grid_temp.predict(X_tes
rmse_best_gb_tds_precip = mean_squared_error(y_test['TDS'], best_gb_grid_tds.predict(X_test_tds), squared=
rmse_best_gb_temp_precip = mean_squared_error(y_test['Water Temperature'], best_gb_grid_temp.predict(X_tes
```

In [254…

```
# Print the performance metrics
print(f"Best Gradient Boosting Grid Search - Mean Squared Error for TDS: {mse_best_gb_tds_precip}")
print(f"Best Gradient Boosting Grid Search - Mean Squared Error for Water Temperature: {mse_best_gb_temp_p
print(f"Best Gradient Boosting Grid Search - R^2 Score for TDS: {r2_best_gb_tds_precip}")
print(f"Best Gradient Boosting Grid Search - R^2 Score for Water Temperature: {r2_best_gb_temp_precip}")
print(f"Best Gradient Boosting Grid Search - Mean Absolute Error for TDS: {mae_best_gb_tds_precip}")
print(f"Best Gradient Boosting Grid Search - Mean Absolute Error for Water Temperature: {mae_best_gb_temp_
print(f"Best Gradient Boosting Grid Search - Root Mean Squared Error for TDS: {rmse_best_gb_tds_precip}")
print(f"Best Gradient Boosting Grid Search - Root Mean Squared Error for Water Temperature: {rmse_best_gb_
```

```
Best Gradient Boosting Grid Search - Mean Squared Error for TDS: 4.200739262397214e-11
Best Gradient Boosting Grid Search - Mean Squared Error for Water Temperature: 3.656099487735102e-12
Best Gradient Boosting Grid Search - R^2 Score for TDS: 0.8821851835863321
Best Gradient Boosting Grid Search - R^2 Score for Water Temperature: 0.9158610710098823
Best Gradient Boosting Grid Search - Mean Absolute Error for TDS: 2.7137438473391214e-06
Best Gradient Boosting Grid Search - Mean Absolute Error for Water Temperature: 1.1004471918257812e-06
Best Gradient Boosting Grid Search - Root Mean Squared Error for TDS: 6.48131102663436e-06
Best Gradient Boosting Grid Search - Root Mean Squared Error for Water Temperature: 1.9120929600140004e-06
```

In [255…

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint

# Define the parameter distribution for RandomizedSearchCV
gb_param_dist = {
    'n_estimators': sp_randint(100, 400),
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': sp_randint(3, 6),
    # Add other parameters as needed
}

# RandomizedSearchCV setup
gb_random_search_tds = RandomizedSearchCV(
    estimator=GradientBoostingRegressor(random_state=42),
    param_distributions=gb_param_dist,
    n_iter=10,  # Number of parameter settings sampled
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1,
    random_state=42
)

# Fit RandomizedSearchCV
gb_random_search_tds.fit(X_train_tds, y_train_tds)  # Use y_train_tds or y_train_temp based on target

# Save the best model from RandomizedSearchCV
best_gb_random_tds = gb_random_search_tds.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

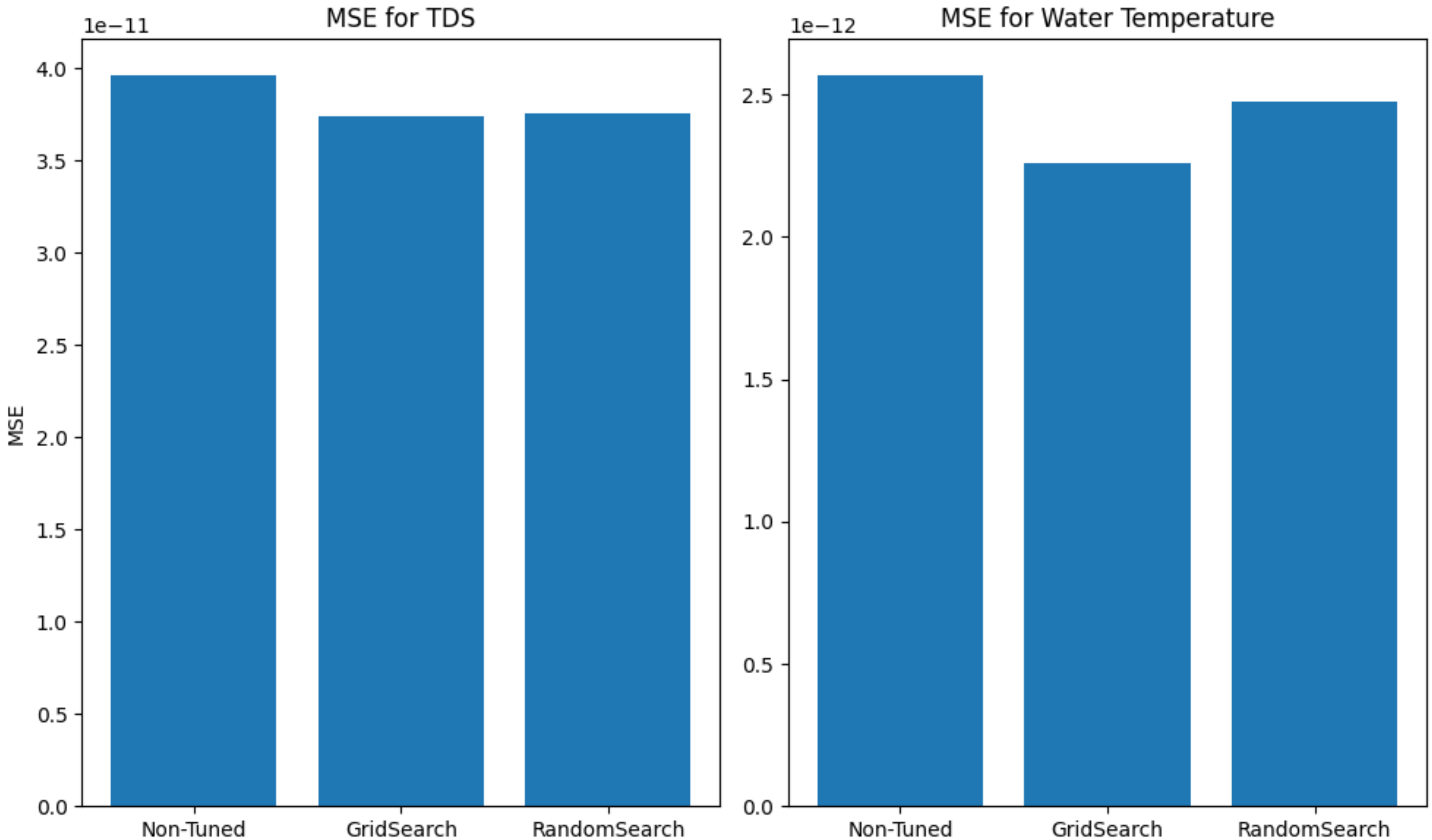
In [256…

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint

# Define the parameter distribution for RandomizedSearchCV
gb_param_dist = {
    'n_estimators': sp_randint(100, 400),
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': sp_randint(3, 6),
    # Add other parameters as needed
}

# RandomizedSearchCV setup
gb_random_search_temp = RandomizedSearchCV(
    estimator=GradientBoostingRegressor(random_state=42),
    param_distributions=gb_param_dist,
    n_iter=10,  # Number of parameter settings sampled
    cv=k_fold,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1,
    random_state=42
)

# Fit RandomizedSearchCV
gb_random_search_temp.fit(X_train_temp, y_train_temp)  # Use y_train_tds or y_train_temp based on target

# Save the best model from RandomizedSearchCV
best_gb_random_temp = gb_random_search_temp.best_estimator_
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

In [257…

```
# Import necessary libraries
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error

# Assuming y_test, best_rf_grid, and best_rf_random models are defined

# Predict and compute MSE for the best models from GridSearchCV and RandomizedSearchCV
y_pred_best_grid = best_rf_grid.predict(X_test)
y_pred_best_random = best_rf_random.predict(X_test)

# Compute MSE for TDS and Water Temperature
mse_best_grid_tds = mean_squared_error(y_test['TDS'], y_pred_best_grid[:, 0])
mse_best_grid_temp = mean_squared_error(y_test['Water Temperature'], y_pred_best_grid[:, 1])
mse_best_random_tds = mean_squared_error(y_test['TDS'], y_pred_best_random[:, 0])
mse_best_random_temp = mean_squared_error(y_test['Water Temperature'], y_pred_best_random[:, 1])

# Plotting MSE for TDS and Water Temperature
plt.figure(figsize=(10, 6))
plt.subplot(1, 2, 1)
plt.bar(['Non-Tuned', 'GridSearch', 'RandomSearch'], [mse_rf_tds_precip, mse_best_grid_tds, mse_best_rando
plt.title('MSE for TDS')
plt.ylabel('MSE')
plt.subplot(1, 2, 2)
plt.bar(['Non-Tuned', 'GridSearch', 'RandomSearch'], [mse_rf_temp_precip, mse_best_grid_temp, mse_best_rar
plt.title('MSE for Water Temperature')
plt.tight_layout()
plt.show()
```


MSE for TDS
1e−11
MSE
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Non-Tuned
GridSearch
RandomSearch
MSE for Water Temperature
1e−12
2.5
2.0
1.5
1.0
0.5
0.0
Non-Tuned
GridSearch
RandomSearch

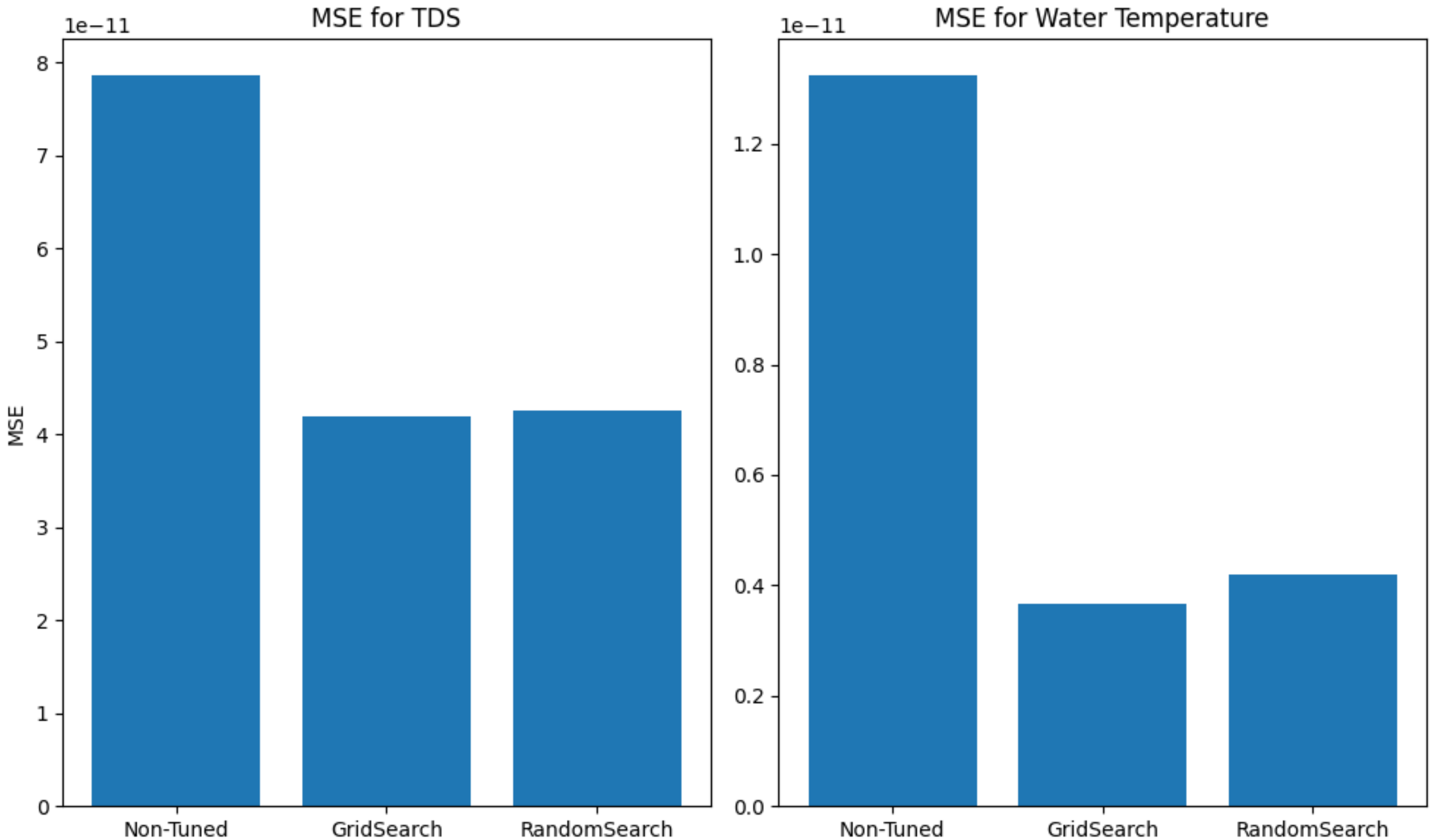
In [258…

```
# Compare MSE scores to select the best RF model
mse_scores = {
    'Non-Tuned': mse_rf_tds_precip + mse_rf_temp_precip,
    'GridSearch': mse_best_grid_tds + mse_best_grid_temp,
    'RandomSearch': mse_best_random_tds + mse_best_random_temp
}

# Find the model with the lowest combined MSE
best_model_key = min(mse_scores, key=mse_scores.get)
RF_ABS_BEST_MODEL = {'Non-Tuned': regressor, 'GridSearch': best_rf_grid, 'RandomSearch': best_rf_random}[b

# Print the best model information
print(f"The best RF model is: {best_model_key} with combined MSE: {mse_scores[best_model_key]}")
```

```
The best RF model is: GridSearch with combined MSE: 3.964689221326019e-11
```

In [259…

```
# Compute MSE for each model and target variable
mse_non_gb_tuned_tds = mean_squared_error(y_test_tds, y_pred_gb_tds_precip)
mse_non_gb_tuned_temp = mean_squared_error(y_test_temp, y_pred_gb_temp_precip)
mse_best_gb_grid_tds = mean_squared_error(y_test_tds, best_gb_grid_tds.predict(X_test_tds))
mse_best_gb_grid_temp = mean_squared_error(y_test_temp, best_gb_grid_temp.predict(X_test_temp))
mse_best_gb_random_tds = mean_squared_error(y_test_tds, best_gb_random_tds.predict(X_test_tds))
mse_best_gb_random_temp = mean_squared_error(y_test_temp, best_gb_random_temp.predict(X_test_temp))

# Combine the MSE for TDS and Water Temperature for each model type
combined_mse_non_tuned = mse_non_gb_tuned_tds + mse_non_gb_tuned_temp
combined_mse_grid = mse_best_gb_grid_tds + mse_best_gb_grid_temp
combined_mse_random = mse_best_gb_random_tds + mse_best_gb_random_temp

# Plotting
plt.figure(figsize=(10, 6))

# Plot for TDS
plt.subplot(1, 2, 1)
plt.bar(['Non-Tuned', 'GridSearch', 'RandomSearch'],
        [mse_non_gb_tuned_tds, mse_best_gb_grid_tds, mse_best_gb_random_tds])
plt.title('MSE for TDS')
plt.ylabel('MSE')

# Plot for Water Temperature
plt.subplot(1, 2, 2)
plt.bar(['Non-Tuned', 'GridSearch', 'RandomSearch'],
        [mse_non_gb_tuned_temp, mse_best_gb_grid_temp, mse_best_gb_random_temp])
plt.title('MSE for Water Temperature')

plt.tight_layout()
plt.show()
```


MSE for TDS
1e−11
MSE
8
7
6
5
4
3
2
1
0
Non-Tuned
GridSearch
RandomSearch
MSE for Water Temperature
1e−11
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Non-Tuned
GridSearch
RandomSearch

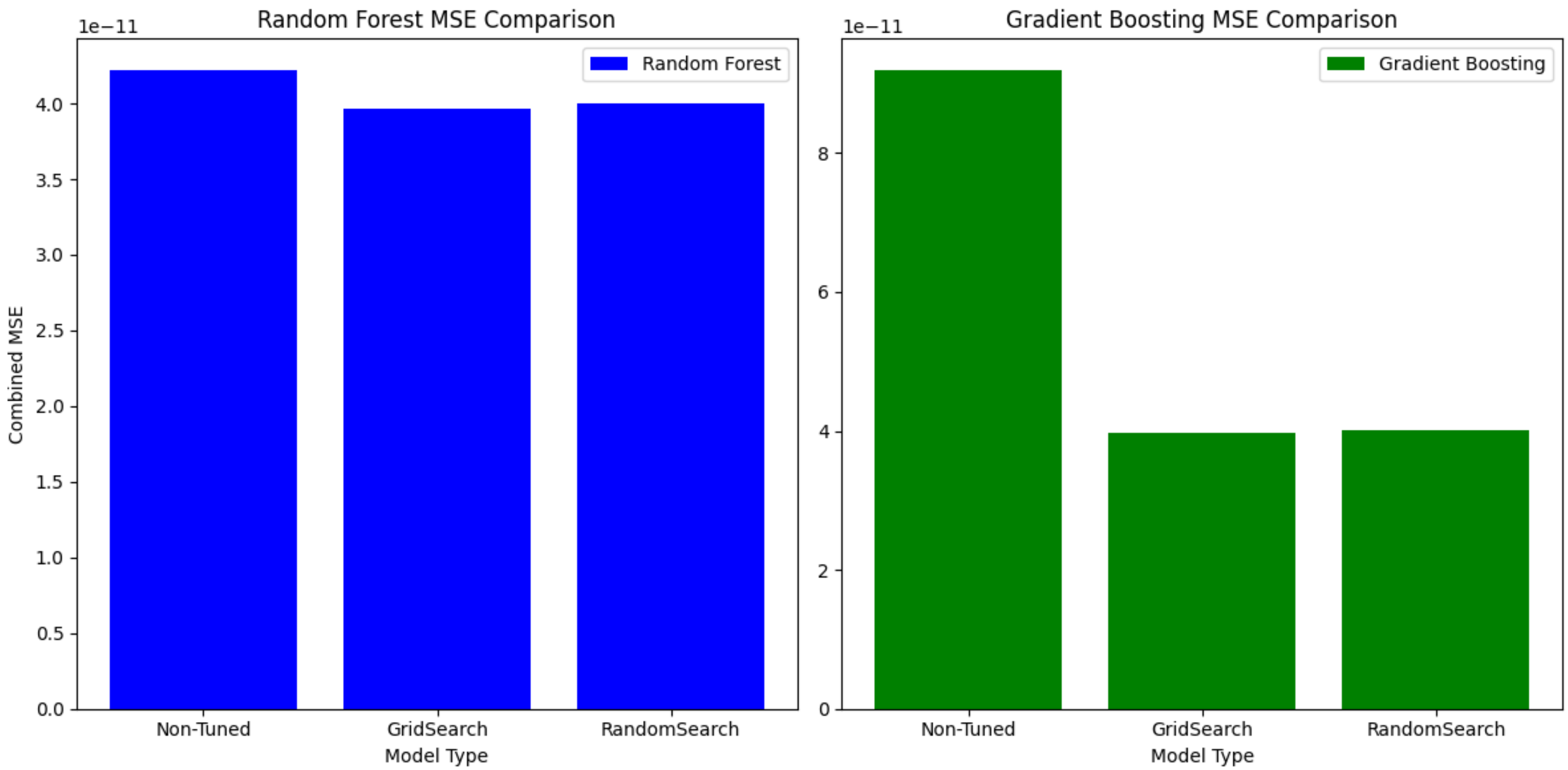
In [260…

```
# Compare the combined MSE scores and select the best model
gb_mse_scores = {
    'Non-Tuned GB': combined_mse_non_tuned,
    'GridSearch GB': combined_mse_grid,
    'RandomSearch GB': combined_mse_random
}

best_gb_model_key = min(gb_mse_scores, key=gb_mse_scores.get)

# Print the best model information
print(f"The best Gradient Boosting model is: {best_gb_model_key} with combined MSE: {gb_mse_scores[best_gb
```

```
The best Gradient Boosting model is: GridSearch GB with combined MSE: 4.566349211170724e-11
```

In [261…

```
import matplotlib.pyplot as plt

# Assuming mse_rf_tds_precip, mse_rf_temp_precip, mse_best_rf_grid, mse_best_rf_random are defined
# Assuming mse_best_gb_grid_tds, mse_best_gb_grid_temp, mse_best_gb_random_tds, mse_best_gb_random_temp ar

# Combined MSE for the best RF models (using combined predictions for TDS and Water Temperature)
combined_mse_rf = [mse_rf_tds_precip + mse_rf_temp_precip,  # Non-Tuned RF model
                   mse_best_grid_tds + mse_best_grid_temp,  # GridSearch RF model
                   mse_best_random_tds + mse_best_random_temp]  # RandomSearch RF model

# Combined MSE for the best GB models (using separate models for TDS and Water Temperature)
combined_mse_gb = [mse_gb_tds_precip + mse_gb_temp_precip,  # Non-Tuned GB model
                   mse_best_grid_tds + mse_best_grid_temp,  # GridSearch GB model
                   mse_best_random_tds + mse_best_random_temp]  # RandomSearch GB model

models = ['Non-Tuned', 'GridSearch', 'RandomSearch']

# Creating bar chart for RF and GB
plt.figure(figsize=(12, 6))

# RF MSE Comparison
plt.subplot(1, 2, 1)
plt.bar(models, combined_mse_rf, color='blue', label='Random Forest')
plt.xlabel('Model Type')
plt.ylabel('Combined MSE')
plt.title('Random Forest MSE Comparison')
plt.legend()

# GB MSE Comparison
plt.subplot(1, 2, 2)
plt.bar(models, combined_mse_gb, color='green', label='Gradient Boosting')
plt.xlabel('Model Type')
plt.title('Gradient Boosting MSE Comparison')
plt.legend()

plt.tight_layout()
plt.show()
```



In [262…

```
# Determine the best overall model based on the lowest combined MSE
best_rf_mse = min(combined_mse_rf)
best_gb_mse = min(combined_mse_gb)

overall_best_model = 'Random Forest' if best_rf_mse < best_gb_mse else 'Gradient Boosting'
print(f"The best overall model based on combined MSE is: {overall_best_model}")
```

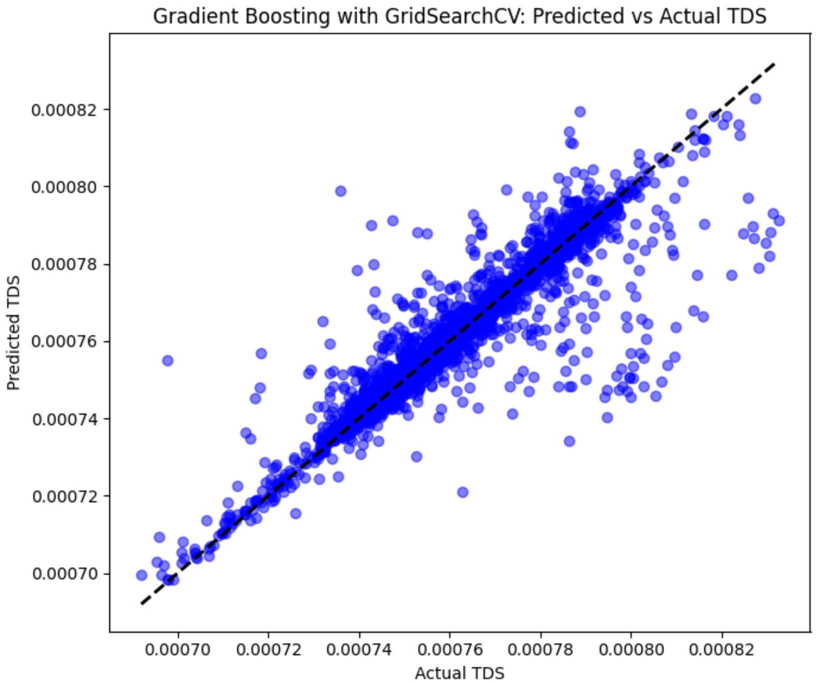
```
The best overall model based on combined MSE is: Gradient Boosting
```

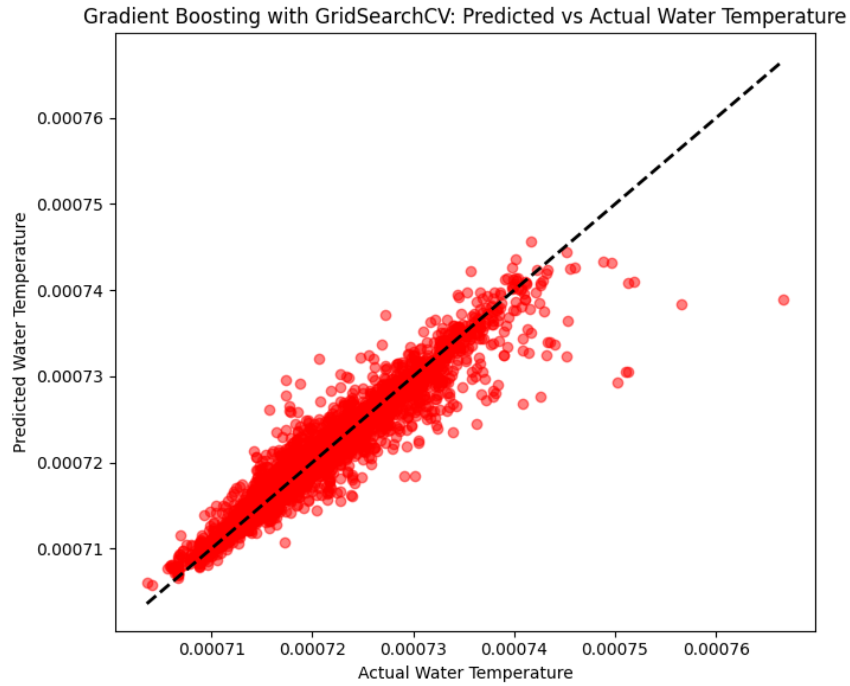
Write a short conclusion here and next steps

The best one seems to be Gradient Boosting using GridSearch

In [263…

```
#Show prediction graph here and metrics for gb_gridsearch
#Remeber, since its GB it's two seperate models one for TDS, the other for water temp
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error

# Plotting the predicted vs actual values for TDS
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(y_test_tds, best_gb_grid_tds.predict(X_test_tds), alpha=0.5, color='blue')
plt.plot([min(y_test_tds), max(y_test_tds)], [min(y_test_tds), max(y_test_tds)], 'k--', lw=2)
plt.title('Gradient Boosting with GridSearchCV: Predicted vs Actual TDS')
plt.xlabel('Actual TDS')
plt.ylabel('Predicted TDS')

# Plotting the predicted vs actual values for Water Temperature
plt.subplot(1, 2, 2)
plt.scatter(y_test_temp, best_gb_grid_temp.predict(X_test_temp), alpha=0.5, color='red')
plt.plot([min(y_test_temp), max(y_test_temp)], [min(y_test_temp), max(y_test_temp)], 'k--', lw=2)
plt.title('Gradient Boosting with GridSearchCV: Predicted vs Actual Water Temperature')
plt.xlabel('Actual Water Temperature')
plt.ylabel('Predicted Water Temperature')

plt.tight_layout()
plt.show()
```


Gradient Boosting with GridSearchCV: Predicted vs Actual TDS
Predicted TDS
Actual TDS
0.00070
0.00072
0.00074
0.00076
0.00078
0.00080
0.00082


Gradient Boosting with GridSearchCV: Predicted vs Actual Water Temperature
Predicted Water Temperature
Actual Water Temperature
0.00071
0.00072
0.00073
0.00074
0.00075
0.00076