FinalProject

April 12, 2024

1 Prediction of Sea Surface Temperature Using Atmospheric Features.

1.1 Introduction

Raising temperatures lead to heavy rainfalls, destructive floods, and droughts in many places. To escape from devastating events in the future, prediction of sea surface temperature (SST) using atmospheric features has emerged as a vital area of research, offering insights into climate dynamics and forecasting potential environmental impacts. The relationship between atmospheric conditions and SST fluctuations, particularly during phenomena like El Niño, presents a complex yet intriguing challenge for predictive analytics. In this study, I aim to explore the predictive capabilities of atmospheric variables in forecasting SST variations, contributing to the advancement of climate modeling and predictive analytics.

1.1.1 Import essential libraries

[ ]:
```
import numpy as np              # Handling array
import pandas as pd             # Handling data frame
import matplotlib.pyplot as plt  # To draw plot
import seaborn as sns           # To draw plot
from sklearn.model_selection import train_test_split   # To split the dataset
from sklearn.feature_selection import SelectKBest    # To Choose the best␣
 ↪features
from sklearn.feature_selection import f_regression   # To Choose the best␣
 ↪features
from sklearn.preprocessing import RobustScaler       # To normalise features
from sklearn.preprocessing import StandardScaler     # To normalise features
from sklearn.pipeline import Pipeline                # To chining multiple␣
 ↪methods
from sklearn.linear_model import LinearRegression    # Prediction method
from sklearn.tree import DecisionTreeRegressor       # Prediction method
from sklearn.ensemble import RandomForestRegressor   # Prediction method
from sklearn.model_selection import GridSearchCV     # To find the best K value
from sklearn.neighbors import KNeighborsRegressor    # Prediction method
from sklearn.metrics import r2_score, mean_squared_error  # Evaluation metrics
from sklearn.model_selection import KFold            # K Fold Cross Validation␣
 ↪method
```

1.2 Data Preprocessing

1.2.1 Loading Dateset into the environment

```
[ ]: el_df = pd.read_csv(r'D:/Kaggle/elnino.csv')
```

1.2.2 Exploring the dataset to understand

```
[ ]: el_df.shape
```

```
[ ]: (178080, 12)
```

```
[ ]: el_df.head()
```

```
[ ]:    Observation   Year   Month   Day     Date   Latitude   Longitude  \
     0            1     80       3     7   800307      -0.02     -109.46
     1            2     80       3     8   800308      -0.02     -109.46
     2            3     80       3     9   800309      -0.02     -109.46
     3            4     80       3    10   800310      -0.02     -109.46
     4            5     80       3    11   800311      -0.02     -109.46

        Zonal Winds  Meridional Winds  Humidity  Air Temp  Sea Surface Temp
     0         -6.8               0.7         .     26.14             26.24
     1         -4.9               1.1         .     25.66             25.97
     2         -4.5               2.2         .     25.69             25.28
     3         -3.8               1.9         .     25.57             24.31
     4         -4.2               1.5         .      25.3             23.19
```

```
[ ]: el_df.columns
```

```
[ ]: Index(['Observation', ' Year', ' Month', ' Day', ' Date', ' Latitude',
            ' Longitude', ' Zonal Winds', ' Meridional Winds', ' Humidity',
            ' Air Temp', ' Sea Surface Temp'],
           dtype='object')
```

1.2.3 Renaming variables

Due to having white space before the variable names.

Reformating that as I desired.

```
[ ]: el_df.columns = [col.strip() for col in el_df.columns]
     el_df.columns = [col.replace(' ','_') for col in el_df.columns]
```

```
[ ]: el_df.dtypes
```

```
[ ]: Observation              int64
     Year                     int64
     Month                    int64
```

```
Day                      int64
Date                     int64
Latitude               float64
Longitude              float64
Zonal_Winds             object
Meridional_Winds        object
Humidity                object
Air_Temp                object
Sea_Surface_Temp        object
dtype: object
```

1.2.4 Changing variables datatype

It seems some variables are in object datatype, but they are supposed to be numeric.

Changing object datatype into numeric datatype.

I converted the whole data frame into numeric values in a single step since the dataset contains numeric values.

[ ]:
```
el_df= el_df.apply(pd.to_numeric, errors='coerce')
el_df.dtypes
```

[ ]:
```
Observation              int64
Year                     int64
Month                    int64
Day                      int64
Date                     int64
Latitude               float64
Longitude              float64
Zonal_Winds            float64
Meridional_Winds       float64
Humidity               float64
Air_Temp               float64
Sea_Surface_Temp       float64
dtype: object
```

[ ]:
```
el_df.isna().sum()
```

[ ]:
```
Observation              0
Year                     0
Month                    0
Day                      0
Date                     0
Latitude                 0
Longitude                0
Zonal_Winds          25163
Meridional_Winds     25162
Humidity             65761
```

```
Air_Temp            18237
Sea_Surface_Temp    17007
dtype: int64
```

1.2.5 Replacing missing values

Replacing missing values from each column with their most occurred value.

[ ]:
```
el_df = el_df.apply(lambda x:x.fillna(x.value_counts().index[0]))
el_df.isna().sum()
```

[ ]:
```
Observation         0
Year                0
Month               0
Day                 0
Date                0
Latitude            0
Longitude           0
Zonal_Winds         0
Meridional_Winds    0
Humidity            0
Air_Temp            0
Sea_Surface_Temp    0
dtype: int64
```

[ ]:
```
el_df.describe()
```

[ ]:
```
         Observation           Year          Month            Day  \
count  178080.000000  178080.000000  178080.000000  178080.000000
mean    89040.500000      93.302325       6.504869      15.720536
std     51407.412306       3.393818       3.459657       8.800487
min         1.000000      80.000000       1.000000       1.000000
25%     44520.750000      92.000000       4.000000       8.000000
50%     89040.500000      94.000000       6.000000      16.000000
75%    133560.250000      96.000000      10.000000      23.000000
max    178080.000000      98.000000      12.000000      31.000000

                Date       Latitude      Longitude    Zonal_Winds  \
count  178080.000000  178080.000000  178080.000000  178080.000000
mean   933689.455374       0.473626     -54.025233      -3.572571
std     33900.474320       4.583041     135.363994       3.195025
min    800307.000000      -8.810000    -180.000000     -12.400000
25%    920116.000000      -2.010000    -154.950000      -5.500000
50%    940601.000000       0.010000    -111.260000      -4.600000
75%    960617.000000       4.980000     147.010000      -2.000000
max    980623.000000       9.050000     171.080000      14.300000

       Meridional_Winds       Humidity       Air_Temp  Sea_Surface_Temp
```

```
count    178080.000000  178080.000000  178080.000000    178080.000000
mean          0.186212      81.813881      26.971791        27.859010
std           2.783660       4.286456       1.738878         2.006072
min         -11.600000      45.400000      17.050000        17.350000
25%          -1.400000      79.800000      26.270000        26.990000
50%          -0.200000      82.800000      27.550000        28.520000
75%           1.900000      82.800000      28.080000        29.220000
max          13.000000      99.900000      31.660000        31.260000
```

2 Exploratory Data Analysis

2.0.1 Questions

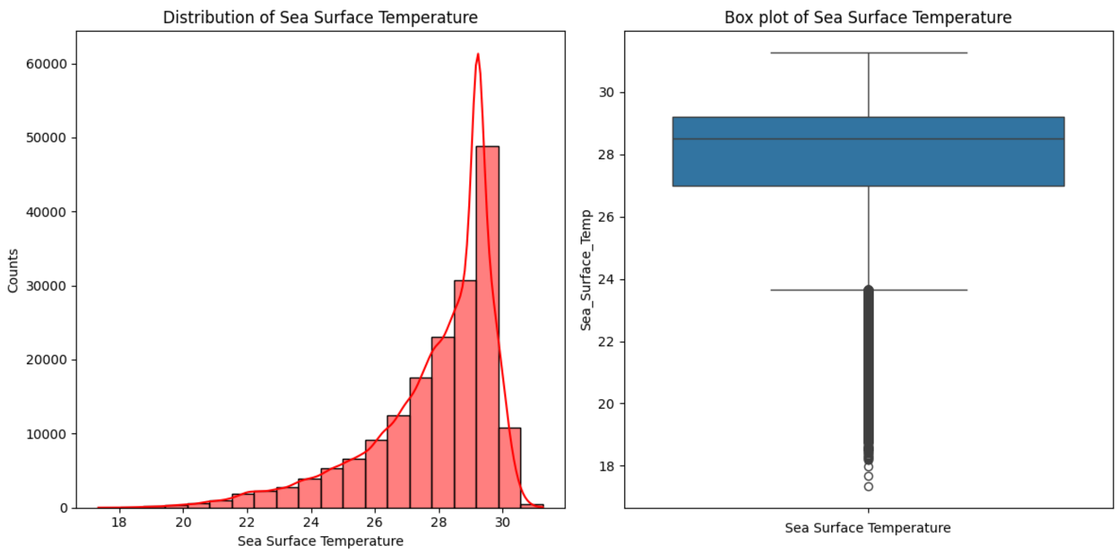
Q1. How do the variables relate to each other?

Q2. Which variables have a greater effect on climate variations?

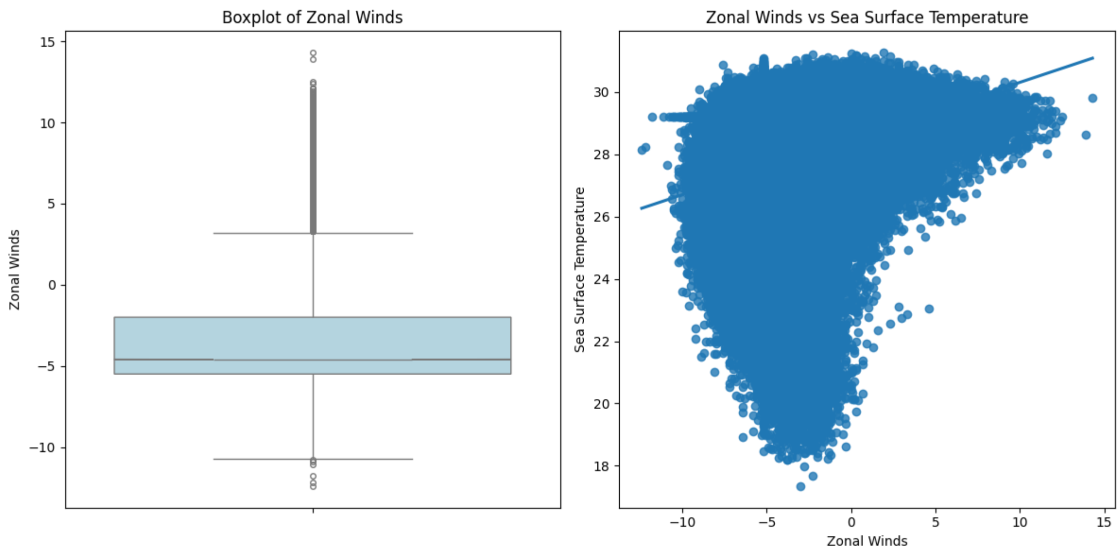
I am specifically interested in relevant features including Zonal Winds, Meridional Winds, Humidity, Air Temperature, and Sea Surface Temperature. The target variable is Sea Surface Temperature because this El Nino data set studies the El Nino effect in the Tropical Pacific, and Sea Surface Temperature indicates the change of the El Nino effect. Therefore, I want to investigate the association between Sea Surface Temperature and the rest of the variables, so I know whether the rest showcase any sign of the El Nino effect.

2.0.2 Univariate and Bivariate Analysis

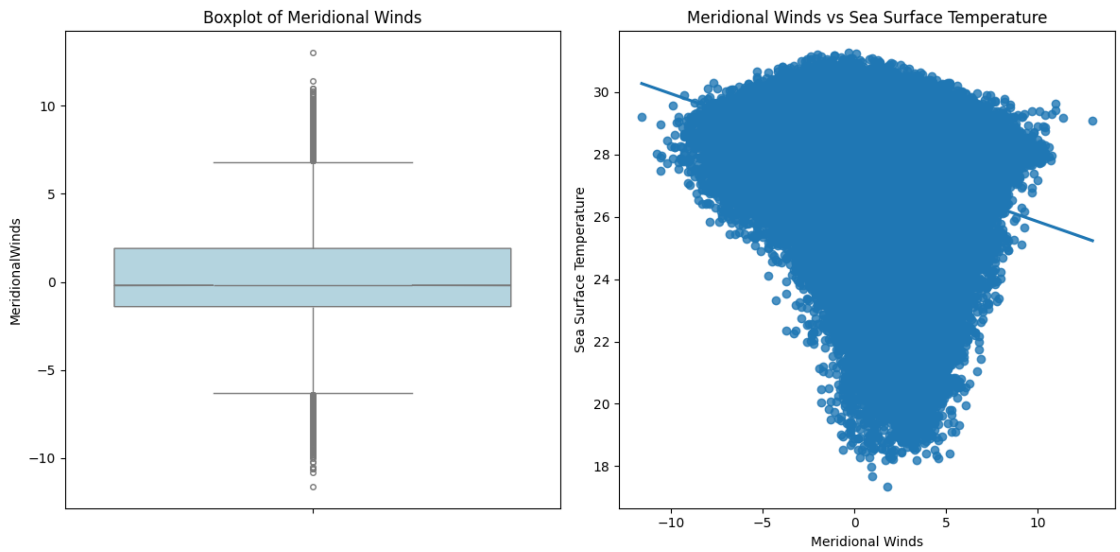
[ ]:
```python
# Distribution of the target variable (Sea Surface Temperature)

# Spliting columns to draw two plots
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Histogram of Sea Surface Temperature
sns.histplot(el_df['Sea_Surface_Temp'], bins=20, kde=True, color='red',␣
 ↪ax=axes[0])
axes[0].set_title('Distribution of Sea Surface Temperature')
axes[0].set_xlabel('Sea Surface Temperature')
axes[0].set_ylabel('Counts')

# Box plot of Sea Surface Temperature
sns.boxplot(el_df['Sea_Surface_Temp'], ax=axes[1])
axes[1].set_title('Box plot of Sea Surface Temperature')
axes[1].set_xlabel('Sea Surface Temperature')

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



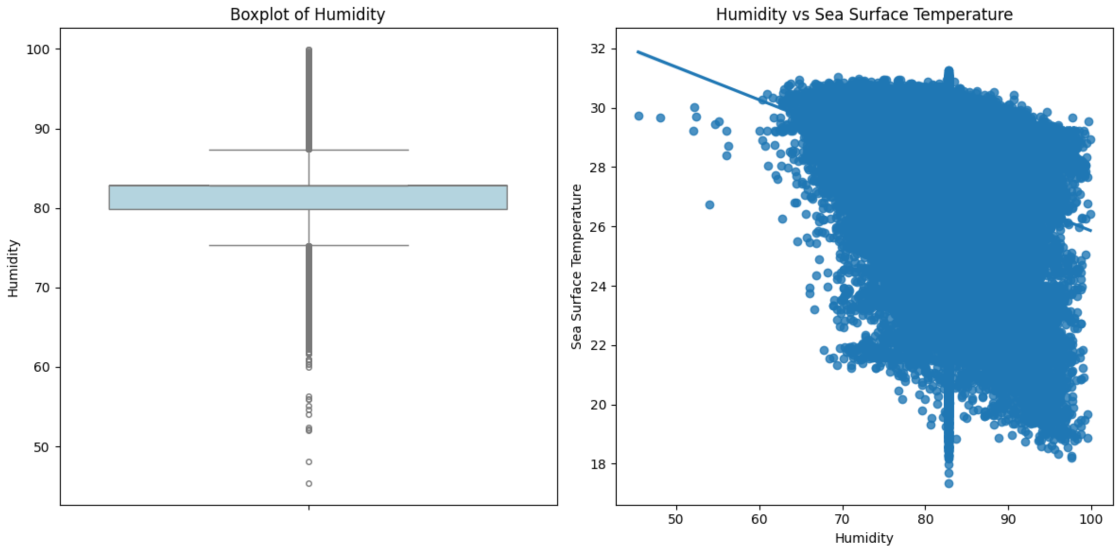
[ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Boxplot of Zonal Winds
sns.boxplot(y=el_df['Zonal_Winds'], color="lightblue", notch=True, fliersize=4,␣
    ↪ax=axes[0])
axes[0].set_ylabel('Zonal Winds')
axes[0].set_title('Boxplot of Zonal Winds')

# Regression plot of Zonal Winds vs Sea Surface Temperature
sns.regplot(x=el_df['Zonal_Winds'], y=el_df['Sea_Surface_Temp'], ax=axes[1])
axes[1].set_ylabel('Sea Surface Temperature')
axes[1].set_xlabel('Zonal Winds')
axes[1].set_title('Zonal Winds vs Sea Surface Temperature')

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



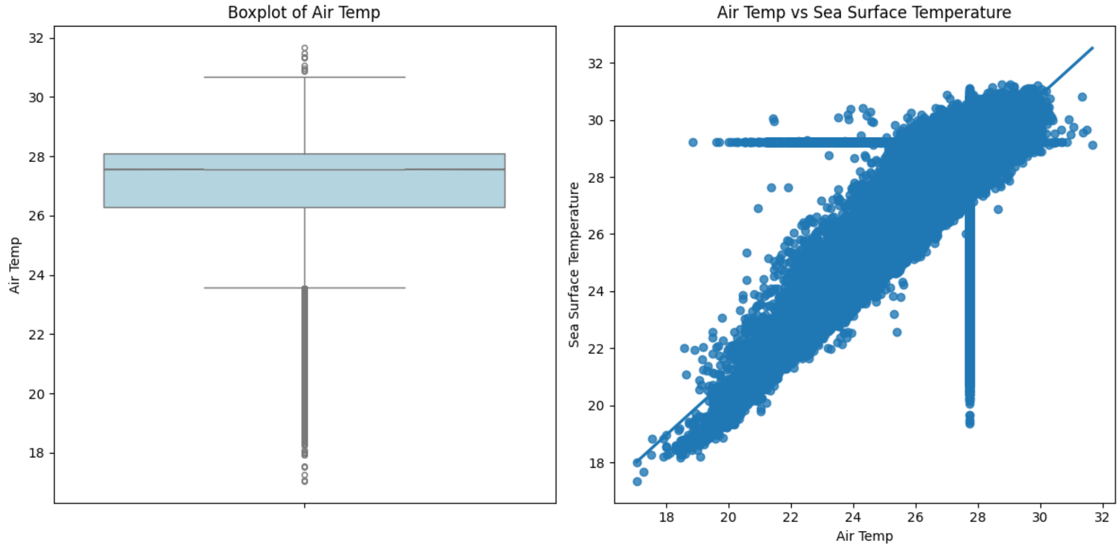

```
[ ]: fig, axes = plt.subplots(1, 2, figsize=(12, 6))

     # Boxplot of MeridionalWinds
     sns.boxplot(y=el_df['Meridional_Winds'], color="lightblue", notch=True,␣
      ↪fliersize=4, ax=axes[0])
     axes[0].set_ylabel('MeridionalWinds')
     axes[0].set_title('Boxplot of Meridional Winds')

     # Regression plot of Meridional Winds vs Sea Surface Temperature
     sns.regplot(x=el_df['Meridional_Winds'], y=el_df['Sea_Surface_Temp'],␣
      ↪ax=axes[1])
     axes[1].set_ylabel('Sea Surface Temperature')
     axes[1].set_xlabel('Meridional Winds')
     axes[1].set_title('Meridional Winds vs Sea Surface Temperature')

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



[ ]:
```python
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Boxplot of Humidity
sns.boxplot(y=el_df['Humidity'], color="lightblue", notch=True, fliersize=4,␣
 ↪ax=axes[0])
axes[0].set_ylabel('Humidity')
axes[0].set_title('Boxplot of Humidity')

# Regression plot of Meridional Winds vs Sea Surface Temperature
sns.regplot(x=el_df['Humidity'], y=el_df['Sea_Surface_Temp'], ax=axes[1])
axes[1].set_ylabel('Sea Surface Temperature')
axes[1].set_xlabel('Humidity')
axes[1].set_title('Humidity vs Sea Surface Temperature')

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



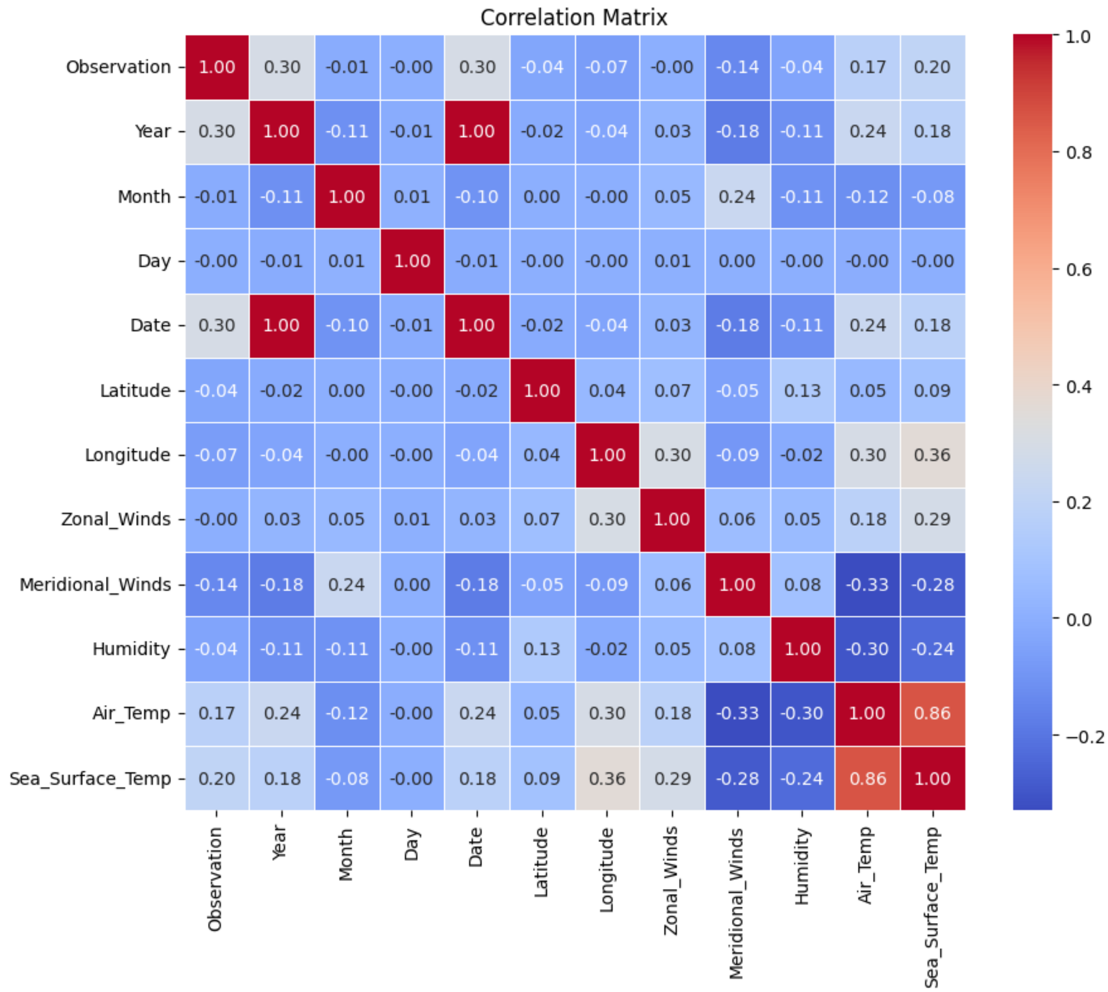
[ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Boxplot of Air Temperature
sns.boxplot(y=el_df['Air_Temp'], color="lightblue", notch=True, fliersize=4,␣
↪ax=axes[0])
axes[0].set_ylabel('Air Temp')
axes[0].set_title('Boxplot of Air Temp')

# Regression plot of Meridional Winds vs Sea Surface Temperature
sns.regplot(x=el_df['Air_Temp'], y=el_df['Sea_Surface_Temp'], ax=axes[1])
axes[1].set_ylabel('Sea Surface Temperature')
axes[1].set_xlabel('Air Temp')
axes[1].set_title('Air Temp vs Sea Surface Temperature')

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



It Seems all the predictor variables have some linear relationship with the target variable (Sea Surface Temperature).

2.0.3 Relationship between variables

[ ]:
```
# Correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(el_df.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.
  ↪5)
plt.title('Correlation Matrix')
plt.show()
```



Q1. Air temperature and sea surface temperature have a strong positive correlation. Otherwise variables have low negative to low positive correlation with each other.

3 Training and Test Set

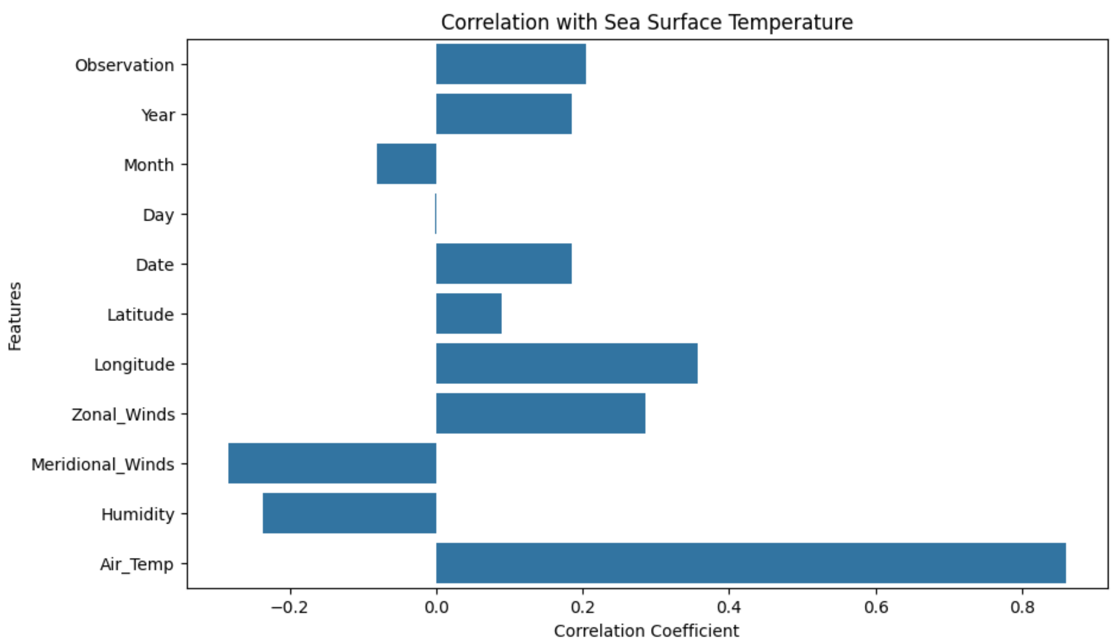
[ ]:
```
# Feature variables
X = el_df.drop(columns = 'Sea_Surface_Temp')
```

[ ]:
```
# Target variable
y = el_df.Sea_Surface_Temp
```

[ ]:
```
# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state = 1)
```

3.0.1 Feature Selection

[ ]:
```
# Compute correlation between features and target variable
correlation = X_train.corrwith(y_train)

# Visualize correlation
plt.figure(figsize=(10, 6))
sns.barplot(x=correlation.values, y=correlation.index)
plt.title('Correlation with Sea Surface Temperature')
plt.xlabel('Correlation Coefficient')
plt.ylabel('Features')
plt.show()

# Select features with the highest correlation using SelectKBest
selector = SelectKBest(score_func=f_regression, k=5)
selector.fit(X_train, y_train)

# Selected features
selected_features = X_train.columns[selector.get_support()]
print('Selected Features based on Correlation: ', selected_features)
```




```
Selected Features based on Correlation:  Index(['Longitude', 'Zonal_Winds',
'Meridional_Winds', 'Humidity', 'Air_Temp'], dtype='object')
```

[ ]:
```
# Making selected Features as predicting features
X = el_df[selected_features]
```

```
[ ]: # Split the data into training, and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=2)
```

4 Prediction Models

4.1 Methods

I used a range of regression algorithms to predict sea surface temperature (SST) using atmospheric features. Linear regression serves as a baseline model, providing insights into the linear relationships between predictors and the target variable. Decision tree regression offers a non-linear approach, capturing complex interactions between atmospheric factors and SST fluctuations. Random forest regression further enhances predictive performance by aggregating multiple decision trees, reducing overfitting, and increasing robustness to noise in the data. Additionally, k-nearest neighbor (KNN) regression is utilized to identify similar atmospheric conditions and infer SST values based on their proximity. Each algorithm offers unique advantages suited to the complex and dynamic nature of SST prediction.

4.1.1 Linear Regression model

```
[ ]: # LinearRegression
# Creating a pipeline with RobustScaler and a linear regression model
# Using RobustScaler for feature scaling

pipeline = Pipeline([
    ('scaler', RobustScaler()),
    ('regressor', LinearRegression())
])

# Fitting the pipeline on the training data
pipeline.fit(X_train, y_train)

# Predict on the test set
y_predict = pipeline.predict(X_test)

# Calculate mean squared error (MSE) and r2 value to measure the performance of␣
 ↪the model
mse_lr = mean_squared_error(y_test, y_predict)
r2_lr = r2_score(y_test, y_predict)

print('Mean Squared Error:' , mse_lr)
print('r2 Value:', r2_lr)
```

```
Mean Squared Error: 0.944835144140002
r2 Value: 0.765618166525813
```

4.1.2 Decision Tree Regressor

[ ]:
```
# DecisionTreeRegressor
# Creating a pipeline with StandardScaler and a Decision Tree Regressor
# Using StandardScaler for feature scaling

pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', DecisionTreeRegressor())
])

# Fitting the pipeline on the training data
pipeline.fit(X_train,y_train)

# Predict on the test set
y_predict = pipeline.predict(X_test)

# Calculate mean squared error (MSE) and r2 value to measure the performance of␣
↪the model
mse_dr = mean_squared_error(y_test, y_predict)
r2_dr = r2_score(y_test, y_predict)

print('Mean Squared Error:' , mse_dr)
print('r2 Value:', r2_dr)
```

```
Mean Squared Error: 0.6070466387777683
r2 Value: 0.8494121381031173
```

4.1.3 K Nearest Neighbor and K Fold Cross Validation

[ ]:
```
# Define the range of k values to search over
k_values = range(1, 21)

# Create a dictionary containing the hyperparameters to search
param_grid = {'n_neighbors': k_values}

# Initialize the KNeighborsRegressor
knn = KNeighborsRegressor()

# Initialize GridSearchCV with the KNeighborsRegressor, parameter grid, and␣
↪cross-validation strategy
grid_search = GridSearchCV(knn, param_grid, cv=5,␣
↪scoring='neg_mean_squared_error')

# Perform grid search with cross-validation
grid_search.fit(X_train, y_train)

# Get the best k value
```

```
k = grid_search.best_params_['n_neighbors']

print("Best k value:", k)
```

```
Best k value: 12
```

[ ]:
```
# Converting dataframe into numpy array
X = X.values
y = y.values
```

[ ]:
```
# Initialize the KFold object
kf = KFold(n_splits=10, shuffle=True, random_state=4)

# Initialising lists to store kfold, R2 score and MSE for each fold
Kfold = []
r2_scores = []
mse_values = []

# Iterate over the folds
for fold, (train_indices, val_indices) in enumerate(kf.split(X)):
    print(f"Fold {fold+1}:")

    # Split the data into training and validation sets
    X_train, X_val = X[train_indices], X[val_indices]
    y_train, y_val = y[train_indices], y[val_indices]

    # Initialize and train the KNN model
    knn_regressor = KNeighborsRegressor(k)
    knn_regressor.fit(X_train, y_train)

    # Make predictions on the validation set
    y_pred = knn_regressor.predict(X_val)

    # Calculate the R-squared score and MSE for the current fold
    r2 = r2_score(y_val, y_pred)
    mse = mean_squared_error(y_val, y_pred)

    # Append the R-squared score and MSE to the list
    Kfold.append(fold+1)
    r2_scores.append(r2)
    mse_values.append(mse)

    print("MSE:", mse)
    print("R-squared (R2) Score:", r2)
    print()

metrics = pd.DataFrame({'Kfold':Kfold, 'r2': r2_scores, 'mse': mse_values})
best = metrics[metrics['r2'] == metrics['r2'].max()]
```

```python
print(f'Highest R-Squared Value: {best.iloc[0, 1]} and lowest Mean Square Error␣
↪{best.iloc[0, 2]} obtained from fold: {best.iloc[0, 0]}')
```

```
Fold 1:
MSE: 0.5821458555611709
R-squared (R2) Score: 0.8540454911985098

Fold 2:
MSE: 0.6131780321890286
R-squared (R2) Score: 0.8491920867563074

Fold 3:
MSE: 0.6197401518980231
R-squared (R2) Score: 0.8459412369569763

Fold 4:
MSE: 0.6067624806968777
R-squared (R2) Score: 0.8505839185233783

Fold 5:
MSE: 0.6228092364854745
R-squared (R2) Score: 0.8412187877610038

Fold 6:
MSE: 0.5884979242709268
R-squared (R2) Score: 0.8541494620938399

Fold 7:
MSE: 0.5990203173745258
R-squared (R2) Score: 0.8522653510897329

Fold 8:
MSE: 0.6147522530448235
R-squared (R2) Score: 0.8450105364324185

Fold 9:
MSE: 0.5963224124847134
R-squared (R2) Score: 0.852781526983003

Fold 10:
MSE: 0.6332623681148297
R-squared (R2) Score: 0.8445805929472476

Highest R-Squared Value: 0.8541494620938399 and lowest Mean Square Error
0.5884979242709268 obtained from fold: 6
```

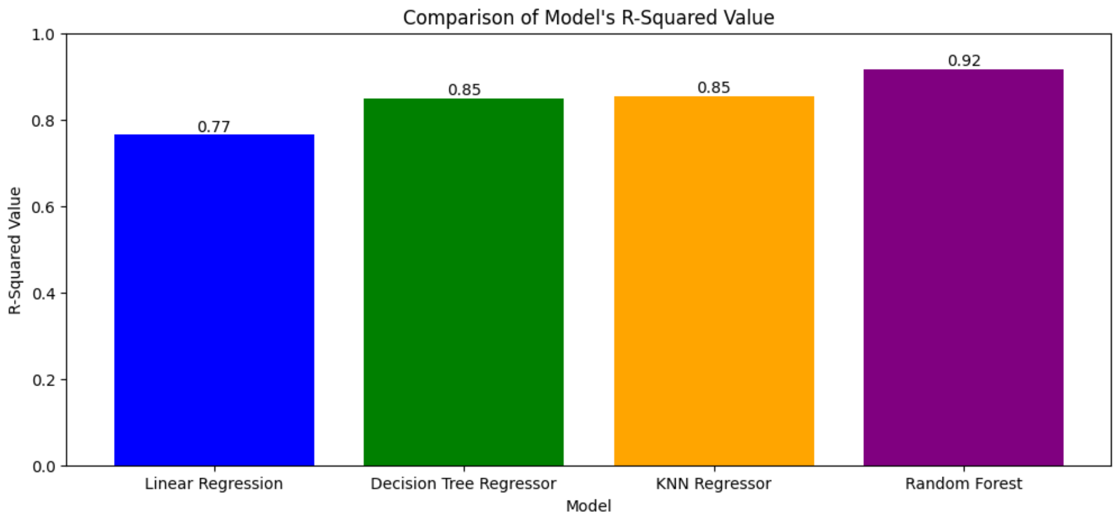
4.1.4 Random Forest Regressor

[ ]:
```
# RandomForestRegressor

# Split the data into training, validation, and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,␣
↪random_state=1)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.
↪1, random_state=2)

# Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

# Initialize and train a Random Forest classifier
rfr = RandomForestRegressor(n_estimators = 100, random_state=3)

# fitting the model on to the training data
rfr.fit(X_train_scaled, y_train)

# Evaluate the model on the validation set
y_predict = rfr.predict(X_val_scaled)

# Calculate mean squared error (MSE) and r2 value to measure the performance of␣
↪the model
mse_rf = mean_squared_error(y_val, y_predict)
r2_rf = r2_score(y_val, y_predict)

print('Mean Squared Error:' , mse_rf)
print('r2 Value:', r2_rf)
```

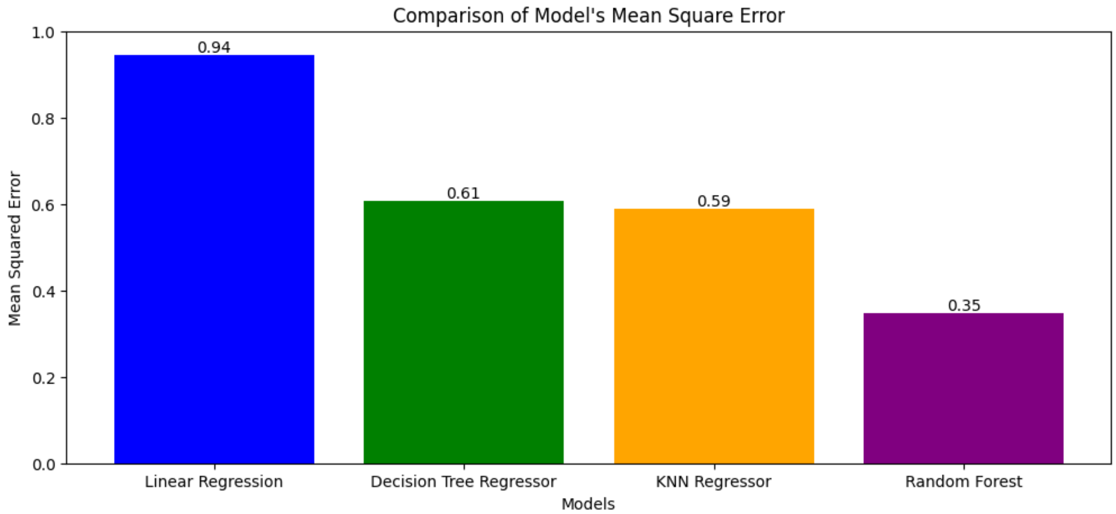
```
Mean Squared Error: 0.3461954540527298
r2 Value: 0.9168928518722298
```

[ ]:
```
# Plot metrics
models = ['Linear Regression',  'Decision Tree Regressor', 'KNN Regressor',␣
↪'Random Forest']
r2 = [r2_lr, r2_dr, best.iloc[0, 1], r2_rf]

plt.figure(figsize=(12, 5))
bars = plt.bar(models, r2, color=['blue', 'green', 'orange', 'purple'])
plt.xlabel('Model')
plt.ylabel('R-Squared Value')
plt.title("Comparison of Model's R-Squared Value")
plt.ylim([0.0, 1.0])
```

```
# Annotate bars with their values
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2),␣
 ↪va='bottom', ha='center')
plt.show()
```




```
[ ]: # Plot metrics
models = ['Linear Regression',  'Decision Tree Regressor', 'KNN Regressor',␣
 ↪'Random Forest']
mse = [mse_lr, mse_dr, best.iloc[0, 2], mse_rf]

plt.figure(figsize=(12, 5))
bars = plt.bar(models, mse, color=['blue', 'green', 'orange', 'purple'])
plt.xlabel('Models')
plt.ylabel('Mean Squared Error')
plt.title("Comparison of Model's Mean Square Error")
plt.ylim([0.0, 1.0])

# Annotate bars with their values
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2),␣
 ↪va='bottom', ha='center')
plt.show()
```



Q2. The Random Forest Regressor method, with over 91% R-squared value, indicates that atmospheric variables such as zonal winds, meridional winds, humidity, and air temperature significantly influence climate variations. Its superior performance underscores its efficacy in forecasting sea surface temperature fluctuations, enriching climate science insights.

5 Results

Among the regression algorithms used, the Random Forest Regressor method emerged as the most effective in predicting sea surface temperature (SST) based on atmospheric features. With a notably high R-squared value and the lowest Mean Squared Error compared to linear regression, decision tree regression, and k-nearest neighbor regression, the Random Forest model demonstrated superior performance in capturing the complex relationships between atmospheric conditions and SST dynamics. The achieved R-squared value of over 91% indicates the model's ability to explain the variation in SST with exceptional accuracy, leveraging features such as zonal winds, meridional winds, humidity, and air temperature. This suggests that the Random Forest algorithm effectively harnesses the collective predictive power of these atmospheric variables to forecast SST fluctuations with a high degree of precision. The robustness and adaptability of the Random Forest approach make it a promising tool for advancing predictive modeling in the realm of climate science, offering valuable insights into the intricate interplay between atmospheric dynamics and oceanic processes.

6 Conclusion

In this study, I investigated the prediction of sea surface temperature (SST) using atmospheric features, employing a range of regression algorithms including linear regression, decision tree regression, random forest regression, and k-nearest neighbor regression. Our results demonstrate that the Random Forest Regressor method outperforms the other algorithms, achieving a remarkable R-squared value of over 90% and the lowest Mean Squared Error. This indicates the Random Forest model's exceptional ability to explain SST variation with high accuracy. Moving forward, further research could explore additional predictors and refine modeling techniques to enhance the accuracy and robustness of SST predictions, ultimately contributing to our understanding of climate dynamics and environmental forecasting.