

## Contents

1. ABSTRACT.....	2
2. PROBLEM STATMENT .....	2
3. Justification for Actions Performed .....	3
3.1 Data Cleaning and Preprocessing: .....	3
3.2 Script in R For Data Cleaning and Pre-Processing .....	3
3.3 Exploratory Data Analysis (EDA):.....	5
3.3.1 EDA Script.....	6
4. Visualization of Cleaned Data .....	7
5. Model Building .....	9
5.1 Model Evaluation:.....	9
5.2 Script of Models.....	10
5.2.1 Linear Regression Model.....	10
5.2.2 Random Forest Model.....	11
5.2.3 Gradient Boosting Model .....	11
6. Results and Interpretation: Model Comparison and Analysis .....	12
6.1 Interpretation .....	12
Linear Regression:.....	12
Random Forest: .....	12
Gradient Boosting Machine (GBM):.....	13
7. Usefulness for Organizations.....	15
7.1 Agriculture:.....	15
7.2 Environmental Monitoring:.....	15
7.3 Resource Management:.....	15
8. Conclusion.....	15
9. References.....	16
9.1 Journal References:.....	16
9.2 Book References: .....	16

# 1. ABSTRACT

The report highlights data-analysis ranging from a brief to the depth and predictive modelling of soil moisture (SMOIS) by variables from the provided data set that are skin temperature (TSK) and 2-meter specific humidity (Q2). These variables which have been used to forecast soil moisture through simple predictive models. A weather dataset was used with over five thousand entries about variables like Skin temperature, Surface pressure, Soil Temperature among others. I performed analysis of these data by dividing my work into chunks. At First, the data was cleaned and Pre-Processed. After that I performed EDA on the cleaned dataset and then do different types of visualization such as histograms box plots and timeseries plot on it for my better understandings. After that I define my Problem statement based on given dataset and data description. It was to predict Soil Moisture. The machine learning techniques helps me to predict soil moisture. Choosing three different models on my preferences as per the given requirement. These models are Linear Regression, Random Forest, and Gradient Boosting Machine (GBM). From these three models, Random Forest model came out as the best model that is most accurate in predicting soil moisture with an R-squared value Of 0.932 approximately 93%, followed by GBM at 91% while Linear Regression shows the least accuracy of 83%. This whole Process from cleaning of data to prediction the soil moisture is meant to help particularly for those companies that are specially working in agriculture environmental monitoring or resource management; thus enhance its ability to predict soil moisture and make prediction about it.

# 2. PROBLEM STATMENT

Soil moisture prediction is a very important and critical part of many areas such as farming, environmental monitoring and resource management. Soil moisture greatly affects crops growth, irrigation needs as well as ecosystem balance. As Soil moisture connects in influencing factors like temperature and humidity in complex ways, we must have a same model to predict it.

To solve the problem, I want to create a model able of predicting soil moisture (SMOIS) using cleaned data on skin temperature (TSK) and 2-meter specific humidity (Q2). The dataset that is given includes the environmental stimulus of skin temperature or surface temperature. It is the recorded temperature, surface pressure and rainfall at intervals of time. The main goal is to find effective statistical and machine learning models to predict soil moisture, at its best.

**My major tasks include:**

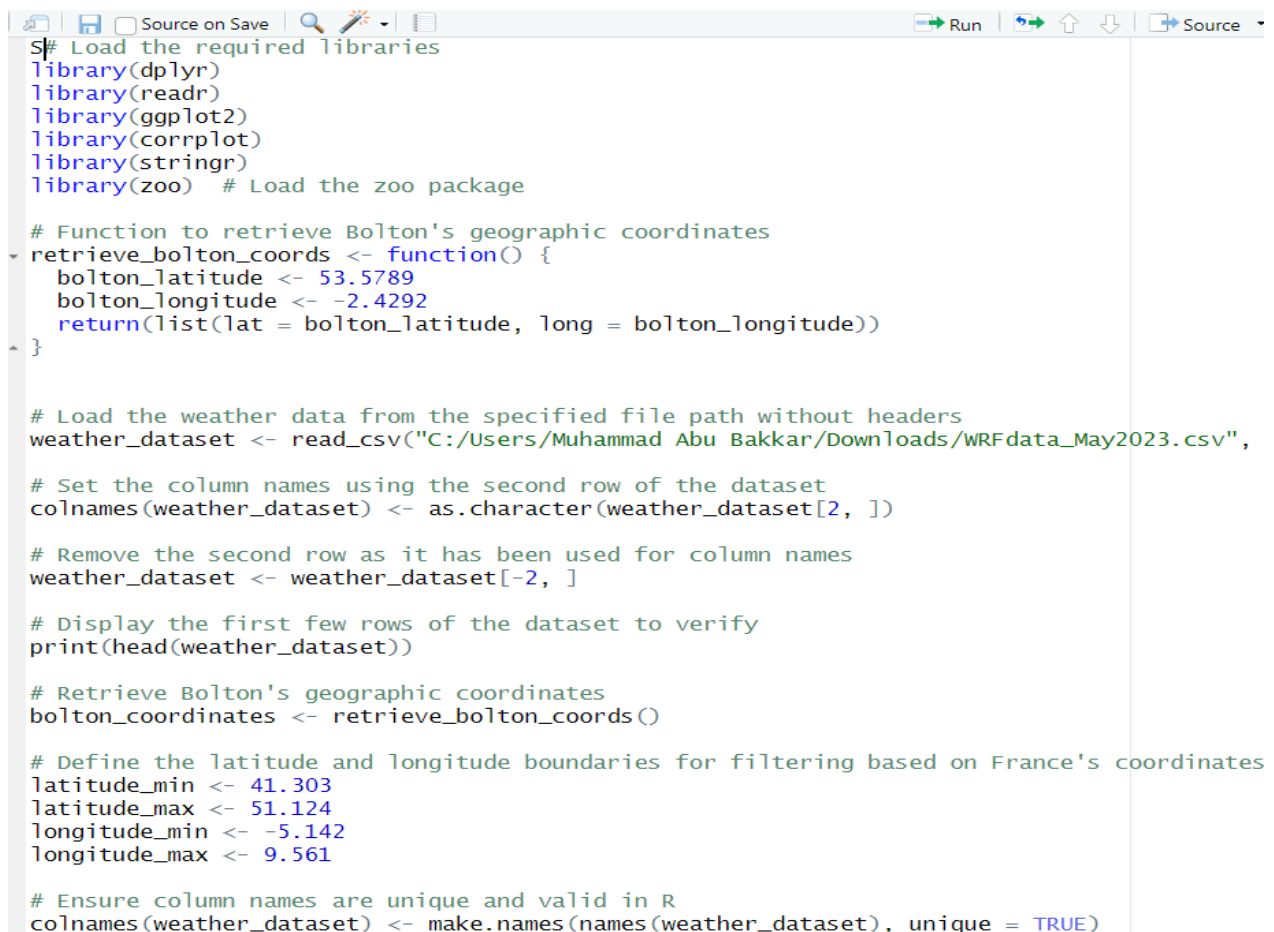
1. Clean and process data to deal with missing values and outliers.
2. Perform Exploratory Data Analysis (EDA) to understand data distributions and relationships.
3. Build Model using Linear Regression, Random Forest, and Gradient Boosting Machine (GBM).
4. Run each model and then choose the model with most accuracy percentage.

## 3. Justification for Actions Performed

### 3.1 Data Cleaning and Preprocessing:

- **Handling Missing Values:** In data cleaning process handling missing values are very important. A technique named as imputation technique is used to adjust missing values and replace NA values with the average of the previous non-missing two components (taking the mean) in the given dataset. This technique will help to make the dataset complete so it can be utilized for modelling.
- **Removing Columns:** For the soil moisture prediction, I just focus on the independent variables that are (TSK and Q2) for my prediction task. I also removed columns of XLAT and XLONG after getting the France coordinate that are approximately ranges between latitude 41°N and 51°N and longitude 5°W to 8°. Now my problem statement becomes more dominant for prediction at specific area.
- **Outlier Detection:** Outliers can affect my model, so I use the IQR method to identify and to prevent extreme values. So, I calculated IQR and removed the outliers.

### 3.2 Script in R For Data Cleaning and Pre-Processing



```
Source on Save | Run | Source
# Load the required libraries
library(dplyr)
library(readr)
library(ggplot2)
library(corrplot)
library(stringr)
library(zoo) # Load the zoo package

# Function to retrieve Bolton's geographic coordinates
retrieve_bolton_coords <- function() {
  bolton_latitude <- 53.5789
  bolton_longitude <- -2.4292
  return(list(lat = bolton_latitude, long = bolton_longitude))
}

# Load the weather data from the specified file path without headers
weather_dataset <- read_csv("C:/Users/Muhammad Abu Bakkar/Downloads/WRFdata_May2023.csv",

# Set the column names using the second row of the dataset
colnames(weather_dataset) <- as.character(weather_dataset[2, ])

# Remove the second row as it has been used for column names
weather_dataset <- weather_dataset[-2, ]

# Display the first few rows of the dataset to verify
print(head(weather_dataset))

# Retrieve Bolton's geographic coordinates
bolton_coordinates <- retrieve_bolton_coords()

# Define the latitude and longitude boundaries for filtering based on France's coordinates
latitude_min <- 41.303
latitude_max <- 51.124
longitude_min <- -5.142
longitude_max <- 9.561

# Ensure column names are unique and valid in R
colnames(weather_dataset) <- make.names(names(weather_dataset), unique = TRUE)
```

Figure 1: First Script of Data Cleaning and Pre-Processing

```

# Filter the dataset to include only rows within the geographic boundaries of France
france_data <- weather_dataset %>%
  filter(!(XLAT == bolton_coordinates$lat & XLONG == bolton_coordinates$long)) %>%
  filter(XLAT >= latitude_min & XLAT <= latitude_max) %>%
  filter(XLONG >= longitude_min & XLONG <= longitude_max)

# Ensure that at least 350 rows are randomly sampled from the filtered dataset
france_data <- france_data %>%
  sample_n(min(n(), 350))

# Remove the latitude and longitude columns from the dataset
data_without_coordinates <- france_data %>%
  select(-XLAT, -XLONG)

# Function to replace NA values using interpolations
fill_na_with_mean <- function(x) {
  na_fill <- na.approx(x, maxgap = Inf, rule = 2) # Use na.approx from the zoo package
  return(na_fill)
}

# Apply the NA filling function to all columns in the dataset
data_filled <- data_without_coordinates %>%
  mutate(across(everything(), ~ fill_na_with_mean(.)))

# Display the first few rows of the dataset with NA values filled
print(head(data_filled))

# Define the starting date and time for the data processing
start_datetime <- as.POSIXct("2018-05-01 00:00:00", format="%Y-%m-%d %H:%M:%S")

# Initialize an empty dataframe to store processed data
processed_data <- data.frame()

# List of columns to keep (excluding geographic coordinates)
base_columns <- c("TSK", "PSFC", "X.U10.", "X.V10.",
                  "X.Q2.", "RAINC", "RAINNC", "SNOW", "TSLB", "SMOIS")

```

*Figure 2: Second Script of Data Cleaning*

```

# Create a sequence for time increments, every 3 hours up to 120 intervals
time_increments <- seq(0, 120 * 3 * 3600, by = 3 * 3600) # Every 3 hours up to 120 intervals

# Process the filtered data with the alternative method
for (time_increment in time_increments) {
  # Create a copy of the base columns for the current time increment
  temp_df <- data_filled[, base_columns]

  if (time_increment > 0) {
    # Create suffix for the column names based on the current time increment
    suffix <- paste0(".", time_increment / (3 * 3600))
    columns_with_suffix <- paste0(base_columns, suffix)
    temp_df[, ] <- data_filled[, columns_with_suffix]
  }

  # Compute the datetime for the current time increment
  current_datetime <- start_datetime + time_increment

  # Format the datetime for inclusion in the dataframe
  temp_df$date_time <- format(current_datetime, "%d.%m.%Y.%H.%M")

  # Combine the processed data with the main dataframe
  processed_data <- bind_rows(processed_data, temp_df)
}

# Calculate the wind speed and add it to the processed data
processed_data <- processed_data %>%
  mutate(windspeed = sqrt(`X.U10.`^2 + `X.V10.`^2)) %>%
  mutate(windspeed = round(windspeed, 2)) # Round wind speed to 2 decimal places

# Display the first few rows of the processed data
print(head(processed_data))

# Save the filtered and processed data to a new CSV file
write_csv(processed_data, "C:/Users/Muhammad Abu Bakkar/Downloads/Filtered_France_Data.csv")

# Print a message indicating that the data has been saved
cat("Filtered and processed data has been saved to 'C:/Users/Muhammad Abu Bakkar/Downloads/F")

```

*Figure 3: Third Script of R for Data Cleaning*

### 3.3 Exploratory Data Analysis (EDA):

- **Univariate investigation:** For this purpose, each feature was analysed separately as to understand their dispersion, central location and variability. Histograms and summary statistics were used.
- **Finding Correlations:** Relationships between variables were identified by calculating the correlation matrix. This allows us to examine predictors' relationship with soil moisture and with each other.

### 3.3.1 EDA Script

```
# Load the required libraries
library(dplyr)
library(readr)
library(ggplot2)
library(corrplot)
library(stringr)
library(zoo) # For handling NA values

# Load the processed data
processed_data <- read_csv("C:/Users/Muhammad Abu Bakkar/Downloads/Filtered_France_Data.csv")

# Display the first few rows of the dataset
print(head(processed_data))

# Convert date_time to POSIXct for proper time handling
processed_data$date_time <- as.POSIXct(processed_data$date_time, format="%d.%m.%Y.%H.%M")

# Univariate Analysis
# Define columns of interest for analysis
columns_of_interest <- c("TSK", "PSFC", "X.U10.", "X.V10.", "X.Q2.", "RAINC", "RAINNC", "SNOW", "S")
# Summary Statistics
summary_stats <- processed_data %>%
  select(all_of(columns_of_interest)) %>%
  summary()

print(summary_stats)

# Create histograms for each variable
for (column in columns_of_interest) {
  p <- ggplot(processed_data, aes_string(x = column)) +
    geom_histogram(binwidth = ifelse(column == "Windspeed", 1, 10), fill = "blue", color = "black") +
    labs(title = paste("Histogram of", column), x = column, y = "Frequency") +
    theme_minimal()

  # Save the histogram plot
  ggsave(filename = paste0("C:/Users/Muhammad Abu Bakkar/Downloads/", column, "_histogram.png"), p)
```

Figure 4: Plotting Histogram

```
# Create boxplots for each variable
for (column in columns_of_interest) {
  p <- ggplot(processed_data, aes_string(y = column)) +
    geom_boxplot(fill = "lightblue", color = "blue") +
    labs(title = paste("Boxplot of", column), y = column) +
    theme_minimal()

  # Save the boxplot
  ggsave(filename = paste0("C:/Users/Muhammad Abu Bakkar/Downloads/", column, "_boxplot.png"), p)
}

# Plot time series for each variable
for (column in columns_of_interest) {
  p <- ggplot(processed_data, aes(x = date_time, y = get(column))) +
    geom_line(color = "blue") +
    labs(title = paste("Time Series of", column), x = "Date and Time", y = column) +
    theme_minimal()

  # Save the time series plot
  ggsave(filename = paste0("C:/Users/Muhammad Abu Bakkar/Downloads/", column, "_timeseries.png"), p)
}

# Save summary statistics to a CSV file
write_csv(as.data.frame(summary_stats), "C:/Users/Muhammad Abu Bakkar/Downloads/Summary_Statistics.csv")

# Print a message indicating that the EDA results have been saved
cat("Univariate analysis results and visualizations have been saved to the specified directory")
```

Figure 5: Boxplot and Time Series Plot

## 4. Visualization of Cleaned Data

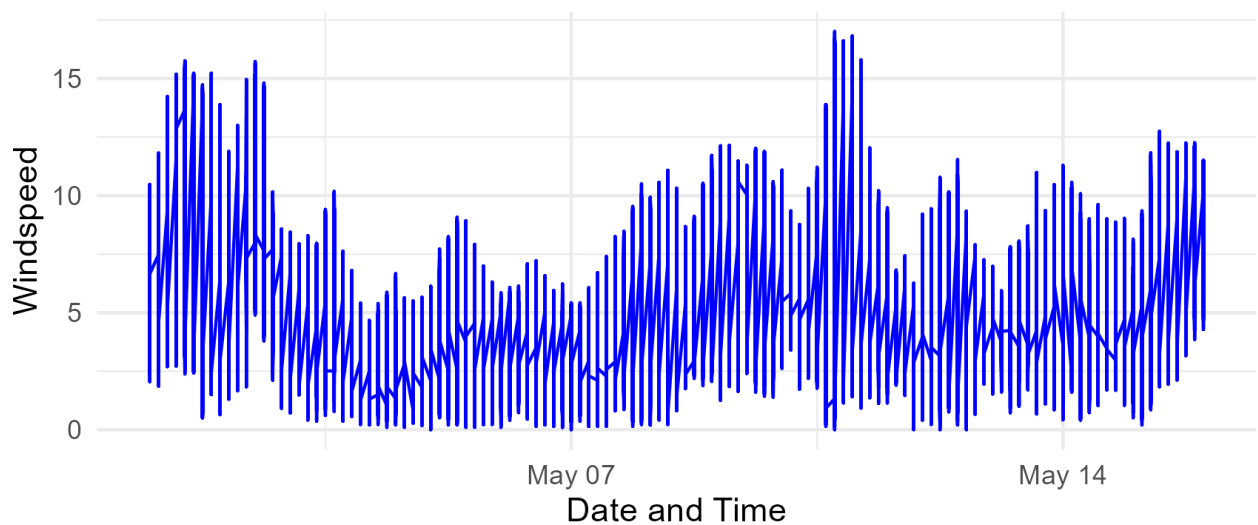
### 4.1 Wind-Speed

Wind Speed is calculated by using the X and Y component. In dataset the variables X.U10 and X.V.10 represent these components that is 10 meters above ground level in X (east-west) and y (north-south) respectively.

Then I calculated the wind speed by applying Pythagorean theorem:

**Formula:**  $\text{Wind Speed} = \sqrt{U^2 + V^2}$

#### Time Series of Windspeed

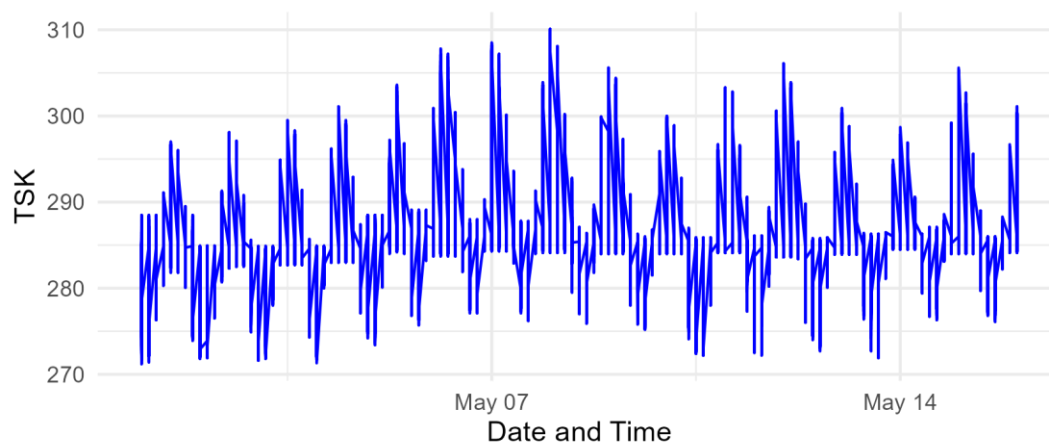


*Figure 6: Graphical Representation of Wind-Speed*

### 4.2 TSK (Skin temperature or surface temperature)

After cleaning the data as per my defined problem, I plotted the TSK for better understanding.

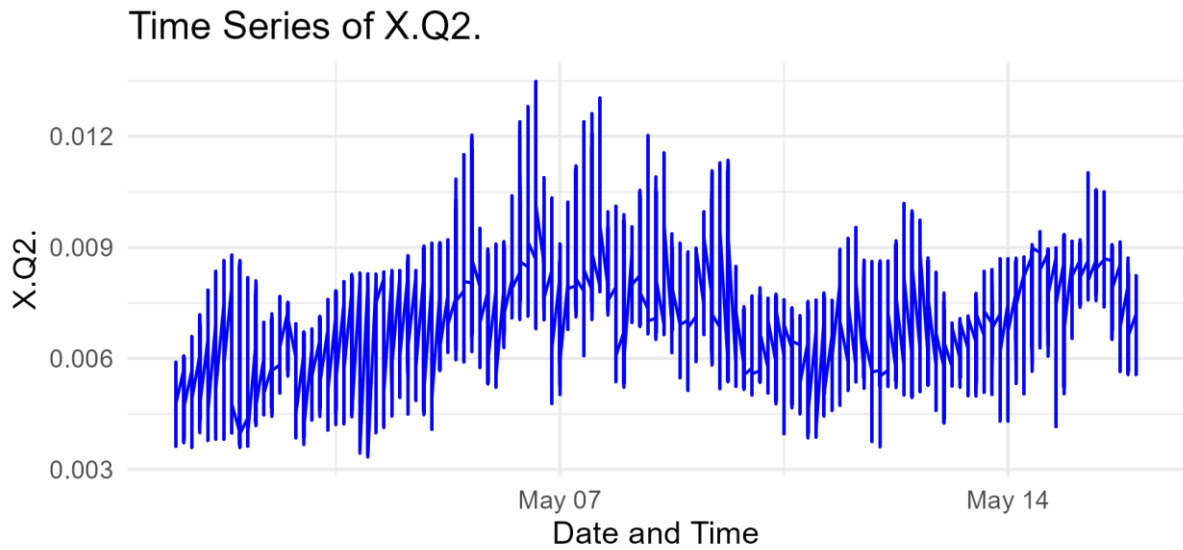
#### Time Series of TSK



*Figure 7: TSK Plotting*

### 4.3 Q2 (2- meter specific humidity)

This helps me to understand and visualize the data in a better way also to understand my problem statement by visualizing and then choosing the model for predication.



*Figure 8: Plotting of Humidity (Q2)*



## 5. Model Building

The below three models were chosen to predict soil moisture based on TSK and Q2. Their justification is mentioned below

- **Linear Regression:** To describe linear relationships between predictors and SMOIS, an initial simple model was constructed. Linear regression is fairly easy; it tells how each predictor affects SMOIS.
- **Random Forest:** This composite approach captures intricate interactions involving predictors and soil moistures. It can also handle nonlinearities due to its resistance against overfitting.
- **Gradient Boosting Machine (GBM):** GBM is a sequential tree building algorithm that improves the prediction accuracy by correcting errors made in the previous model. For this reason, it is highly predictive and flexible.

### 5.1 Model Evaluation:

- **Performance Metrics:** I evaluated models using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R<sup>2</sup>). These metrics help us understand how accurate and precise the models are.
- **Comparison of Models:** The Random Forest model showed the best performance in accuracy and fit. GBM came in second, and Linear Regression third.

## 5.2 Script of Models

### 5.2.1 Linear Regression Model

```
library(dplyr)
library(caret)
library(randomForest)
library(e1071)
library(gbm)
library(Metrics)

# Load the dataset
data <- read.csv("C:/Users/Muhammad Abu Bakkar/Downloads/Filtered_France_Data.csv")

# Print the column names to confirm
colnames(data)
# Select the first 28,000 rows
train_data <- data[1:28000, ]
# Select the relevant columns for features and target
features <- c("TSK", "PSFC", "X.U10.", "X.V10.", "X.Q2.", "RAINC", "RAINNC", "SNOW", "TSLB",
target <- "SMOIS"

# Split train_data into a training set and a testing set
set.seed(123) # For reproducibility
train_index <- createDataPartition(train_data$SMOIS, p = 0.8, list = FALSE)
train_set <- train_data[train_index, ]
test_set <- train_data[-train_index, ]
# 1. Linear Regression Model
linear_model <- lm(SMOIS ~ ., data = train_set[, c(features, target)])

# Evaluate the linear regression model
linear_predictions <- predict(linear_model, newdata = test_set[, features])
linear_mae <- mae(test_set$SMOIS, linear_predictions)
linear_mse <- mse(test_set$SMOIS, linear_predictions)
linear_rmse <- rmse(test_set$SMOIS, linear_predictions)
linear_r2 <- R2(linear_predictions, test_set$SMOIS)

# Print the results for Linear Regression
cat("Linear Regression Results:\n")
cat("MAE:", linear_mae, "\n")
cat("MSE:", linear_mse, "\n")
cat("RMSE:", linear_rmse, "\n")
cat("R2:", linear_r2, "\n")
```

Figure 9: R code of Linear Regression Model

## 5.2.2 Random Forest Model

```
# 2. Random Forest Model
rf_model <- randomForest(SMOIS ~ ., data = train_set[, c(features, target)], ntree = 100)

# Evaluate the random forest model
rf_predictions <- predict(rf_model, newdata = test_set[, features])
rf_mae <- mae(test_set$SMOIS, rf_predictions)
rf_mse <- mse(test_set$SMOIS, rf_predictions)
rf_rmse <- rmse(test_set$SMOIS, rf_predictions)
rf_r2 <- R2(rf_predictions, test_set$SMOIS)

# Print the results for Random Forest
cat("Random Forest Results:\n")
cat("MAE:", rf_mae, "\n")
cat("MSE:", rf_mse, "\n")
cat("RMSE:", rf_rmse, "\n")
cat("R2:", rf_r2, "\n")
```

Figure 10: Code of Random Forest Model

## 5.2.3 Gradient Boosting Model

```
# 3. Gradient Boosting Model (GBM)
gbm_model <- train(SMOIS ~ ., data = train_set[, c(features, target)], method = "gbm", verbose = FALSE)

# Evaluate the GBM model
gbm_predictions <- predict(gbm_model, newdata = test_set[, features])
gbm_mae <- mae(test_set$SMOIS, gbm_predictions)
gbm_mse <- mse(test_set$SMOIS, gbm_predictions)
gbm_rmse <- rmse(test_set$SMOIS, gbm_predictions)
gbm_r2 <- R2(gbm_predictions, test_set$SMOIS)

# Print the results for GBM
cat("GBM Results:\n")
cat("MAE:", gbm_mae, "\n")
cat("MSE:", gbm_mse, "\n")
cat("RMSE:", gbm_rmse, "\n")
cat("R2:", gbm_r2, "\n")
```

Figure 11: GMB Model

## 6. Results and Interpretation: Model Comparison and Analysis

Table 1: Comparison of Models

Results	Linear Regression	Random Forest	Gradient Boosting Machine
MAE (Mean Absolute Error):	0.0899	0.0292	0.0327
MSE (Mean Squared Error)	0.0189	0.0079	0.0094
RMSE (Root Mean Squared Error)	0.1376	0.0891	0.0971
R <sup>2</sup> (R-Squared)	0.8384	0.9324	0.9196

Best Fit Model: Random Forest, Accuracy 93%

### 6.1 Interpretation

- MAE:** Lower the MAE value better the accuracy.
- MSE:** Lower the MSE value better the precision.
- RMSE:** This shows the magnitude of prediction errors.
- R-Squared:** Higher R2 value better model performance

#### Linear Regression:

**MAE: 0.0899:** This means that on average, the model's predictions are off by 0.0899 units.

**MSE: 0.0189:** This shows the average squared difference between predicted and actual values.

**RMSE: 0.1376:** This shows how much the predictions deviate from the actual values pointing to a fair amount of error.

**R2: 0.8384:** The model accounts for 83.84% of the changes in soil moisture. This suggests a good match, but there's still room to get better.

#### Random Forest:

**MAE: 0.0292:** This reveals a smaller average error than Linear Regression hinting at improved accuracy.

**MSE: 0.0079:** This reflects a lower average squared error suggesting higher precision.

**RMSE: 0.0891:** This gives a smaller typical deviation of prediction errors showing higher accuracy.

**R2: 0.9324:** The model accounts for 93.24% of the variance showing a great fit and strong ability to predict.

## Gradient Boosting Machine (GBM):

**MAE: 0.0327:** A bit higher than Random Forest pointing to a bigger average error.

**MSE: 0.0094:** Shows a moderate average squared error.

**RMSE: 0.0971:** Points to a higher spread of errors compared to Random Forest.

**R2: 0.9196:** The model explains 91.96% of the variance demonstrating solid performance but not quite as effective as Random Forest.

## Output of Model

```
>
> # Evaluate the GBM model
> gbm_predictions <- predict(gbm_model, newdata = test_set[, features])
> gbm_mae <- mae(test_set$SMOIS, gbm_predictions)
> gbm_mse <- mse(test_set$SMOIS, gbm_predictions)
> gbm_rmse <- rmse(test_set$SMOIS, gbm_predictions)
> gbm_r2 <- R2(gbm_predictions, test_set$SMOIS)
>
> # Print the results for GBM
> cat("GBM Results:\n")
GBM Results:
> cat("MAE:", gbm_mae, "\n")
MAE: 0.03075221
> cat("MSE:", gbm_mse, "\n")
MSE: 0.008935457
> cat("RMSE:", gbm_rmse, "\n")
RMSE: 0.09452755
> cat("R2:", gbm_r2, "\n")
R2: 0.9209653
> |
```

*Figure 12: GMB Model Result*

```
> # Evaluate the random forest model
> rf_predictions <- predict(rf_model, newdata = test_set[, features])
> rf_mae <- mae(test_set$SMOIS, rf_predictions)
> rf_mse <- mse(test_set$SMOIS, rf_predictions)
> rf_rmse <- rmse(test_set$SMOIS, rf_predictions)
> rf_r2 <- R2(rf_predictions, test_set$SMOIS)
>
> # Print the results for Random Forest
> cat("Random Forest Results:\n")
Random Forest Results:
> cat("MAE:", rf_mae, "\n")
MAE: 0.02760003
> cat("MSE:", rf_mse, "\n")
MSE: 0.00759081
> cat("RMSE:", rf_rmse, "\n")
RMSE: 0.08712525
> cat("R2:", rf_r2, "\n")
R2: 0.9328502
> |
```

*Figure 13: Random Forest Results*

```
> # Evaluate the linear regression model
> linear_predictions <- predict(linear_model, newdata = test_set[, features])
> linear_mae <- mae(test_set$SMOIS, linear_predictions)
> linear_mse <- mse(test_set$SMOIS, linear_predictions)
> linear_rmse <- rmse(test_set$SMOIS, linear_predictions)
> linear_r2 <- R2(linear_predictions, test_set$SMOIS)
>
> # Print the results for Linear Regression
> cat("Linear Regression Results:\n")
Linear Regression Results:
> cat("MAE:", linear_mae, "\n")
MAE: 0.08662225
> cat("MSE:", linear_mse, "\n")
MSE: 0.0178722
> cat("RMSE:", linear_rmse, "\n")
RMSE: 0.1336869
> cat("R2:", linear_r2, "\n")
R2: 0.842024
> |
```

*Figure 14: Linear Regression Model*

## **7. Usefulness for Organizations**

Regarding agriculture, monitoring of the environment, and resource management as they relate to soil moisture predictions, irrigate effectively, manage water resources well and have an assessment of the health status of crops. Soils moisture levels can be understood by means of models established in this study thus giving organizations an opportunity to make informed decisions. The areas covered here are.

### **7.1 Agriculture:**

Forecasts on soil moisture could improve scheduling of irrigation, minimize water wastage and boost crop production.

### **7.2 Environmental Monitoring:**

Proper estimates about soil moisture enable a better understanding of ecological situations for better natural resource management and ability to respond appropriately to environmental changes.

### **7.3 Resource Management:**

Soil moisture forecasts help organizations reduce risks from water scarcity and land degradation through proper resource allocation.

This is how they can benefit from enhanced prediction capabilities for managing soil moisture through adoption Random Forest model which demonstrated the highest level of accuracy and fit among other regression models used.

## **8. Conclusion**

This report presents a process of predicting soil moisture using different statistical and machine learning methods. This is a detailed approach that encompasses data cleansing, EDA, as well as model evaluation to guarantee in-depth analysis. Using the Random Forest model resulted in the best prediction of soil moisture which has tremendous advantages for agricultural operations, environmental monitoring agencies, resource management firms. The knowledge obtained from this analysis can help to improve decision making procedures and operational effectiveness in these areas.

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