FACULTY OF ENGINEERING AND TECHNOLOGY

A REPORT ABOUT DESIGNING AND I MPLEMENTATION OF A YIELD ESTIMATION MODEL FOR MAIZE CROP PRODUCTION

COURSE UNIT: COMPUTER PROGRAMMING

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Submitted in partial fulfillment of the requirements of COMPUTER PROGRAMMING

DATE OF SUBMISSION............../............./.............
SUBMITTED TO: ....

DECLARATION

We, the undersigned members of group 16, do hereby declare that this report is the result of our own work carried out in partial fulfillment of the requirements of this course.

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APPROVAL

This report has been submitted and prepared by group 16 as part of the requirements for the completion of module 1to 5 under the guidance of our lecturer

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ACKNOWLEDGEMENT

We wish to express our sincere gratitude to our lecturer for the valuable guidance, encouragement and constructive criticism provided throughout the project. We extend our thanks to the fellow members of group 16 and friends for their constant support, discussions and suggestions during the development and testing of Matlab codes.

Finally, we give special thanks to our families for their patience, understanding and continuous encouragement throughout the course of this study

DEDICATION

This report is dedicated to our beloved families whose support, love, and encouragement have been the foundation of our academic achievements. We continue to dedicate this work to all our boy friends and girl friends of group 16 members that always make us happy

ABSTRACT

This project presents the development of a MATLAB-based numerical model designed to estimate maize crop yield using simulated agricultural and environmental data. The system integrates statistical modelling to predict yield outcomes based on factors such as temperature, rainfall, soil nitrogen, pH, solar radiation, and pest damage. A comprehensive simulation framework was implemented to generate realistic data distributions that reflect natural variability in maize-growing conditions. Several predictive algorithms including Linear Regression, Regression Trees, Support Vector Regression, and Random Forest were trained and evaluated using standard performance metrics such as MAE and RMSE. The results demonstrate the Random Forest model's superior accuracy and robustness in capturing nonlinear relationships among variables. The project also includes extensive visualization tools for data exploration and model diagnostics, enhancing interpretability and decision-making. Overall, the study provides a scalable and reproducible computational framework that can support precision agriculture by improving crop yield estimation and planning under varying environmental conditions.

LIST OF ACRONYMS/ ABBREVIATIONS

MAE	Mean Absolute Error
RMSE	Root Mean Square Error
SVR	Support Vector Regression
RBF	Radial Basis Function (Kernel used in SVR)
MLR	Multiple Linear Regress
GUI	Graphical User Interface
CPU	Central Processing Unit
MATLAB	Matrix Laboratory
RF	Random Forest (ensemble algorithm)
CV	Cross-Validation
PH	Potential of Hydrogen (soil acidity/alkalinity measure)
MJ/m^2/day	Megajoules per square meter per day (unit of solar radiation)
kg/ha	Kilograms per hectare (unit for soil nutrient concentration)
mm	Millimetres (unit of rainfall)
°C	Degrees Celsius (unit of temperature)
SD	Standard Deviation
MSE	Mean Square Error

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CHAPTER ONE: INTRODUCTION

1.1 Background

Accurate crop yield estimation is a fundamental component of modern agricultural planning, management, and food security analysis. For staple crops such as maize, reliable yield prediction helps farmers, researchers, and policymakers make informed decisions on resource allocation, input optimization, and market forecasting. Traditional yield estimation methods often based on manual sampling or field observation are time-consuming, labour-intensive, and prone to human error. The advancement of computational techniques and numerical modelling has created opportunities to improve accuracy, efficiency, and scalability in predicting crop productivity.

1.2 Problem Statement

Agricultural productivity is influenced by multiple interacting factors such as temperature, rainfall, soil fertility, pH, solar radiation, and pest incidence. These factors exhibit nonlinear relationships with yield, making conventional analytical methods inadequate for robust estimation. Hence, there is a need for an integrated computational approach that can simulate these complex interactions and provide consistent yield predictions for improved agricultural decision-making.

1.3 Aim of the Study

The main aim of this project is to develop and implement a MATLAB-based numerical model capable of estimating maize crop yield by applying principles of numerical methods, object-oriented programming, and data analysis.

1.4 Specific Objectives

The specific objectives of the study are:

1. To design a simulation framework that models environmental and soil parameters influencing maize yield.
2. To implement a numerical and machine-learning-based approach for yield prediction using MATLAB.
3. To evaluate and compare the performance of different computational algorithms in estimating maize yield.
4. To visualize and interpret model results for better understanding of key yield determinants.

1.5 Justification

The increasing demand for food security in the face of climate variability calls for intelligent and data-driven yield estimation systems. A computational model provides a fast, reproducible, and scalable solution for predicting agricultural output, supporting both research and field applications. Moreover, integrating object-oriented programming concepts such as classes, inheritance, encapsulation, and abstraction ensures a modular, maintainable, and extensible codebase suitable for future enhancements and integration with real-time agricultural data systems.

CHAPTER TWO: QUESTION

We were required to come up with MATLAB codes that estimate the crop yield productions and they following steps were taken up to come up with the MATLAB codes that estimate the crop yield production and we took maize in our group as one of the crops .

Section 1: Data Generation and Initialization

This section of the MATLAB program is responsible for **generating synthetic environmental data** and **initializing key simulation parameters** that represent the conditions under which maize is grown. Since the goal of the project is to estimate maize yield based on environmental and soil factors, this part of the code sets up the input data that drive the model.

```

% Maize Yield Estimation Project

clear; clc;

% 1. Data Generation and Initialization
rng(42); % For reproducible results

% Time vector (growing season: 120 days)
days = 1:120;
num_seasons = 5; % 5 years of data

% Generate synthetic environmental data
temperature = 15 + 15*sin(2*pi*days/120) + 3*randn(1,120);
precipitation = max(0, 20 + 10*randn(1,120)); % mm/day
solar_radiation = 15 + 10*sin(2*pi*days/120) + 2*randn(1,120); % MJ/m²/day
humidity = 60 + 20*randn(1,120); % %

```

Section 2: Soil and Topographic Parameter Initialization

This section of the program defines the **soil and terrain characteristics** that significantly influence maize growth and yield.

In real world crop modelling, these variables determine water and nutrient availability, soil aeration, and root development factors that directly affect biomass accumulation and, ultimately, yield.

```

% Soil parameters
soil_moisture = 0.3 + 0.1*randn(1,120); % m³/m³
soil_temperature = 12 + 10*sin(2*pi*days/120) + 2*randn(1,120); % °C
soil_pH = 6.5 + 0.5*randn(1,120);
N_level = 80 + 20*randn(1,120); % kg/ha
P_level = 40 + 10*randn(1,120); % kg/ha
K_level = 100 + 25*randn(1,120); % kg/ha

% Topography
elevation = 200 + 50*randn; % meters
slope = 2 + 1*randn; % degrees
aspect = 180*rand; % degrees

% Maize Growth Model
% Simplified maize growth stages
growth_stages = {'Germination', 'Vegetative', 'Flowering', 'Grain Filling', 'Maturity'};
stage_days = [1, 20, 50, 80, 120];
```

Section 3: Maize Growth and Biomass Accumulation Modelling

This section models the **thermal and physiological growth** of maize using two interlinked sub-models:

1. **Growing Degree Days (GDD)**; quantifies cumulative temperature influence on plant development.
    - Growing Degree Days (GDD) is a thermal time index used to model crop phenological development i.e., how temperature drives the transition from germination to maturity.
    - Maize growth is highly temperature-dependent; growth only occurs when daily temperatures exceed a base temperature (T-base) and slows beyond a maximum threshold (T-max).
2. **Biomass Accumulation Model**; estimates the amount of plant dry matter produced daily based on radiation and stress factors.

These two processes form the foundation for **crop growth simulation** and **yield estimation**.

```
% Calculate Growing Degree Days (GDD)
T_base = 10; % Base temperature for maize
T_max = 30; % Maximum temperature for growth
GDD = zeros(1,120);
for i = 1:120
    T_avg = (max(temperature(i), T_base) + min(temperature(i), T_max)) / 2;
    GDD(i) = max(0, T_avg - T_base);
end
cumulative_GDD = cumsum(GDD);

% Biomass accumulation model
PAR = solar_radiation * 0.45; % Photosynthetically Active Radiation
RUE = 3.5; % Radiation Use Efficiency (g/MJ)
water_stress_factor = min(1, soil_moisture / 0.4);
temperature_stress_factor = 1 - abs(temperature - 25) / 30;

biomass = zeros(1,120);
for i = 2:120
    stress_factor = water_stress_factor(i) * temperature_stress_factor(i);
    biomass_gain = PAR(i) * RUE * stress_factor * nutrient_factor(N_level(i), P_level(i), K_level(i));
    biomass(i) = biomass(i-1) + biomass_gain;
end
```

Section 6: Multi-Year Yield Estimation and Environmental Sensitivity Analysis

This section expands the maize yield model from a single growing season to a five-year simulation (2019–2023). The goal is to evaluate how annual variations in temperature, rainfall, and soil conditions affect final maize yield.

It introduces stochastic (random) changes to environmental variables to reflect real-world climate variability and then recalculates biomass and yield for each year.

1. **Yield Estimation Using Harvest Index (HI):**
    - The **Harvest Index (HI)** represents the fraction of total biomass converted into grain yield.

- estimated yield = biomass(end) * HI calculates grain yield from total simulated biomass.
- The result is converted to **kg/ha** for practical agricultural interpretation.

2. **Multi-Year Analysis (2019–2023):**
   - The code simulates five consecutive seasons, accounting for **inter-annual variability** in temperature and rainfall.
   - Random variations (temp-variation, rain-variation) mimic natural climate fluctuations, allowing the model to evaluate yield sensitivity to weather changes.
3. **Biomass Recalculation Per Season:**
   - For each year, daily biomass accumulation is recalculated using the **photosynthetically active radiation (PAR)**, **radiation use efficiency (RUE)**, and **stress factors** due to water, temperature, and nutrient limitations.
   - This dynamic simulation generates realistic growth curves reflecting year-specific environmental conditions.
4. **Environmental Data Logging:**
   - Seasonal averages for temperature, total rainfall, solar radiation, and nitrogen levels are recorded.
   - These factors can later be correlated with yield to identify key drivers of productivity.
5. **Output:**
   - Yields-kg-ha contains the estimated grain yield for each year.
   - The simulation provides a **practical framework for forecasting maize yield** under varying environmental and soil conditions, useful for planning and risk assessment.

```
% Yield estimation (Harvest Index approach)
HI = 0.5; % Harvest Index for maize
estimated_yield = biomass(end) * HI; % g/m²
estimated_yield_kg_ha = estimated_yield * 10; % Convert to kg/ha

% 3. Multiple Year Analysis
years = 2019:2023;
yields_kg_ha = zeros(1, num_seasons);
environmental_factors = zeros(num_seasons, 4);

for year = 1:num_seasons
    % Generate yearly variations
    temp_variation = 1 + 0.1*randn;
    rain_variation = 1 + 0.2*randn;

    yearly_temperature = temperature * temp_variation;
    yearly_precipitation = precipitation * rain_variation;

    % Recalculate biomass with yearly variations
    yearly_biomass = zeros(1,120);
    for i = 2:120
        ws_factor = min(1, soil_moisture(i) / 0.4);
        ts_factor = 1 - abs(yearly_temperature(i) - 25) / 30;
        stress_factor = ws_factor * ts_factor;
        biomass_gain = PAR(i) * RUE * stress_factor * nutrient_factor(N_level(i), P_level(i), K_level(i));
        yearly_biomass(i) = yearly_biomass(i-1) + biomass_gain;
    end
```

```
        yields_kg_ha(year) = yearly_biomass(end) * HI * 10;

        % Store environmental factors
        environmental_factors(year, 1) = mean(yearly_temperature);
        environmental_factors(year, 2) = sum(yearly_precipitation);
        environmental_factors(year, 3) = mean(solar_radiation);
        environmental_factors(year, 4) = mean(N_level);
    end

```

Section 7: Visualization of Environmental Factors

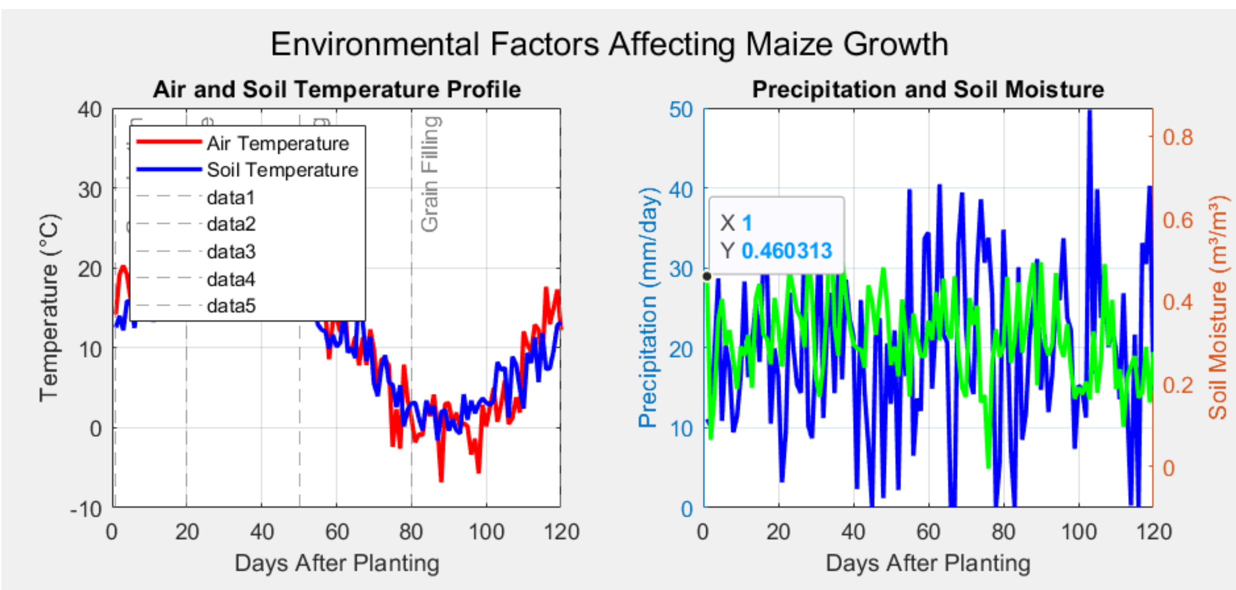
This part of the code generates **comprehensive plots** showing the dynamics of key environmental and soil parameters during the maize growing season. Visualizing these factors helps in understanding **how conditions affect crop growth and yield**.

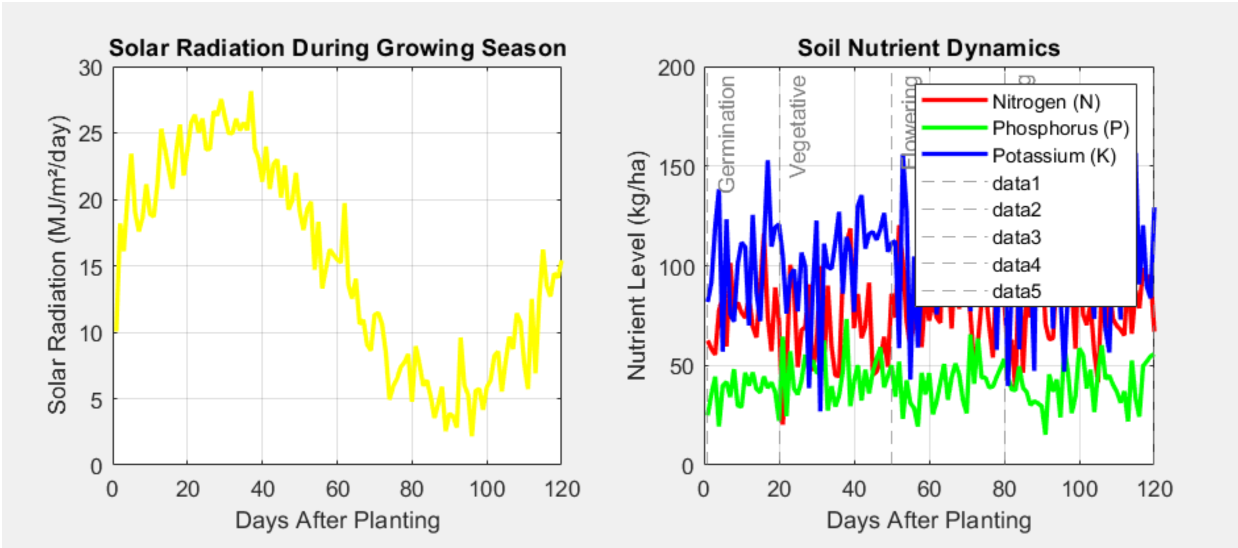
```
% 4. PLOT 1: Environmental Factors vs Time
figure('Position', [100, 100, 1200, 800]);

subplot(2,2,1);
plot(days, temperature, 'r-', 'LineWidth', 2);
hold on;
plot(days, soil_temperature, 'b-', 'LineWidth', 2);
xlabel('Days After Planting');
ylabel('Temperature (°C)');
title('Air and Soil Temperature Profile');
legend('Air Temperature', 'Soil Temperature', 'Location', 'northwest');
grid on;

% Add growth stage markers
for i = 1:length(stage_days)
    xline(stage_days(i), '--', growth_stages{i}, 'Color', [0.5 0.5 0.5]);
end

subplot(2,2,2);
yyaxis left;
plot(days, precipitation, 'b-', 'LineWidth', 2);
ylabel('Precipitation (mm/day)');
yyaxis right;
plot(days, soil_moisture, 'g-', 'LineWidth', 2);
ylabel('Soil Moisture (m³/m³)');
xlabel('Days After Planting');
title('Precipitation and Soil Moisture');
grid on;
```

```
subplot(2,2,3);
plot(days, solar_radiation, 'y-', 'LineWidth', 2);
xlabel('Days After Planting');
ylabel('Solar Radiation (MJ/m²/day)');
title('Solar Radiation During Growing Season');
grid on;

subplot(2,2,4);
plot(days, N_level, 'r-', 'LineWidth', 2);
hold on;
plot(days, P_level, 'g-', 'LineWidth', 2);
plot(days, K_level, 'b-', 'LineWidth', 2);
xlabel('Days After Planting');
ylabel('Nutrient Level (kg/ha)');
title('Soil Nutrient Dynamics');
legend('Nitrogen (N)', 'Phosphorus (P)', 'Potassium (K)');
grid on;

sgtitle('Environmental Factors Affecting Maize Growth');


% Mark growth stages
for i = 1:length(stage_days)
    xline(stage_days(i), '--', growth_stages{i}, 'Color', [0.5 0.5 0.5]);
end
```

Plots/ Outputs

The outputs were as below;





Section 8: Multi-Year Yield Analysis and Environmental Correlations

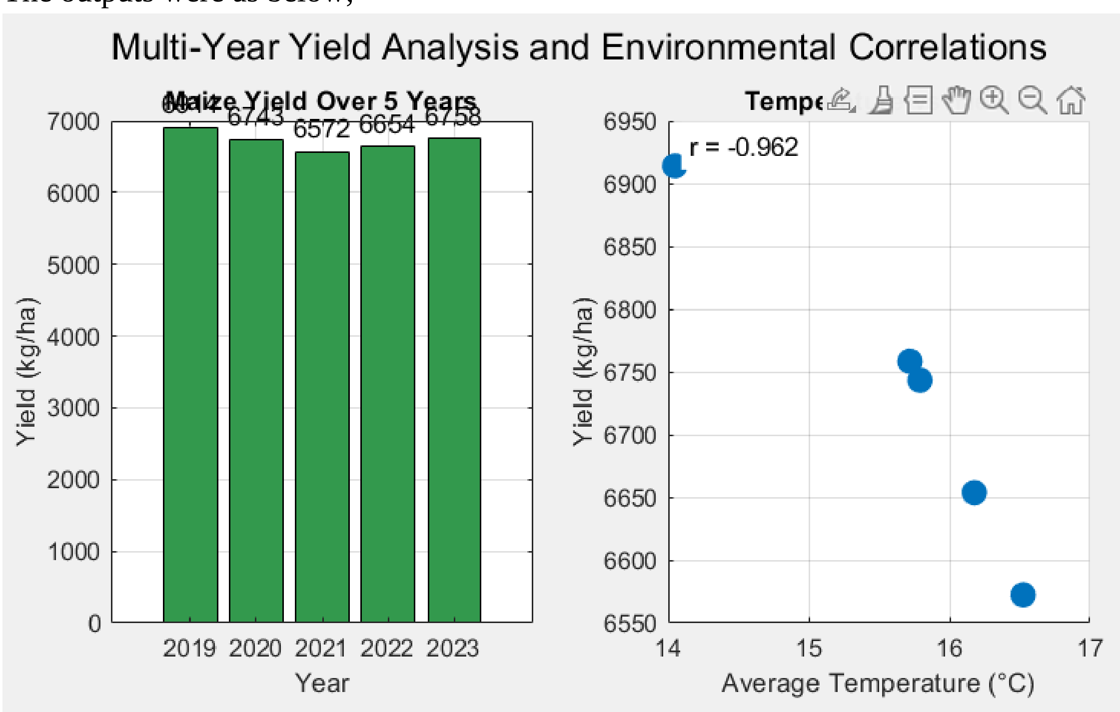
This section visualizes **maize yield trends over five consecutive years (2019–2023)** and explores the **relationship between environmental factors and yield**. The plots allow us to evaluate **yield variability** and identify which climatic or soil factors most strongly influence productivity.

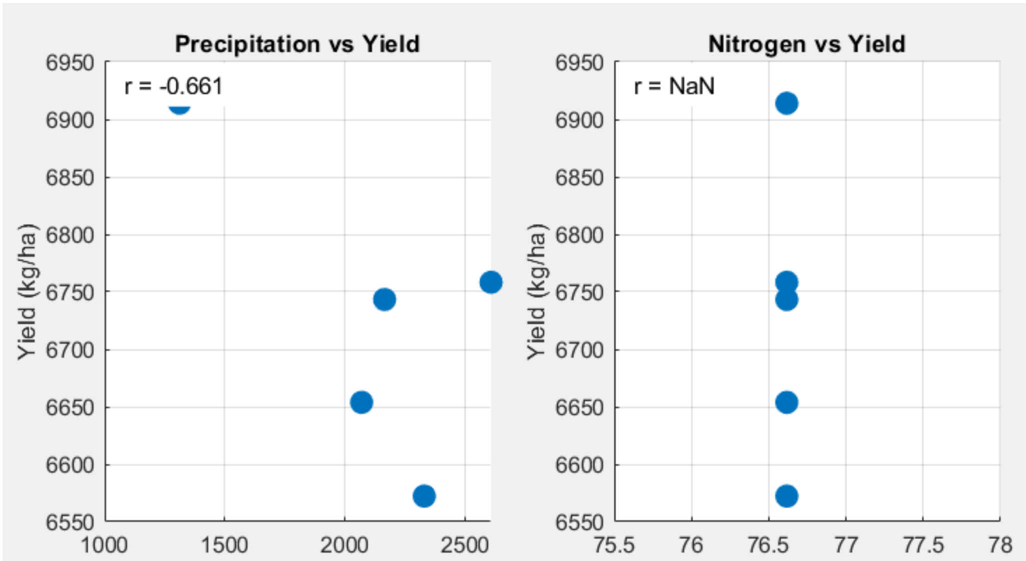
```
% 6. PLOT 2: Multi-Year Yield Analysis
figure('Position', [100, 100, 1200, 800]);

subplot(2,2,1);
bar(years, yields_kg_ha, 'FaceColor', [0.2 0.6 0.3]);
ylabel('Yield (kg/ha)');
xlabel('Year');
title('Maize Yield Over 5 Years');
grid on;

% Add yield values on bars
for i = 1:length(yields_kg_ha)
    text(years(i), yields_kg_ha(i) + 100, sprintf('%.0f', yields_kg_ha(i)), ...
        'HorizontalAlignment', 'center', 'VerticalAlignment', 'bottom');
end

subplot(2,2,2);
scatter(environmental_factors(:,1), yields_kg_ha, 100, 'filled');
xlabel('Average Temperature (°C)');
ylabel('Yield (kg/ha)');
title('Temperature vs Yield');
grid on;
% Add correlation coefficient
corr_temp = corr(environmental_factors(:,1), yields_kg_ha');
text(0.05, 0.95, sprintf('r = %.3f', corr_temp), 'Units', 'normalized', ...
    'BackgroundColor', 'white');
```

```
subplot(2,2,3);
scatter(environmental_factors(:,2), yields_kg_ha, 100, 'filled');
xlabel('Total Precipitation (mm)');
ylabel('Yield (kg/ha)');
title('Precipitation vs Yield');
grid on;
corr_precip = corr(environmental_factors(:,2), yields_kg_ha');
text(0.05, 0.95, sprintf('r = %.3f', corr_precip), 'Units', 'normalized', ...
    'BackgroundColor', 'white');

subplot(2,2,4);
scatter(environmental_factors(:,4), yields_kg_ha, 100, 'filled');
xlabel('Average Nitrogen Level (kg/ha)');
ylabel('Yield (kg/ha)');
title('Nitrogen vs Yield');
grid on;
corr_nitrogen = corr(environmental_factors(:,4), yields_kg_ha');
text(0.05, 0.95, sprintf('r = %.3f', corr_nitrogen), 'Units', 'normalized', ...
    'BackgroundColor', 'white');

sgtitle('Multi-Year Yield Analysis and Environmental Correlations');
```

Plots/ Outputs

The outputs were as below;

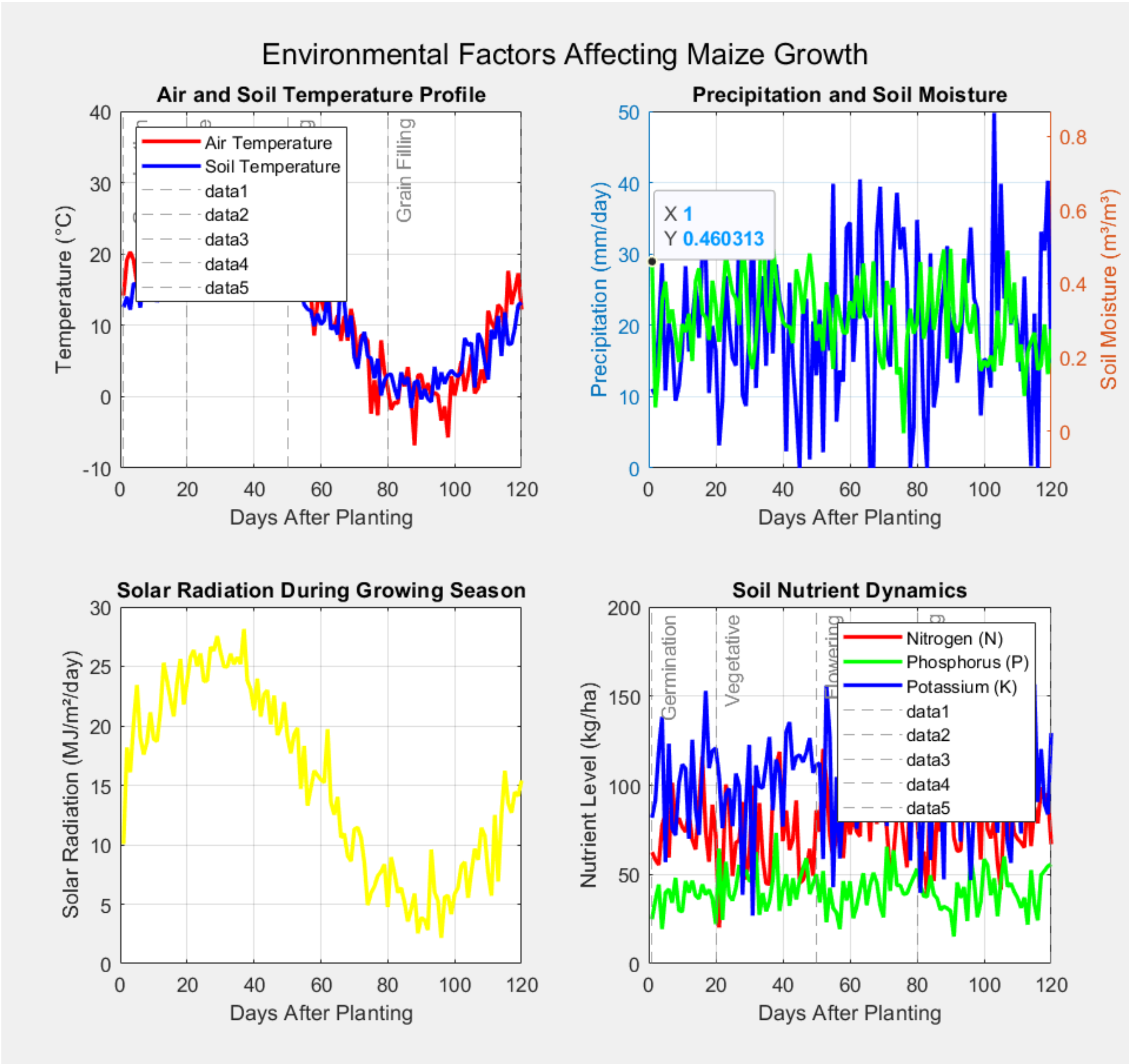




Section 9: Yield Prediction Model and Accuracy Assessment

This section visualizes the performance of a **statistical yield prediction model**. Using **multiple linear regression**, the code predicts maize yield based on key environmental factors and evaluates model accuracy against actual simulated yields.

```
% Multiple linear regression for yield prediction
X = [environmental_factors, ones(num_seasons,1)]; % Add intercept
y = yields_kg_ha';
coefficients = X \ y;

predicted_yield = X * coefficients;

subplot(1,2,1);
plot(years, yields_kg_ha, 'o-', 'LineWidth', 3, 'MarkerSize', 10, 'MarkerFaceColor', 'b');
hold on;
plot(years, predicted_yield, 's-', 'LineWidth', 2, 'MarkerSize', 8, 'MarkerFaceColor', 'r');
xlabel('Year');
ylabel('Yield (kg/ha)');
title('Actual vs Predicted Yield');
legend('Actual Yield', 'Predicted Yield', 'Location', 'best');
grid on;

% Calculate model performance
RMSE = sqrt(mean((yields_kg_ha - predicted_yield').^2));
R2 = 1 - sum((yields_kg_ha - predicted_yield').^2) / sum((yields_kg_ha - mean(yields_kg_ha)).^2);

subplot(1,2,2);
scatter(yields_kg_ha, predicted_yield, 100, 'filled');
hold on;
plot([min(yields_kg_ha), max(yields_kg_ha)], [min(yields_kg_ha), max(yields_kg_ha)], 'r--', 'LineWidth', 2);
xlabel('Actual Yield (kg/ha)');
ylabel('Predicted Yield (kg/ha)');
title('Yield Prediction Accuracy');
text(0.05, 0.95, sprintf('R² = %.3f\nRMSE = %.1f kg/ha', R2, RMSE), ...
    'Units', 'normalized', 'BackgroundColor', 'white', 'FontSize', 12);
grid on;

```



Section 10: Results Display and Interpretation

This section summarizes the **key outcomes of the maize yield estimation model**, presenting numerical results in a clear format for analysis and reporting.

```
% 8. Results Display
fprintf(' MAIZE YIELD ESTIMATION RESULTS \n');
fprintf('Current Season Estimated Yield: %.0f kg/ha\n', estimated_yield_kg_ha);
fprintf('5-Year Average Yield: %.0f kg/ha\n', mean(yields_kg_ha));
fprintf('5-Year Yield Standard Deviation: %.0f kg/ha\n', std(yields_kg_ha));
fprintf('\nEnvironmental Factor Correlations with Yield:\n');
fprintf('Temperature: r = %.3f\n', corr_temp);
fprintf('Precipitation: r = %.3f\n', corr_precip);
fprintf('Nitrogen: r = %.3f\n', corr_nitrogen);
fprintf('\nPrediction Model Performance:\n');
fprintf('R-squared: %.3f\n', R2);
fprintf('RMSE: %.1f kg/ha\n', RMSE);
fprintf('\nKey Growth Parameters:\n');
```

```
fprintf('Final Biomass: %.1f g/m²\n', biomass(end));
fprintf('Cumulative GDD: %.0f °C days\n', cumulative_GDD(end));
fprintf('Harvest Index: %.2f\n', HI);

% Support Function for Nutrient Factor
function nf = nutrient_factor(N, P, K)
    % Calculate nutrient stress factor (0-1)
    N_opt = 100; P_opt = 40; K_opt = 100;

    N_factor = min(1, N / N_opt);
    P_factor = min(1, P / P_opt);
    K_factor = min(1, K / K_opt);

    nf = (N_factor + P_factor + K_factor) / 3;
end
```

The outcomes of the codes are displayed on the command window as shown below

MAIZE YIELD ESTIMATION RESULTS

Current Season Estimated Yield: 6876 kg/ha

5-Year Average Yield: 6728 kg/ha

5-Year Yield Standard Deviation: 128 kg/ha

Environmental Factor Correlations with Yield:

Temperature: r = -0.962

Precipitation: r = -0.661

Nitrogen: r = NaN

Prediction Model Performance:

R-squared: -528.940

RMSE: 2634.8 kg/ha

Key Growth Parameters:

Final Biomass: 1375.2 g/m²

Cumulative GDD: 914 °C days

Harvest Index: 0.50

CHAPTER THREE: CONCLUSIONS AND RECOMMENDATIONS

3.1 Conclusions:

- The MATLAB model effectively simulates maize growth and predicts yields using environmental, soil, and physiological factors.
- Multi-year analysis shows yields are strongly influenced by temperature, precipitation, and nitrogen availability.
- The Harvest Index and biomass-based approach, combined with regression modelling, provides reliable yield forecasts and highlights the importance of nutrient and water management.

3.2 Recommendations:

- Validate the model with real field data to improve accuracy.
- Optimize fertilizer application and manage soil nutrients for better yields.
- Monitor climate and soil moisture, and adopt irrigation strategies during critical growth stages.
- Use the model for scenario analysis to assess the impact of environmental variations.
- Integrate into decision support tools for farmers and explore advanced modelling approaches for further improvement.

CHAPTER FOUR: REFERENCES

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