# Crop Growth Simulation and Analysis Integrating Sensor Based Data

**Subject: Molecular Biology and Basic cellular physiology (24AIM112)**
**Ethics, Innovative research, business and IPR (24AIM115)**


Team Members:

| | |
|---|---|
| A V Piyush | CB.AI.U4AIM24006 |
| M R Bharath | CB.AI.U4AIM24022 |
| J Soven Reddy | CB.AI.U4AIM24044 |
| Machavarapu Sri Ram | CB.AI.U4AIM24024 |

# Introduction

This project focuses on simulating crop growth using real-time environmental data to predict and visualize plant development. By analyzing factors such as soil moisture, temperature, and chlorophyll content, the simulation generates growth patterns and trends. The output of the project is a dynamic graphical representation of crop health, allowing for informed decision-making and optimized crop management.

# Problem Statement

- Farmers often struggle to monitor crop health and predict growth accurately.
- Traditional methods lack real-time data integration, leading to inefficient resource use and lower yields.
- This project aims to simulate crop growth using sensor data and MATLAB, providing visual insights for better decision-making.

# Computational Aspects

1. **Data Collection:** Gather real-time environmental data using sensors such as: - TCS3200 for chlorophyll content , Soil moisture sensors, DHT11 for temperature and humidity.
2. **Data Integration:** Integrate collected data into MATLAB for preprocessing and analysis.
3. **Model Development:** We will simulate growth patterns, calculate plant stress indicators, and optimize resource use.
4. **Visualization:** Generate dynamic graphs and visual representations of crop health trends for informed decision-making.

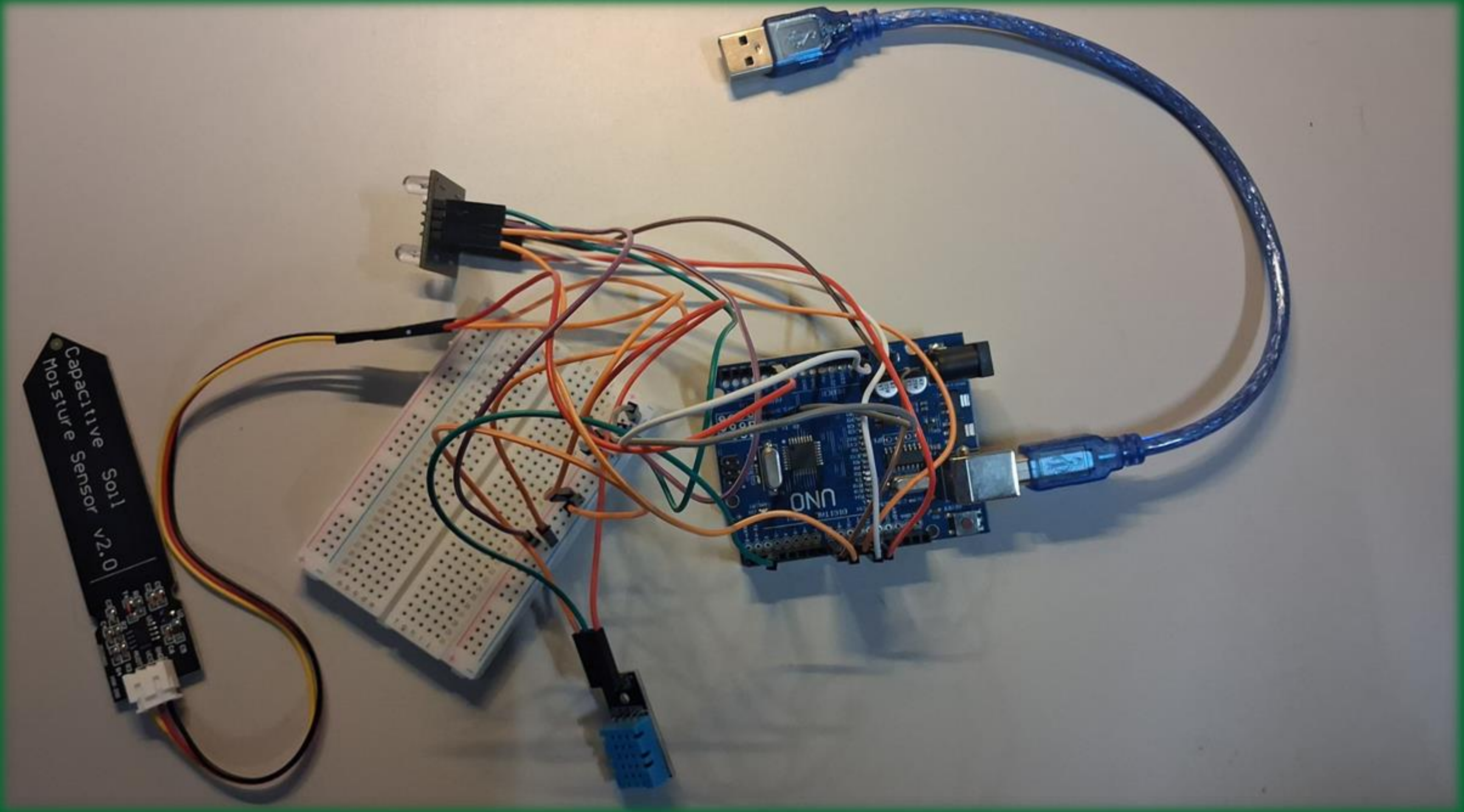
# Cellular Aspects

1. **Stomatal Regulation and Gas Exchange**
Stomatal opening and closing, controlled by guard cells, regulate $CO_2$ uptake for photosynthesis and water loss through transpiration. Our sensor data simulate how environmental factors like moisture and humidity influence these cellular processes.

2. **Water Transport and Cellular Turgor**
Soil moisture affects water potential and turgor pressure in plant cells, impacting cell expansion and growth. Our simulations model how changes in soil moisture influence these physiological responses.

3. **Photosynthesis and Chlorophyll Content**
Chlorophyll, measured by the TCS3200, reflects photosynthetic capacity driven by light absorption and energy conversion in cells. Our project simulates how chlorophyll variations affect crop growth at the cellular level.

# Hardware



# Day-wise Monitoring

1

3

5

6


8


10

# After a week

## Cup 1
Low moisture
High humidity

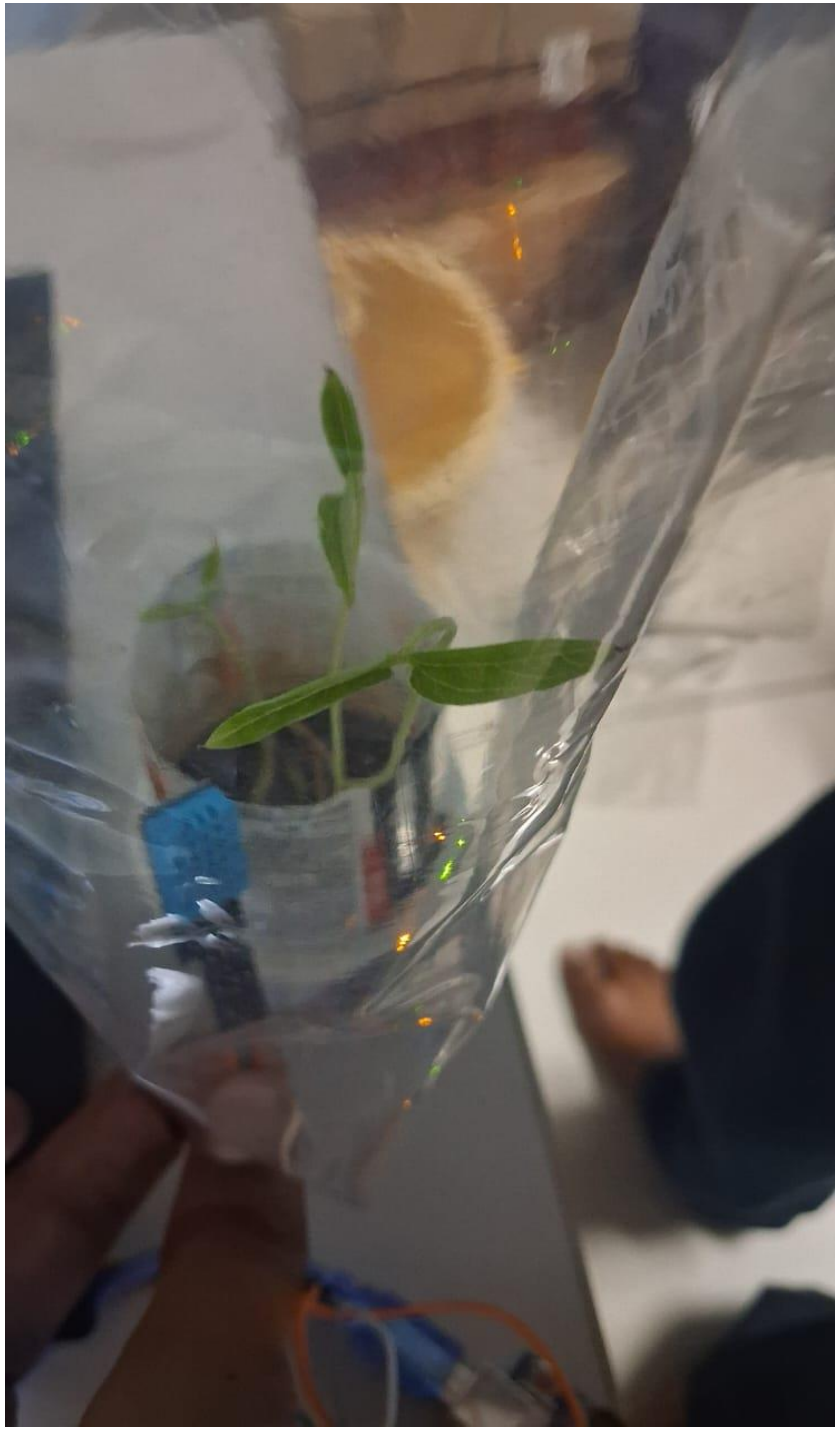
## Cup 2
High moisture
High humidity

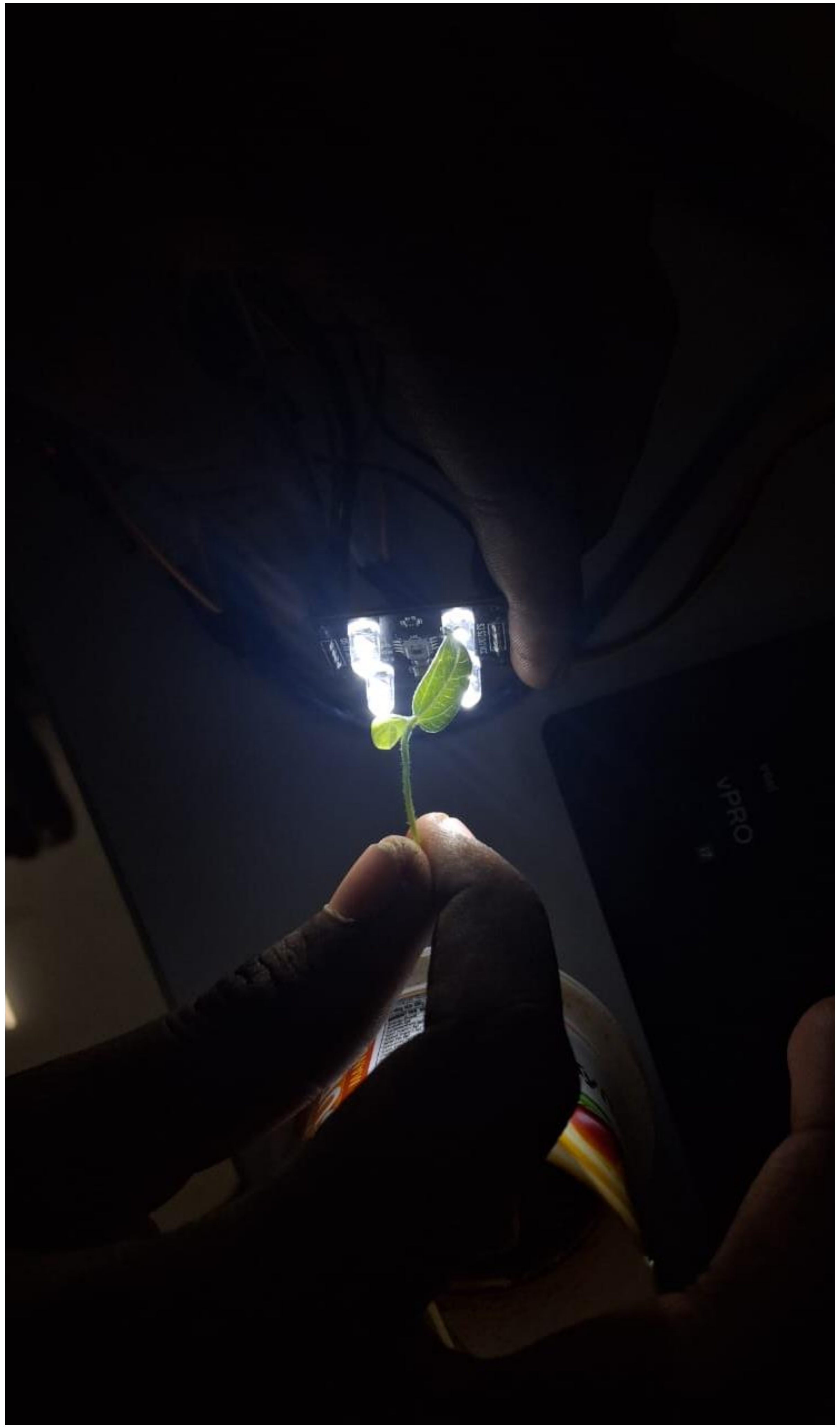
## Cup 3
Optimal moisture
Optimal humidity

## Cup 4
Optimal moisture
High humidity

## Cup 5
High moisture
Optimal humidity

## Cup 6
Low moisture
Optimal humidity





# Growth Index

**EXPLANATION:**

It's single metric to quantify crop health by considering key sensor inputs. The values of alpha, beta, gamma, have a fixed ratio, but not fixed value. What this means is, that the values can be multiplied by any constant, but the ratio between them must be same.

Let's say the importance of chlorophyll is more, so alpha value is bigger.

***(alpha * chlorophyll) + (beta * VPD) + (gamma * soil moisture) - (delta * temperature)***

# Methodology

*For the Experimental Methodology we took 6 different cases with plants being grown at various controls.*

***Control 1 – Optimal Moisture + Optimal Humidity***

To maintain optimal moisture level we poured 45-60 ml of water every morning .
For humidity we considered the humidity of the room as optimal.

***Control 2 – Optimal Moisture + High Humidity***

To maintain optimal moisture level we poured 45-60 ml of water every morning .
For high humidity we covered the plant with a cover so that the humidity inside the cover increases compared to the room's humidity.

***Control 3 – Low Moisture + Optimal Humidity***

To maintain low moisture level we poured 15-30 ml of water in every 2 days .
For humidity we considered the humidity of the room as optimal.

# Methodology

***Control 4 – Low Moisture + High Humidity***

To maintain low moisture level we poured 15-30 ml of water in every 2 days.
For high humidity we covered the plant with a cover so that the humidity inside the cover increases compared to the room's humidity.

***Control 5 – High Moisture + Optimal Humidity***

To maintain high moisture level we poured 60-75 ml of water every morning and also in the evening if water is completely absorbed by soil.
For humidity we considered the humidity of the room as optimal.

***Control 6 – High Moisture + High Humidity***

To maintain high moisture level we poured 60-75 ml of water every morning and also in the evening if water is completely absorbed by soil.
For high humidity we covered the plant with a cover so that the humidity inside the cover increases compared to the room's humidity.

# Sensor Outputs

```
Temperature: 29.50 °C    Humidity: 62.00 %
Vapor Pressure Deficit (VPD): 1.16 kPa
Soil Moisture: 510
Soil Condition: Optimal
Red: 135   Green: 72   Blue: 145
Chlorophyll Level: High (Healthy)
```

# Results

| Control Group | Key Condition | Days Healthy |
|---|---|---|
| Control 1 | Low Moisture + High Humidity | 0 |
| Control 2 | Low Moisture + Optimal Humidity | 2 |
| Control 3 | Optimal Moisture + High Humidity | 7 |
| Control 4 | Optimal Moisture + Optimal Humidity | 9 |
| Control 5 | High Moisture + High Humidity | 4 |
| Control 6 | High Moisture + Optimal Humidity | 4 |

- **Best Performance: Control 4** (Optimal Moisture + Optimal Humidity)
- **Worst Performance: Control 1** (Low Moisture + Optimal Humidity)

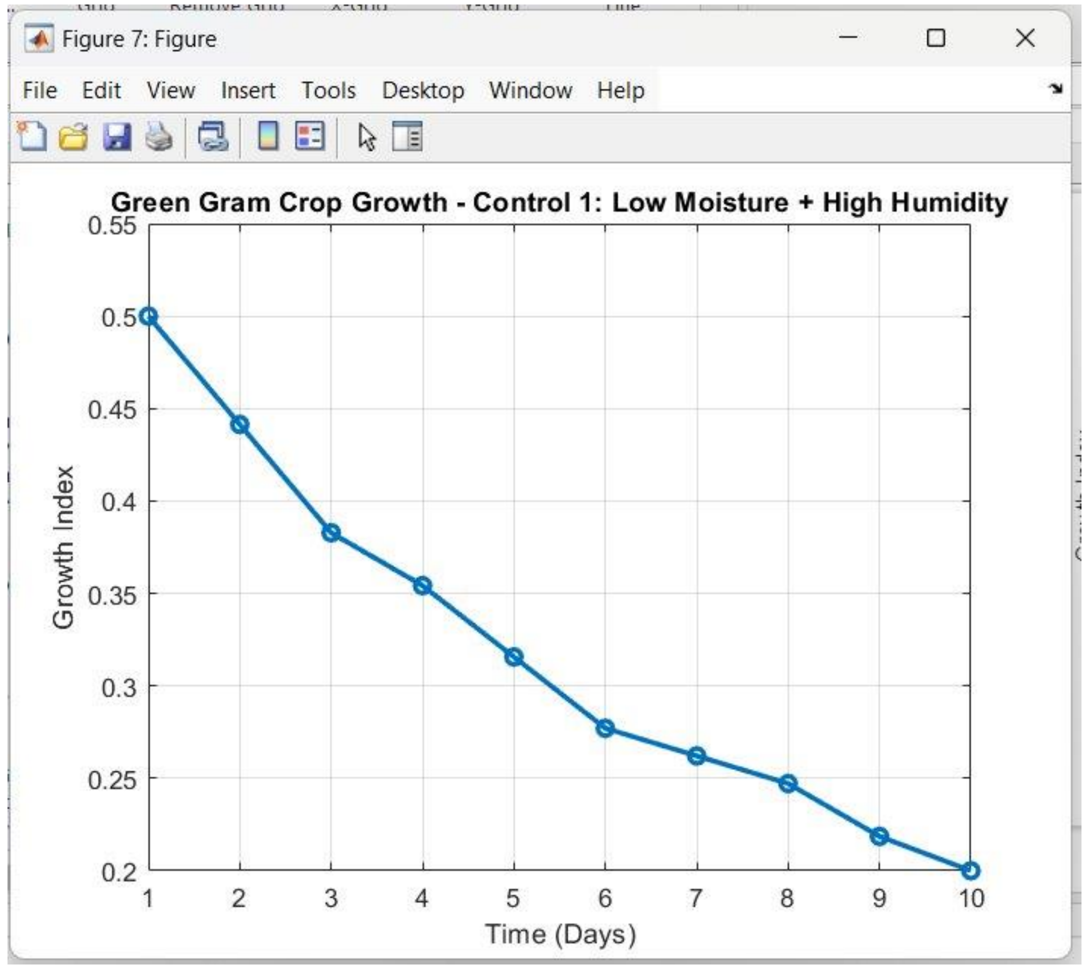


Figure 7: Figure
File Edit View Insert Tools Desktop Window Help
Green Gram Crop Growth - Control 1: Low Moisture + High Humidity
Growth Index
Time (Days)

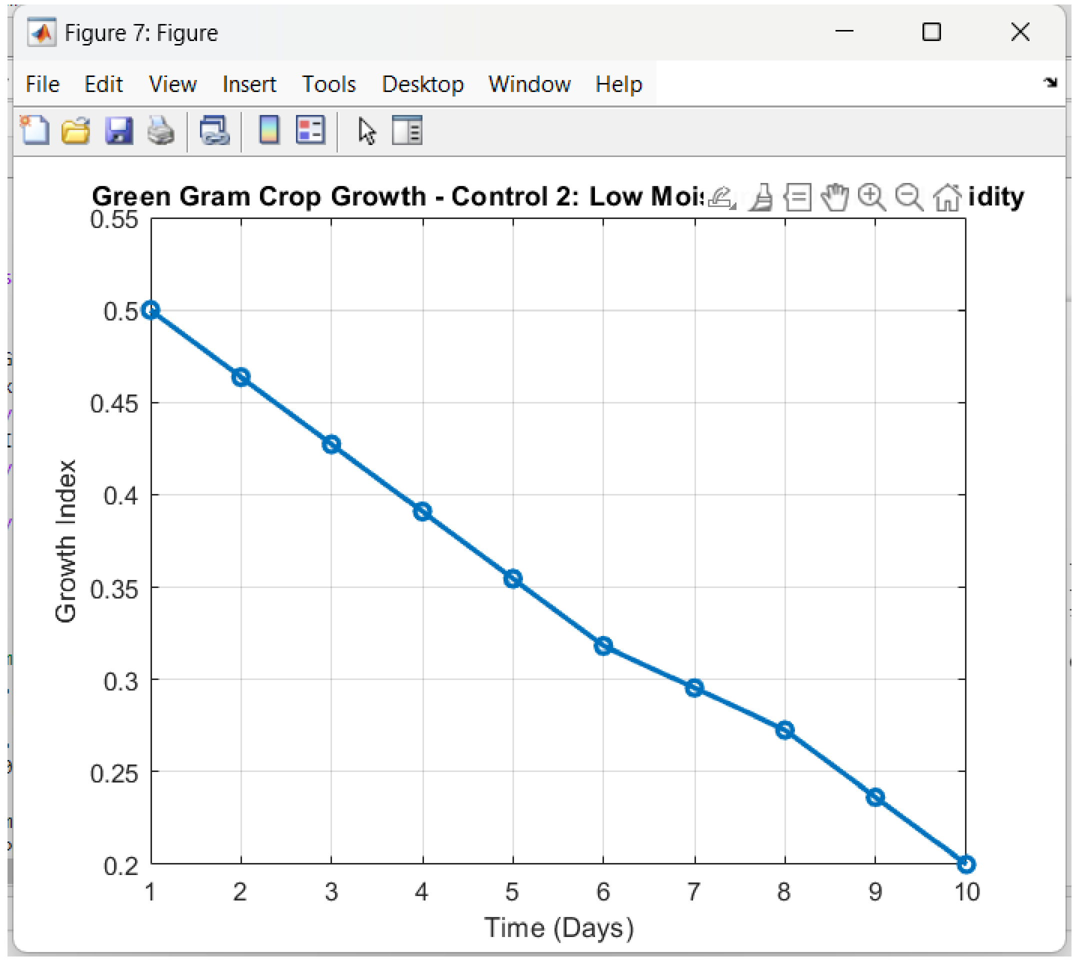


Figure 7: Figure
File Edit View Insert Tools Desktop Window Help
Green Gram Crop Growth - Control 2: Low Moi
idity
Growth Index
Time (Days)

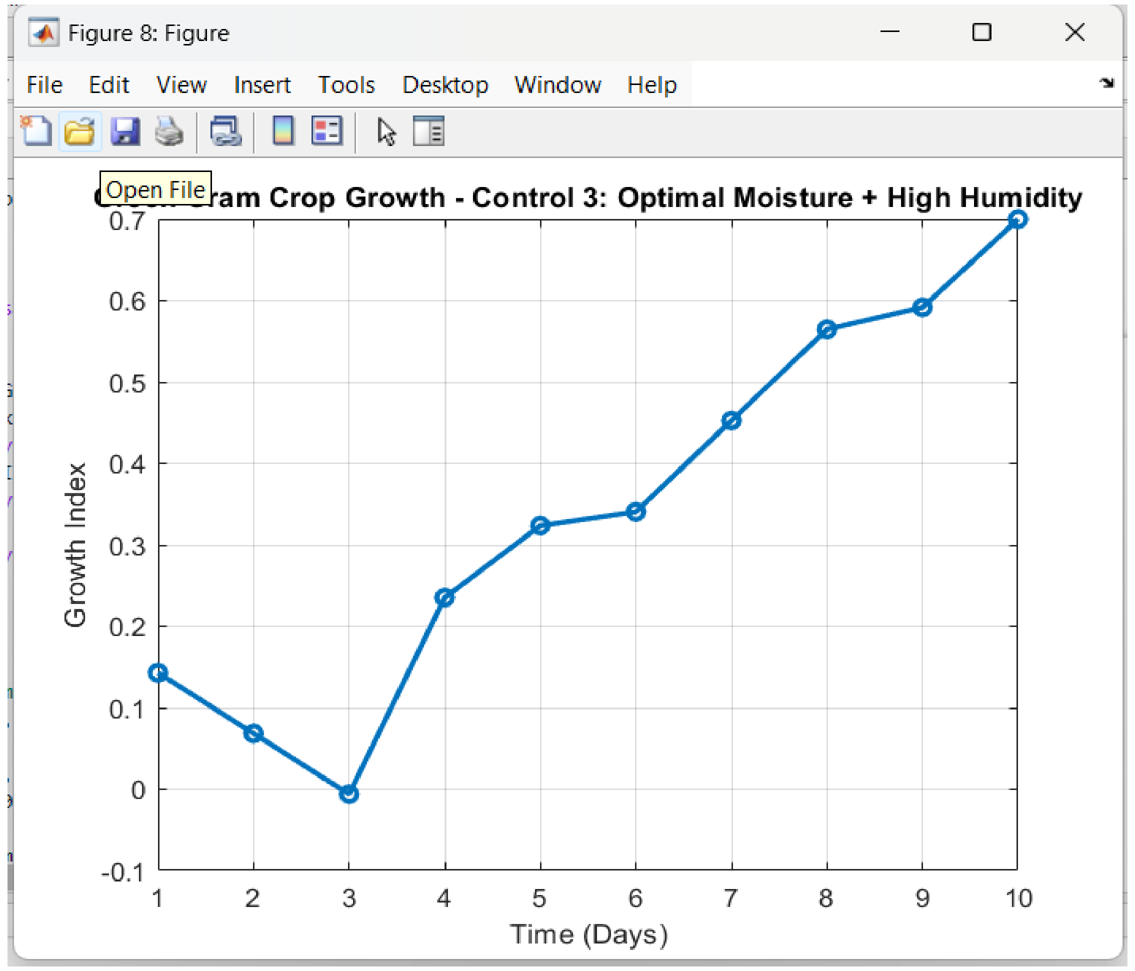


Figure 8: Figure
File Edit View Insert Tools Desktop Window Help
Open File
ram Crop Growth - Control 3: Optimal Moisture + High Humidity
Growth Index
Time (Days)

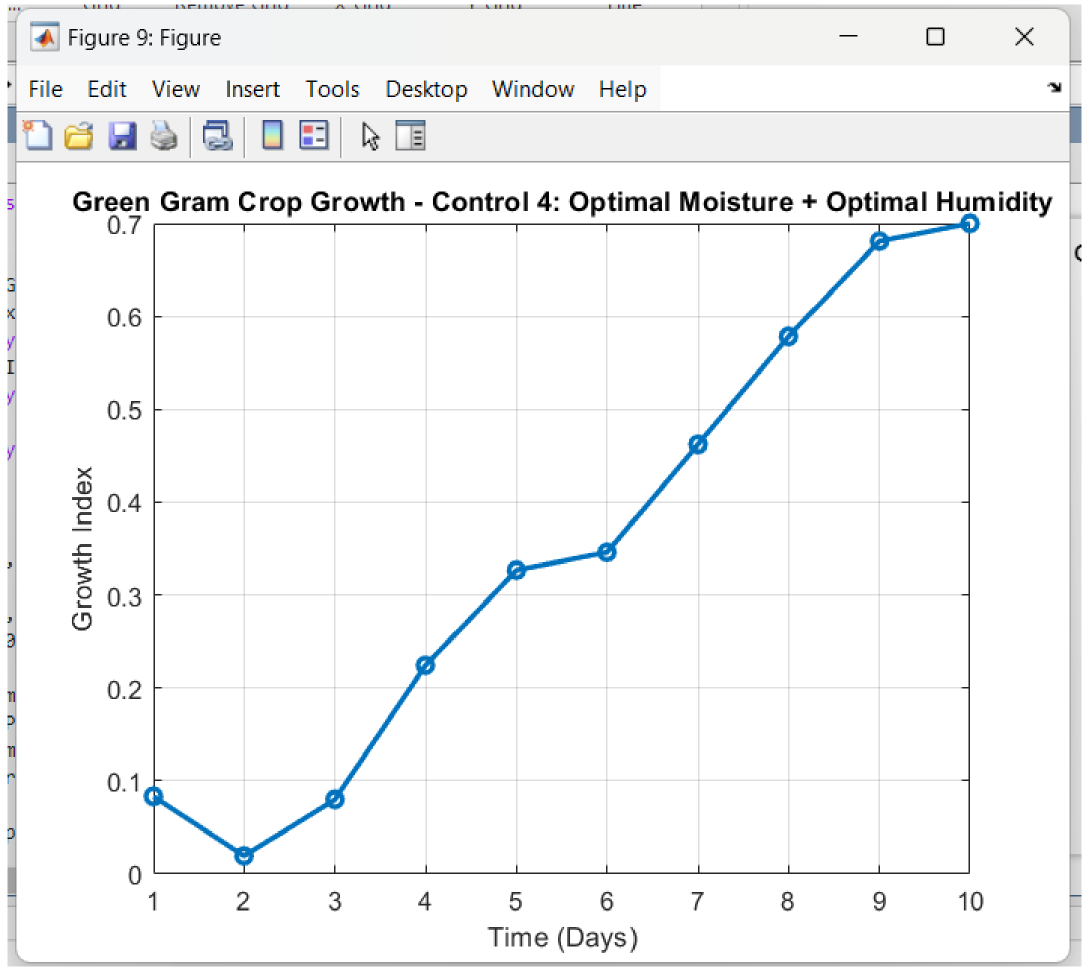


Figure 9: Figure
File Edit View Insert Tools Desktop Window Help
Green Gram Crop Growth - Control 4: Optimal Moisture + Optimal Humidity
Growth Index
Time (Days)

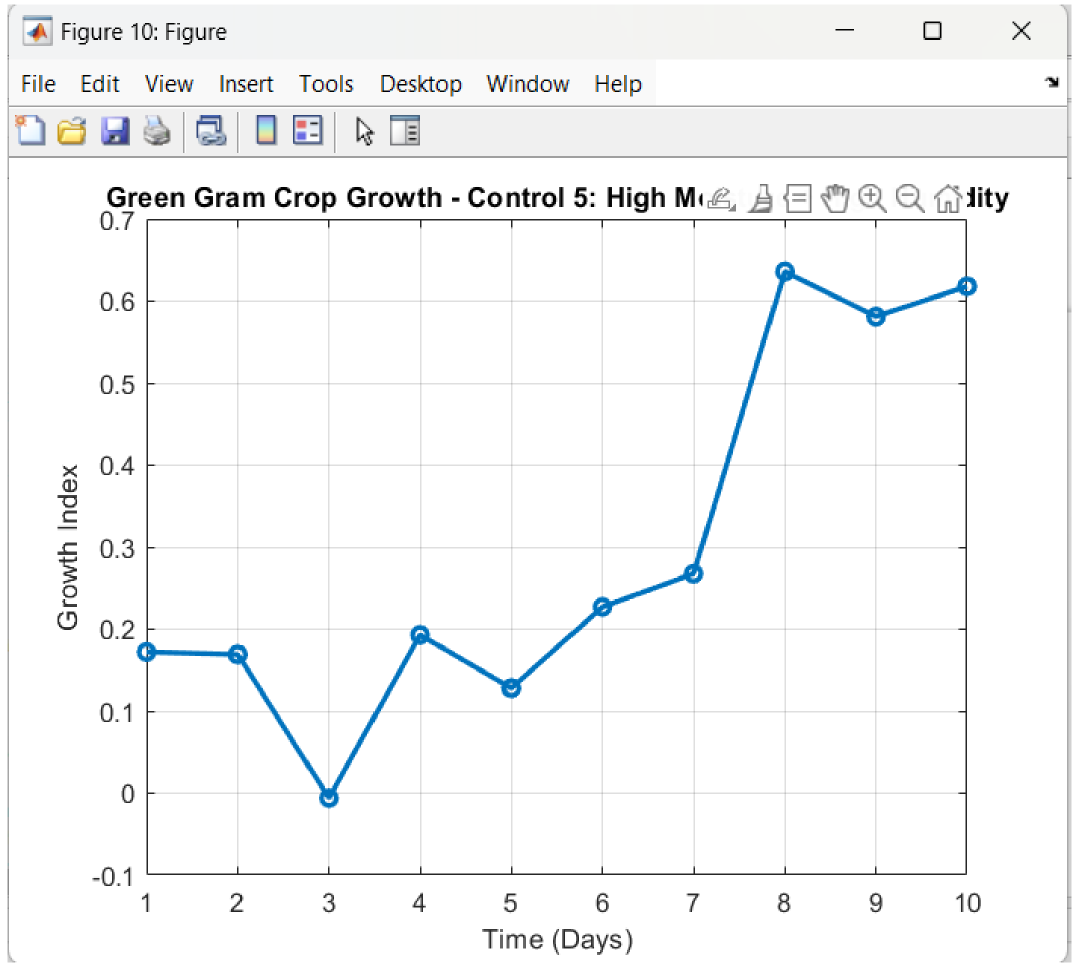


Figure 10: Figure
File Edit View Insert Tools Desktop Window Help
Green Gram Crop Growth - Control 5: High M
idity
Growth Index
Time (Days)

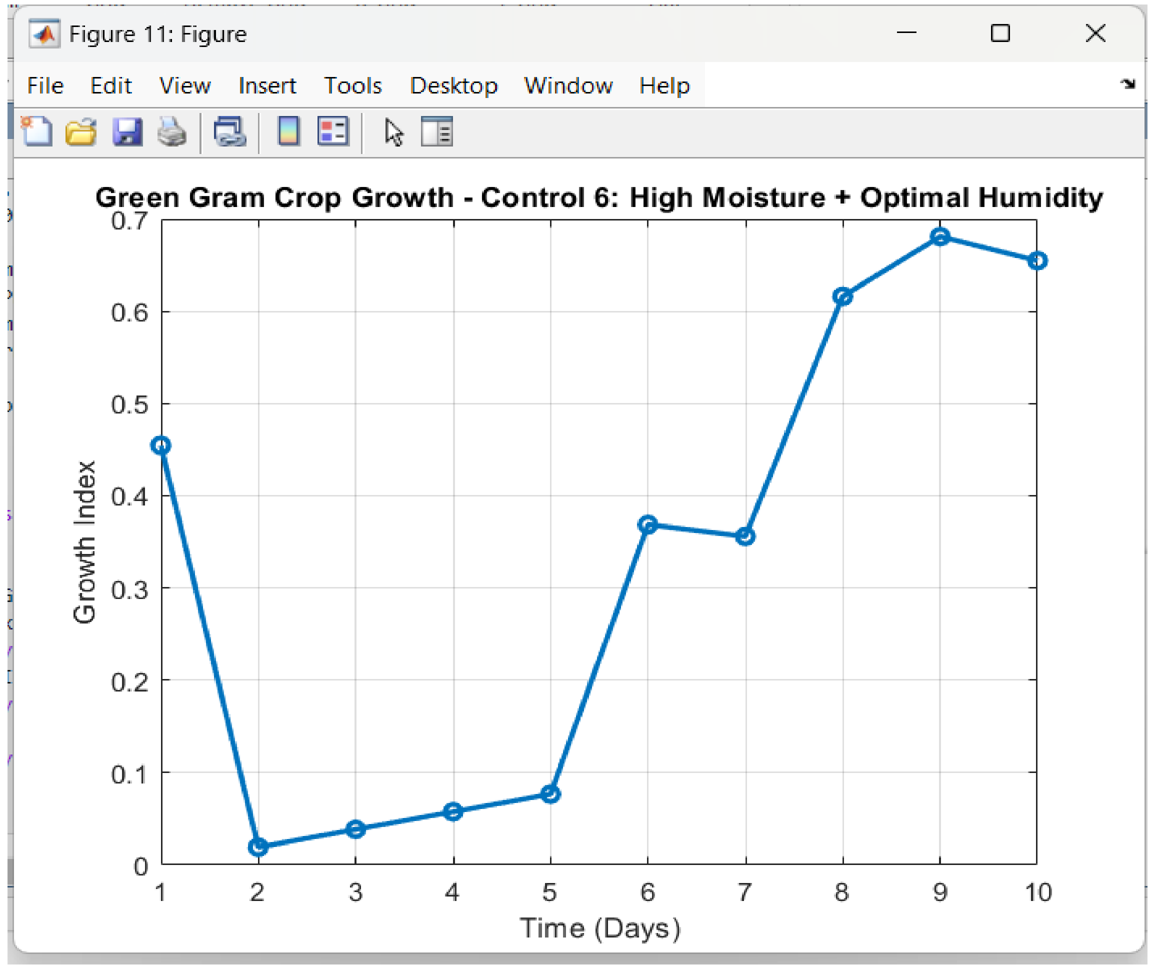


Figure 11: Figure
File Edit View Insert Tools Desktop Window Help
Green Gram Crop Growth - Control 6: High Moisture + Optimal Humidity
Growth Index
Time (Days)

As we expected by day 20 the plant with low moisture + high humidity & low moisture + optimal humidity expired.

The plant with optimal moisture + optimal humidity & plant with optimal moisture + high humidity are healthy.

The plants with remaining conditions did grow but not as good as the one having optimal conditions.

# Ethical Guidelines

**Transparency** – Clearly state model assumptions and sensor data sources while acknowledging limitations in real world factors.

**Environmental Responsibility** – Model predictions should promote eco-friendly techniques based on environmental factors.

**Farmer Inclusivity & Accessibility** – Outputs should be clear and visual for non-technical users, with considerations for offline or mobile access in remote areas.

**Data Privacy & Security** – Sensor data and farm information must be securely stored, with encryption and informed consent.

**Over-Reliance on Simulation Validity -** Without validating sensor data with real world measurements leads to uncertainty in growth predictions, affecting accuracy.

# Paper 1 : Challenges and opportunities in crop simulation modelling under seasonal and projected climate change scenarios for crop production in South Africa

In South Africa, there is a notable lack of legislation that obliges public access to private owned data, a lack of sustainable funding mechanisms for long-term collection and curation of important classes of data, and technical difficulties in managing and sharing data. A study by Koopman and De Jager [96] carried out at the University of Cape Town (UCT) showed that even though past research had generated digital data in many different formats, these data are being reused and shared within a controlled group of collaborating researchers.

These snippets highlight the importance of **Transparency in model limitations & Data security.**

Accordingly, their study indicates that very few researchers were willing to allow free use of data sets under their control. Hence, data ownership was found to be a significant limiting factor for data sharing. Data ownership var-

just beginning to gain traction [3]. According to Alter and Vardigan [3], most authors acknowledge the potential for the exploitation of the local population and other forms of harm that might affect research participants, including loss of privacy, and issues around informed consent, including questions about the rights of research subjects and potential benefits to the local community. Other bar-

# Paper 2 : Simulation and visualization of plant growth using a functional–structural model

Belesky, 2015; 2018). The validity of the use of such simulation tools by landscape architects has been discussed by Ervin and Raxworthy (Ervin 2001, Raxworthy 2018). Criticisms include the challenges in accurately simulating highly complex systems, and an over-reliance on their assumed validity. Kullman also discussed the challenges associated with the use of

This snippet highlights the **Over-Reliance on Simulation Validity** guideline

# Paper 3 : The role of crop simulation modeling in assessing potential climate change impacts

agriculture is still highly dependent on weather conditions for sufficient plant production to meet the world's growing needs. The global scale climate, which is defined by the long-term changes in weather, has been relatively stable for millennia and this stability contributed to the development of agriculture (Joan & Alexander, 2018). However, this longterm stability is being threatened. Due to industrialization and an increase in agricultural activities, atmospheric $CO_2$ and other greenhouse gases (GHGs) have been increasing, and there is widespread consensus that this is driving longterm changes in weather, notably temperature increases, more flooding, and longer drought periods (van der Wiel & Bintanja, 2021). The Intergovernmental Panel on

These snippets highlight the importance of **Environmental Responsibility & Climate change**

Intergovernmental Panel on Climate Change (IPCC) in 1990, crop simulation models have been actively used for climate change impact assessment in conjunction with evolving GCMs. The initial works focused on the responses of major staple crop yields (rice, wheat, maize, and soybean) to increasing $CO_2$ and climate change scenarios (Curry et al., 1990; Rosenzweig & Iglesias, 1994; Rosenzweig & Parry, 1994). Since then, the scope of crop model applications has expanded to broader geographic areas, diverse climatic variables,

become more severe in the future. Furthermore, limitations in resources such as water, arable land, and fertilizers can reduce the potential for food and fiber production. Driving factors behind these limitations include increased urban and industrial land use, competition for energy sources, depletion of groundwater resources, more frequent extreme weather events, and global warming.

# Paper 4 : Data-driven crop growth simulation on time-varying generated images using multi-conditional generative adversarial networks

the output of a processbased model. The minimum MAE/ME is not reached at 100:100, mainly due to the slight dataset bias towards SW and the resulting under-prediction of FB plants in the images, as already discussed. Assuming an unbiased image generation model, this type of analysis can serve to improve the calibration of the process-based model and bring it closer to image-based field observations. If the minimum MAE deviates from the

This snippet infers to the Fair and Equitable Access to Agricultural Technology which comes under **Farmer Inclusivity & Accessibility** guideline.

# IPR Patents involved

**Yield Estimation in Agricultural Harvesters :** US10295703B2

**Intelligent Irrigation Decision Support System** WO2022190124A1

**Chlorophyll and Turbidity Sensor System** EP2389447A1

**LIVING PLANT MONITORING SYSTEMS** US 2015/0149090 A1

# References


- 1. Lukas Drees, Dereje T. Demie, Madhuri R. Paul, et al. (2023). Data-driven Crop Growth Simulation on Time-varying Images using Multi-conditional GANs.
- 2. J.W. Jones, G. Hoogenboom, C.H. Porter, et al. (2022). The role of crop simulation modeling in assessing potential climate change impacts on crops.
- 3. Y. Zhang, X. Li, L. Wang, et al. (2022). Research on Simulation Model and 3D Visualization of Crop Growth Based on Parametric Design.
- 4. S. Asseng, F. Ewert, P. Martre, et al. (2021). Challenges and opportunities in crop simulation modelling under a changing climate.