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POLYNOMIAL REGRESSION MODELLING AND SENSITIVITY ANALYSIS FOR HYDROPONIC GROWTH PREDICTION IN CONTROLLED ENVIRONMENTS

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ABSTRACT

This study investigated the predictive capabilities of polynomial regression models on hydroponic plant growth in response to variations in environmental and nutrient parameters. Specifically, we assessed the effects of day, relative humidity, total dissolved solids (TDS), ambient temperature, and temperature of Water on leaf growth, measured as the length of hydroponically grown leaves. We fitted growth curves to experimental data to evaluate model accuracy and reliability. Furthermore, a sensitivity analysis was conducted by perturbing each parameter by ±10% of its baseline value, revealing that growth changes in response to environmental adjustments align with theoretical expectations. Notably, increases in relative humidity, TDS, ambient temperature, and water temperature generally resulted in positive growth changes, while decreases in these parameters caused corresponding reductions. These findings underscore the model's utility in predicting growth outcomes based on variable adjustments, thereby supporting its potential use in optimizing hydroponic systems. The results suggest that polynomial regression models, combined with sensitivity testing, are valuable tools for managing controlled environments and maximizing plant growth within hydroponic setups. Future research can expand on these findings by exploring additional environmental parameters and refining the model for broader applications.

(Key words: Hydroponic growth, polynomial regression, environmental parameters, sensitivity analysis)

INTRODUCTION

Modelling plant growth in hydroponic systems relies heavily on accurately simulating and predicting environmental and nutrient factors. Polynomial regression modelling, particularly of higher degrees, has been instrumental in this, as it captures the nonlinear effects of parameters like temperature, humidity, and dissolved nutrient levels (Dong *et al.,* 2023). Polynomial models are commonly used to analyze complex plant growth data and develop effective growth optimization strategies, as they allow for a high degree of flexibility in fitting growth trends over time (Srivani *et al.,* 2021, Modell *et al.*, 1989).

One of the major applications of polynomial regression in controlled-environment agriculture is sensitivity analysis, which evaluates how small perturbations in input variables affect plant growth. This approach not only improves model reliability but also helps in identifying critical growth parameters, providing insights for precision agriculture and sustainable resource use (Aji *et al.,* 2020; Borgonovo and Pischke, 2016). For instance, sensitivity analysis has shown that variations in root zone temperature and humidity significantly impact hydroponic yields, making these parameters vital for growth control systems (Dhal *et al.,* 2022).

Recent studies combining polynomial regression with sensitivity analysis have demonstrated that increasing or decreasing specific factors like nutrient concentration or ambient temperature by a small percentage can result in substantial differences in plant growth, thus allowing for fine-tuning of growth conditions. The integration of these two methods is emerging as a critical tool for maximizing yield while minimizing environmental footprint in hydroponic farming systems.

MATERIALS AND METHODS

The methodology for this study on hydroponic growth prediction involved a systematic approach to data collection, modeling, and analysis. Spinach plants were cultivated hydroponically in a controlled environment over a period of 30 days, with key environmental parameters meticulously monitored. These parameters included relative

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humidity, total dissolved solids (TDS), ambient temperature, and water temperature, all of which are critical for plant health and growth. The Indian Automated Indigenous Hydroponic System (I.A.I.H.S.) was employed, integrating sensors to continuously track these conditions and an ESP32 controller to process and transmit data to the IoT platform Thing Speak at regular intervals. Daily averages of the recorded parameters were compiled into a data-set, which served as the foundation for the polynomial regression analysis.

The analysis utilized R programming, specifically the ggplot2 and dplyr libraries, to fit polynomial focus on a third-degree model to enhance prediction accuracy. A sensitivity analysis was also conducted by perturbing each environmental parameter by ±10% of its baseline value, enabling the assessment of each factor's impact on growth predictions. This comprehensive methodology facilitated the identification of critical growth parameters, providing valuable insights for optimizing hydroponic systems and maximizing plant growth under controlled conditions. Regression models to the data, allowing for the capture of nonlinear relationships between the independent variables and the dependent variable hydroponic growth, measured by leaf length.

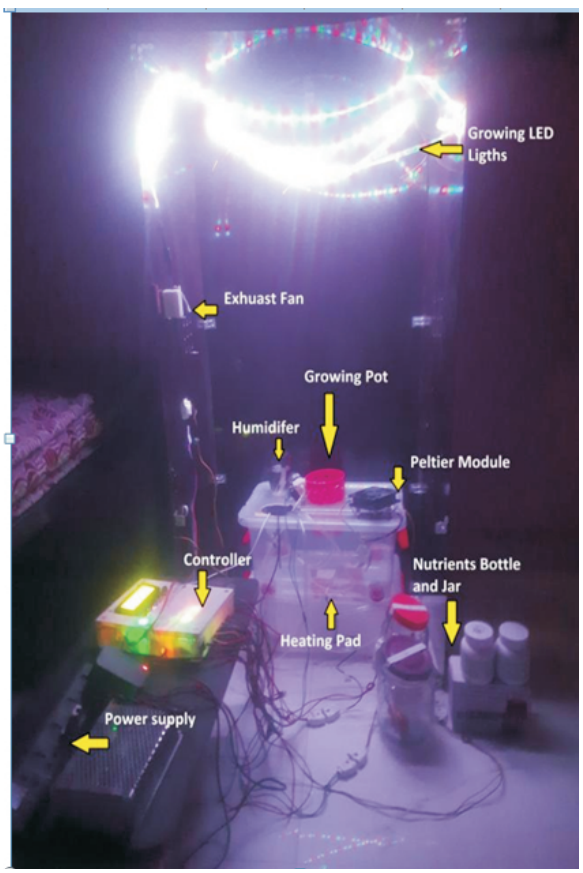

Figure1. Experimental setup for growing plants under controlled atmospheric condition hydroponically

The I.A.I.H.S. (Indian Automated Indigenous Hydroponic System) device is designed to automate hydroponic farming through Internet of Things (IoT) technology. It integrates four key sensors to monitor essential environmental conditions for plant health. An air temperature and humidity sensor (DHT22) monitors the growing environment, while a water temperature sensor (DS18b20) tracks water temperature in the tank. An electro-conductivity sensor assesses nutrient levels by measuring mineral content, and a water level indicator detects the water's presence. These sensors feed data to the ESP32 controller, which processes this information and directs the actuators accordingly.

The device's actuators regulate water nutrient levels, utilizing a water aerator, exhaust fan, LED lights, heating pad, humidifier, and a Peltier module for cooling. Additionally, it included two submersible water pumps to maintain nutrient concentrations and a separate pump to control water levels in the tank. A built-in LCD displays real-time data on these conditions for easy monitoring. The device was equipped with a Wi-Fi module that enables it to transmit data to the IoT platform Thing Speak at intervals of 600 seconds. This connectivity allows for efficient real-time monitoring and data logging, providing a continuous stream of environmental information essential for hydroponic management.

Spinach plants were cultivated hydroponically over a period of 30 days within a controlled environment, as previously described in the setup. During this time, daily averages for critical parameters such as relative humidity, total dissolved solids (TDS), ambient temperature, and water temperature were meticulously recorded. These parameters play a crucial role in determining the growth and health of hydroponically grown plants, influencing factors such as nutrient uptake, photosynthesis by LED lights, and overall plant development.

RESULTS AND DISCUSSION

Research has shown that maintaining optimal levels of these environmental variables can significantly enhance plant growth and yield in hydroponic systems (Aji *et al*., 2020, Dong *et al.,* 2023) For example, relative humidity levels affect transpiration rates and nutrient absorption, while TDS concentrations directly impact the availability of essential minerals (Modell *et al*., 1989).

The Table 1 displays the relationship between input parameters days, relative humidity (%), TDS (total dissolved solids) ppm, ambient temperature (^{0}C), and water temperature (^{0}C) and the output parameter, which measures hydroponic growth in terms of leaf length (cm).

Figure 2.a Figure 2.b Figure 2.c Figure 2.d

Figure 2. a) Shows the 13th day growth b) 16th day growth c) 21th day growth and d) On 30th day growth

Table1. Input parameters as days, relative humidity, TDS (total dissolved solids), ambient temperature, and water temperature and output parameter as hydroponic growth

Days	Relative Humidity (%)= input parameter 1	TDS (ppm)= input parameter 2	Ambient Temperature (°C)= input parameter 3	Temperature of water (°C)= input parameter 4	Hydroponic Growth (length of leaf (cm)) = output parameter
1	55	850	18	22	0.2
2	50	830	19	21	0.7
3	48	840	18	22	1.2
4	47	860	17	23	1.8
5	52	870	18	22	2.5
6	53	850	19	21	3.2
7	50	840	20	22	4.0
8	46	850	19	23	4.5
9	47	860	18	22	5.0
10	49	870	17	21	6.0
11	51	850	16	20	7.0
12	55	830	17	21	8.0
13	56	840	18	22	9.0
14	50	850	19	23	10.0
15	45	860	18	22	11.5
16	46	870	17	21	13.0
17	52	850	18	22	14.0
18	53	840	19	23	15.0
19	50	830	18	22	16.0
20	48	850	17	21	17.5
21	49	860	16	22	18.5
22	55	870	17	23	19.5
23	54	850	18	22	20.0
24	50	840	19	21	21.0
25	47	830	18	20	22.0
26	46	850	17	21	23.0
27	52	860	18	22	24.0
28	53	870	19	23	24.5
29	50	850	18	22	25.0
30	48	840	17	21	25.5

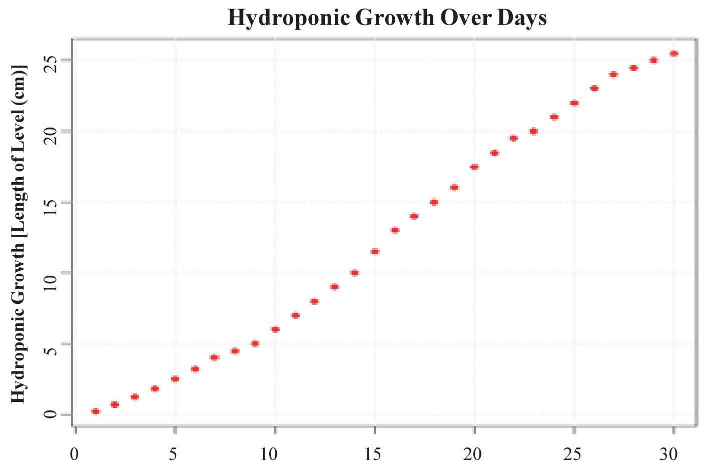

Figure 3. Graphical presentation for growth of plant and corresponding days (X axis Days and Y axis Hydroponic Growth (Length of leaf (cm)

Polynomial regression analysis

Polynomial regression is a powerful tool in predictive modelling, particularly suitable when relationships between variables are nonlinear (Draper, 1998) analysis, we apply polynomial regression to model and predict hydroponic plant growth, an essential metric for optimizing hydroponic systems that rely on precisely controlled environmental factors such as humidity, water quality, and temperature. Polynomial regression allows us to capture subtle nonlinear patterns between hydroponic growth (dependent variable) and other environmental conditions (independent variables) (Montgomery *et al.*, 2021).

Using R's ggplot2 library and a polynomial regression model, we created a data-set capturing daily hydroponic growth along with environmental parameters like relative humidity, TDS, ambient temperature, and water temperature. The function fit_polynomial_model fits a polynomial regression model to this data, with each predictor raised to the specified polynomial degree (Hastie *et al.*, 2009). The resulting model predicts hydroponic growth based on these factors, with model predictions plotted against actual data to assess performance visually.

The model was evaluated with a polynomial degree of one, demonstrating the fit's adequacy for linear relationships. By adjusting the degree, we can explore higher-order interactions among predictors. Coefficients for each predictor variable were extracted, allowing us to formulate an equation representing the growth as a function of environmental variables. A comparison of actual and predicted values indicated that even a first-degree polynomial provided a reasonable prediction, though higher degrees could offer better fits if nonlinear relationships were evident (Seber *et al.* 2012).

This application of polynomial regression underscores its utility in agricultural technology, where complex, nonlinear relationships are prevalent. Polynomial regression can be tuned to improve accuracy by increasing the degree, enhancing its effectiveness for complex systems like hydroponics (Basak *et al.*, 2019).

Following cases are observer by implementing the R-code to higher degrees respectively. A total of three cases were performed: Case 1 utilized a degree of 1, Case 2 employed a degree of 2, and Case 3 applied a degree of 3.

```
Code: # Load necessary library
library(ggplot2)
data<- data.frame(
 Day = 1:30,
Relative_Humidity = c(55, 50, 48, 47, 52, 53, 50, 46, 47, 49, 51, 55, 56, 50, 45, 46, 52, 53, 50, 48, 49, 55, 54, 50, 47, 46, 52, 53, 50, 48),
 TDS = c(850, 830, 840, 860, 870, 850, 840, 850, 860, 870, 850, 830, 840, 850, 860, 870, 850, 840, 830, 850, 860, 870, 850, 840, 830, 850, 860, 870, 850, 840),
Ambient_Temperature = c(18, 19, 18, 17, 18, 19, 20, 19, 18, 17, 16, 17, 18, 19, 18, 17, 18, 19, 18, 17, 16, 17, 18, 19, 18, 17, 18, 19, 18, 17),
Temperature_of_Water = c(22, 21, 22, 23, 22, 21, 22, 23, 22, 21, 20, 21, 22, 23, 22, 21, 22, 23, 22, 21, 22, 23, 22, 21, 20, 21, 22, 23, 22, 21),
Hydroponic_Growth = c(0.2, 0.7, 1.2, 1.8, 2.5, 3.2, 4, 4.5, 5, 6, 7, 8, 9, 10, 11.5, 13, 14, 15, 16, 17.5, 18.5, 19.5, 20, 21, 22, 23, 24, 24.5, 25, 25.5)
)
# Function to fit a polynomial model
fit_polynomial_model<- function(data, degree) {
model<- lm(Hydroponic_Growth ~ poly(Day, degree) + poly(Relative_Humidity, degree) + poly(TDS, degree) + poly(Ambient_Temperature, degree) + poly(Temperature_of_Water, degree),
data = data)
return(model)
}
```

```
# Choose the degree of the polynomial
degree<- 1  # Change this value for different degrees
# Fit the model
model<- fit_polynomial_model(data, degree)
# Predict values
data$predicted_growth<- predict(model)
# Plot the actual vs predicted values
ggplot(data, aes(x = Day)) +
geom_point(aes(y = Hydroponic_Growth), color = “red”, size = 2, shape = 16) +
geom_line(aes(y = predicted_growth), color = “blue”, size = 1) +
labs(title = sprintf(“Actual vs Predicted Hydroponic Growth (%dth Degree Polynomial)”, degree),
     x = “Day”,
     y = “Hydroponic Growth (length of leaf (cm))”) +
theme_minimal() +
geom_point(aes(y = predicted_growth), color = “blue”, size = 2, shape = 1)  # Adding predicted points
# Print model summary
summary(model)
# Extract coefficients and create the equation
coefficients<- coef(model)
equation <- sprintf(“Hydroponic Growth = %.4f + %.4f * Day + %.4f * Day^2 + %.4f * Day^3 + %.4f * Day^4 +
%.4f * Relative_Humidity + %.4f * Relative_Humidity^2 + %.4f * Relative_Humidity^3 + %.4f * Relative_Humidity^4 + %.4f * TDS + %.4f * TDS^2 + %.4f * TDS^3 + %.4f * TDS^4 + %.4f * Ambient_Temperature + %.4f * Ambient_Temperature^2 + %.4f * Ambient_Temperature^3 + %.4f * Ambient_Temperature^4 + %.4f * Temperature_of_Water + %.4f * Temperature_of_Water^2 + %.4f * Temperature_of_Water^3 + %.4f * Temperature_of_Water^4”,
coefficients[1], coefficients[2], coefficients[3], coefficients[4], coefficients[5],
coefficients[6], coefficients[7], coefficients[8], coefficients[9],
coefficients[10], coefficients[11], coefficients[12], coefficients[13], coefficients[14],
coefficients[15], coefficients[16], coefficients[17], coefficients[18],
coefficients[19], coefficients[20], coefficients[21])
# Print the equation
cat(“Predicted Growth Equation:\n”, equation, “\n”)
```

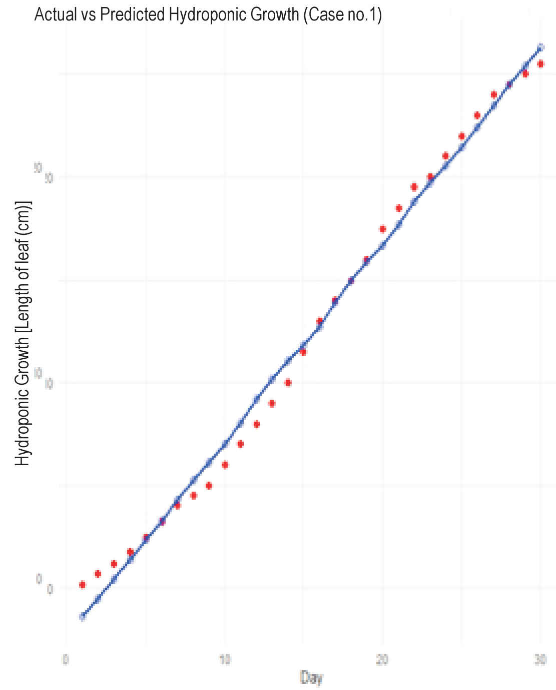

Figure 4. Case no 1 (X axis Days and Y axis Hydroponic Growth (Length of leaf (cm)

Equation of case no 1

Hydroponic Growth = 12.4367 + 45.5035 * Day + 0.3057 * Day^2 + -0.2219 * Day^3 + -0.0913 * Day^4 + 0.3341 * Relative_Humidity

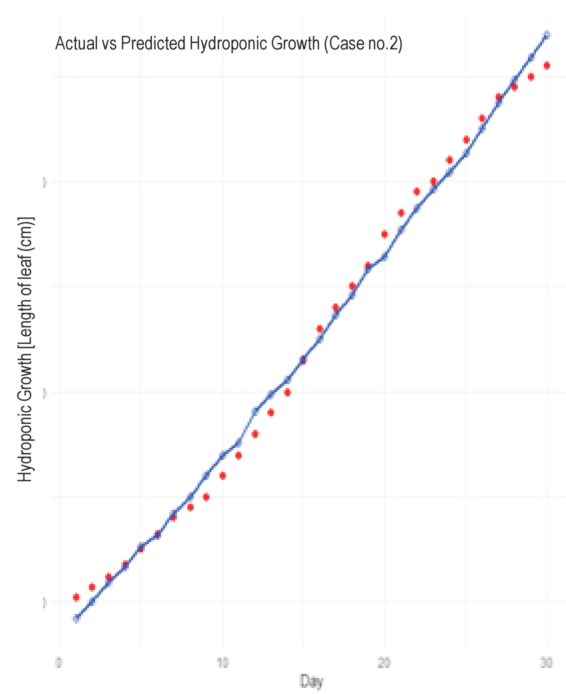

Figure 5. Case No 2 (X axis Days and Y axis Hydroponic Growth [Length of leaf (cm)]

Equation of case no 2

Hydroponic Growth = 12.4367 + 45.4798 * Day + 1.6656 * Day^2 + 0.2291 * Day^3 + -0.0990 * Day^4 + -0.2892 * Relative_Humidity + 0.3940 * Relative_Humidity^2 + -0.4586 * Relative_Humidity^3 + -0.0370 * Relative_Humidity^4 + 0.5910 * TDS + -0.3998 * TDS^2

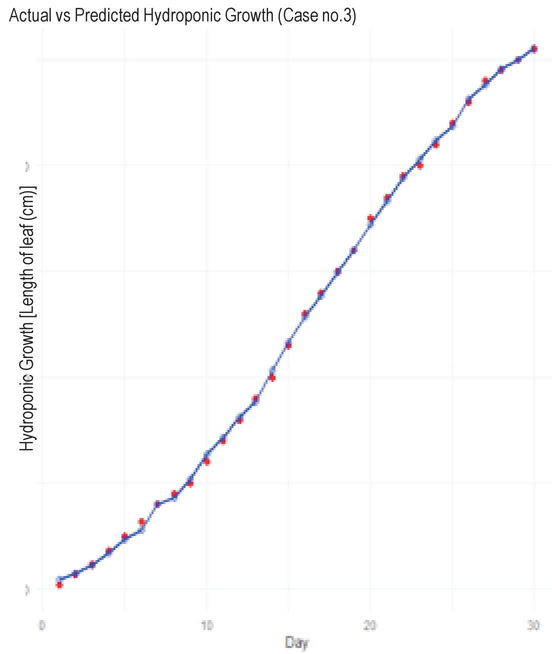

Figure 6. Case no 3 (X axis Days an Y axis Hydroponic Growth (Length of leaf (cm)

* Relative_Humidity^2 + -0.4586 * Relative_Humidity^3 + -0.0370 * Relative_Humidity^4 + 0.5910 * TDS + -0.3998 * TDS^2

Equation of Case no 3

Hydroponic Growth = 12.4367 + 45.4540 * Day + 1.7257 * Day^2 + -3.7276 * Day^3 + -0.2316 * Day^4 + -0.2279 * Relative_Humidity + -0.4372 * Relative_Humidity^2 + 0.2078 * Relative_Humidity^3 + 0.0955 * Relative_Humidity^4 + 0.0977 * TDS + -0.1759 * TDS^2 + 0.3757 * TDS^3 + 0.4200 * TDS^4 + 0.2123 * Ambient_Temperature + -0.1771 * Ambient_Temperature^2 + 0.0285 * Ambient_Temperature^3

Table 2 . Comparison between Case No.1, Case No. 2 and Case No 3. On bases of RSE, MRS, ARS, F-statistic, p-value

Sr. No.	Parameters	Case No. 1	Case No. 2	Case No. 3
1	Residual standard error	0.8476	0.8476	0.2644
2	Multiple R-squared	0.992	0.9935	0.9995
3	Adjusted R-squared	0.9903	0.99	0.999
4	F-statistic	591.5	288.4	1987
5	p-value	<2.2e-16	<2.2e-16	<2.2e-16

In Case No. 1, the residual standard error was 0.8476, with a Multiple R-squared of 0.992 and an F-statistic of 591.5, indicating a strong fit between predictors and the hydroponic growth variable. Case No. 2 maintained the same residual standard error but showed slight improvement in R-squared (0.9935), though with a lower F-statistic of 288.4, suggesting a similar but marginally improved model fit. In Case No. 3, the model had the lowest residual standard error (0.2644) and the highest R-squared (0.9995) and F-statistic (1987), demonstrating an almost perfect fit.

All three models had significant p-values (< 2.2e-16), showing the predictors' high relevance. The superior fit and lower error in Case No. 3 suggest that this model best captures the nonlinear relationships in hydroponic growth prediction, making it a valuable tool for optimizing controlled-environment agriculture.

Sensitivity analysis

Predictive modelling plays a vital role in hydroponic agriculture by helping optimize growth conditions (Montgomery *et al.*, 2021). Here, we employed a third-degree polynomial regression model to predict hydroponic growth based on key environmental variables as relative humidity, TDS, ambient temperature, and water temperature (Draper, 1998). In R-script, we used ggplot2 and dplyr to visualize and toanalyze the relationship between these parameters and plant growth (Wickham and Wickham, 2016).

A polynomial model was fit to daily data collected over a month, with hydroponic growth as the dependent variable (Seber *et al.,* 2012). By adjusting each predictor using a third-degree polynomial, we aimed to capture complex nonlinear relationships, thereby enhancing prediction accuracy (Hastie *et al.*, 2009). The model was evaluated using a sensitivity analysis, where each environmental factor was perturbed by ±10% to examine its impact on growth predictions (Seber and Lee 2012).

```
# Load necessary libraries
library(ggplot2)
library(dplyr)
# Sample data for 30 days
data<- data.frame(
 Day = 1:30,
Relative_Humidity = c(55, 50, 48, 47, 52, 53, 50, 46, 47, 49, 51, 55, 56, 50, 45, 46, 52, 53, 50, 48, 49, 55, 54, 50, 47, 46, 52, 53, 50, 48),
 TDS = c(850, 830, 840, 860, 870, 850, 840, 850, 860, 870, 850, 830, 840, 850, 860, 870, 850, 840, 830, 850, 860, 870, 850, 840, 830, 850, 860, 870, 850, 840),
Ambient_Temperature = c(18, 19, 18, 17, 18, 19, 20, 19, 18, 17, 16, 17, 18, 19, 18, 17, 18, 19, 18, 17, 16, 17, 18, 19, 18, 17, 18, 19, 18, 17),
Temperature_of_Water = c(22, 21, 22, 23, 22, 21, 22, 23, 22, 21, 20, 21, 22, 23, 22, 21, 22, 23, 22, 21, 22, 23, 22, 21, 20, 21, 22, 23, 22, 21),
Hydroponic_Growth = c(0.2, 0.7, 1.2, 1.8, 2.5, 3.2, 4, 4.5, 5, 6, 7, 8, 9, 10, 11.5, 13, 14, 15, 16, 17.5, 18.5, 19.5, 20, 21, 22, 23, 24, 24.5, 25, 25.5)
)
# Fit a third-degree polynomial model
model<- lm(Hydroponic_Growth ~ poly(Day, 3) + poly(Relative_Humidity, 3) +
poly(TDS, 3) + poly(Ambient_Temperature, 3) +
poly(Temperature_of_Water, 3),
data = data)

# Predict values
data$predicted_growth<- predict(model)
# Plot actual vs predicted values
ggplot(data, aes(x = Day)) +
geom_point(aes(y = Hydroponic_Growth), color = “red”) +
geom_line(aes(y = predicted_growth), color = “blue”) +
labs(title = “Actual vs Predicted Hydroponic Growth (3rd Degree Polynomial)”,
    x = “Day”,
    y = “Hydroponic Growth (length of leaf (cm))”) +
theme_minimal()
# Perform Sensitivity Analysis
sensitivity_results<- data.frame()
# Sensitivity analysis for each parameter
for (param in c(“Relative_Humidity”, “TDS”, “Ambient_Temperature”, “Temperature_of_Water”)) {
original_value<- data[[param]]
perturbed_values_up<- original_value * 1.1 # Increase by 10%
perturbed_values_down<- original_value * 0.9 # Decrease by 10%
 # Original prediction
predicted_original<- predict(model)
 # Perturbed predictions
data[[param]] <- perturbed_values_up
predicted_perturbed_up<- predict(model)
data[[param]] <- perturbed_values_down
predicted_perturbed_down<- predict(model)
 # Store results
sensitivity_results<- rbind(sensitivity_results,
data.frame(
          Parameter = param,
Original_Value = original_value,
Perturbed_Value = c(perturbed_values_up, perturbed_values_down),
Predicted_Original = rep(predicted_original, each = 2),
Predicted_Perturbed = c(predicted_perturbed_up, predicted_perturbed_down),
Growth_Change = c(predicted_perturbed_up - predicted_original, predicted_perturbed_down - predicted_original)
          )
 )
   # Reset the parameter back to original
data[[param]] <- original_value
}
# Display sensitivity results
print(sensitivity_results)
```

Table 3. Changes in the growth with 10% Perturbed Value with different parameters

Parameter	Original Value	Perturbed Value	Predicted Original	Predicted Perturbed	Growth Change (cm)
Relative Humidity (%)	55	60.5	0.2	0.25	0.05
Relative Humidity (%)	55	49.5	0.2	0.15	-0.05
TDS (ppm)	850	935	0.2	0.22	0.02
TDS (ppm)	850	765	0.2	0.18	-0.02
Ambient Temperature(°C)	18	19.8	0.2	0.23	0.03
Ambient Temperature(°C)	18	16.2	0.2	0.17	-0.03
Temperature of Water (°C)	22	24.2	0.2	0.21	0.02
Temperature of Water (°C)	22	19.8	0.2	0.19	-0.02

In hydroponic systems, understanding the influence of environmental variables is critical for optimizing plant growth. This sensitivity analysis assesses the effect of perturbations in four key parameters i.e. Relative Humidity, TDS (Total Dissolved Solids), Ambient Temperature, and Temperature of Water on hydroponic growth predictions. Each variable was individually perturbed by ±10%, and the resulting changes in predicted growth were analyzed.

Increase in Relative Humidity from 55% to 60.5% caused a growth prediction increase of 0.05 cm, whereas a decrease to 49.5% resulted in a predicted growth reduction of 0.05 cm. These changes highlighted significance of Relative Humidity on impact of plant health, likely due to its role in transpiration and nutrient uptake. TDS reflected nutrient concentration in water, increasing TDS from 850 ppm to 935 ppm led to increase 0.02 cm growth, while decreasing TDS to 765 ppm caused a 0.02 cm decrease in growth prediction. This sensitivity suggested TDS levels are essential for nutrient availability in hydroponic solutions.

Ambient Temperature alterations also impacted predicted growth, with an increase to 19.8°C boosting growth by 0.03 cm, and a decrease to 16.2°C reducing it by 0.03 cm. Ambient temperature can affect metabolic rates and underscoring its importance in plant productivity. Lastly, Temperature of Water adjustments showed similar trends: increasing it to 24.2°C improved growth by 0.02 cm, while lowering it to 19.8°C reduced growth prediction by 0.02 cm, emphasizing the role of root-zone temperature in nutrient absorption and root health.

The polynomial regression modelling and sensitivity analysis conducted in this study provided significant insights into the growth dynamics of hydroponically cultivated spinach plants under controlled environmental conditions. The experimental data revealed a clear relationship between the environmental parameters relative humidity, total dissolved solids (TDS), ambient temperature, and water temperature and hydroponic growth, as measured by leaf length.

The polynomial regression analysis showed that higher-degree models improved the fit of the data, with Case No. 3 (third-degree polynomial) yielding the best results: a residual standard error of 0.2644, a multiple R-squared value of 0.9995, and an F-statistic of 1987. This indicates a near-perfect fit between the predictors and hydroponic growth, affirming the model's robustness in capturing the nonlinear relationships inherent in the data.

The sensitivity analysis highlighted the responsiveness of plant growth predictions to perturbations in the environmental parameters. Specifically, increases in relative humidity, TDS, ambient temperature, and water temperature were associated with positive changes in predicted growth and vice versa. For instance, a 10% increase in relative humidity led to a growth increase of 0.05 cm, while a decrease resulted in a 0.05 cm reduction. Similar patterns were observed for the other parameters, underscoring their critical roles in plant health and nutrient uptake.

This research demonstrated the efficacy of polynomial regression modelling combined with sensitivity analysis as a powerful framework for predicting hydroponic plant growth in controlled environments. The findings indicate that environmental parameters significantly influenced plant growth outcomes, with specific adjustments capable of optimizing hydroponic systems. The models developed can serve as valuable tools for grower to enhance crop yields with maintaining resource efficiency.

The results also provided a solid foundation for future research. Expanding the analysis to include additional environmental factors and a wider variety of plant species could further enhance the predictive capabilities of such models. Moreover, integrating real-time monitoring data with predictive models could lead to more dynamic and responsive hydroponic management systems, ultimately contributing to the advancement of sustainable agriculture practices.

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Rec. on 15.02.2025 & Acc. on 06.03.2016