

Mathematical and Machine Learning-Based Modeling of Plant Recovery Dynamics Under Environmental Stress

Yenula Wickramasinghe

Bridgeland High School, 10707 Mason Rd, Cypress, TX 77433, USA; yenulawickramasinghe@gmail.com

Mentor: Rayvan Watson

ABSTRACT: Studying plant recovery from environmental stress and how recovery dynamics differ by stress type is important yet remains insufficiently understood. This study aims to model plant recovery dynamics under water and light stress, and to predict the growth of the plant under the stress. Using three mathematical models, recovery rates of the under-stress plants are modeled and compared for accuracy. Random Forest model is used to predict the growth of the plant exposed to stress. According to the experimental findings, light-stress recovery is best described by exponential behavior, agreeing with the rapid, reversible physiological adjustment, whereas water-stress recovery follows power-law scaling, indicative of prolonged, scale-dependent recovery. A Random Forest model further showed that it can be used effectively to forecast the future growth of the plant under stress. Overall, these findings indicate the importance of time-resolved mathematical modeling for understanding plant resilience and developing predictive tools for adaptive agricultural management.

KEYWORDS: Plant Recovery Modeling, Environmental Stress in Plants, Nonlinear Regression, Machine Learning in Agriculture, Predictive Modeling.

■ Introduction

Plants are continuously exposed to changes in environmental conditions such as water limitations, reduced light, extreme temperatures, and nutrient deficiencies. Compared to the studies on the physiological impacts of environmental stress, relatively less attention has been given to understanding the dynamics of plant recovery following stress removal. Most of the past studies focused on the damage induced by stress at a single point instead of characterizing how recovery progresses over time.¹ However, studying recovery kinetics will reveal how quickly plants return to the baseline, providing deeper insight into stress resilience.

The impact of the water and light stress on plants takes place in distinct physiological pathways. Water limitation disrupts plant functions, such as cellular turgor pressure, stomatal conductance, photosynthetic efficiency, and metabolic balance.² Light-stress impacts plants primarily with photosystem performance and chlorophyll dynamics.¹ The above two stresses operate through different mechanisms and are different in their recovery trajectory and structural patterns.

Recent research indicates that these response patterns to stress depend on the plant's exposure to prior stress, and it forms a phenomenon known as "stress memory."³ This suggests that recovery is not merely passive but a time-dependent biological process. Furthermore, environmental stress responses involve multi-scale interaction across cellular and whole plant levels, suggesting the entire recovery dynamics may follow non-linear behavior.⁴

With the understanding that the plant stress recovery is a non-linear time-dependent process, it is interesting to know how the recovery progresses: Does it occur at a constant rate? Does it follow an exponential path toward stability? Math-

ematical modeling of the recovery process will provide a framework to formally characterize these dynamics. Linear models describe a constant rate of recovery, exponential models capture acceleration toward stability, while power-law models allow exploration of scale-dependent behavior often used in biological growth systems.⁴

Recent advances in data-driven modeling, such as machine learning models, extend this framework. Machine learning algorithms allow recovery patterns to be treated and forecasted without enforcing predetermined parametric forms. By incorporating biological characteristics of the plants, such as plant height, leaf angle, and leaf color, into predictive algorithms, these machine learning algorithms allow us to estimate future recovery states based on present measurements. This integration of predictive models offers a pathway toward precise agricultural applications, easing the process of irrigation scheduling and adaptive management strategies.

Although many previous studies have examined how environmental stress damages plants, most have focused mainly on the immediate effects of stress rather than on how plants recover over time once the stress is removed. Much less is known about how recovery patterns differ between different types of stress, such as water and light limitation, or whether these recovery processes are best explained by different mathematical models. In addition, only a limited number of studies have combined traditional biological modeling with machine learning to both analyze and predict plant recovery. To address this gap, the present study investigates how plants recover over time from water and light stress, compares multiple mathematical models to describe these recovery patterns, and incorporates machine learning methods to improve prediction and understanding of plant resilience.

This manuscript investigates the time-resolved recovery dynamics of plants exposed to water and light stress. Combining controlled experimentation, nonlinear regression, and machine learning modeling, this work aims to (1) quantify the recovery trajectories of the plant due to the two types of stresses, (2) assess the appropriateness of linear, exponential, and power-law models for describing recovery kinetics, and (3) study the feasibility of forecasting the next-day recovery states.

■ Methods

Experimental Setup:

A total of 30 snow pea plants were grown under identical indoor conditions for two weeks prior to stress application. Plants were then randomly assigned into three groups: water-stress ($n = 10$), light-stress ($n = 10$), and standard-condition group ($n = 10$). For the first group, water stress was applied, and for the second, light stress was applied. The third group was considered the control group. Water stress was applied through controlled reduction of irrigation, while light stress was introduced by limiting light exposure for a defined period. For the control plants, standard conditions were maintained under consistent irrigation and light schedules.

During recovery, plant height, leaf angle, turgor, and leaf color were measured repeatedly at consistent time intervals to capture time-resolved responses. Plant height was documented using a metric ruler from the soil surface to the highest point of the stem, and leaf angle was measured using a handheld protractor relative to the main stem. Measurements were performed by the same observer using identical handling pressure and assessment criteria at each time point to minimize subjective variability. Leaf color and turgor were evaluated using predefined visual assessment scales under consistent indoor lighting conditions.

Measurements were performed at similar times of day using consistent procedures to ensure consistency across plants and time points. Qualitative physiological observations, such as leaf color and turgor, were converted into standardized numerical scores using predefined rating scales.

Recovery function $R(t)$:

We normalize the collected data of height, leaf angle, turgor, and leaf color and then compute the recovery index, $R(t)$ as follows.

Then, for each observation under light or water stress, the measurements were normalized:

$$\text{normalized metric} = \frac{\text{metric}(t)}{\text{baseline mean}} \quad (1)$$

A composite recovery index was then defined:

$$R(t) = \frac{1}{4}(\tilde{H}(t) + \tilde{A}(t) + \tilde{T}(t) + \tilde{C}(t)) \quad (2)$$

where the $\tilde{H}, \tilde{A}, \tilde{T}, \tilde{C}$ variables represent normalized height, leaf angle, turgor, and leaf color.

Modeling Approach:

Plant recovery following environmental stress was modeled as a time-dependent process, $R(t)$, where time $t \geq 0$. Although recovery is continuous, measurements were obtained

at discrete, evenly spaced time points: $R(t_i)$, $i = 1, 2, \dots, n$, where $\Delta t = t_{i+1} - t_i$ is the sampling interval.

Linear Model:

A baseline linear model was defined as:

$$R(t) = at + b \quad (3)$$

where a represents the constant recovery rate and b the initial condition. This model assumes uniform recovery over time and serves primarily as a comparison benchmark.

Exponential Recovery Model:

To capture diminishing recovery rates over time, an exponential model was considered:

$$R(t) = R_{\infty} - Ae^{-kt} \quad (4)$$

where R_{∞} represents the asymptotic recovery level, A the recovery amplitude, and k the recovery constant. This model allows for rapid early recovery followed by slower convergence, a common feature in biological recovery processes.

Power-Law (Scaling) Model:

To explore scale-dependent behavior, a power-law model was evaluated:

$$R(t) = ct^{\alpha} \quad (5)$$

where the exponent α characterizes how recovery scales with time. Power-law behavior is consistent with fractal-like or scale-dependent dynamics, where recovery rates vary depending on the temporal scale of observation.

The applications of these models can be seen in the literature.⁵⁻⁷

Machine Learning Models:

A machine learning model was constructed to evaluate the possibility of forecasting plant recovery dynamics using physiological measurements collected during the recovery phase. In this case, we used a Random Forest regression approach to model nonlinear relationships between time-resolved plant traits and the composite recovery index $R(t)$. We used the characteristics such as plant height, leaf angle, leaf color, turgor, and stress type as features when constructing this model.

When running machine learning models, the dataset was divided into training and testing subsets using a 70/30 split. To improve model robustness and reduce overfitting, 5-fold cross-validation was employed during model training. Random Forest regression performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

Statistical Model Comparison:

To compare the above models, we used the R^2 statistics, Residual analysis, and Akaike Information Criterion (AIC) value.

R^2 statistic:

To quantitatively compare candidate recovery models, the coefficient of determination (R^2) was computed to assess the proportion of variance in recovery explained by the model.

$$R^2 = 1 - \frac{\sum_{i=1}^n (R(t_i) - \hat{R}(t_i))^2}{\sum_{i=1}^n (R(t_i) - \bar{R})^2} \quad (6)$$

where $R(t_i)$ denotes the observed recovery metric, $\hat{R}(t_i)$ the model prediction, and $\bar{R}$ the mean recovery value. Higher R^2 values indicate improved explanatory power. However, this metric alone does not capture model adequacy.

Residual Structure:

To evaluate whether model assumptions were satisfied, residuals were analyzed as a function of time:

$$\varepsilon(t_i) = R(t_i) - \hat{R}(t_i) \quad (7)$$

To account for differences in model complexity, models were further compared using the Akaike Information Criterion (AIC).

$$AIC = 2k - 2\ln(\mathcal{L}) \quad (8)$$

Akaike Information Criterion (AIC):

where k is the number of estimated parameters and L is the maximum likelihood of the model given the data. Lower AIC values indicate a preferable balance between goodness-of-fit and model parsimony.

Results and Discussion

Residual plots were inspected for systematic structure, temporal correlation, and heteroscedasticity. Linear models frequently exhibited time-dependent residual patterns, suggesting that recovery dynamics were not well described by a constant-rate process.

In contrast, non-linear models reduced residual structure, indicating improved representation of time-varying recovery behavior.

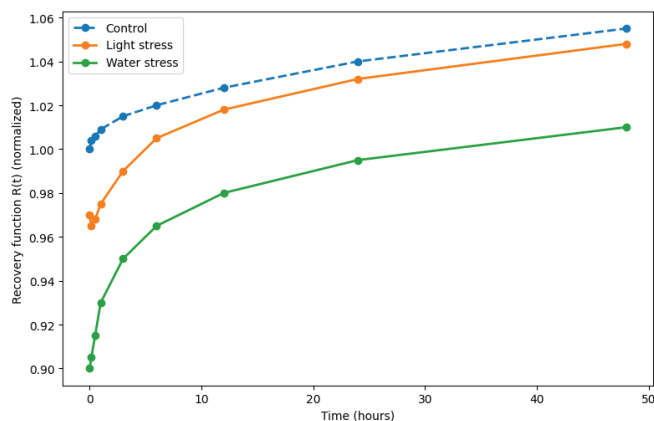


Figure 1: Recovery index of plants over time under different stress conditions. The plot shows the normalized recovery index measured at different time points during the recovery period. The blue line represents the control of plants grown under normal conditions, the orange line represents plants exposed to light stress, and the green line represents plants exposed to water stress. The trajectories illustrate how plant recovery changes over time depending on the type of stress.

As Figure 1 illustrates, control plants show an uninterrupted, steady, and approximately linear trajectory. In contrast, plants that are exposed to stress show a moderate initial decline in recovery immediately after the stress exposure followed by a relatively rapid partial recovery. This pattern suggests that light stress has produced a temporary physiological disruption that

was largely reversible with the resumption of normal conditions.

In contrast, water-stressed plants demonstrated higher deviation of the control group's trajectory, indicating a substantial decline in recovery for both control and light-stressed plants. These results suggest that recovery dynamics are strongly influenced by stress type and are best characterized as time-dependent processes rather than single endpoint outcomes.

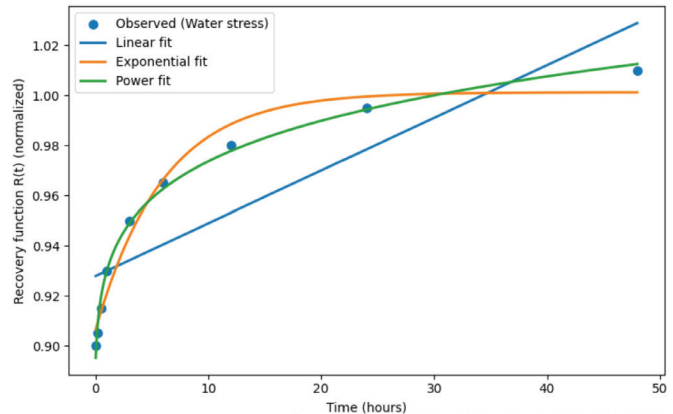


Figure 2: Model fits describing recovery dynamics under water stress. The figure shows the observed recovery index values for water-stressed plants together with the fitted nonlinear models. The plotted curves represent the linear model (blue), exponential model (orange), and power-law model (green), which describe recovery changes over time. The figure allows comparison of how well each model follows the observed recovery trajectory.

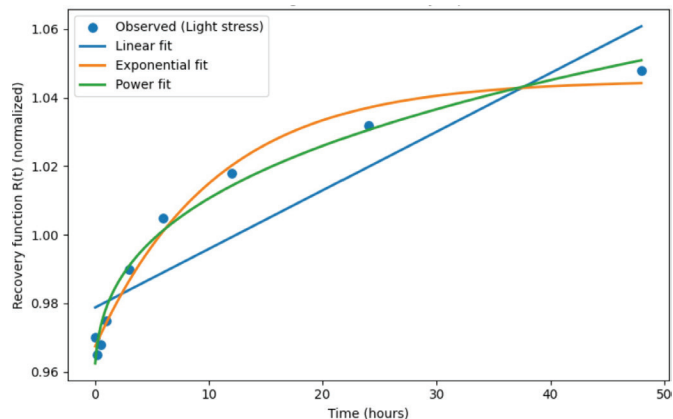


Figure 3: Model fits describing recovery dynamics under light stress. The figure displays the observed recovery index values for plants exposed to light stress along with the fitted nonlinear models. The plotted curves represent the linear (blue), exponential (orange), and power-law (green) models describing the recovery dynamics over time. This visualization allows comparison between the two models in describing the recovery trajectory.

As Figure 2 shows, the observed recovery dynamics of plants under stress clearly follow a nonlinear pattern. The power-law model closely follows the trajectory of the observed recovery dynamics more than the exponential model, indicating that it provides the best fit for the data. Based on Figure 3, the recovery dynamics under light stress are well described by both exponential and power-law models, although the exponential model shows a slight advantage.

As Table 1 shows, the exponential model provides the best fit for the light-stress plants' recovery dynamics, with the lowest AIC value and the highest R^2 value.

In contrast, the power-law model provides the best fit for water-stress recovery. As Table 1 shows, this model records the lowest AIC value and the highest R^2 value, justifying its selection as the preferred model for the recovery trajectory of the water-stress plants.

Furthermore, residual analysis justifies the above model selection. These findings suggest that plants' recovery dynamics after exposure to light and water stress differ fundamentally by stress type, with exponential behavior describing rapid reversible recovery and power-law scaling capturing prolonged recovery following water limitation.

Table 1: The table presents the performance of the linear, exponential, and power-law models for plants exposed to light and water stress. Model performance is evaluated using statistical metrics including the coefficient of determination (R^2), root mean square error (RMSE), and Akaike Information Criterion (AIC), allowing comparison of how well each model fits the recovery data.

Stress	Model	R^2	RMSE	AIC
Light	Linear	0.8129	0.0125	-74.945
Light	Exponential	0.9865	0.0033	-96.629
Light	Power	0.9801	0.0040	-93.096
Water	Linear	0.7120	0.0203	-66.132
Water	Exponential	0.9729	0.0062	-85.414
Water	Power	0.9938	0.0030	-98.664

Based on the forecasting of the plant's recovery index using the Machine Learning model, the results demonstrated that the model successfully captured recovery trends across stress conditions, producing accurate predictions of future recovery trajectories. Figure 4 illustrates the importance of the above features when forecasting the plant's recovery index. Based on the outcomes, stress type, leaf color, leaf angle, and the plant's height are dominant features when forecasting the recovery index. These findings suggest that machine learning methods can support traditional mathematical models by improving the ability to forecast the plant recovery after stress. Such data-driven approaches may help guide agricultural decision-making and support more effective stress management strategies.

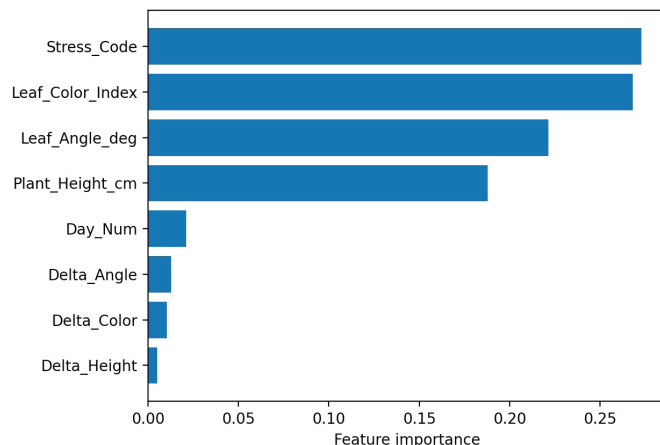


Figure 4: Feature importance for predicting plant recovery index using a Random Forest model. The bar chart shows the relative importance of the variables used in the machine learning model. Each bar represents a predictor variable, including stress type, leaf color, leaf angle, plant height, and turgor. The height of each bar indicates the contribution of that variable to predicting the recovery index.

■ Limitations of the Study

The authors identify several limitations of this study. First, the experimental study was conducted using a single plant species under controlled indoor conditions. This may limit the ability to generalize the results across different plant types or environmental conditions. Secondly, when recording the qualitative physiological measurements, such as leaf color and turgor, observer-based scoring is used despite standardized procedures. This may introduce potential subjectivity. Finally, the observation duration was restricted to a finite recovery window and may not fully describe the long-term adaptation or stress memory effects. Future studies should conduct similar investigations incorporating multiple plant species, extended observation periods, and automated sensing technologies to further improve model robustness and biological generalizability.

■ Conclusion

This study showed that the recovery trajectory of plants experiencing environmental stress, such as light limitation and water deficit, is fundamentally time-dependent and influenced by the type of stress. Based on the experimental findings, it is clear that the linear models are insufficient to capture the recovery dynamics of the plant, where non-linear models provide an improved description of the observed dynamics. Furthermore, exponential behavior best characterizes light-stress recovery, capturing the rapid physiological stabilization after stress removal. For the recovery of water stress, power-law models nicely captured the prolonged and gradual recovery. Furthermore, these results support the interpretation that plants' recovery processes after exposure to environmental stress operate across multiple biological time scales. The integration of machine learning prediction further illustrates the ability to predict plant recovery states using physiological measurements. Future research will extend this framework to multiple plant species to examine whether a generalized recovery model can describe plant resilience across diverse biological systems. This will support practical applications in precision agriculture and environmental stress management.

■ Acknowledgments

The author would like to thank the teachers and mentors whose support and encouragement made this research possible. Their guidance and willingness to share their knowledge played an important role throughout this project. Special thanks are extended to Mr. Rayvan Watson for his mentorship, advice, and continuous support during the research process. His guidance helped strengthen both the direction and quality of this work and was greatly appreciated. The author is also thankful for the supportive academic environment that encouraged curiosity, learning, and independent research.

■ References

1. Lamers, J.; van der Meer, T.; Testerink, C. How Plants Sense and Respond to Stressful Environments. *Plant Physiol.* **2020**, *182* (4), 1624–1635.

2. Osakabe, Y.; Osakabe, K.; Shinozaki, K.; Tran, L.-S. P. Response of Plants to Water Stress. *Front. Plant Sci.* **2014**, *5*, 86.
3. Jacques, C.; Salon, C.; Barnard, R. L.; Vernoud, V.; Prudent, M. Drought Stress Memory at the Plant Cycle Level: A Review. *Plants* **2021**, *10* (9), 1873.
4. Smithers, E. T.; Luo, J.; Dyson, R. J. Mathematical Principles and Models of Plant Growth Mechanics: From Cell Wall Dynamics to Tissue Morphogenesis. *J. Exp. Bot.* **2019**, *70* (14), 3587–3600.
5. Draper, N. R.; Smith, H. *Applied Regression Analysis*; Wiley: New York, 1998.
6. von Bertalanffy, L. Quantitative Laws in Metabolism and Growth. *Q. Rev. Biol.* **1957**, *32*, 217–231.
7. West, G. B.; Brown, J. H.; Enquist, B. J. A General Model for the Origin of Allometric Scaling Laws in Biology. *Science* **1997**, *276*, 122–126.

■ Author

Yenula Wickramasinghe is a sophomore who is curious about how mathematics and machine learning can be used to solve real-world problems. He enjoys exploring data-driven approaches to understanding complex systems and is especially interested in applied mathematics and artificial intelligence.