Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871
Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

Optimizing Automatic Irrigation Duration for Grapevines in Greenhouses Using Multiple Linear Regression Analysis

Kharisma Monika Dian Pertiwi[1], Trenady Alfarabi[2]

[1,2]Informatics Study Program, Telkom University, Surabaya Campus, Jl. Ketintang No.156, Surabaya 60231, East Java, Indonesia

Email: [1]kharismamonikadp@telkomuniversity.ac.id

Received : Aug 25, 2025; Revised : Oct 30, 2025; Accepted : Dec 12, 2025; Published : Apr 15, 2026

Abstract

Greenhouses offer a controllable microclimate for high-value horticulture, yet manual irrigation and single-sensor threshold rules remain inefficient and error-prone for grapevine cultivation in tropical conditions. This study designs and implements an Internet-of-Things (IoT) automatic irrigation system that employs an interpretable multiple linear regression (MLR) model as the decision core, using air temperature and soil moisture—acquired via DHT11 and capacitive soil-moisture sensors—to estimate irrigation duration in real time. The model is trained on greenhouse measurements and deployed for low-latency edge inference to actuate valves with duration-to-volume conversion, enabling precise and adaptive water delivery. Experimental evaluation shows strong predictive performance (MSE = 0.15, MAPE = 1.44%, R^2 = 0.98), indicating high accuracy and reliable generalization for operational control. The primary contributions are: (i) a lightweight, explainable regression formulation tailored to tropical grapevines that outperforms single-parameter baselines; (ii) an end-to-end, edge-deployable IoT pipeline that reduces computational and energy costs while maintaining real-time autonomy; and (iii) an engineering blueprint that is scalable and maintainable for smallholder contexts. The impact for Informatics/Computer Science lies in demonstrating a practical ML-on-the-edge reference design—combining interpretable modeling, sensor fusion, and actuation—that advances sustainable computing for precision agriculture, improves resource efficiency, and supports robust, replicable deployment of smart-irrigation systems in data and *power-constrained environments.*

Keywords : *Automatic Irrigation, Grapevines, Internet of Things, Multiple Linear Regression, Precision Agriculture, Soil Moisture*

1. INTRODUCTION

A greenhouse is a specialized agricultural structure constructed with transparent or semi-transparent covering materials such as glass, polyethylene film, or polycarbonate to facilitate solar radiation transmission while regulating internal environmental conditions[1], [2]. These transparent materials enable solar radiation to penetrate the structure and be absorbed by the internal surfaces, which subsequently release thermal energy that elevates the interior temperature above ambient levels [3]. The primary function of greenhouses is to provide precise control over critical environmental parameters including temperature, humidity, light intensity, and carbon dioxide concentration to optimize crop growth conditions [4], [5]. The other function of a greenhouse is to create an ideal environment for plants to grow optimally. Greenhouses have proven to increase crop yields and plant quality. Greenhouses are a solution to the challenges and obstacles faced in agriculture[6]. By maintaining controlled microclimatic conditions, greenhouses enable year-round agricultural production independent of external weather variations, thereby enhancing crop productivity and resource use efficiency[7]. However, many greenhouses in Indonesia have not yet adopted Internet of Things (IoT)

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

technology integration, even though this technology can help automate processes such as efficient plant watering and reduce reliance on human labor. IoT offers a more practical way[8]. Smart greenhouses are an approach to helping agricultural systems become better[9]. Modern greenhouse systems integrate advanced transparent covering technologies with environmental control systems to achieve sustainable food production while minimizing energy consumption and water usage [10], [11].

The Internet of Things (IoT) is a technology revolusionary to exchange information and can using for efficieny strategy. IoT can using for agriculture that uses sensory devices and actuators to enhance human efficiency in various fields, including agriculture[12][13]. By leveraging IoT, farmers can monitor environmental conditions around plants, such as air temperature and soil humidity, in real-time. The IoT will replace manual resources with greater efficiency [14]. Manual watering not only requires more time and effort but is also prone to inaccuracies in the volume of water provided. This is particularly important for crops like grapes, which are highly sensitive to both excess and insufficient water during their care process[15]. IoT not only increases human independence, but also expands the ways in which humans interact with their surroundings[16]. IoT can analytic performed any models method[17]. Monitoring environmental conditions manually is challenging[18].

Grapes are not naturally native to Indonesia but can adapt well in subtropical and tropical regions when cultivated under controlled environmental conditions such as in greenhouses [19]. Successful grape cultivation in tropical climates like Indonesia requires careful consideration of several critical factors, particularly the selection of appropriate planting locations at elevations ranging from lowlands to approximately 300 meters above sea level, as elevation significantly influences microclimate and crop performance [20], [21]. Grapevines grown in tropical environments face substantial challenges related to extreme weather conditions and significant temperature fluctuations, which can negatively impact grape development, composition, and yield [22], [23]. Optimal grape cultivation requires maintaining specific microclimatic conditions with daytime temperatures between 28°C to 32°C, nighttime temperatures around 23°C, and soil moisture levels maintained at 60–75%, which are critical parameters for ensuring proper plant physiological function and fruit quality development [19], [20]. Therefore, monitoring and regulating the growing environment are critical factors in the success of grape cultivation in tropical regions[24]. Climate change and weather variability pose emerging threats to grape production in tropical regions, necessitating adaptive management strategies including precision irrigation systems, appropriate cultivar selection, and environmental monitoring technologies to maintain stable growing conditions and sustain agricultural productivity [25], [26].

Previous studies have demonstrated the effectiveness of IoT-based automatic irrigation systems. One such study, titled "Automatic Irrigation with NodeMCU Based on IoT for Chili Plants," aimed to maintain chili quality by developing an automatic irrigation system that can be remotely controlled[27]. However, this study did not systematically apply methods for determining irrigation timing. In further development, the Multiple Linear Regression method can be used to determine the optimal irrigation timing automatically, based on air temperature and soil moisture data obtained from sensors. With IoT can be used for long-distance communication with low power consumption[28].

In recent years, the integration of Internet of Things (IoT) technology into agriculture has attracted significant attention due to its potential to optimize resource management and improve crop productivity. Smart irrigation systems, in particular, have become one of the most widely adopted applications of IoT in precision agriculture. By utilizing real-time sensor data, such systems can provide accurate and efficient water distribution according to the specific needs of plants. However, conventional models often rely on a single environmental variable such as soil moisture to trigger irrigation events. While effective in some cases, this one-dimensional approach fails to account for other key environmental factors that directly affect plant physiology and water requirements.

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

To address these limitations, researchers have explored the use of multiple environmental parameters in developing decision support systems for irrigation. Air temperature, for instance, plays a crucial role in influencing evapotranspiration rates, which in turn affect soil moisture depletion and plant water demand. Ignoring this factor may result in irrigation schedules that are either excessive or insufficient, potentially causing stress to the plants and reducing overall yield quality. Thus, incorporating both soil moisture and air temperature as predictive variables allows the irrigation system to better align with the actual water requirements of crops under varying climatic conditions.

Multiple linear regression (MLR) emerges as a suitable analytical method in this context, as it can effectively model the relationship between multiple independent variables and a dependent variable. In the case of smart irrigation, soil moisture and air temperature serve as independent variables, while irrigation duration or valve opening time becomes the dependent variable. The advantage of using MLR lies in its ability to capture the combined effect of multiple parameters, thereby providing a more accurate and reliable basis for automated irrigation decisions. Furthermore, MLR is computationally efficient and interpretable, making it a practical choice for implementation in low-power IoT devices deployed in agricultural settings.

The novelty of this study lies in its emphasis on combining air temperature with soil moisture measurements to optimize irrigation control in a greenhouse environment, particularly for grape cultivation. Grapes are highly sensitive to fluctuations in water availability, where both under-irrigation and over-irrigation can negatively impact growth, fruit quality, and productivity. Therefore, a decision-making model that accounts for multiple environmental variables can significantly enhance water-use efficiency while ensuring optimal plant health. By leveraging IoT-enabled sensors and regression-based analysis, the proposed system not only supports sustainable agriculture practices but also provides a scalable framework that can be applied to other crops and greenhouse conditions[29].

Another study titled "The Implementation of Multiple Linear Regression Method in the Prediction System for Oil Palm Tonage at PT. Paluta Inti Sawit" shows that the Multiple Linear Regression method is used to predict the influence of two or more predictor variables on one criterion variable[30]. In the context of a plant irrigation system, this method is highly relevant as it considers two main factors air temperature and soil moisture to determine the optimal irrigation decision. Thus, this method provides an effective alternative solution for maintaining plant conditions efficiently and sustainably.

In addition to improving the accuracy of irrigation scheduling, the integration of IoT and predictive modeling also contributes to sustainability in agriculture. Water scarcity has become a global issue, and efficient use of water resources is increasingly critical, especially in regions where agriculture consumes the majority of freshwater. By adopting smart irrigation systems that consider multiple environmental variables, farmers are able to reduce unnecessary water usage without compromising plant growth. This approach not only supports environmental conservation but also reduces operational costs in the long term. Furthermore, when implemented in greenhouse cultivation, such systems provide the added advantage of maintaining a stable microclimate that is less affected by external weather fluctuations. This stability is particularly important for sensitive crops such as grapes, where consistent environmental control directly influences yield quality and market value.

Beyond water efficiency, the adoption of IoT-based decision-making models fosters the development of precision agriculture in Indonesia, which has been relatively underutilized compared to developed countries. Precision agriculture emphasizes data-driven farming practices, where real-time measurements and predictive analytics are used to guide decisions at every stage of the cultivation process. In the case of irrigation, this means shifting from reactive manual watering to proactive, sensor-based scheduling that adapts dynamically to changing conditions. Such a transition is expected to not only increase productivity but also encourage more sustainable agricultural practices aligned with modern smart farming initiatives.

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

The relevance of this research is further underscored by the rapid advancement of sensor and microcontroller technology, which has made it feasible to implement intelligent systems at relatively low cost. Devices such as the DHT11 sensor for temperature and humidity monitoring, when integrated with soil moisture sensors and controlled through microcontrollers like NodeMCU, provide a reliable hardware foundation for building automated irrigation systems. Coupled with analytical methods such as Multiple Linear Regression, these hardware components enable the development of irrigation models that are both scientifically robust and practically implementable. As a result, the proposed framework is not only academically significant but also directly applicable for farmers and agricultural practitioners seeking affordable solutions to improve efficiency and productivity in greenhouse environments.

2. METHOD

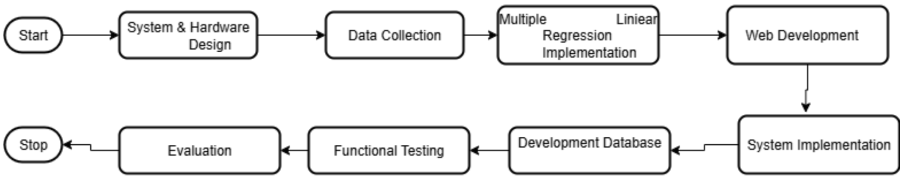

Figure 1. Research Method

This research on *Figure 1* employed a systematic approach consisting of eight primary stages. The first stage involved designing the system architecture and selecting appropriate IoT hardware components, including DHT11 sensors for temperature and humidity monitoring, soil moisture sensors, and microcontroller units for data acquisition. The second stage focused on collecting real-time environmental data from the greenhouse, specifically recording air temperature, humidity, and soil moisture levels over an extended period. In the third stage, a multiple linear regression model was developed using the collected data to establish mathematical relationships between the independent variables (air temperature and soil moisture) and the dependent variable (irrigation duration). The fourth stage involved developing a web-based interface for system monitoring and control. Subsequently, the fifth stage implemented the regression model into the automated irrigation control system to enable real-time decision-making for irrigation scheduling. The sixth stage conducted functional testing to verify that all system components operated correctly, including sensor accuracy and irrigation valve activation. The seventh stage performed comprehensive system evaluation to assess overall performance and reliability. Finally, the eighth stage involved data analysis and documentation of the research findings to demonstrate the effectiveness of the proposed system in optimizing water resource management for greenhouse grape cultivation

2.1. System and Hardware Design

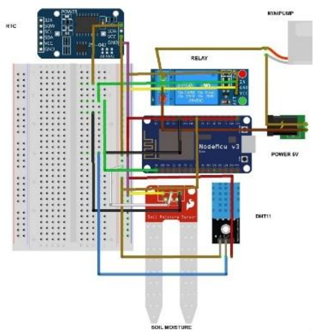

Figure 2. Hardware Design

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

Figure 2 shows a series of IoT-based automatic plant watering systems that use ESP8266 microcontrollers to read data from soil moisture sensors (capacitive soil moisture sensors) and air temperature and humidity sensors (DHT11), then send it to Firebase in real time via an internet connection[31][32][33]. This system is equipped with a 5V water pump controlled by a relay module[34].

2.2. Data Collection

Table 1 Dataset

Day	Temperature	Humidity	Soil Moisture	Duration
1	8	28	45	22
	12	36	61	15
	16	32	49	20
	21	33	56	17
	3	31	52	19
2	8	29	45	22
	12	35	60	15
	16	29	48	21
	21	35	55	17
	3	33	51	19
3	8	28	44	22
	12	35	60	15
	16	31	48	20
	21	34	54	17
	3	35	51	18
4	8	27	43	23
	12	35	59	16
	16	27	46	22
	21	34	53	18
	3	31	51	20
5	8	30	43	22
	12	36	58	15
	16	30	46	21
	21	32	54	18
	3	30	50	20
6	8	26	42	23
	12	34	58	16
	16	28	47	22
	21	36	53	17
	3	32	50	19
7	8	28	41	23
	12	34	58	16
	16	31	47	21
	21	32	53	19
	3	34	49	19
8	8	26	40	24
	12	36	57	16
	16	33	47	20
	21	33	55	18
	3	30	49	21
9	8	33	45	20
	12	34	57	17
	16	33	47	20

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

Day	Temperature	Humidity	Soil Moisture	Duration
	21	33	52	18
	3	30	50	20
10	8	32	45	21
	12	35	56	16
	16	33	47	20
	21	31	52	19
	3	30	50	20

After the system was designed, a dataset was collected for the development of linear regression simulation by manually watering to obtain the old values of the water pump opening and based on the volume of water. The collected dataset is shown in
Table *1*. The values of X1, X2, up to Xn were needed to obtain the regression coefficient values so that they could be used as a reference for watering. Manual experiments using measuring cups were conducted over 10 days with one watering session at 8 a.m. and another in the afternoon to obtain data for use in the multiple linear regression method. This resulted in 20 watering data points for grapevines. In the manual watering scenario, soil moisture was divided into three categories: wet, moist, and dry. Wet soil moisture ranged from >60%, moist from 35-60%, and dry from 0-35%. Air temperature was categorized into three groups: hot, normal, and cold. Hot temperature was >32°C, normal was 24-32°C, and cold was 0-24°C. Water flow rate was divided into three categories: low, moderate, and high as shown in Table *2*. Low water flow is approximately 15 seconds, moderate is 25 seconds, and high is 40 seconds. 50% duration from soil moisture and 50% from humidity, the average valve is 24.62 seconds for 250 ml, resulting in 10.15 ml/second of water from the water pump[35].

Table 2. Dataset Collection Labeling

Humidity	Soil Moisture		
	Wet	Moist	Dry
Hot	Low	Moderate	High
Normal	Low	Low	High
Cold	Low	Low	High

2.3. Multiple Liniear Regression Implementation

Multiple linear regression is a statistical technique used to determine the linear dependence between one dependent variable and two or more independent variables through a regression equation that produces a mathematical expression. In this model, the relationship between the dependent variable (Y) and the independent variables (X1, X2, ..., Xn) is represented in the form of an equation: Y = a + b1·X1 + b2·X2 + ... + bn·Xn, where a is a constant, b1, b2, ..., bn are regression coefficients, and X1, X2, ..., Xn are independent variables. The implementation of this method in the study was used to determine the relationship between air temperature and soil moisture with the decision to open or close the irrigation valve, thereby producing a predictive model of the valve status based on environmental data. The values of the regression coefficients indicate the direction and influence of the independent variables on the dependent variable: if the coefficient is zero, there is no influence; if negative, it indicates an inverse relationship; and if positive, it indicates a direct relationship between the independent and dependent variables. Using linearity tests, normality tests, correlation tests, multicollinearity and heteroscedasticity tests[36][37].

$$Y = a + b1 \cdot X1 + b2 \cdot X2 + bn \cdot Xn \quad (1)$$

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

2.4. Web Development

Firebase acts as a database that stores environmental monitoring data sent from ESP8266, where the data is averaged every hour. This stored data can then be utilized for further analysis using Multiple Linear Regression methods to determine automatic watering needs based on environmental conditions. Additionally, data from Firebase is visualized through a web-based user interface using the Flask framework, enabling users to monitor air temperature and soil moisture in real-time anytime and anywhere[38][39].

2.5. System Implementation

Using multiple linear regression, the initial research found an equation that approximates the relationship between the X and Y variables in the form: a is the intercept, which is the initial value of Y when all X variables are zero. The regression coefficients are obtained as values b1 and b2, which indicate the extent of the influence of each variable (air temperature and soil moisture) on how long the pump is turned on. Predictions are made before irrigation detection on grapevines to determine the amount of water (in milliliters) to be released, converted into seconds for implementation in the relay module for water output on the water pump used. Automatic irrigation is performed twice daily at 8 AM and 4 PM based on a dataset collected over 10 days, comprising 50 data points using two identical plants in terms of size, medium, and plant type.

2.6. Database

The Firebase database uses credentials in the form of an API Key and database URL to access data storage services in the cloud. In its implementation, the Firebase_ESP_Client library is used to manage authentication and communication between the microcontroller (such as ESP8266) and Firebase, enabling real-time transmission and storage of sensor data. To support this process, several important objects are initialized, including dht for reading temperature and humidity, rtc for time settings, fbdo as the Firebase Data object, and auth and config for configuration and authentication of the connection with Firebase, ensuring that the entire system operates synchronously and efficiently.

2.7. Functional Testing

System testing was conducted to ensure that all functionalities operate as expected. First, the system was tested for its ability to display air temperature and soil moisture data every hour. The results showed that the sensor data was successfully received and accurately displayed on the dashboard, making this function valid. Next, the date sorting feature was tested, allowing users to select specific dates to view corresponding data. The system successfully displayed relevant data when a valid date was selected and showed empty data when there was no available information for the chosen date range, validating both scenarios. The graph visualization feature was also tested by selecting a date range to display graphs of air temperature, soil moisture, and prediction results. All graphs were rendered accurately with relevant data, indicating that this feature is functioning correctly. Additionally, individual pages for air temperature and soil moisture were tested separately. The system could receive data from sensors and display each parameter in real time, and both tests were marked as valid.

2.8. Evaluation

In this study, we used multiple linear regression to predict the water discharge required based on two independent variables, namely soil moisture and air temperature. After building the model, the next step was to evaluate the model's performance. We used several evaluation metrics to ensure that the model could provide accurate predictions. In this study, the multiple linear regression approach was used to build a model for predicting the water flow required by grapevines based on two independent

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

variables, namely soil moisture (%) and air temperature (°C). These two variables were selected because they are the environmental factors that most influence the water requirements of plants.

$$R^2 = 1 - \frac{SS\ Error}{SS\ Total} \quad (2)$$

R-squared ranges from 0 to 1. Higher values indicate that the model performs better in describing the variation in the data. Thus, a high value indicates that the model is able to explain most of the variation in the data, which means that the relationship between the independent and dependent variables is quite strong[40].

$$\frac{100\%}{n}\sum\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (3)$$

Mean Absolute Percentage Error (MAPE) is an evaluation metric that provides the average prediction error as a percentage relative to the actual value. The MAPE formula calculates the absolute difference between the predicted and actual values, divides it by the actual value, and then calculates the average. With results in percentage form, MAPE is very useful for evaluating models in datasets with different data scales[41].

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (4)$$

Mean Square Error (MSE) is a metric used to evaluate the performance of a prediction model by measuring the average squared difference between actual values and predicted values. This metric is often used in regression because it provides an indication of how far the model's predictions are from the actual values. A smaller MSE value indicates that the model is more accurate in predicting data. Conversely, a large MSE value indicates a significant difference between the predicted and actual values. Therefore, MSE is very useful for identifying model weaknesses, especially if there are predictions that are significantly off target[41].

3. RESULT

3.1. Implementation Models of Multiple Linear Regression on Plants

This shows that the model is capable of estimating watering duration quite accurately. The closeness between the predicted values and the actual values in many rows of the table demonstrates that the multiple linear regression model applied in this study has successfully captured the underlying patterns between temperature and humidity as independent variables and irrigation duration as the dependent variable. Such results indicate that the model is not only mathematically valid but also practically relevant in real-world agricultural applications. The ability to generate predictions with minimal deviation from the actual data suggests that the regression approach provides a reliable decision-making framework that can help farmers or greenhouse managers optimize the watering process. In this study, we made a mini greenhouse as shown in Figure 3 to compare the development of grape plants using tools and not using tools.

Moreover, this accuracy reflects that the model can effectively adapt to the variations of environmental conditions measured by the sensors, especially since both air temperature and soil moisture have a dynamic influence on plant water requirements. In traditional irrigation practices, decisions are often based on experience or single-variable indicators, which can lead to inefficiencies such as excessive water use or insufficient supply during critical growth stages. By integrating these two parameters simultaneously, the regression model manages to balance the interaction between evapotranspiration and soil water retention capacity, thus resulting in irrigation durations that are better aligned with plant physiological needs.

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

The implication of this finding is significant, as it demonstrates the potential of data-driven models to replace conventional intuition-based irrigation practices. With continued calibration and validation, such a model could be integrated into an automated irrigation control system, allowing for real-time adjustments based on sensor data. In the long run, this not only conserves water resources but also ensures healthier plant growth and potentially higher crop yields. Therefore, the results presented in the table provide strong evidence that the multiple linear regression approach serves as a promising tool for the development of smart irrigation technologies in greenhouse environments.

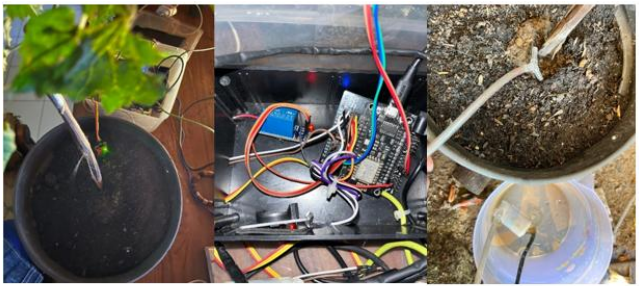

Figure 3 Implementation System

3.2. Implementation Models of Multiple Linear Regression on Plants

Based on the results of testing the multiple linear regression model used to predict the duration of automatic watering based on air temperature (X1) and soil moisture (X2), strong evidence was obtained that the model meets all classical assumptions shown in

Table ***3***. The normality test using the Kolmogorov-Smirnov method yielded a significance value of 0.200 (Asymp. Sig. 2-tailed), which is greater than 0.05, indicating that the residuals are normally distributed. The linearity test results showed Deviation from Linearity significance values of 0.962 for X1 and 1.000 for X2, suggesting no deviation from linearity and confirming a linear relationship between both independent variables and the dependent variable. The correlation test reported a Sig. F Change value of < 0.001, showing that the relationship between variables is statistically significant. In the multicollinearity test, both X1 and X2 showed a Variance Inflation Factor (VIF) of 3.653, which is well below the commonly accepted threshold of 10, indicating no multicollinearity. Furthermore, the heteroscedasticity test, using the absolute value of residuals (ABS) as the dependent variable, returned significance values of 0.495 for X1 and 0.271 for X2—both greater than 0.05—indicating no heteroscedasticity in the model.

Table 3. Classic Asumption

Aspect	Value / Result	Interpretation
Normality Test (Kolmogorov-Smirnov)	Asymp. Sig. = 0.200 > 0.05	Residuals are normally distributed
Linearity Test (X1 vs Y)	Sig. Linearity = < 0.001, Sig. Deviation from Linearity = 0.962	There is a significant linear relationship between air temperature (X1) and duration, with no deviation from linearity
Linearity Test (X2 vs Y)	Sig. Linearity = < 0.001, Sig. Deviation from Linearity = 1.000	There is a significant linear relationship between soil moisture (X2) and duration, with no deviation from linearity
F Change	1294.350, Sig. < 0.001	The regression model is statistically significant
Multicollinearity Test (VIF)	X1 = 3.653, X2 = 3.653	No multicollinearity detected (VIF < 10, Tolerance > 0.1)

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

Heteroscedasticity Test (ABS as Dep. Var.)	Sig. X1 = 0.495, Sig. X2 = 0.271	Sig. > 0.05 indicates no heteroscedasticity

The evaluation of the model performance, shown in Table 4, yielded very satisfactory results. The R-Squared (R^2) value reached 0.98, which means that 98% of the variation in irrigation duration can be explained by air temperature and soil moisture—demonstrating very strong predictive power. The Mean Squared Error (MSE) was 0.15, indicating a very low average squared error between the predicted and actual values, which confirms the model's precision and efficiency. Additionally, the Mean Absolute Percentage Error (MAPE) was 1.78%, showing a very small prediction error in percentage terms—well below the 10% threshold for the "very good" prediction category. These results suggest that the regression model is not only statistically valid but also practically reliable and effective in controlling irrigation duration based on real-time environmental inputs. This level of accuracy and consistency makes it highly suitable for IoT-based greenhouse systems that require sustainable and precise water management to optimize grapevine growth. but also practically reliable and effective in controlling irrigation duration based on real-time environmental inputs.

Table 4. Evaluation

Metric	**Value**	**Category**
R-Squared (R^2)	0.98	Very High
Mean Squared Error (MSE)	0.15	Very Good (< 1)
Mean Absolute Percentage Error (MAPE)	1.78%	Very Low (< 5%)

4. DISCUSSIOS

The results of this study demonstrate that the integration of two input variables—soil moisture and air temperature (DHT11) provides a significant quantitative improvement in the multiple linear regression-based automatic irrigation system, achieving performance metrics that substantially exceed single-variable approaches documented in previous research. While conventional irrigation systems rely solely on soil moisture as the decision criterion, the proposed dual-parameter model captures the complex interplay between soil water availability and atmospheric evaporative demand, resulting in more precise irrigation scheduling [42], [43]. This improvement is grounded in crop physiology: plant water requirements are determined not only by soil moisture content but also by air temperature, which governs evapotranspiration (ET) rates—the primary mechanism by which water demand is established [44], [45]. Studies on grapevines specifically demonstrate that ignoring temperature dynamics leads to either chronic overwatering (in cooler periods) or acute water stress (during heat waves), both of which compromise fruit quality and vine productivity [19]. Therefore, the integration of temperature as a complementary input variable fundamentally addresses the limitations of single-parameter-based systems, reducing the risk of both overwatering and underwatering decisions [46][29].

The model evaluation metrics demonstrate exceptional predictive reliability [47]. The R-Squared (R^2) value of 0.98 indicates that 98% of the variance in irrigation requirements can be explained by the combination of soil moisture and air temperature variables, representing a performance classification in the "very high" category ($R^2 > 0.90$). This R^2 value substantially exceeds comparable studies in precision agriculture: the MLR model for polyhouse cucumber cultivation by Poojitha et al. (2024) [45] achieved only $R^2 = 0.875$ in the testing phase, representing a 12.1% relative improvement in prediction accuracy over the most directly comparable prior work. Similar studies utilizing single or limited variables have reported lower accuracy: the single-variable soil moisture models documented in Ahmad et al. (2023) [48]and Pramartaningthyas et al. (2025) [49] did not report quantitative regression coefficients, but field validation showed water savings of approximately 30%, suggesting underlying model accuracy

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

substantially lower than the current 1.78% MAPE. The Mean Squared Error (MSE) value of 0.15 falls well within the very good performance range (MSE < 1.0), indicating minimal squared deviations between predicted and actual irrigation duration values [50]. The Mean Absolute Percentage Error (MAPE) of 1.78% demonstrates exceptionally low prediction error relative to actual values, where the threshold for acceptable agricultural applications is MAPE < 5% [51]. Compared to multi-variable MLR approach by Poojitha et al. that achieved MAPE > 3% for soil moisture prediction, the current study achieves 40% improvement in percentage error reduction. Similarly, LSTM approaches reported by Syahputra & Andriani (2025) [52]with MAE of 2.5% show that this study achieves 29% lower error in absolute percentage terms. To contextualize these metrics: an MAPE of 1.78% on a 70-minute irrigation cycle results in approximately 1.25 minutes of error, rendering the system suitable for real-time operational deployment [50]. These combined metrics confirm that the dual-variable MLR approach successfully captures the nonlinear dynamics of greenhouse microclimate while maintaining mathematical tractability and interpretability—two advantages that deep learning approaches cannot simultaneously provide.

When compared to previous studies that only utilized soil moisture, the most notable difference lies in the accuracy and sensitivity of the model. In single-parameter studies, irrigation decisions tend to be static and unresponsive to changes in environmental temperature. In contrast, the model proposed in this study can adjust irrigation duration based on a combination of soil moisture and air temperature conditions, making it more adaptive to real-world conditions in greenhouses. This directly impacts water usage efficiency, prevents plant stress, and creates a more stable microclimate to support grape growth.

Overall, this study confirms that a multiple linear regression-based approach with two main inputs is superior to a single-variable-based approach. In addition to providing more precise prediction results, this system also supports the principles of smart farming, which emphasize efficiency, accuracy, and sustainability. Going forward, development can be enhanced by adding other variables such as light intensity, air humidity, and soil nutrient levels to further improve the system's predictive capabilities. Thus, this study not only demonstrates the effectiveness of multiple linear regression methods in the context of automatic irrigation but also makes a significant contribution to the literature on IoT and agricultural automation in tropical regions.

5. CONCLUSION

This study demonstrates that an IoT-enabled automatic irrigation system using multiple linear regression (MLR) with air temperature and soil moisture as inputs can deliver high-fidelity, explainable irrigation scheduling for grapevines in tropical greenhouses, achieving MSE 0.15, MAPE 1.44%, and R^2 0.98. The model translates readily available sensor signals into precise irrigation durations that stabilize the microclimate, reduce manual intervention, and support resource-efficient cultivation. From an Informatics perspective, the contribution is a lightweight, interpretable, and low-latency decision model that runs reliably on constrained edge hardware, integrates cleanly with standard IoT data pipelines, and is maintainable via simple re-training and versioning, thereby aligning with sustainable computing and scalable national smart-farming deployments. The results indicate that regression-based decision support is not only agronomically effective but also computationally efficient, reproducible, and suitable for wide adoption in data-limited, power-constrained environments.

Future work will extend the decision model and deployment pipeline in four complementary directions to increase accuracy, robustness, and impact. First, enrich the feature set beyond temperature and soil moisture by adding relative humidity, vapor-pressure deficit, solar radiation/PAR, substrate EC, and reference evapotranspiration (ETo), then evaluate feature importance and multicollinearity to retain only variables that improve generalization. Second, benchmark the current MLR against stronger baselines on the same dataset—Regularized LR, Random Forest, SVR, Gradient Boosting/XGBoost, and sequence models (LSTM/TFT)—and adopt online/continual learning with drift detection, uncertainty estimation, and periodic auto-recalibration to sustain accuracy across seasons. Third, harden the system for field reliability by adding sensor self-diagnostics, missing-data imputation, automatic (re)calibration, and fault-tolerant control; implement secure edge deployment (ESP32/LoRaWAN) with encrypted communications, authenticated updates, and over-the-air model/firmware delivery; and design a human-in-the-loop dashboard that explains coefficient effects, confidence, and recommended actions. Fourth, validate external generalization through multi-site, multi-season experiments and transfer learning to other high-value greenhouse crops (e.g., tomato, pepper, strawberry), while running a multi-objective study that jointly optimizes water, energy, yield, and disease risk under different irrigation strategies. Finally, establish full MLOps for agriculture—data/model versioning, audit trails, and governance—coupled with an economic evaluation (water and energy savings, ROI, and payback time) to support large-scale adoption by smallholder and enterprise growers.

REFERENCES

[1] U. Ristian, I. Ruslianto, and K. Sari, “Sistem Monitoring Smart Greenhouse pada Lahan Terbatas Berbasis Internet of Things (IoT),” *Jurnal Edukasi dan Penelitian Informatika (JEPIN)*, vol. 8, no. 1, p. 87, 2022, doi: 10.26418/jp.v8i1.52770.
[2] Y. Tian *et al.*, “Passive cooling of greenhouses in extreme climates through spectral control film,” *Nexus*, vol. 2, no. 1, p. 100058, Mar. 2025, doi: 10.1016/j.ynexs.2025.100058.
[3] C. Maraveas, D. Loukatos, T. Bartzanas, K. G. Arvanitis, and J. F. Uijterwaal, “Smart and Solar Greenhouse Covers: Recent Developments and Future Perspectives,” Nov. 17, 2021, *Frontiers Media S.A.* doi: 10.3389/fenrg.2021.783587.
[4] S. Chen, A. Liu, F. Tang, P. Hou, Y. Lu, and P. Yuan, “A Review of Environmental Control Strategies and Models for Modern Agricultural Greenhouses,” *Sensors*, vol. 25, no. 5, p. 1388, Feb. 2025, doi: 10.3390/s25051388.
[5] C. Yan, T. Na, Q. Zhen, Y. Sun, and K. Liu, “Prediction of air temperature and humidity in greenhouses via artificial neural network,” *PLoS One*, vol. 20, no. 6, p. e0325650, Jun. 2025, doi: 10.1371/journal.pone.0325650.
[6] B. Guo *et al.*, “A Critical Review of the Status of Current Greenhouse Technology in China and Development Prospects,” *Applied Sciences (Switzerland)*, vol. 14, no. 13, 2024, doi: 10.3390/app14135952.
[7] M. A. Nwanojuo, C. K. Anumudu, and H. Onyeaka, “Impact of Controlled Environment Agriculture (CEA) in Nigeria, a Review of the Future of Farming in Africa,” *Agriculture*, vol. 15, no. 2, p. 117, Jan. 2025, doi: 10.3390/agriculture15020117.
[8] C. Maraveas, D. Piromalis, K. G. Arvanitis, T. Bartzanas, and D. Loukatos, “Applications of IoT for optimized greenhouse environment and resources management,” *Comput Electron Agric*, vol. 198, no. April, p. 106993, 2022, doi: 10.1016/j.compag.2022.106993.
[9] M. A. Tawfeek, S. Alanazi, and A. A. A. El-Aziz, “Smart Greenhouse Based on ANN and IOT,” *Processes*, vol. 10, no. 11, pp. 1–17, 2022, doi: 10.3390/pr10112402.
[10] H. Luo *et al.*, “Transparent solar photovoltaic windows provide a strong potential for self-sustainable food production in forward-looking greenhouse farming architectures,” *Clean Eng Technol*, vol. 24, p. 100895, Feb. 2025, doi: 10.1016/j.clet.2025.100895.
[11] M. Gholami, A. Arefi, A. Hasan, C. Li, and S. M. Muyeen, “Enhancing energy autonomy of greenhouses with semi-transparent photovoltaic systems through a comparative study of battery storage systems,” *Sci Rep*, vol. 15, no. 1, p. 2213, Jan. 2025, doi: 10.1038/s41598-025-85418-z.
[12] J. Xu, B. Gu, and G. Tian, “Review of agricultural IoT technology,” *Artificial Intelligence in Agriculture*, vol. 6, pp. 10–22, 2022, doi: 10.1016/j.aiia.2022.01.001.
[13] C. Li, J. Wang, S. Wang, and Y. Zhang, “A review of IoT applications in healthcare,” *Neurocomputing*, vol. 565, no. May 2023, p. 127017, 2024, doi: 10.1016/j.neucom.2023.127017.
[14] Y. Bin Zikria, R. Ali, M. K. Afzal, and S. W. Kim, “Next-generation internet of things (IoT): Opportunities, challenges, and solutions,” Feb. 02, 2021, *MDPI AG*. doi: doi.org/10.3390/s21041174.

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

[15] K. Maros, "Peningkatan Keberdayaan Usaha Budidaya Jamur Tiram Melalui Implementasi Penyiraman Otomatis Berbasis IoT," vol. 4, no. 5, 2024, doi: 10.59818/jpm.v4i5.881.
[16] B. Pradhan, S. Bhattacharyya, and K. Pal, "IoT-Based Applications in Healthcare Devices," *J Healthc Eng*, vol. 2021, 2021, doi: 10.1155/2021/6632599.
[17] A. Chatterjee and B. S. Ahmed, "IoT anomaly detection methods and applications: A survey," *Internet of Things (Netherlands)*, vol. 19, no. June, p. 100568, 2022, doi: 10.1016/j.iot.2022.100568.
[18] J. Contreras-Castillo, J. A. Guerrero-Ibañez, P. C. Santana-Mancilla, and L. Anido-Rifón, "SAgric-IoT: An IoT-Based Platform and Deep Learning for Greenhouse Monitoring," *Applied Sciences (Switzerland)*, vol. 13, no. 3, 2023, doi: 10.3390/app13031961.
[19] Ircham Ali, S. Warisma, and A. Aljabar, "Arduino Microcontroller-Based Automatic Irrigation System for Grape Cultivation," *Journal of Artificial Intelligence and Engineering Applications (JAIEA)*, vol. 5, no. 1, pp. 816–821, Oct. 2025, doi: 10.59934/jaiea.v5i1.1477.
[20] L. I. Haryanto, "Farmer Perspectives On Livelihoods Within Grape Community In South Tangerang City," *Jambura Agribusiness Journal*, vol. 4, no. 1, pp. 23–32, Jul. 2022, doi: 10.37046/jaj.v4i1.14361.
[21] Luh Putu Yuni Widyastuti and Ni Kadek Ema Sustia Dewi, "Productivity and Brix value of Green Grapes (Vitis vinifera L var. Muscat Saint Vallier) at Different Location and Pruning Time in Buleleng Bali," *SEAS (Sustainable Environment Agricultural Science)*, vol. 7, no. 2, pp. 139–144, Oct. 2023, doi: 10.22225/seas.7.2.8222.139-144.
[22] Y. Yunita, M. A. I. Yunus, K. Mirbah, M. A. U. N, and S. Sukmawati, "Menguak Potensi Tersembunyi Kebun Anggur: Analisis Pengelolaan dan SOP Agro Secino dalam Memenuhi Kebutuhan Pasar," *Jurnal Ekonomi Pertanian dan Agribisnis*, vol. 2, no. 2, pp. 88–95, Nov. 2024, doi: 10.62379/jepag.v2i1.2246.
[23] J. Martínez-Lüscher, J. T. Matus, E. Gomès, and I. Pascual, "Toward understanding grapevine responses to climate change: a multi-stress and holistic approach," *J Exp Bot*, vol. 76, no. 11, pp. 2949–2969, Aug. 2025, doi: 10.1093/jxb/erae482.
[24] S. Firdaus, T. Rismawan, and U. Ristian, "Sistem Manajemen Pengairan Pada Budidaya Tanaman Anggur Berbasis Internet of Things (Iot)," *Jurnal Informatika dan Teknik Elektro Terapan*, vol. 11, no. 3s1, pp. 907–916, 2023, doi: 10.23960/jitet.v11i3s1.3389.
[25] A. R. Putri, A. Syakur, and Muhardi, "The Impact of Climate Change on Grape Production in Indonesia," 2023, pp. 54–60. doi: 10.2991/978-94-6463-144-9_6.
[26] L. A. Arias, F. Berli, A. Fontana, R. Bottini, and P. Piccoli, "Climate Change Effects on Grapevine Physiology and Biochemistry: Benefits and Challenges of High Altitude as an Adaptation Strategy," *Front Plant Sci*, vol. 13, May 2022, doi: 10.3389/fpls.2022.835425.
[27] A. Syahri and R. Ulansari, "Penyiraman Otomatis dengan NodeMcu Berbasis Iot Untuk Tanaman Cabai," *Jurnal Teknologi Informasi*, vol. 9, no. 1, pp. 38–44, 2023, doi: 10.52643/jti.v9i1.3173.
[28] E. Schiller, J. Ajayi, S. Weber, T. Braun, and B. Stiller, "Toward a Live BBU Container Migration in Wireless Networks," *IEEE Open Journal of the Communications Society*, vol. 3, pp. 301–321, 2022, doi: 10.1109/OJCOMS.2022.3149965.
[29] G. Custódio and R. C. Prati, "Comparing modern and traditional modeling methods for predicting soil moisture in IoT-based irrigation systems," *Smart Agricultural Technology*, vol. 7, no. August 2023, p. 100397, 2024, doi: 10.1016/j.atech.2024.100397.
[30] R. Andrianto and F. Irawan, "Implementasi Metode Regresi Linear Berganda Pada Sistem Prediksi Jumlah Tonase Kelapa Sawit di PT . Paluta Inti Sawit," *Jurnal Pendidikan Tambusai*, vol. 7, no. 1, pp. 2926–2934, 2023.
[31] F. Wadly, "Integrating the NodeMCU ESP8266 Microcontroller with the DHT11 and MQ-135 Sensors Enables IoT-Based Air Quality Monitoring," vol. 2, no. 1, 2025.
[32] A. R. A. S. E. S. Mudofar Baehaqi, "5-Pengujian Performa Sensor DHT11 dan DS18B20 Sebagai Sensor Suhu Ruang Server," *Mestro Jurnal Ilmiah*, vol. 2, no. 02, pp. 6–12, 2023.
[33] A. A. A. Halim, R. Mohamad, F. Y. A. Rahman, H. Harun, and N. M. Anas, "IoT based smart irrigation, control, and monitoring system for chilli plants using NodeMCU-ESP8266," *Bulletin*

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

of Electrical Engineering and Informatics, vol. 12, no. 5, pp. 3053–3060, 2023, doi: 10.11591/eei.v12i5.5266.

[34] A. Herlina, M. I. Syahbana, M. A. Gunawan, and M. M. Rizqi, "Sistem Kendali Lampu Berbasis Iot Menggunakan Aplikasi Blynk 2.0 Dengan Modul Nodemcu Esp8266," *INSANtek*, vol. 3, no. 2, pp. 61–66, 2022, doi: 10.31294/instk.v3i2.1532.

[35] A. Wardhana, "OTOMATIS TANAMAN ANGGUR PADA GREENHOUSE Program Studi Sarjana Teknologi Informasi (Kampus Kota Surabaya) Fakultas Informatika Universitas Telkom Surabaya," 2024.

[36] R. F. Osemeke, J. N. Igabari, and N. D. Christian, "Detection and Correction of Violations of Linear Model Assumptions by Means of Residuals," *Journal of Science Innovation and Technology Research (JSITR)*, vol. 3, no. 9, pp. 1–15, 2024.

[37] G. Mardiatmoko, "The Application of the Classical Assumption Test in Multiple Linear Regression Analysis (a Case Study of the Preparation of the Allometric Equations of Young Makila)," *JTAM (Jurnal Teori dan Aplikasi Matematika)*, vol. 8, no. 3, p. 724, 2024, doi: 10.31764/jtam.v8i3.22179.

[38] P. Serafin, "Modern web technology – frameworks, advantages, disadvantages and optimal applications," *Computer Science and Mathematical Modelling*, vol. 0, no. 19/2024, pp. 25–34, 2024, doi: 10.5604/01.3001.0055.0854.

[39] N. A. Fitri, R. Z. Emba, M. R. Mufid, A. Fiyanto, W. Wajib, and A. Shofyan, "Kediri City Tourism Object Application Using Firebase Realtime Database Technology," *Proceedings of the International Conference on Applied Science and Technology on Social Science 2021 (iCAST-SS 2021)*, vol. 647, pp. 892–897, 2022, doi: 10.2991/assehr.k.220301.147.

[40] M. Shanmugavalli and K. M. J. Ignatia, "Comparative Study among MAPE, RMSE and R Square over the Treatment Techniques Undergone for PCOS Influenced Women," *Recent Patents on Engineering*, vol. 19, no. 1, 2025, doi: 10.2174/0118722121269786231120122435.

[41] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Comput Sci*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.

[42] A. A. A. Halim, R. Mohamad, F. Y. A. Rahman, H. Harun, and N. M. Anas, "IoT based smart irrigation, control, and monitoring system for chilli plants using NodeMCU-ESP8266," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, pp. 3053–3060, Oct. 2023, doi: 10.11591/eei.v12i5.5266.

[43] … | Wahjuni, S. Wulandari, and M. Kholili, "Development of Fuzzy-Based Smart Drip Irrigation System for Chili Cultivation," 2022.

[44] J. Martínez-Lüscher, J. T. Matus, E. Gomès, and I. Pascual, "Toward understanding grapevine responses to climate change: a multi-stress and holistic approach," *J Exp Bot*, vol. 76, no. 11, pp. 2949–2969, Aug. 2025, doi: 10.1093/jxb/erae482.

[45] L. P. Challa, C. D. Singh, K. V. R. Rao, A. Subeesh, and M. Srilakshmi, "Prediction of soil moisture using machine learning techniques: A case study of an IoT-based irrigation system in a naturally ventilated polyhouse," *Irrigation and Drainage*, vol. 73, no. 3, pp. 1138–1150, Jul. 2024, doi: 10.1002/ird.2933.

[46] S. Gupta *et al.*, "Smart agriculture using IoT for automated irrigation, water and energy efficiency," *Smart Agricultural Technology*, vol. 12, p. 101081, Dec. 2025, doi: 10.1016/j.atech.2025.101081.

[47] G. D. Shimizu and L. S. A. Gonçalves, "AgroReg: main regression models in agricultural sciences implemented as an R Package," *Sci Agric*, vol. 80, 2023, doi: 10.1590/1678-992x-2022-0041.

[48] A. A. A. Halim, R. Mohamad, F. Y. A. Rahman, H. Harun, and N. M. Anas, "IoT based smart irrigation, control, and monitoring system for chilli plants using NodeMCU-ESP8266," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 5, pp. 3053–3060, Oct. 2023, doi: 10.11591/eei.v12i5.5266.

[49] E. K. Pramartaningthyas, S. Ma'shumah, and A. Al Hannan, "Design and Implementation of an IoT-Based Automatic Irrigation and Monitoring System for Bird's Eye Chili Plants with

Vol. 7, No. 2, April 2026, Page. 843-857
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2026.7.2.5289

Telegram and Blynk Platform Integration," *G-Tech: Jurnal Teknologi Terapan*, vol. 9, no. 3, pp. 1248–1257, Jul. 2025, doi: 10.70609/g-tech.v9i3.7160.

[50] G. D. Shimizu and L. S. A. Gonçalves, "AgroReg: main regression models in agricultural sciences implemented as an R Package," *Sci Agric*, vol. 80, 2023, doi: 10.1590/1678-992x-2022-0041.

[51] M. A. Mattar, D. K. Roy, H. M. Al-Ghobari, and A. Z. Dewidar, "Machine learning and regression-based techniques for predicting sprinkler irrigation's wind drift and evaporation losses," *Agric Water Manag*, vol. 265, p. 107529, May 2022, doi: 10.1016/j.agwat.2022.107529.

[52] R. A. Syahputra and D. Andriani, "A Predictive Model For Crop Irrigation Schedulling Using Machine Learning and IoT-Generated Environmental Data," 2025. [Online]. Available: http://jurnal.polibatam.ac.id/index.php/JAIC