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SoPoSIS: An AI-Integrated Framework Linking Evapotranspiration and Photovoltaic Power Predictions for Sustainable Irrigation

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Abstract: Solar smart irrigation is one of the significant techniques to enhance water and energy resources in sustainable agriculture. Despite this, current systems in common use typically treat water and energy separately with few operational indicators to predict irrigation adequacy, particularly in tropical growing environments. This research aims to design and validate the Solar-Powered Smart Irrigation System (SoPoSIS) as a holistic and predictive tool of irrigation management. Meteorological data and historical solar energy production were collected from field experiments in tropical locations for this research. The system is constructed based on an Extreme Gradient Boosting model for estimating reference evapotranspiration (ETo) and a Hybrid Autoregressive + Wavelet Gated Recurrent Unit residual model for predicting photovoltaic (PV) power output. The performance of the system was assessed by the use of Predictive Irrigation Adequacy Index (PIAI) to measure the suitability of PV power prediction for crop water demand. For the ETo model, a mean absolute error (MAE) of 0.006 mm day^{-1} and accuracy of 98% were obtained, whereas for the PV model, it was an MAE of 188.50 watts with an accuracy level of 89.9%. The equipment could irrigate up to 51.6 m^3 of water per application, whereas crop water requirement was between 2.6 and 3.0 m^3 ha^{-1}. The PIAI values indicated that the irrigation was right in all weather conditions. These results show that SoPoSIS offers an operational means of integrated water and energy management and supports resource-efficient and low-carbon farming in tropical regions.

Keywords: artificial intelligence, prediction, evapotranspiration, photovoltaic power, sustainability

1. Introduction

Sustainable agriculture, as well as its system, came under various pressures due to global climate change. In light of those issues, the agro-sector is confronted with the task of maintaining productivity and resource efficiency while acceptable environmental conditions are preserved. According to the Food and Agriculture Organization of the United Nations (FAO), world food production will need to be 50–60% higher by 2050 to meet population demand. Meanwhile, the agricultural industry already consumes around 70% of the world's freshwater [1, 2]. Climate change, particularly rising temperatures and increasingly variable rainfall patterns, may adversely affect water availability and intensify water-related risks [1, 3]. These pressures underscore the need for irrigation systems that jointly manage water and energy resources [4].

The Solar-Powered Irrigation Schemes (SPIS) are gradually becoming a viable and sustainable practice in the field of smallholder farming, especially in tropical areas characterized by abundant solar energy [5]. These systems are composed of photovoltaic (PV) panel modules that convert the radiant energy of the sun into electrical power to drive water pumps, enabling them to become independent of diesel fuel and grid electricity. This method reduces operating and maintenance costs and helps cut greenhouse gas emissions, in line with the world's growing concern about green practices [6]. The SPIS also provides other benefits, including a low environmental impact, low maintenance needs, and applicability in remote rural regions with limited energy availability, etc. Its modular design makes it adaptable and scalable to land size and irrigation demand [7]. However, the majority of existing SPIS implementations are still either manually controlled or work on a fixed time schedule. However, such a method fails to account for time-based factors in environmental conditions, such as solar radiation intensity or evapotranspiration (ETo), in soil moisture and microclimate. The conflicts between irrigation demand and changes in solar radiation also result in an imbalance between water demand and energy supply, leading to system inefficiency [8]. Under such conditions, water may not be enough on cloudy days, or over-irrigation in high-radiation conditions

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may occur, resulting in plant stress and water waste, as well as an unfavorable use of the limited energy [4, 9]. These drawbacks emphasize the importance of smart irrigation systems that can act autonomously and adapt to changing climate and energy realities.

Three remaining research gaps in smart irrigation systems are that existing approaches treat crop water demands and solar energy separately. Hence, irrigation scheduling and energy generation are not synchronized, resulting in the water supply misaligning with solar energy. This imbalance causes resource waste and reduced reliability of solar-powered irrigation systems [10]. Second, there is insufficient field testing, particularly in tropical regions where climate oscillates widely, and solar radiation and weather can be erratic. Models that work robustly under controlled conditions are not as successful when applied to tropical natural environments, where cloud cover and humidity levels can vary rapidly [11, 12]. Third, no standard methods exist for comparing how well predicted irrigation needs align with available solar energy. Without that standard, it's difficult to compare how well homes in different areas and climates perform. These challenges pose difficulties for upscaling and replicating smart irrigation systems, particularly for smallholder farmers who can benefit from these low-cost, reliable, and proven innovations [13].

To achieve this, the following section presents a novel integrated predictive framework based on artificial intelligence (AI) and solar modeling for irrigation management, which bridges the identified research gaps in the literature. This research presents an integrated operational system, named the Solar-Powered Smart Irrigation System (SoPoSIS), to combine crop water demand with solar energy availability within a single decision-making system. The SoPoSIS architecture combines the XGBoost model, the ETo model, and the Hybrid Autoregressive (AR) + Wavelet–Gated Recurrent Unit (GRU) PV power forecasting model into a unique integrated decision-making flow. The two models are coupled via a Comparative Predictive Irrigation Adequacy Assessment (CPIAA) scheme that generates a Predictive Irrigation Adequacy Index (PIAI). It quantifies the relationship between crop water demand and solar radiation supply and facilitates decision-making regarding adaptation of irrigation scheduling, as well as helping to support sustainable energy–water–ecosystem management in tropical agriculture. SoPoSIS seeks to provide a practical operational solution for sustainable tropical agriculture, and this work is intended to design, develop, and validate SoPoSIS. In particular, this study seeks to develop a data-driven predictive framework that combines environmental and solar energy data for real-time irrigation management, evaluate the predictive performance of XGBoost and Hybrid AR + Wavelet–GRU models based on field measurements, and assess the suitability of irrigation using the suggested PIAI index under tropical conditions. Using AI-based predictions and solar radiation forecasts, SoPoSIS increases efficiency in water and energy management through a scalable pathway to implement precision irrigation in tropical agricultural systems.

2. Related Work

AI and precision irrigation enable the application of predictive control systems to enhance irrigation efficiency using available environmental information. Sheline et al. [14] presented the Predictive Optimal Water and Energy Irrigation controller, which uses an inventory control scheme to combine plant water demand models with real-time solar energy availability. Findings from this research indicated that the application depended on irrigation reliability (66%) and energy use efficiency (74%) over conventional systems. In addition, other researchers claim that the feedback-based predictive irrigation control strategies can save 20–35% of water without negatively affecting crop production [15, 16]. Nsoh et al. also demonstrated that machine learning models trained on environmental sensors enhanced water-use efficiency. However, the majority of current systems optimize water independently of energy [12]. Furthermore, validation has been scarce under tropical conditions, which are characterized by high humidity and variable solar radiation, and data limitations would influence system reliability [17].

Reliable estimation of ETo is essential for irrigation scheduling and water resources management. Estimates from physical models, such as the FAO-56 Penman–Monteith approach, are reliable, but they require a full meteorological dataset, which is often unavailable in tropical areas [18]. On the other hand, temperature-dependent empirical methods like the Hargreaves–Samani method are easier to use but have low accuracy in variable climates. Therefore, data-driven methods and models have gained popularity for addressing these challenges, such as Support Vector Regression, Random Forests, Artificial Neural Networks, and ensemble models [19]. Among those methods, XGBoost shows the best generalization and accuracy. The strength of the model is its ability to fit nonlinearity between climate factors and avoid overfitting through regularization and at the same time remain stable when it comes to incomplete or noisy data [20]. Moreover, XGBoost can reveal the importance of input factors, allowing a more informed determination of climatic parameters [21]. Motivated by the above analysis, this study selects XGBoost as the primary model for ETo forecasting on the SoPoSIS platform.

Power forecasting of PV generation requires approaches to manage high temporal variability due to cloud dynamics and rapid solar irradiance variations [22]. Traditional statistical models, such as autoregressive and autoregressive integrated moving-average, perform well in the steady state but are less effective with nonlinear, nonstationary solar data. Physics-based models are also constrained, as they require detailed technical and environmental parameters that are often missing in field applications [23]. On the other hand, machine learning (ML) and deep learning methods show better prediction accuracy for PV power production forecasts. The first group includes long short-term memory (LSTM) and GRU to model solar time-series dynamics [22, 24]. Wavelet–GRUs are commonly used because they decompose high- and low-frequency signals before forecasting, making learning more efficient by reducing data noise [25]. However, its performance is heavily influenced by the selection of wavelet type and transform scale level, and it tends to be poor at modeling short-term linear dependencies, such as those in rapid weather changes [26]. To overcome these difficulties, we propose a Hybrid AR + Wavelet–GRU model in this paper. The AR component accounts for short-term linear dependencies [27], while the Wavelet–GRU component addresses nonlinear and nonstationary dynamics. This hybrid approach improves the accuracy of predictions and the stability of our models, especially in tropical regions with high-radiation variability where data are scarce.

The SoPoSIS architecture combines the XGBoost model, the ETo model, and the Hybrid AR + Wavelet–GRU PV power forecasting model into a unique integrated decision-making flow. The two models are coupled via a CPIAA scheme that generates a PIAI. It quantifies the relationship between crop water demand and solar radiation supply and facilitates decision-making regarding adaptation of irrigation scheduling, as well as helping to support sustainable energy–water–ecosystem management in tropical agriculture. SoPoSIS seeks to provide a practical operational solution for sustainable tropical agriculture, and this work is intended to design, develop, and validate SoPoSIS. In particular, this study seeks to develop a data-driven predictive framework that combines environmental and solar energy data for real-time irrigation management, evaluate the predictive performance of XGBoost and Hybrid AR + Wavelet–GRU models based on field measurements, and assess the suitability of irrigation using the suggested PIAI index under tropical conditions. Using AI-based predictions and solar radiation forecasts, SoPoSIS increases efficiency in water and energy management through a scalable pathway to implement precision irrigation in tropical agricultural systems.

3. Methodology

This study adopts a structured methodological framework organized into four sequential stages: data acquisition, preprocessing, predictive modeling, and decision-oriented integration. The first stage involves collecting meteorological and PV measurements under field conditions. These observations are then processed through data cleaning, normalization, denoising, and temporal alignment to ensure consistency within the multivariate time series. The next stage focuses on the development of two predictive components: reference ETo estimation, representing irrigation demand, and PV power forecasting, representing energy supply. In the final stage, both outputs are integrated through the PIAI to support irrigation scheduling decisions. This methodological structure reflects recent developments in smart irrigation research, which increasingly emphasize transparent workflows that connect field sensing, prediction, and operational control within a unified framework.

3.1. Research framework and system architecture

This research integrates AI, photovoltaic (PV) solar energy forecasting, and precision irrigation control into an integrated decision-making system called the Solar-Powered Smart Irrigation System (SoPoSIS). The main contribution of this research is the development of a predictive control architecture that simultaneously models irrigation water demand and solar-based water supply to optimize energy-efficient irrigation in tropical regions. The SoPoSIS architecture, as illustrated in Figure 1, comprises three hierarchical steps.

3.1.1. Data source stage

The data source stage is the process of collecting field data in real time. The data include solar radiation intensity (W/m²), air temperature (°C), humidity (%), sunlight, and PV module electrical parameters, including voltage (V) and current (A). The collected data serve as the main basis for the predictive modeling process and system performance validation in the face of natural tropical environmental variability.

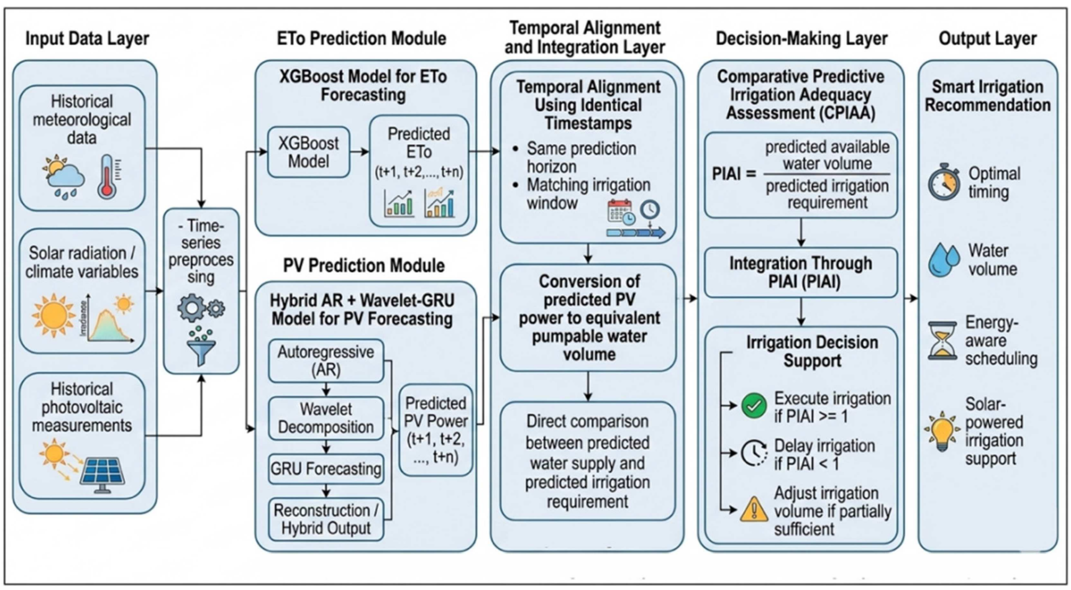
3.1.2. Prediction model stage

The prediction model stage is the analytical core of the SoPoSIS framework. This system integrates two complementary AI subsystems, designed to model irrigation water demand and solar energy availability. The first subsystem, the Water Demand Prediction Module, uses the Extreme Gradient Boosting (XGBoost) algorithm to estimate daily reference ETo based on key meteorological variables such as solar radiation intensity, air temperature, relative humidity, and sunshine duration. This prediction process enables accurate estimates of irrigation needs under varying climatic conditions. The second subsystem, the Solar Energy Prediction Module, applies a Hybrid Autoregressive and Wavelet–Gated Recurrent Unit (AR + Wavelet–GRU) model to predict PV power output by capturing linear temporal trends and nonlinear fluctuations in solar radiation. Together, these models produce synchronized outputs in the form of predicted ETo (ETo_p) and predicted PV power, which are then sent to the comparative adequacy module for integrated analysis and decision-making in the SoPoSIS system.

3.1.3. Decision and control layer

This is the stage of the CPIAA for calculating the PIAI. The irrigation actions according to the PIAI value are automatically

Figure 1
The proposed SoPoSIS architecture



calculated as either to execute ($P \geq 1$), delay ($PIAI < 1$), or apply a percentage of the total water volume. This decision-making logic enables real-time irrigation action based on forecasted sufficiency. This architectural integration is the conceptual basis of SoPoSIS for the connection between environmental monitoring, AI-based forecasting, and adaptive irrigation control in sustainable water–energy management.

To clarify the system-level integration, SoPoSIS operates through a structured and sequential workflow. Environmental and PV measurements are first collected and preprocessed to ensure temporal consistency, as reliable time-aligned inputs are fundamental for irrigation planning and water-use assessment under dynamic field conditions [28]. The processed meteorological variables are then used to estimate daily reference ETo, while historical PV signals are used to forecast PV power output over the same prediction horizon. Both outputs are aligned using identical time stamps so that projected water demand and expected energy availability correspond to the same irrigation window. The predicted PV power is subsequently converted into an equivalent pumpable water volume using the energy–hydraulic relationship, enabling direct comparison between water supply and irrigation requirement. Such temporal harmonization is essential, particularly under variable solar conditions, where recent studies have shown that improved signal processing enhances the stability and operational reliability of PV forecasting [29]. The synchronized supply–demand estimates are then integrated through the PIAI, which functions as the operational variable guiding irrigation execution, postponement, or adjustment. This workflow clarifies how the predictive components are combined into a coherent decision-making framework for irrigation management.

3.2. Study area and experimental setup

The field experiment was conducted in Tegalmulyo, RT.05/RW.01, Guli Village, Nogosari Subdistrict, Boyolali, Central Java, Indonesia, covering a one-hectare rice field representative of tropical lowland agriculture (Figure 2, Source: Google Maps [−7.462315,110.759042][1]). The site features high humidity, variable irradiance, and strong diurnal temperature fluctuations, making it an ideal testbed for solar-powered irrigation systems.

This observation was performed at 09:00, 12:00, and 15:00 WIB every day during the observation period (intervening period of this research), from July 7 to August 5. This observation window was intended to evaluate the operational performance of SoPoSIS under representative tropical lowland conditions, particularly under daytime fluctuations in irradiance, temperature, and humidity. However, because the dataset covers only a limited period, the findings should be interpreted with appropriate caution. They demonstrate system performance during the monitored interval, but further validation across wet and dry seasons is still required before broader seasonal applicability can be established. The measurements were carried out to describe the dynamic state of solar radiation and the atmosphere. The experimental platform used a collection of sensors to acquire environmental and energy-related attributes essential to SoPoSIS. Solar radiation (W/m²) was measured with a Solar Power Meter, air temperature and relative humidity were recorded with a digital thermohydrometer, and soil moisture was measured with a soil moisture sensor. Furthermore, a sunlight duration logger was placed to record daily changes in photoperiod for accurate assessment of solar radiation. Four 550 W PV panels were placed on the power generation

Figure 2
Study location of research

side of the system and connected in parallel to measure voltage and current output. All sensor measurements were automatically acquired and saved as multivariate time-series data in a CSV file. These swept datasets were used as a basis for later models and parameter calibration, as well as for simulation-based validation of the SoPoSIS system.

3.3. Data acquisition and variable definition

The data-collection methodology used in this study included measurements of six main variables, grouped into two domains: environmental and solar energy characteristics. The climatic parameters were solar radiation (W/m²), air temperature (°C), relative humidity (%), and sunlight duration (hours), all these being decisive factors related to ETo rates and therefore total irrigation demands. The solar energy parameters included voltage (V) and current (A), which were measured from the PV system to assess energy production capacity. G and Alfa) were chosen because they directly influence water demand and the solar-based energy supply in the SoPoSIS model. The PV power P_{PV} was calculated as:

$$P_{PV} = V \times I \tag{1}$$

where V and I are the voltage and current of the PV array, respectively [30]. All data were time-stamped with high precision to maintain temporal consistency and synchronization among variables, upon which multivariate time-series analysis was performed during model building and validation.

3.4. Data preprocessing

The raw field data are typically noisy due to environmental noise, sensor shifts, and temporary changes in cloud cover. To mitigate these problems, this study presents a procedural preprocessing protocol that aims to enhance data reliability and increase the accuracy of subsequent analysis. In the first step, an interquartile range (IQR) method is used to identify and remove outliers from the data. And then it addresses the missing samples using linear interpolation across short-term gaps, preserving the continuity of observations. To normalize the scale of variables and stabilize model performance, min–max standardization is also performed in the above-mentioned process, converting all variables to [0, 1]. The dataset was then denoised using wavelet-based

[1] https://maps.app.goo.gl/mZzVTpe26eV6VR1D6

techniques (Daubechies-4 mother wavelet, db4), resulting in a reduction of high-frequency atmospheric noise that does not affect the main temporal patterns. In the last stage, the system aligns features by equating the meaning of each timestamp across all variables, such as solar radiation, temperature, humidity, and PV signals, to handle temporal consistency in multivariate data. This preprocessing pipeline provides statistically consistent, low-noise, high-quality data for time-series modeling and advanced predictive analysis in the SoPoSIS computational platform.

3.5. Predictive modeling of crop water demand (ETo)

The XGBoost algorithm was used to simulate daily ETo, an important agricultural water demand index. This model was chosen for its ability to represent nonlinear relationships and the ability of the genetic programming optimization process to handle high-dimensional meteorological measurements. The input variables were solar radiation, air temperature, relative humidity, and sunshine duration, while the target variable was daily ETo values estimated by use of the FAO-56 Penman–Monteith method as follows:

$$ET_0 = \frac{0.408\Delta\left(R_n - G\right) + \gamma \frac{900}{T+273} u_2\left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34u_2\right)} \tag{2}$$

where ET_0 denotes the baseline evapotranspiration ($mm\ day^{-1}$), R_n represents the total radiation at the agricultural surface ($MJ\ m^{-2}\ day^{-1}$), G signifies the soil heat flux ($MJ\ m^{-2}\ day^{-1}$), T indicates the average daily air temperature (°C), u_2 is the wind speed at 2 m height ($m\ s{-}^{1}$), $(e_s - e_a)$ is the vapor pressure deficit (kPa), Δ is the slope of the saturation vapor pressure curve ($kPa\ {}^{\circ}C^{-1}$), and γ is the psychrometric constant ($kPa\ {}^{\circ}C^{-1}$) [31].

The XGBoost model builds an additive regression tree ensemble to gradually reduce residual errors in the difference between predicted and observed ETo. The model prediction can be expressed as:

$$\hat{y}_i = \sum\nolimits_{k=1}^{K} f_k\left(x_i\right),\ f_k \in \mathscr{F} \tag{3}$$

where $\hat{y}_i$ represents the projected ETo for the i^{th} instance, f_k denotes a singular regression tree, and $\mathscr{F}$ illustrates the functional space of potential trees [31]. The optimization objective is formulated as:

$$Obj(\theta) = \sum\nolimits_{i=1}^{n} l\left(y_i, \hat{y}_i\right) + \sum\nolimits_{k=1}^{K} \Omega\left(f_k\right) \tag{4}$$

where $l\left(y_i, \hat{y}_i\right)$ measures the loss between actual and predicted values and $\Omega\left(f_k\right)$ serves as a regularization term to control model complexity and prevent overfitting [32]. Hyperparameters were tuned for the model using grid search. The dataset was split into a training (70%) and testing (30%) set; five-fold cross-validation was performed to improve the generalization ability. Model performance under variability conditions of tropical climate was assessed by the mean absolute error (MAE), root mean square error (RMSE), and prediction accuracy (ACC) in order to obtain a broad assessment of predictive ability.

For clarity, the accuracy metric reported in this study is derived from the relative magnitude of prediction error and is computed as:

$$Accuracy\ (\%) = \left(1 - \frac{MAE}{\bar{y}}\right) \times 100 \tag{5}$$

where MAE represents the mean absolute error and $\bar{y}$ denotes the mean of the observed values. This formulation expresses prediction performance relative to the scale of the target variable, facilitating comparison across different units. To ensure consistency with established hydrological and energy forecasting practice, model performance is primarily evaluated using MAE and RMSE, with the reported accuracy serving as an auxiliary interpretative indicator rather than a stand-alone metric.

3.6. Predictive modeling of solar energy availability (PV power)

An AR + Wavelet–GRU model was proposed to predict solar energy generation by exploiting both linear and nonlinear time-series patterns in PV data. We mathematically describe the hybrid model by:

$$\widehat{P}(t) = P_{AR}(t) + f_{GRU}(W(t)) \tag{6}$$

where $P_{AR}(t)$ is short-term linear dependence modeled by the autoregressive part and $f_{GRU}(W(t))$ is for nonlinear residual variations obtained from wavelet-decomposed components $(W(t))$. The hybrid model is favorable in mitigating the nonlinearity of solar radiation, and it's difficult to capture the nonstationary characteristics in the tropical region due to the interpretability of autoregressive models paired with the adaptive learning capability of recurrent neural networks (RNNs).

The mother wavelet function for the wavelet decomposition was Daubechies-4 (db4), which was used to extract high- and low-frequency bands before GRU modeling [29]. The GRU network has 128 hidden units, and the tanh activation function is utilized to achieve a nonlinear representation. The Adam optimizer with a learning rate of 0.001 was used to speed up convergence, and we used a 70:30 training-validation split for both balanced learning and testing. Early stopping was also used to control overfitting by setting a limit at the minimum validation loss. The precision, accuracy, and overall reliability of model predictions (PV power) relative to observed values at both the average level and at the point were assessed using metrics MAE, RMSE, and R^2. Such a methodological setting enables the AR + Wavelet–GRU model to serve as a reliable forecasting technique for solar energy availability in the SoPoSIS system.

3.7. Conversion of PV power to available water volume

The forecast values of PV power output were transformed into corresponding hydraulic water volumes using an energy–hydraulic transformation model to illustrate the relationship between solar energy availability and replenishment capacity. The conversion was expressed as:

$$V_{water} = \frac{P_{PV} \times \eta \times t}{\rho g H} \tag{7}$$

where V_{water} denotes the volume of water that can be pumped (m^3), P_{PV} represents the predicted PV power (W), η is the overall efficiency of the pump–inverter system, t is the operational duration (h), ρ is the density of water (1000 $kg{\cdot}m^{-3}$), g is the gravitational acceleration (9.81 $m{\cdot}s^{-2}$), and H is the average pumping head (m) [33]. This expression yields a mathematical relationship between PV power forecasts and estimated water production, enabling the SoPoSIS methodology to align energy availability with irrigation needs. The inclusion of this transformation ensures energy-efficient irrigation programming and adaptability under varying solar conditions.

3.8. Comparative Predictive Irrigation Adequacy Assessment (CPIAA)

The CPIAA was proposed to assess the temporal and spatial relationships between Solar Energy Online's predicted water supply and the level of crop irrigation demand. This evaluation is based on the PIAI, representing a quantitative index of system adequacy as follows [34, 35]:

$$PIAI = \frac{W_{Supply}}{W_{demand}} \tag{8}$$

where W_{Supply} represents the predicted water volume available from solar-powered pumping and W_{demand} denotes the predicted irrigation requirement estimated from ETo modeling. A PIAI value greater than or equal to one ($PIAI \geq 1$) indicates that the available solar energy is sufficient to meet irrigation needs, while a value less than one ($PIAI < 1$) signifies a potential shortfall requiring irrigation adjustment or delay. The index is the primary decision-making basis in the SoPoSIS control structure for adaptive irrigation scheduling in terms of water and energy across different environments, solar conditions, and operating conditions.

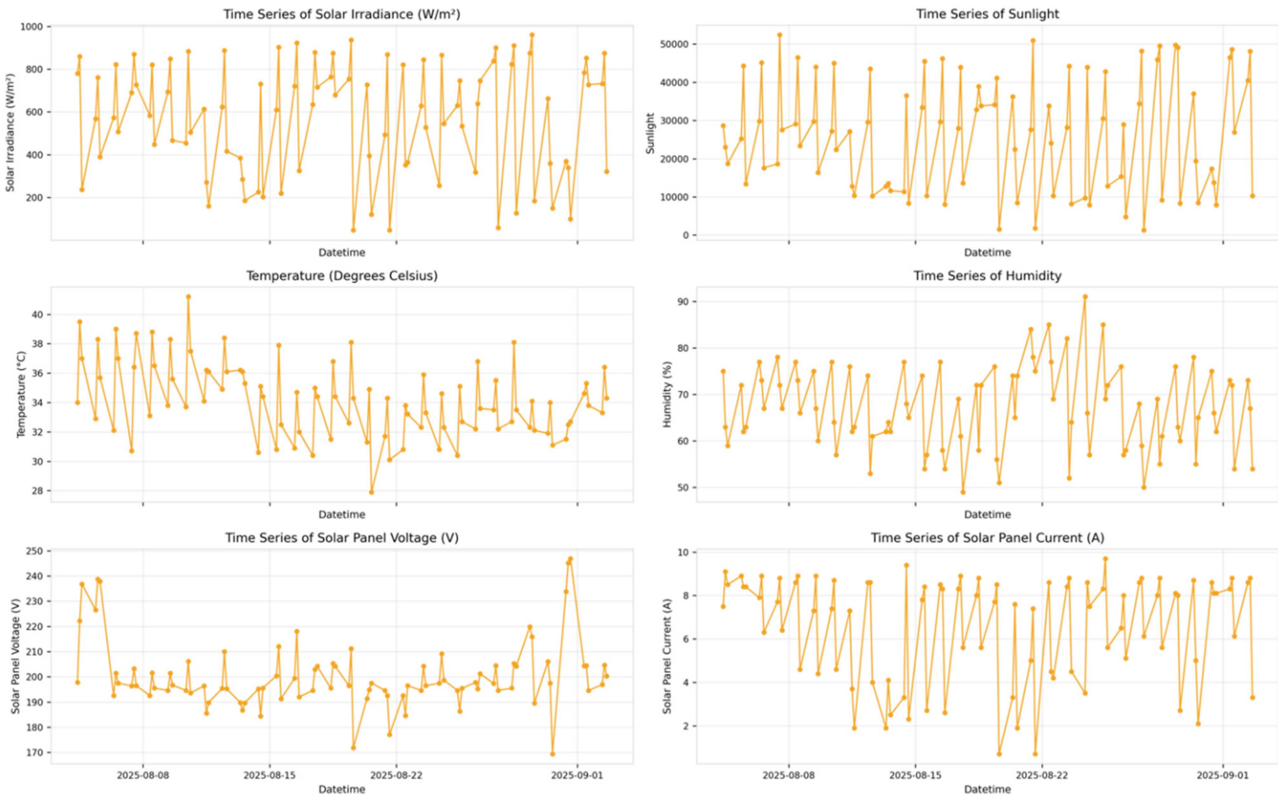
In this study, the PIAI is defined as the ratio between the predicted water volume available from solar-powered pumping (W_{Supply}) and the predicted irrigation requirement derived from ETo estimates (W_{demand}). From a physical perspective, the index reflects the balance between available pumping capacity and crop water demand under forecasted conditions. A value of PIAI ≥ 1 indicates that the expected water supply is sufficient to meet irrigation requirements, whereas PIAI < 1 signals a likely shortfall that may necessitate scheduling adjustments or supplemental measures. Conceptually, this formulation aligns with established irrigation adequacy and reliability assessments that compare delivered and required water volumes. However, unlike conventional metrics that are typically evaluated retrospectively, PIAI is structured as a forward-looking indicator intended to support operational planning under variable supply–demand conditions [35].

4. Result

4.1. Field measurements and time-series dynamics

Field observations at the experimental site in Tegal Mulyo Hamlet, from July 7 to August 5, 2025, produced a continuous multivariate time series in which six variables were repeatedly measured at three fixed time intervals: 09:00, 12:00, and 15:00 WIB. The observational environmental parameters were solar radiation, air temperature, relative humidity, and sunshine duration, whereas the PV domain was represented by PV voltage and current. The diurnal curves presented in Figure 3 show well-defined peaks around noonday for irradiation and air temperature, as well as a sharp fall in the humidity index typical of tropical lowlands. The PV current is closely proportional to the irradiation pattern, while the voltage remains almost constant over a long time period, thus maintaining stable power generation. This and the above time-correlation show a natural alignment between the solar energy generation operation and the irrigation water demand cycle.

Figure 3
Diurnal variation of solar irradiance, temperature, humidity, and PV power measured at 09:00, 12:00, and 15:00 WIB



4.2. Data preprocessing outcomes

The raw data exhibit intermittent spikes and gaps, primarily due to temporary clouds and long-term sensor drift. To overcome these problems, this work uses a structured preprocessing process comprising five steps: outlier removal using the IQR, linear interpolation to fill missing data, min–max normalization, noise suppression using the Daubechies-4 (db4) wavelet, and timestamp alignment across variables. This sequence of operations leads to considerable enhancements in the quality of data and preserves the temporal coherence of the series. We can see in Figure 4 that the post-processing histogram has a more centered distribution and lower skewness, indicating better signal stability. Furthermore, smoothed PV profiles improve model convergence during training. Accordingly, the resulting dataset is statistically consistent with low noise and was designed to support time-series modeling and learning.

4.3. Prediction of crop water demand (ETo)

In this study, daily ETo was estimated using an XGBoost model with solar irradiance, air temperature, sunshine duration, and relative humidity as predictor variables. The predictive performance of the model was evaluated against a Hybrid LSTM approach to assess its accuracy and robustness. As shown in Table 1, the XGBoost model performed well across all instances and excelled at 15:00 (MAE = 0.0047; RMSE = 0.0052; Accs = 98.45%). On the other hand, the Hybrid LSTM showed instability on small datasets and suboptimal overall performance. The fit between observed and estimated ETo values is shown in Figure 5, from which it can be concluded that the XGBoost model's predictions were excellent.

The XGBoost model produced consistently lower error and higher accuracy, particularly during midday irradiance fluctuations. Predicted ETo values were 0.2625, 0.2969, and 0.2874 mm at 09:00, 12:00, and 15:00, corresponding to irrigation demands of 2.63, 2.97, and 2.87 m^3 ha^{-1} (Table 2).

The irrigation water requirement was calculated based on a land area of one hectare. The prediction results indicate a relatively low hourly water demand, with a total daily requirement of approximately 8.5 m^3 per hectare.

To contextualize the reported accuracy of up to 98.45% for ETo prediction, the XGBoost model was evaluated against a hybrid LSTM-based alternative under identical data partitions.

Figure 4
Effect of preprocessing on signal smoothness and variance reduction across measured variables

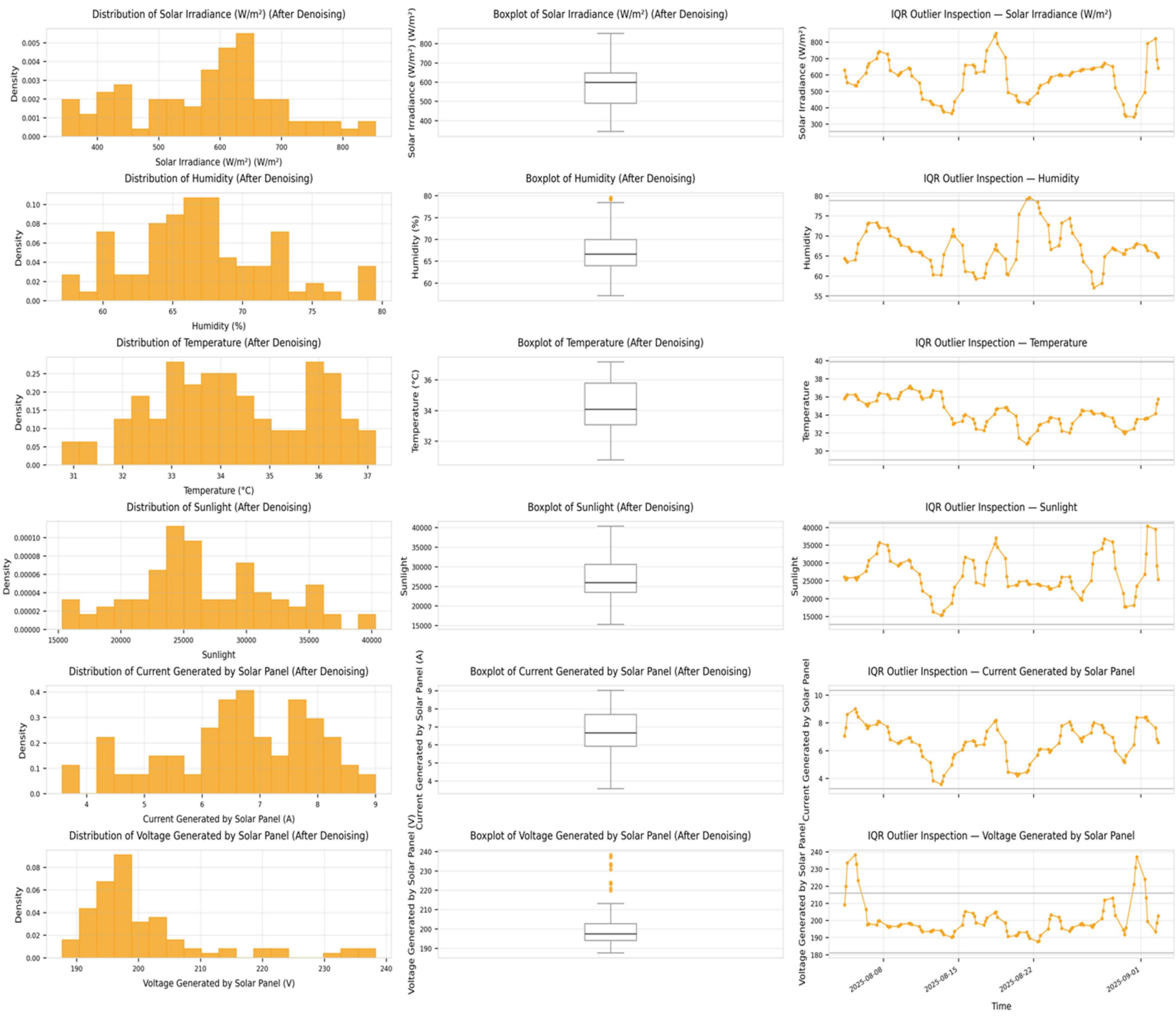


Table 1
Comparison of ETo prediction model evaluation (test data)

Time	Model	MAE	RMSE	Accuracy (%)
09:00	XGBoost	0.0073	0.0109	97.52
	Hybrid LSTM + XGBoost	0.0138	0.0164	95.31
12:00	XGBoost	0.0065	0.0083	97.86
	Hybrid LSTM + XGBoost	0.02	0.0213	93.32
15:00	XGBoost	0.0047	0.0052	98.45
	Hybrid LSTM + XGBoost	0.01	0.0164	96.66

Figure 5
Comparison between actual and predicted daily ETo values using XGBoost

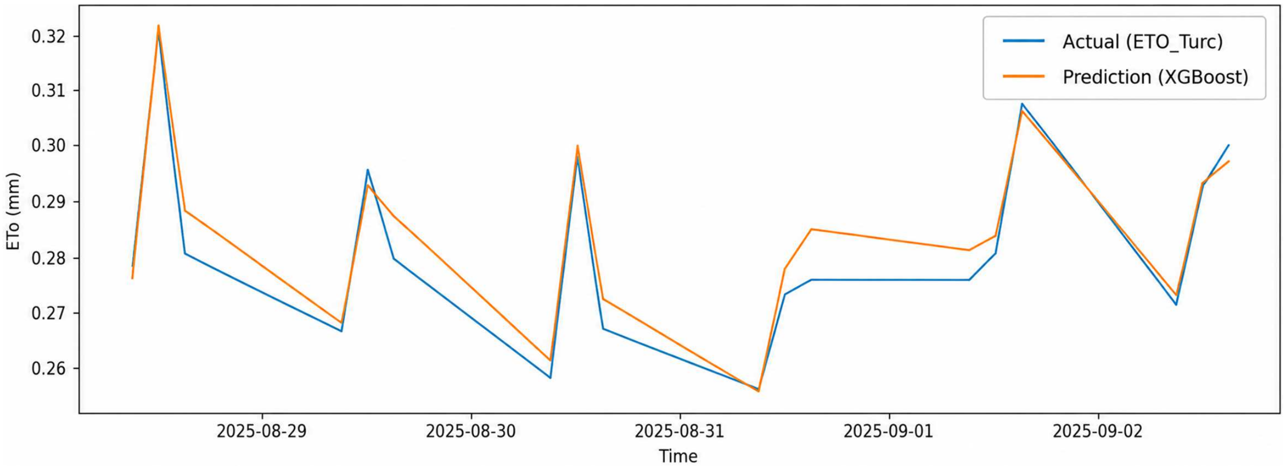


Table 2
Predicted ETo and irrigation demand (per ha)

Time (WIB)	Predicted ETo (mm day^{-1})	Irrigation demand (m^3 ha^{-1})
09:00	0.2625	2.63
12:00	0.2969	2.97
15:00	0.2874	2.87

Table 3
Comparison of solar PV power prediction model evaluation

Model	MAE	RMSE	Accuracy (%)
AR baseline	424.56	439.90	76.64
Wavelet–GRU	409.24	424.71	77.49
Hybrid AR + Wavelet–GRU	188.50	234.71	89.9

As shown in Table 1, XGBoost consistently produced lower MAE and RMSE values across all observation periods, particularly under midday radiation variability. The performance improvement is therefore supported not only by relative accuracy values but also by reduced absolute error metrics when compared with an established nonlinear benchmark model.

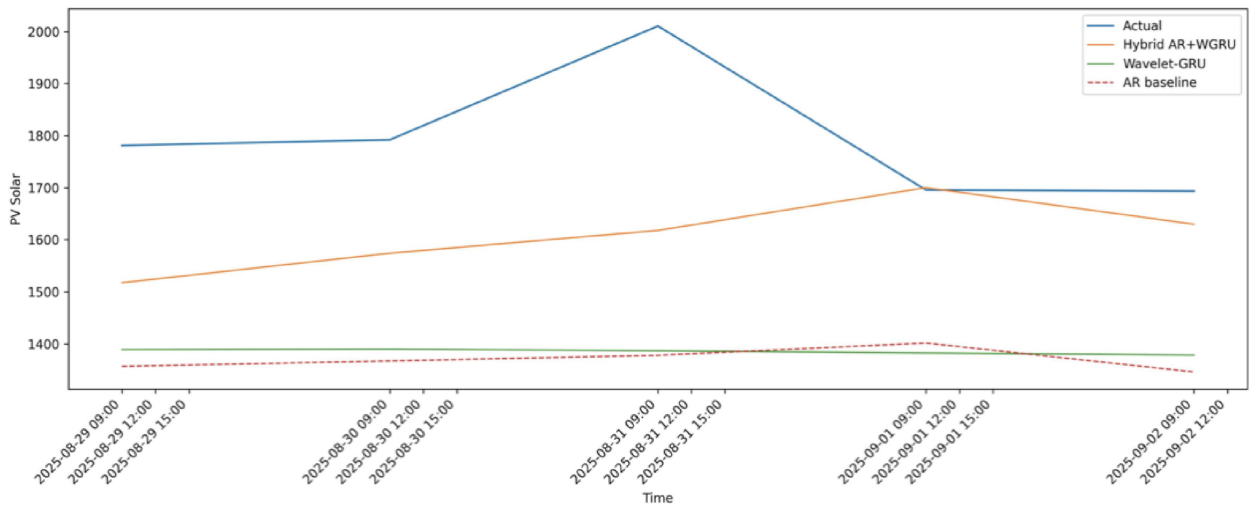
4.4. Prediction of solar PV power using the Hybrid AR + Wavelet–GRU model

The solar PV power modeling was conducted using a Hybrid AR + Wavelet—GRU approach, where the AR component captures short-term linear patterns, while the Wavelet–GRU processes nonlinear components derived from wavelet decomposition. The hybrid model was compared with the baseline AR model and the stand-alone Wavelet–GRU model to evaluate its predictive performance.

Table 3 shows that the Hybrid AR + Wavelet–GRU model consistently produced more accurate results compared to both the baseline AR and the stand-alone Wavelet–GRU models. The hybrid model successfully reduced the MAE from 424.56 W in the baseline AR model to 188.50 W and improved the prediction accuracy from 76.64% to 89.9%. The comparison between predicted and actual PV power data is illustrated in Figure 6, where the predicted curve of the Hybrid AR + Wavelet–GRU model more closely follows the actual power pattern than the other models. The hybrid prediction line accurately tracks the daily fluctuations of PV power with relatively small deviations, particularly during midday peak periods.

Figure 6 shows that the Hybrid AR + Wavelet–GRU model produced predictions that most closely matched the actual data compared to the baseline AR and stand-alone Wavelet–GRU models. During midday periods, when PV power reached its peak, the hybrid model was able to more accurately follow the rising and falling trends, resulting in smaller deviations from the observed values. This demonstrates that the hybrid approach is more effective in simultaneously capturing both linear and nonlinear patterns, thereby providing more accurate and stable predictions for solar PV power estimation. The next step involves forecasting solar PV power for the following day using the

Figure 6
Comparison between actual and predicted daily solar PV power



best-performing model, the Hybrid AR + Wavelet–GRU, with the prediction results presented in Table 4.

Table 4
Predicted solar PV power for the next day

Time	Hybrid AR + Wavelet–GRU	Wavelet–GRU (W)	AR (W)
09:00	1488.52	1364.28	1311.27
12:00	1488.25	1362.26	1311.04
15:00	1487.14	1358.93	1311.08

Table 4 shows that the Hybrid AR + Wavelet–GRU model produced consistent predicted PV power values of approximately 1488 watts across all three observation times, which were higher and more stable compared to the Wavelet–GRU and baseline AR models. This difference indicates the hybrid model's ability to capture both linear and nonlinear patterns simultaneously, resulting in more accurate estimations. The predicted power values can then be converted into estimates of effective energy and the corresponding volume of water pumped to support irrigation adequacy for the following day.

Similarly, the reported PV prediction accuracy of 89.9% should be interpreted in relation to baseline models. The Hybrid AR + Wavelet–GRU configuration was compared with a standalone autoregressive (AR) model and a Wavelet–GRU model using the same validation framework. The hybrid approach reduced MAE from 424.56 W in the AR baseline to 188.50 W and substantially lowered RMSE values, indicating improved stability under fluctuating solar conditions. These comparative results provide a transparent performance reference and allow the reported gains to be assessed against established linear and single-model alternatives rather than in isolation.

4.5. Water availability prediction

Based on the predicted solar PV power obtained using the Hybrid AR + Wavelet–GRU model, the estimated availability of pumped water for the following day was calculated by converting the generated electrical energy into water volume. This calculation considered the combined efficiency of the solar panel and pump system ($\mu_{pv} \times \mu_{pump} = 0.63$), allowing the predicted electrical power to be directly translated into the corresponding hydraulic energy potential [36]. The estimation results are presented in Table 5, which shows the predicted PV power values at three key time points (09:00, 12:00, and 15:00), along with the corresponding conversions into effective energy (Wh) and the volume of water that can be pumped (m^3).

Table 5
Estimated water availability from the Hybrid AR + Wavelet–GRU model

Time	Predicted PV (W)	Effective energy (Wh)	Available water (m^3)
09:00	1488.52	2813.30	51.62
12:00	1488.25	2812.80	51.61
15:00	1487.14	2810.69	51.57

As shown in Table 5, the predicted PV power also kept almost constant at thousands of W (1487–1489 W to be precise), with about 51.6 m^3 of pumped water being detected per observation period. This stability indicates that the hybrid model can quickly capture diurnal patterns in solar radiation with minimal variation and thus produce accurate estimates of water supply. Compared with the crop water requirements, calculated from daily ETo predictions and ranging from 2.6 to 3.0 m^3 per hectare per irrigation event, this is an overwhelming structural surplus of available water volume beyond actual field demand. It means that the system can exactly satisfy irrigation demand and have a certain reserve for extreme climate or crop water demand changes. The coupling of PV power prediction with ETo-based water demand estimation provides an efficient and practical basis for automatic irrigation system control, promoting reliable operation and sustainable water management in solar energy-assisted precision farming.

It should be clarified that the water availability values presented in this section are not produced by an independently trained prediction model. Rather, they are obtained deterministically from the predicted PV output using the energy hydraulic conversion relationship described earlier. Consequently, the reliability of the estimated pumped-water volume depends primarily on the forecasting performance of the Hybrid AR + Wavelet–GRU model reported in Section 3.4. Recent studies indicate that broader model benchmarking, particularly involving optimized LSTM-based configurations and hybrid comparative baselines evaluated under varying climatic conditions, can provide stronger evidence of model robustness and transferability across regions. In this regard, future research should expand the current benchmarking framework to include additional recurrent and ensemble models tested on more diverse tropical and non-tropical datasets, thereby strengthening confidence in the general applicability of the proposed system.

5. Discussion

The results of this research indicate that pre-emptive irrigation scheduling using forecasted ETo and water availability from PV is superior to the reactive approach where real-time conditions are only considered. Mainly, this result is described by two mechanisms. The XGBoost model is able to offer precise predictions of water demand by modeling nonlinear relationships between critical meteorological factors, which are solar irradiance, temperature, humidity, and sunlight duration. This capacity permits the early detection of a possible water stress, prior to any critical phase of growth. Second, the water supply is precisely forecasted by the hybrid AR model integrated with a Wavelet–GRU network. These, along with the second predictive element, produce robust and non-transient predictions for solar energy availability in field applications.

The findings of two empirical studies are consistent with this conclusion. On the test dataset, the hybrid model showed a significant improvement of prediction errors against benchmark models with an MAE value of 188.50 W, an RMSE of 234.71 W, and a MAPE of 10.10%. These were significantly better than the baseline AR model (MAPE 23.36%) and the stand-alone Wavelet–GRU predictions (MAPE of 22.51%). Furthermore, the conversion of predicted PV power to potential pumped water of the next day generated a convincing estimate of around 51.6 cubic meters per observation session (09:00, 12:00, and 15:00). This amount was higher than the ETo-based irrigation demand of 2.6–3.0 m^3 ha^{-1} $session^{-1}$. Taken together, these results served as the basis for calculating the PIAI, which classified all tested scenarios as surplus conditions, indicating that the predicted water supply exceeded the estimated irrigation demand. This evidence emphasizes the contribution of the study to model accuracy as well as the complete decision process from prediction outputs to supply–demand balance and operational scheduling.

The findings are in line with previous studies, which found two consistent patterns. While accounting for ETo, gradient boosting learning algorithms such as XGBoost have been reported to be more consistent compared to the empirical approaches in that they consider nonlinear effects, especially the leading part of both radiation terms and temperature. This makes XGBoost an applicable model to predict the crop water requirement under different climatic conditions [37–41]. In solar forecasting, some research works have been reported showing how wavelet decomposition followed by RNNs can improve the accuracy of predictions, isolating high-frequency noise prior to modeling [42–46]. This research's method, which treated wavelet decomposition before GRU processing, agrees with these previous studies. Other trials, like that of Pierre et al. (2023), have also shown that available hybrid residuals, which are a combination of linear and nonlinear models such as ARIMA with neural networks, do provide a suitable performance for complex energy data [47, 48]. These observations are particularly valuable to the field application, where PV pumping effectiveness is heavily subject to solar radiation variation and sunshine duration. A precise forecast is thus an important requirement for the purpose of energy estimation and irrigation scheduling. Previous work in predictive irrigation has demonstrated that data-driven scheduling can conserve water and maintain yield. The present study extends the work in References [49, 50] by considering both the demand (ETo) and supply (PV) as part of a combined predictive capability.

Moreover, this study strengthens two key observations from the literature. First, ETo estimation is more accurate when the interactions among climate variables are nonlinear and captured by ML models [39, 41, 49]. Second, PV forecasting is significantly enhanced when wavelet decomposition (WVD) is employed for denoising and combined with recurrent neural network (RNN) models [42, 43, 46, 51]. At the same time, the results call into question the assumption that it is enough to make either the accuracy of models forecasting the irrigation demand or the ones estimating the supply side better. The performance of the system depends on the interaction between predicted demand and supply at the same time, and both have to be evaluated before the operational decision is made. The main contribution of this study is the proposed workflow: the data preprocessing stage, the ETo predictions by XGBoost, PV power prediction by the Hybrid AR with Wavelet–GRU model, and the computed adequacy index. This workflow is systematic and transparent, and it is ready to be implemented in the control systems for irrigation timing and adjusted volume. From a methodological perspective, the hybrid residual strategy mitigates the risks of overfitting and underfitting in small datasets by separating the linear component modeled by AR from the nonlinear high-frequency residuals captured by the Wavelet–GRU model. From a practical perspective, the predicted water supply of approximately 51.6 m^3 per irrigation session substantially exceeded the estimated irrigation demand of 2.6–3.0 m^3 ha^{-1} per session for the one-hectare study area. This surplus pumping capacity could be used to improve water and energy efficiency by shortening pump operation, irrigating additional plots, or providing a reserve during periods of lower solar radiation or increased crop water demand. Potential applications comprise optimizing the operating cycle of the pump, scheduling irrigation during the optimal radiation period, and utilizing the supply for several patches.

In practical terms, the synchronization between predicted irrigation demand and solar-powered water supply should be understood as an operational basis for irrigation planning rather than merely as a modeling outcome, in line with recent studies showing that the value of predictive irrigation systems depends on how effectively forecast information can be translated into field-level scheduling and resource allocation decisions [52]. When the PIAI indicates a surplus condition (PIAI ≥ 1), irrigation can be applied in full during periods of favorable solar radiation, while the excess pumping capacity may be redirected to additional plots, used to reduce pump operating time, or retained as a buffer against lower radiation in subsequent periods. This interpretation is supported by recent ETo research showing that gradient boosting approaches are well suited to capturing nonlinear climate water demand relationships for operational irrigation planning [40]. By contrast, when PV power is predicted to be insufficient (PIAI < 1), SoPoSIS can support anticipatory management through delayed irrigation, proportional deficit irrigation, or the use of auxiliary power during critical crop growth stages. Such a planning-oriented approach is consistent with recent PV forecasting studies, which show that wavelet-based denoising and recurrent architectures can improve forecast stability under rapidly varying solar conditions, thereby strengthening short-term operational decision-making in solar-dependent systems [29, 42]. Accordingly, the practical contribution of SoPoSIS lies not only in improving the accuracy of ETo and PV power prediction but also in converting the predicted demand–supply relationship into concrete irrigation actions that enhance reliability, reduce avoidable energy use, and support day-ahead irrigation planning under variable tropical conditions.

Beyond the tropical setting examined in this study, the wider applicability of SoPoSIS will depend on local climatic patterns, crop characteristics, and the consistency of environmental inputs, as the performance of irrigation decision-support systems may vary across agricultural contexts and data conditions [52]. The framework is also sensitive to data availability, particularly the continuity of meteorological observations and the adequacy of historical PV generation records needed to support reliable short-term forecasting. This is especially relevant in data-scarce settings, where incomplete or inconsistent inputs may reduce the robustness of both irrigation demand estimation and energy-supply prediction [12]. In addition, field deployment requires basic but dependable infrastructure, including environmental sensors, stable data logging, and site-specific calibration of PV pump parameters such as conversion efficiency, hydraulic head, and flow losses, given that PV performance is strongly affected by local operating and environmental conditions [17]. Taken together, these considerations suggest that SoPoSIS has the potential to be implemented more broadly, but its reliable application across heterogeneous agroclimatic zones will depend on local recalibration and minimum monitoring standards.

From an implementation standpoint, the broader value of SoPoSIS would benefit from a dedicated techno-economic assessment. Recent studies on solar-powered irrigation systems consistently show that feasibility is determined not only by hydraulic and energy performance but also by installation costs, maintenance requirements, subsidy structures, and the extent to which operational control enhances lifecycle efficiency. Terang and Baruah [53] demonstrated that solar PV water pumps can reduce operating costs and environmental impacts compared with diesel and grid-based alternatives. Similarly, Paudel and Adhikari [54] reported that solar irrigation systems can be technically sound and economically viable for sustainable agriculture, although continued financial support remains important to enable wider adoption. Furthermore, Sheline et al. [55] observed that predictive irrigation scheduling can improve system reliability while lowering long-term operational costs. Within this context, SoPoSIS should be understood as a control and planning framework that has the potential to enhance cost-effectiveness through improved synchronization of water demand and energy availability, even though a comprehensive cost–benefit analysis was beyond the scope of the present study.

A further point concerns the temporal scope of the dataset. Field data were collected from July 7 to August 5, 2025, so the study reflects performance within a defined observation period rather than across a complete seasonal cycle. The results therefore should not be taken as evidence of direct applicability in all seasons. Instead, they indicate that SoPoSIS performed reliably under the tropical conditions captured during the study period. This reading aligns with recent work showing that solar-powered irrigation systems can remain effective across different local settings when weather inputs, crop water demand, and operating conditions are incorporated into the control framework [55]. At the same time, seasonal variation in ETo and crop coefficients is strongly influenced by rainfall, vegetation cover, and local surface conditions, which makes recalibration necessary before broader year-round use can be claimed [56]. Longer observation campaigns covering both wet and dry seasons are therefore needed to confirm wider seasonal applicability.

This study has several limitations. The field dataset was collected within a single observation period, from July 7 to August 5, 2025, and therefore does not capture the full range of seasonal variability. In addition, system performance remains sensitive to sensor accuracy and to PV–pump parameters such as conversion efficiency, hydraulic head, and flow losses, all of which require site-specific calibration. These constraints mean that, although the proposed framework shows clear potential for tropical precision irrigation, its wider application across different seasons and agroecological settings still requires further validation. Future work should combine longer field observations with model predictive control and multi-objective optimization to strengthen system robustness under a broader range of environmental conditions.

6. Conclusion

This work designed, implemented, and validated the SoPoSIS, an AI-informed predictive planning framework that merges crop water demand with solar energy availability under one decision-making system. It should also be noted that the present evaluation was based on field observations collected between July 7 and August 5, 2025. The findings therefore reflect system performance within a defined observation period, rather than across a complete seasonal cycle. While the results support the feasibility of SoPoSIS under the tropical conditions observed in this study, broader seasonal applicability still needs to be confirmed through further validation in both wet and dry periods. The high accuracy delineated in this contribution from SoPoSIS can be traced back to the use of XGBoost for ETo determination together with a residual Hybrid AR + Wavelet–GRU model for PV power forecasting as presented here, which resulted in stable energy predictions under tropical field conditions. Using the PIAI, the system indicated that the predicted irrigation supply exceeded crop water requirements across all evaluated scenarios, thereby supporting anticipatory solar-powered irrigation scheduling, reliable water delivery, and reduced resource waste. These results indicate that SoPoSIS can not only enhance prediction accuracy but also promote the exchange of information between data-driven modeling and actual irrigation control in real tropical environments.

Methodologically, this study adds to the AI in irrigation literature by showing the benefits of embedding ML and residual hybrid time-series models into one water–energy management model. The development and field testing of PIAI as an irrigation suitability criterion contribute to an operational tool for the water–energy nexus in planning for irrigation. From a practical point of view, SoPoSIS provides a reference architecture that is replicable and scalable for solar-based irrigation for tropical agriculture that leads to more efficient water use and renewable energy. The framework can guide technology scaling policies and agricultural development initiatives, especially for smallholders in low-carbon, climate-resilient irrigation options under data-poor environments.

The study also has some weaknesses, despite its encouraging results. System output is sensitive to sensor accuracy, PV–pump efficiency, and site-specific conversion coefficients such as hydraulic head and flow losses, which could limit generalization across agroecological and infrastructural contexts. Future studies will integrate concepts of model predictive control and multi-objective optimization for a simultaneous consideration of water use, energy usage, and cost-effectiveness. Developing SoPoSIS for wider crop systems, larger spatial scales, and different management levels and integrating satellite-based or edge AI monitoring would make it more robust and versatile. Assessing socio-economic effects and adoption constraints will also be key to facilitate further scaling of AI-based solar irrigation for sustainable tropical agriculture.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Nurmalitasari Nurmalitasari: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition. **Nurchim Nurchim:** Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Supervision. **Retna Dewi Lestari:** Validation, Writing – original draft, Writing – review & editing. **Zalizah Awang Long:** Validation, Writing – review & editing, Supervision.

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