EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2026, 27(9), 260–269
https://doi.org/10.12912/27197050/226409
ISSN 2719–7050, License CC-BY 4.0

Received: 2026.07.10
Accepted: 2026.08.03
Published: 2026.08.15

Ecological and agronomic impact of internet of things-based drip fertigation powered by solar energy on pakcoy (*Brassica rapa* L.) and weed dynamics

Eko Noerhayati[1], Soraya Norma Mustika[2*], Siti Asmaniyah Mardiani[3], Mahayu Woro Lestari[3], Novi Arfarita[3], Wahyu Mulyo Utomo[4]

[1] Department of Civil Engineering, Universitas Islam Malang, Jalan M.T. Haryono 193, Malang, Indonesia
[2] Department of Electrical Engineering, Faculty of Engineering, Universitas Negeri Malang, Jalan Semarang 5, Malang, Indonesia
[3] Faculty of Agriculture, Universitas Islam Malang, Jalan M.T. Haryono 193, Malang, Indonesia
[4] Department of Electrical Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Malaysia
* Corresponding author's e-mail: soraya.norma.ft@um.ac.id

ABSTRACT

Conventional irrigation and fertilization methods often lead to resource inefficiency and uncontrolled weed proliferation, which negatively impacts crop productivity and ecological balance. This study aimed to evaluate the effectiveness of a smart drip fertigation system integrated with Internet of Things (IoT) and powered by photovoltaic (PV) solar energy in managing water-fertilizer delivery and its subsequent impact on pakcoy (*Brassica rapa* L.) growth and weed vegetation. The research utilized an experimental design comparing the PV-IoT-based drip system with conventional surface irrigation. Parameters measured included soil moisture stability, water use efficiency, crop yield quality, and weed analysis (species diversity and density). The results indicated that the IoT-controlled system maintained optimal soil moisture levels, leading to a significant increase in pakcoy growth parameters and most yield quality indicators (plant height, leaf number, fresh and dry weight, and ash content), while vitamin C content remained statistically stable, compared to conventional methods. Notably, the localized water distribution of the drip system substantially suppressed weed growth. The weed analysis revealed a significant reduction in weed density and a shift in species composition, where the smart system prevented the dominance of competitive water-demanding weed species such as T-Grass and Kremah, commonly found in conventional irrigation. The PV-integrated system was designed to operate entirely on solar power without grid dependency, supporting its potential as a sustainable solution for precision agriculture. This study concludes that the integration of PV-IoT in drip fertigation not only optimizes resource conservation but also serves as an effective ecological tool for weed management in vegetable cultivation.

Keywords: drip fertigation, internet of things, photovoltaic, weed diversity, water-saving, precision agriculture.

INTRODUCTION

The increasing global population demands higher agricultural productivity, but this sector faces serious challenges, including limited water resources and the impacts of climate change (Lemfarrak et al., 2025; Mahdaoui et al., 2025; Nhemachena et al., 2020). In many developing countries, conventional irrigation systems still dominate horticultural land, but this method is often inefficient, causing uneven nutrient distribution (Fauzan et al., 2025; Orsini et al., 2013). Furthermore, excessive and uneven water application under conventional irrigation creates conditions favorable for massive weed proliferation (Kumar et al., 2025; Zahaf et al., 2025; Zhang et al., 2025). This uncontrolled weed growth triggers intense nutrient competition with key crops such as pakcoy (*Brassica rapa* L.), ultimately reducing crop biological quality (Hassan et al., 2021).

Traditional weed management often relies on chemical herbicides that negatively impact soil ecosystems. Therefore, an ecological engineering approach through drip irrigation offers a crucial solution by delivering water directly to the root zone (Widowati et al., 2024; Xing and Wang, 2024). The integration of Internet of Things (IoT) technology and solar energy (photovoltaic) enables real-time soil moisture monitoring and energy independence in remote areas (Kumaragurubaran et al., 2025). The use of industrial sensors based on the RS485 protocol has been shown to minimize data errors caused by sensor drift, which is crucial for maintaining nutrient homogeneity in the root zone (Abdullah et al., 2025). Recent studies have also emphasized that the practical value of IoT-based environmental sensing extends beyond measurement accuracy alone. Continuous sensor networks enable early detection of environmental changes, improve operational decision-making, and support sustainable resource management, although periodic laboratory validation remains necessary for quantitative assessments. Furthermore, the combination of autonomous photovoltaic energy supply with IoT monitoring enhances the feasibility of precision agriculture in remote areas by reducing dependence on conventional power infrastructure and improving long-term system sustainability (Oladosu et al., 2026; Alsufyani, 2025)

Although drip irrigation efficiency has been widely discussed, there is still a research gap regarding the impact of IoT-PV automation on weed community dynamics (Bouali et al., 2021). Most studies focus on hardware aspects without evaluating ecological shifts in weed species (MacLaren et al., 2020) This study aims to evaluate how IoT-PV-based drip irrigation control can improve water and nutrient use efficiency while ecologically regulating weed density and diversity. Unlike previous studies that have primarily focused on the engineering performance of smart irrigation systems, the present research investigates whether the integration of photovoltaic-powered IoT-controlled drip fertigation can simultaneously enhance agronomic productivity and modify weed community structure through ecological regulation of water availability. We hypothesize that precise localization of water and nutrient delivery creates a more favorable microenvironment for crop development while limiting resource availability for competitive weed species, thereby producing measurable ecological as well as agronomic benefits. Consequently, this study seeks to fill the current knowledge gap regarding the ecological consequences of automated IoT-PV fertigation systems by integrating engineering performance, crop productivity, and weed community responses within a single experimental framework.

MATERIAL AND METHODS

System architecture and design

The construction of the device is illustrated in Figure 1, showcasing a schematic of this smart irrigation system using solar panels (PV) as the main energy source to drive the IoT-based control unit (Okomba et al., 2023). The system architecture consists of a soil moisture sensor connected to a microcontroller to process environmental data in real-time (Tan et al., 2022). To complement the localized moisture tracking, an industrial-grade RS485 NPK electrochemical sensor was strategically integrated within the mainlines of the fertilizer distribution pipeline and cross-validated with periodic in-situ insertions into the crop root zone. This configuration ensures that real-time monitoring captures both the macro-nutrient concentration of the incoming fertigation liquid and the dynamic nutrient availability directly within the solid-liquid soil matrix of the plant beds. Data transmission is carried out via a wireless communication protocol to a cloud platform, which allows remote monitoring (Iranpak et al., 2021). The solenoid valve is activated automatically according to a pre-programmed schedule managed through the IoT control system, ensuring efficient and consistent water use (Benbatouche and Kadri, 2022; Ferrarezi et al., 2015).

To ensure the reproducibility of the system, the complete technical specifications of the hardware components are described as follows. The control unit is built around a Wi-Fi-enabled ESP32-DEVKITC-32U microcontroller, which reads sensor data and executes the fertigation and irrigation control logic. Soil nutrient and moisture status are monitored using an industrial-grade 7-in-1 multi-parameter soil sensor communicating via the RS485 Modbus protocol, which simultaneously measures nitrogen (N), phosphorus (P), potassium (K), pH, electrical conductivity (EC), soil moisture, and soil temperature. Ambient temperature and humidity are monitored using a DHT22 sensor, a water flow sensor measures the discharge of the fertigation and irrigation lines, and an ultrasonic sensor monitors the liquid level in the water and fertilizer reservoirs. Water and fertilizer delivery to the drip lines is regulated by ½-inch solenoid valves actuated through a multi-channel relay module and an AC power relay/contactor, which switch the water and fertilizer pumps on and off according to commands issued by the microcontroller. The system is powered by a 200 Wp monocrystalline photovoltaic (PV) panel (module dimensions 1188 × 880 × 35 mm, weight 10.7 kg; optimum operating voltage 35.6 V and current 5.62 A; open-circuit voltage 42.6 V; short-circuit current 5.95 A; power tolerance 0/+3%; maximum series fuse rating 20 A) connected to an MPPT solar charge controller and a bank of two 12 V 50 Ah VRLA batteries, supplying the ESP32 unit through a 5 V DC-DC step-down converter, while the RS485 soil sensor is separately powered by a 12 V AC-DC power supply unit (PSU) connected to the local electrical grid. AC and DC protection is provided by MCBs and a DC surge protective device (SPD) installed on the photovoltaic, battery, and load lines.

The fertigation and irrigation control algorithm is based on time-based scheduling executed through a web-based dashboard, rather than a continuous soil-moisture feedback threshold. The system provides two selectable operating modes: a Local/Manual mode, in which the pump and solenoid valves are operated directly through the control panel while the microcontroller continues to acquire and upload sensor data for monitoring; and a Remote/IoT mode, in which the microcontroller retrieves a pre-set schedule from the cloud server and automatically activates the relay module, solenoid valves, and pumps at the programmed times. In this study, irrigation was scheduled twice daily (morning and afternoon), while fertigation was scheduled once a week at 7, 14, and 21 days after transplanting. At each fertigation event, 3 g of NPK (16-16-16) fertilizer per plant was dissolved in 350 mL of water (a concentration of approximately 8.57 g L^{-1}) and delivered through the drip line equipped with emitters, applying a total of 10 L per plot. For comparison, the conventional treatment received manual irrigation using a watering can twice daily at 350 mL per plant per application (700 mL $plant^{-1}$ day^{-1}, equivalent to 63 L day^{-1} per plot), with fertilizer applied manually at the same dose and schedule. All sensor data, including soil nutrient concentration, soil moisture, ambient temperature and humidity, water flow, and reservoir level, together with valve and pump activation status, were transmitted wirelessly to a cloud server (Firebase Realtime Database) and displayed on a web-based dashboard for real-time and historical monitoring. System firmware for the microcontroller and each sensor/actuator module was developed and calibrated individually prior to integration into the complete control system.

Sensor calibration and laboratory validation

Each RS485-based 7-in-1 soil sensor was checked against its factory calibration certificate and cross-checked with a handheld

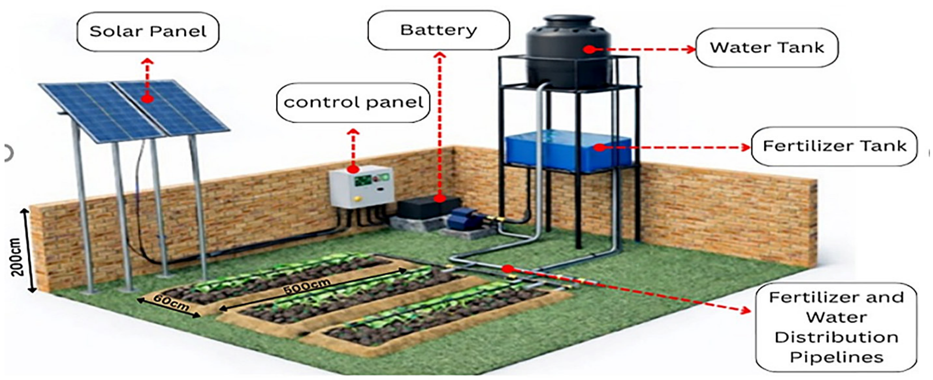

Figure 1. Fertigation and drip irrigation design scheme, showing the solar photovoltaic panel, battery and control panel, water and fertilizer reservoirs, and the drip line network delivering water and nutrient solution to the crop root zone

reference meter prior to field deployment, with correction applied where systematic offset was detected. Sensor readings were logged automatically at fixed intervals, in parallel with periodic destructive soil sampling for laboratory validation. Composite soil samples from the root zone of each plot were air-dried and sieved before chemical analysis.

The sensor-laboratory comparison (Table 1) rests on the principle that the two methods target different nutrient pools: the sensor measures the ionic activity of nutrients in the soil solution under field-moisture conditions (an index of instantaneously plant-available nutrients), whereas laboratory analysis quantifies total extractable nutrients in an oven-dried matrix following digestion, including chemically bound fractions. Because the two are not numerically equivalent, the comparison was intended to assess the consistency of relative trends rather than absolute agreement. Given the weak, non-significant correlations obtained and the small paired sample ($n = 6$), raw sensor readings should not be interpreted as calibrated absolute concentrations without a site-specific calibration curve, and the sensors are susceptible to drift from soil temperature, salinity, and EC. The IoT NPK sensor should therefore be regarded as a tool for continuous, relative, real-time monitoring to support operational decisions, not as a validated substitute for laboratory-grade quantitative NPK determination.

Experimental design and crop management

The experiment was conducted from 20 April to 10 July 2026 at the Prototype Laboratory, Faculty of Engineering, Universitas Islam Malang, located on a rice-field site on Jl. Green Tombro, Tasikmadu, Lowokwaru, Malang City, at an elevation of approximately 500 m above sea level. The comparison between plots was illustrated in Figure 2. The study was conducted by comparing IoT-PV-based drip irrigation systems and conventional surface irrigation using a randomized block design (RBD). Each treatment consisted of 3 replications and each replication consisted of 30 plant samples, resulting in a total of 180 plants. pakcoy plants were cultivated following standard horticultural practices, and their morphological responses to precise nutrient application were measured accordingly (Afifah et al., 2024; Mohamad et al., 2022). Fertigation was regulated automatically through a sensor-based NPK control system to ensure stable nutrient availability (Noerhayati et al., 2026).

Weed and physiological analysis

Weed vegetation analysis was conducted using the quadrat method to determine species density and frequency (Rahayu et al., 2018). Diversity data were analyzed using the Shannon-Wiener index to examine ecological shifts resulting from different water distribution patterns (Zhao and Xu, 2019). Furthermore, plant quality analysis included measuring chlorophyll and vitamin C levels to evaluate the physiological impacts of intelligent water management (Noerhayati et al., 2022; Rodriguez-Ortega et al., 2017). All observed data were statistically analyzed using a paired-samples t-test, treating the three replicate blocks of the Randomized Block Design as matched pairs between the IoT-PV and conventional treatments (Yu et al., 2022). The paired t-test was selected over an independent-samples design because it accounts for block-to-block variation inherent in the RBD structure, thereby increasing statistical power given the limited number of replicates ($n = 3$ per treatment; $df = 2$). The assumptions underlying the paired t-test were considered as follows: observations within each block were treated as dependent (paired) by design, while the blocks themselves were assumed independent of one another; the

Figure 2. Comparison of conventional and IoT-PV drip irrigation plots. Field photographs of (left)the conventional surface-irrigated plot and (right) the IoT-PV drip-irrigated plot, illustrating the visible difference in plant canopy development between treatments during the observation period

distribution of paired differences was assumed to be approximately normal, although this assumption could not be formally verified given the small sample size (n = 3), which is acknowledged as a limitation of the statistical inference in this study. All statistical computations, including the paired T-test, Pearson correlation between paired observations, and the associated test statistics, were performed in Microsoft Excel (Microsoft 365, Data Analysis ToolPak add-in). Statistical significance was set at a two-tailed $\alpha = 0.05$, with results classified as significant (*) when $p \leq 0.05$ and not significant (ns) when $p > 0.05$. To complement the p-values and provide a measure of the magnitude and precision of the treatment effect, the 95% confidence interval (CI) of the mean difference and Cohen's dz effect size (mean paired difference divided by the standard deviation of the paired differences) were calculated for each comparison and are reported alongside the t- and p-values in Table 2.

RESULTS AND DISCUSSION

IoT system performance and nutrient precision

Table 1 presents the average daily sensor readings compared with destructive laboratory analysis for the three primary macronutrients (N, P, K). While the absolute values differ substantially between the two methods due to their different measurement baselines, the IoT sensor system provided continuous, real-time data throughout the observation period, offering practical value for operational monitoring, as examined further below.

A comparison between the conventional and automated moisture dynamic trends over the 7-day observation period shows significant variations (Figure 3). In the conventional system, soil moisture fluctuated drastically, dropping to 71% on days 3, 5, and 6 due to rapid surface evaporation and intermittent manual watering. Conversely, the Solar PV-IoT drip irrigation system demonstrated superior capacity in maintaining stable and optimized soil moisture levels, particularly from Day 5 onwards, maintaining it steadily between 73% and 74%. This stability is attributed to the scheduled operation of the automated system, in which the microcontroller activates the solenoid valve to deliver precise, localized water release at the pre-programmed irrigation times (morning and afternoon), effectively preventing water-logged conditions and drought stress simultaneously.

As presented in Table 1, a noticeable discrepancy was observed between the absolute numerical values yielded by the real-time IoT sensors and the destructive laboratory chemical analysis for all three macronutrients. Pearson correlation analysis revealed weak and statistically non-significant relationships between sensor and laboratory readings for nitrogen ($r = 0.102$, $p = 0.847$), phosphorus ($r = -0.597$, $p = 0.211$), and potassium ($r = 0.044$, $p = 0.935$; n = 6 paired observations each). This lack of a strong linear association does not necessarily indicate sensor malfunction, but rather reflects fundamentally different measurement principles between the two methods. The in-situ IoT electrochemical/optical NPK sensors detect ionic activities and mobile, plant-available nutrient fractions directly dissolved within the dynamic soil solution at current field moisture levels (Reza et al., 2025) which fluctuate continuously with irrigation events, temperature, and root uptake.

Conversely, standard laboratory analysis evaluates the absolute total macro-nutrient content from oven-dried solid soil matrices, extracting both tightly bound (immobilized) and exchangeable chemical pools through intensive acid or salt displacement (Gürbüz, 2025). Given the limited number of paired observations (n = 6) and

Table 1. Comparison of IoT sensor readings vs. laboratory analysis

Nutritional parameters	Sensor average (X)	Lab average (Y)	Pearson r (p-value)
Nitrogen (N)	43.8 ppm	1035.0 ppm	r = 0.102 (p = 0.847)
Phosphorus (P)	61.8 ppm	15.05 ppm	r = -0.597 (p = 0.211)
Potassium (K)	123.6 ppm	70.38 ppm	r = 0.044 (p = 0.935)

Note: X = mean IoT sensor reading (ppm); Y = mean destructive laboratory measurement (ppm); n = 6 paired sensor-laboratory observations per nutrient; Pearson correlation coefficients (r) and associated p-values indicate the strength and significance of the linear association between the two methods.

the conceptual mismatch between the two measurement targets, this study cannot claim that the IoT sensors are a valid quantitative substitute for laboratory analysis. Instead, their practical value lies in providing continuous, real-time relative information operational reliability, providing continuous real-time relative nutrient flux data that supports operational decision-making and complements periodic destructive laboratory analysis. Future studies with a larger number of paired sensor-laboratory samples and site-specific calibration curves are recommended to establish the quantitative reliability of low-cost IoT NPK sensors for precision fertigation (Liu et al., 2025; Reginald, 2024).

Agronomic performance and yield quality

Based on statistical analysis (t-test), the IoT-based drip irrigation system had a significant impact on the growth parameters measured during the generative phase (Table 2).

Data showed that plant height at 21 days after planting (DAP) differed significantly between treatments. This suggests that precise water management through IoT reduces the risk of plants experiencing water stress. Significant increases in plant fresh and dry weights suggest that localized nutrient distribution improves biological efficiency (Fauziah et al., 2026; Xing and Wang, 2024; Zahra et al., 2025). Similar agronomic responses have been reported in studies evaluating nutrient management under field conditions, where improved nutrient availability resulted in enhanced plant growth, biomass accumulation, and mineral uptake. In addition, recent reviews have highlighted that stable soil environmental conditions, particularly within the crop root zone, promote root development and beneficial soil biological processes, thereby improving crop performance under precision irrigation systems. These findings are consistent with the present study and further support the ecological advantages of localized drip fertigation (Oladosu et al., 2026, 2026); (Patah and Othman, 2024)

Weed ecological dynamics

The variation in water distribution mechanisms between conventional surface irrigation and the solar PV-IoT drip system fundamentally altered the weed community structure and biomass accumulation. A detailed summary of species weights is provided in Table 3.

As illustrated in Figure 4, the conventional method accelerated the proliferation of highly competitive weeds, with T-Grass (wild grass) reaching a substantial average biomass of 14.28 g and Kremah (crumbs) at 4.88 g. Conversely, the localized, sub-surface water delivery of the IoT drip system restricted moisture access outside the crop root zone, significantly suppressing T-Grass and Kremah biomass by 69.8% (to 4.30 g) and 77.0% (to 1.12 g), respectively. Interestingly, a minor niche shift occurred in the IoT-drip plots, where *Tradescantia* emerged at 2.22 g due to altered micro-climate dynamics. Overall, these findings confirm that smart drip micro-irrigation provides an efficient, non-chemical ecological engineering tool to control weed density and mitigate crop-weed nutrient competition.

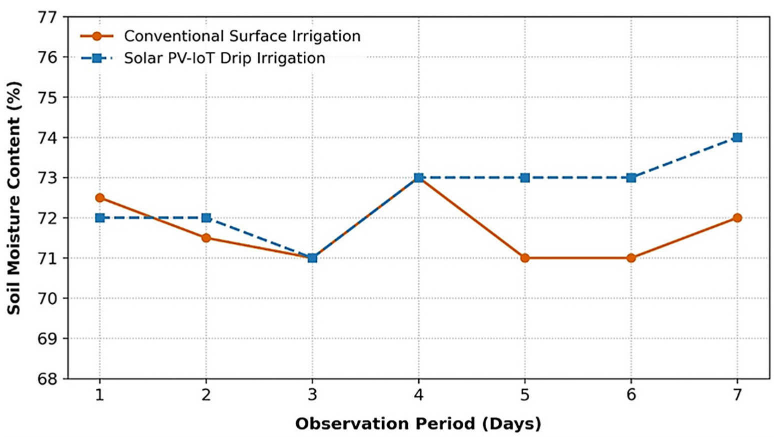

Figure 3. Fluctuations in soil moisture content over the experimental period. Lines represent mean daily soil moisture content (%) under conventional surface irrigation and solar PV-IoT drip irrigation across the observation period

Table 2. Summary of T-test analysis of pakcoy growth and quality

No	Observation variables (unit)	Mean ± SD (IoT-PV)	Mean ± SD (conventional)	t	df	p (2-tailed)	Sig.	Ecological interpretation
1	Plant height (21 DAP) (cm)	19.77 ± 0.10	14.25 ± 1.98	4.639	2	0.043	*	Superior growth
2	Number of leaves (28 DAP units)	15.03 ± 0.60	13.17 ± 0.12	4.557	2	0.045	*	Optimal photosynthesis
3	Fresh weight of plants (g)	117.53 ± 2.89	78.13 ± 12.88	4.370	2	0.049	*	Water absorption efficiency
4	Plant dry weight (g)	5.86 ± 0.20	4.39 ± 0.37	4.682	2	0.043	*	Biomass accumulation
5	Ash content (%)	26.31 ± 2.24	20.48 ± 2.14	5.652	2	0.030	*	High mineral absorption
6	Vitamin C levels (mg/100 g)	82.13 ± 10.16	76.27 ± 10.16	1.000	2	0.423	ns	Stable quality

Note: * = significant at $p \leq 0.05$; ns = not significant. Mean difference and 95% CI were calculated as (mean IoT-PV − mean conventional); a CI that excludes zero indicates a statistically significant difference. Cohen's dz was interpreted following conventional benchmarks (0.2 = small, 0.5 = medium, 0.8 = large), and values above 0.8 as observed here reflect very large effect sizes, consistent with the small number of replicate blocks (n = 3) used in this study.

Table 3. Weed biomass based on species in various irrigation systems. Values represent the mean fresh weight (g) of each weed species per plot, averaged across n = 3 replicate plots per treatment

Weed species	Average weight (g) - conventional	Average weight (g) - IoT-drip
T-Grass (wild grass)	14.28	4.30
Kremah (crumbs)	4.88	1.12
Cyperus rotundus L. (teki)	1.13	0.45
Tradescantia	0.00	2.22

Study limitations

This study has several limitations. First, the small number of replicates (n = 3 blocks per treatment) limits the statistical power and the reliability of the normality assumption underlying the paired T-test. This is reflected in the relatively wide 95% confidence intervals for several variables in Table 2 (e.g., 0.61–78.19 g for fresh weight of plants), indicating that the reported treatment effects and Cohen's dz values should be regarded as indicative rather than precise until confirmed with more replicates.

Second, the weak, non-significant correlations between IoT sensor readings and laboratory analysis for N, P, and K (Table 1) mean that the sensor's absolute nutrient values cannot be assumed to quantitatively track true soil nutrient status. As

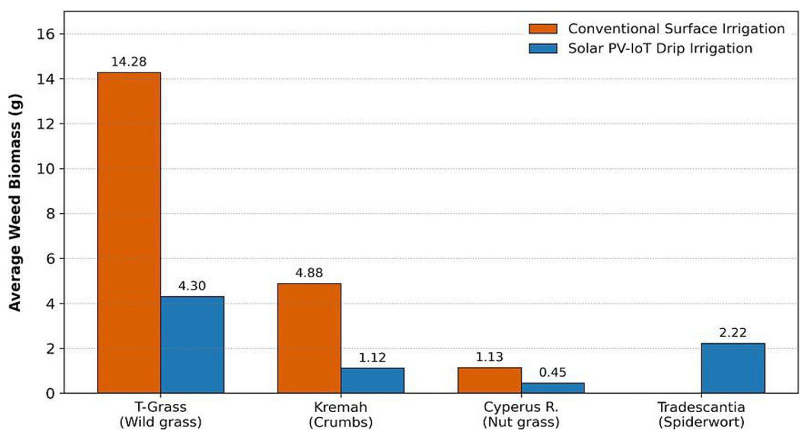

Figure 4. Comparison of average weed biomass across different irrigation systems. Bars represent the mean fresh weight (g) of each weed species under conventional and IoT-PV drip irrigation, averaged across n = 3 replicate plots per treatment (data as presented in Table 3)

discussed in the Sensor calibration and laboratory validation section, this likely reflects the conceptual difference between plant-available and total extractable nutrient fractions, compounded by the small paired sample (n = 6). The nutrient monitoring results should therefore be interpreted as evidence of the sensor's utility for relative, operational trend monitoring rather than as laboratory-equivalent quantitative measurement.

Third, the experiment covered a single, short growing cycle (about one month) at one site under uncontrolled weather conditions, so it does not capture seasonal variation, different soil types, or long-term system performance (e.g., panel degradation, sensor drift, emitter clogging). The findings should therefore not be generalized beyond the specific conditions examined here. Overall, these results provide preliminary evidence of the benefits of the IoT-PV drip fertigation system, which should be corroborated by future studies with more replicates, multiple seasons or sites, and a validated sensor calibration curve.

CONCLUSIONS

This research successfully demonstrated that the integration of Internet of Things technology and solar energy (photovoltaic) into a drip irrigation system provides significant technical and ecological solutions for horticultural cultivation. Based on the data analysis, several key conclusions can be drawn:

- The irrigation system was designed to operate entirely on photovoltaic solar power without dependency on grid electricity, while the IoT-based control system demonstrates high operational reliability, providing continuous real-time relative nutrient flux data that complements periodic destructive laboratory analysis.
- The application of smart drip irrigation significantly improved most pakcoy growth parameters, particularly during the generative phase (21–28 days after planting), and increased fresh weight and ash content, although vitamin C content did not differ significantly between treatments. This indicates better overall nutrient uptake efficiency compared to conventional methods.
- The IoT-PV drip irrigation system evaluated in this study drastically suppressed weed growth by limiting water distribution to the root zone. The biomass of dominant weeds such as T-Grass and Kremah is reduced by over 60%, minimizing biotic competition and reliance on manual and chemical control.

In contrast to previous studies that primarily emphasized the engineering performance of smart irrigation systems, this study provides novel evidence that integrating photovoltaic-powered, IoT-controlled drip fertigation simultaneously enhances crop productivity and reshapes weed community structure through ecological regulation of water availability. This integrated engineering, agronomic, and ecological perspective has not been jointly addressed in previous IoT-PV fertigation research, representing the key scientific contribution of this study.

Overall, this system not only increases agricultural productivity through precise resource management, but it also supports land ecosystem sustainability through natural weed control.

Acknowledgements

The authors highly appreciate the Ministry of Higher Education, Science, and Technology (Kemendiktisaintek) of the Republic of Indonesia for facilitating and providing the research grant that funded this study under Contract No. 021/LL7/DT.05.00/PL-BARU/2026. Grateful acknowledgment is also extended to Universitas Islam Malang for the institutional support and administrative assistance throughout the project. Furthermore, the authors would like to express their sincere gratitude to PT Elevasi Agri Indonesia and CV Erdatamedia for providing the necessary technical facilities, equipment, and field support during the execution of this research.

REFERENCES

1. Abdullah, A., Raharjo, E. I., Iwan, M., Faizal, R. (2025). Development of an IoT-based soil nutrient monitoring and GIS mapping system for precision agriculture. *Advance Sustainable Science Engineering and Technology*, *7*(4), 02504037–02504037.
2. Afifah, R. N., Setyono, P., Rachmawati, S. (2024). Utilization of wastewater treatment plant output into liquid organic fertilizer on the growth of Pak Choi (*Brassica rapa* L.). *Journal of Ecological Engineering*, *25*(10), 76–90. https://doi.org/10.12911/22998993/191746
3. Alsufyani, A. (2025). Sustainability of alternative energy in Yemen: A comprehensive review.

Environmental Engineering, *3*(4), 23–39.

4. Benbatouche, A., Kadri, B. (2022). Design and realization of low-cost solenoid valve remotely controlled, application in irrigation network. *Bulletin of Electrical Engineering and Informatics*, *11*(3), 1779–1788.
5. Bouali, E.-T., Abid, M. R., Boufounas, E.-M., Hamed, T. A., Benhaddou, D. (2021). Renewable energy integration into cloud & IoT-based smart agriculture. *IEEE Access*, *10*, 1175–1191.
6. Fauzan, M. I., Tumanggor, J. A. E., Arafat, S., Safitri, D., Irawan, A. F., Irawati Dwi Arini, D. (2025). Enhancing saline soil fertility through biochar and organic manure combinations: An incubation study. *Journal of Ecological Engineering*, *26*(9), 82–95. https://doi.org/10.12911/22998993/204560
7. Fauziah, N. O., Jaya, M. H. I. S., Zahra, A., Dita, L. A., Fitriatin, B. N., Fakhrurroja, H., Turmuktini, T., Simarmata, T. (2026). Synergy of nanobubble drip-fertigation and soil bio-ameliorant on soil biochemical properties, growth, yield, and chili cash-crop quality in soil media. *Journal of Ecological Engineering*, *27*(3), 327–342. https://doi.org/10.12911/22998993/213436
8. Ferrarezi, R. S., Dove, S. K., van Iersel, M. W. (2015). An automated system for monitoring soil moisture and controlling irrigation using low-cost open-source microcontrollers. *HortTechnology*, *25*(1), 110–118.
9. Gürbüz, M. A. (2025). Identification of multiple extraction methods to be used in extraction of Macro and micronutrients of neutral and alkaline soils by a multi-criteria decision-making technique (TOPSIS). *Journal of Soil Science and Plant Nutrition*, *25*(2), 4669–4686. https://doi.org/10.1007/s42729-025-02422-y
10. Hassan, D. F., Ati, A. S., Neima, A. S. (2021). Effect of irrigation uniformity and efficiency on water consumption, yield of maize using different irrigation and cultivation methods. *International Journal of Agricultural and Statistical Sciences*, *17*(1), 1441–1450.
11. Iranpak, S., Shahbahrami, A., Shakeri, H. (2021). Remote patient monitoring and classifying using the internet of things platform combined with cloud computing. *Journal of Big Data*, *8*(1), 120.
12. Kumar, M., Sharma, D., Mishra, V. (2025). Comparative performance assessment of polymer based bio-carriers for enhanced biological wastewater treatment. *Ecological Engineering & Environmental Technology*, *26*(11), 298–311. https://doi.org/10.12912/27197050/213430
13. Kumaragurubaran, T., Chiranjeevi, R., K, D. K. (2025). Intelligent growth of holy basil: An iot-based hydroponics system empowered by the CRL-SHS Algorithm. *Earth Science Informatics*, *18*(2), 426.
14. Lemfarrak, A., Benzakour, A., Ouhssine, M., Benlemlih, N. (2025). Advancing treated wastewater reuse in Morocco as a pathway to sustainable water management: A review. *Ecological Engineering & Environmental Technology*, *26*(8), 247–267. https://doi.org/10.12912/27197050/207238
15. Liu, J.-J., Wu, H., Riaz, I. (2025). Advanced technologies for smart fertilizer management in agriculture: A review. *IEEE Access*.
16. MacLaren, C., Storkey, J., Menegat, A., Metcalfe, H., Dehnen-Schmutz, K. (2020). An ecological future for weed science to sustain crop production and the environment. A review: An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, *40*(4), 24.
17. Mahdaoui, K., Chafiq, T., Tahiri, M. (2025). Statistical analysis of rainfall trends, hydrological variability, and land cover dynamics in the Bouregreg watershed, Morocco. *Ecological Engineering & Environmental Technology*, *26*(4), 269–289. https://doi.org/10.12912/27197050/201329
18. Mohamad, N. S., Kassim, F. A., Usaizan, N., Hamidon, A., Safari, Z. S. (2022). Effects of organic fertilizer on growth performance and postharvest quality of pak choy (*Brassica rapa* subsp. *Chinensis* L.). *AgroTech-Food Science, Technology and Environment*, *1*(1), 43–50.
19. Nhemachena, C., Nhamo, L., Matchaya, G., Nhemachena, C. R., Muchara, B., Karuaihe, S. T., Mpandeli, S. (2020). Climate change impacts on water and agriculture sectors in Southern Africa: Threats and opportunities for sustainable development. *Water*, *12*(10), 2673.
20. Noerhayati, E., Mustika, S. N., Mardiyani, S. A., Afroni, M. J., Utomo, W. M., Hamzah, S. A. (2026). IoT-based nitrogen, phosphorus, and kalium nutrient control for improving morphological and physiological quality of *Brassica rapa* L. *Journal Europeen Des Systemes Automatises*, *59*(3), 599.
21. Noerhayati, E., Tasarlik, D. A., Rahmawati, A., Norma, S. (2022). Study of The Efficiency of A Drip Irrigation System Model Based on the Internet of Things (IoT). *IOP Conference Series: Earth and Environmental Science*, *1111*(1), 012017.
22. Okomba, N. S., Esan, A. O., Omodunbi, B. A., Sobowale, A. A., Adanigbo, O. O., Oguntuase, O. O. (2023). IOT based solar powered pump for agricultural irrigation and control system. *Fudma Journal of Sciences*, *7*(6), 192–199.
23. Oladosu, M. A., Abah, M. A., Odimgbe, E. I., Adewale, F. E., Arthur, C., Ajayi, A. S., Ezeani, J., Ede, F. O., Oladosu, O. A., Ohanele, E. C. (2026). Smart electrochemical sensors and IoT for monitoring heavy metals in Nigerian water: Review of advances and deployment challenges. *Trends in*

Ecological and Indoor Environmental Engineering, *4*(1), 79–89.

24. Orsini, F., Kahane, R., Nono-Womdim, R., Gianquinto, G. (2013). Urban agriculture in the developing world: A review. *Agronomy for Sustainable Development*, *33*(4), 695–720.
25. Patah, S. F. A., Othman, N. M. I. (2024). Influence of soil temperature on root development and microbial diversity in paddy fields: A comprehensive review. *Trends in Ecological and Indoor Environmental Engineering*, *2*(4), 1–9.
26. Rahayu, M., Yudono, P., Indradewa, D., Hanudin, E. (2018). Weed Diversity Identification on Growth Phases of Twelve Maize Varieties. *IOP Conference Series: Earth and Environmental Science*, *142*(1), 012030.
27. Reginald, P. J. (2024). Integrating IoT and AI for precision irrigation and intelligent nutrient management in smart agriculture. *National Journal of Plant Sciences and Smart Horticulture*, 34–39.
28. Reza, M. N., Lee, K.-H., Karim, M. R., Haque, M. A., Bicamumakuba, E., Dey, P. K., Jang, Y. Y., Chung, S.-O. (2025). Trends of soil and solution nutrient sensing for open field and hydroponic cultivation in facilitated smart agriculture. *Sensors*, *25*(2), 453.
29. Rodriguez-Ortega, W. M., Martinez, V., Rivero, R. M., Camara-Zapata, J. M., Mestre, T., Garcia-Sanchez, F. (2017). Use of a smart irrigation system to study the effects of irrigation management on the agronomic and physiological responses of tomato plants grown under different temperatures regimes. *Agricultural Water Management*, *183*, 158–168.
30. Tan, P., Gebremariam, E. T., Rahman, M. S., Salman, H., Xu, H. (2022). Design and implementation of soil moisture monitoring and irrigation system based on arm and IoT. *Procedia Computer Science*, *208*, 486–493.
31. Widowati, W., Pudjiastuti, A. Q., Prasetyorini, L., Wilujeng, R., Cahya, U. T. W. (2024). Optimizing the application of biochar to improve irrigation efficiency and enhance the growth of chili plants in loam soil. *Journal of Ecological Engineering*, *26*(1), 66–82. https://doi.org/10.12911/22998993/195268
32. Xing, Y., Wang, X. (2024). Precision agriculture and water conservation strategies for sustainable crop production in arid regions. *Plants*, *13*(22), 3184.
33. Yu, Z., Guindani, M., Grieco, S. F., Chen, L., Holmes, T. C., Xu, X. (2022). Beyond t test and ANOVA: applications of mixed-effects models for more rigorous statistical analysis in neuroscience research. *Neuron*, *110*(1), 21–35.
34. Zahaf, M., Oulhaci, D., Zegait, R. (2025). Novel low-cost solution for sustainable irrigation in hyper arid regions: Field evaluation of bottle-based subsurface systems. *Ecological Engineering & Environmental Technology*, *26*(10), 167–181. https://doi.org/10.12912/27197050/210495
35. Zahra, A., Fauziah, N. O., Ambarita, D. D. M., Fakhrurroja, H., Turmuktini, T., Fitriatin, B. N., Simarmata, T. (2025). Deep insights into drip-based nanobubble fertigation technology for enhancing nutrient availability and boosting cash crop vegetable productivity and quality. *Journal of Ecological Engineering*, *26*(9), 459–471. https://doi.org/10.12911/22998993/205227
36. Zhang, Y., Chen, X., Geng, S., Zhang, X. (2025). A review of soil waterlogging impacts, mechanisms, and adaptive strategies. *Frontiers in Plant Science*, *16*, 1545912.
37. Zhao, X., Xu, H. (2019). Study on vegetation change of Taitemar Lake during ecological water transfer. *Environmental Monitoring and Assessment*, *191*(10), 613.