

Energy-Aware Spatial Uniformity Assessment in a Container Farm Using a 24-Node Wireless Sensor Network

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Article Info

Received: 29 July 2026

Revised: 2 September 2026

Accepted: 15 September 2026

Available online: 30 September 2026

Keywords

Container Farm, Energy Monitoring,
Spatial Uniformity, Thermal
Stratification, Wireless Sensor
Network

Abstract

Cooling is a major energy demand in container farms, but a suitable room-average temperature does not necessarily indicate spatially uniform growing conditions. This study examined whether air-conditioning energy consumption was associated with microclimate uniformity in a 10-ft container farm. Conclusions regarding spatial uniformity and energy consumption are drawn from this seven-day exploratory observation period. Seven days of temperature, relative-humidity, and actuator-energy data were collected at 10-min intervals using a wireless sensor network deployed at three vertical levels. A total of 27 indoor sensor nodes were installed, but three nodes became non-operational during the observation period, leaving 24 valid nodes for spatial analysis. Spatial uniformity was quantified using vertical thermal and humidity gradients, spatial temperature standard deviation, and temperature range, while three-dimensional Inverse Distance Weighting was used to visualize the spatial distributions. The AC consumed 28.37 kWh, representing 47.8% of the monitored actuator energy. However, the spatial temperature standard deviation remained nearly unchanged between AC OFF and ON conditions at 1.205 and 1.197 °C, while the temperature range increased from 4.539 to 4.680 °C. The vertical thermal gradient was also higher during AC ON periods. Daily AC energy showed negligible correlations with spatial temperature dispersion. These results indicate that greater AC energy consumption was not consistently associated with improved spatial uniformity. Improving air circulation and redistribution should therefore be investigated as a more relevant engineering intervention.

1. Introduction

Controlled Environment Agriculture (CEA) enables year-round crop production by regulating temperature, relative humidity, lighting, carbon dioxide, irrigation, and nutrients. However, this environmental control requires substantial electrical energy, with lighting and air conditioning among the largest energy-consuming components in closed cultivation systems [1], [2]. Cooling demand in container farms is also influenced by outdoor climate, heat generated by grow lights, building-envelope performance, and operational strategies [3]–[5]. Cooling performance is commonly evaluated using energy consumption, AC duty cycle, and room-average temperature. Broader reviews have also identified thermal-environment control and airflow management as major energy and operational challenges in indoor vertical farming [6]. However, these indicators do not show whether conditioned air is distributed uniformly throughout the growing area. An acceptable average temperature may coexist with warmer and cooler locations. Distributed measurements in greenhouses have demonstrated considerable horizontal, vertical, and temporal variations in temperature and relative humidity [7], [8].

In multilayer container farms, air distribution may be affected by the AC supply direction, rack geometry, crop and hydroponic obstructions, grow-light heat, thermal buoyancy, and limited mixing between vertical layers. Previous airflow studies have shown that supply configuration, airflow rate, exhaust position, and baffles influence environmental uniformity across cultivation layers [9], [10]. Therefore, evaluating room-average conditions alone may overlook important spatial differences. While recent studies have increasingly utilized high-density wireless sensor networks to map spatial microclimates in controlled environment agriculture [13], [14], the practical scientific contribution of this study lies in directly synchronizing high-resolution 3-D spatial uniformity metrics with actuator-level energy consumption to diagnose real-world cooling effectiveness. This study evaluates whether AC energy consumption is associated with microclimate uniformity in a 10-ft container farm. Environmental measurements from the 24 valid nodes of the deployed 27-node wireless sensor network were synchronized with actuator-energy data. Spatial conditions were evaluated using the Vertical Thermal Gradient (VTG), Vertical Humidity Gradient (VHG), spatial temperature standard deviation (σ_T), spatial temperature range (ΔT), and three-dimensional Inverse Distance Weighting (IDW). The study provides an energy-aware diagnostic approach for identifying air-distribution limitations and determining whether improved airflow redistribution should be investigated instead of simply increasing AC operating time.

2. Materials and Methods

2.1 Experimental Facility and System Configuration

The experiment was conducted in a 10-ft container farm with nominal external dimensions of approximately $2.991 \times 2.438 \times 2.591$ m. The interior of the container was equipped with two opposing multilayer hydroponic racks arranged along both sides, forming a central aisle. The interior layout of the container farm, including the hydroponic racks and the position of the AC unit, is presented in Fig. 1.

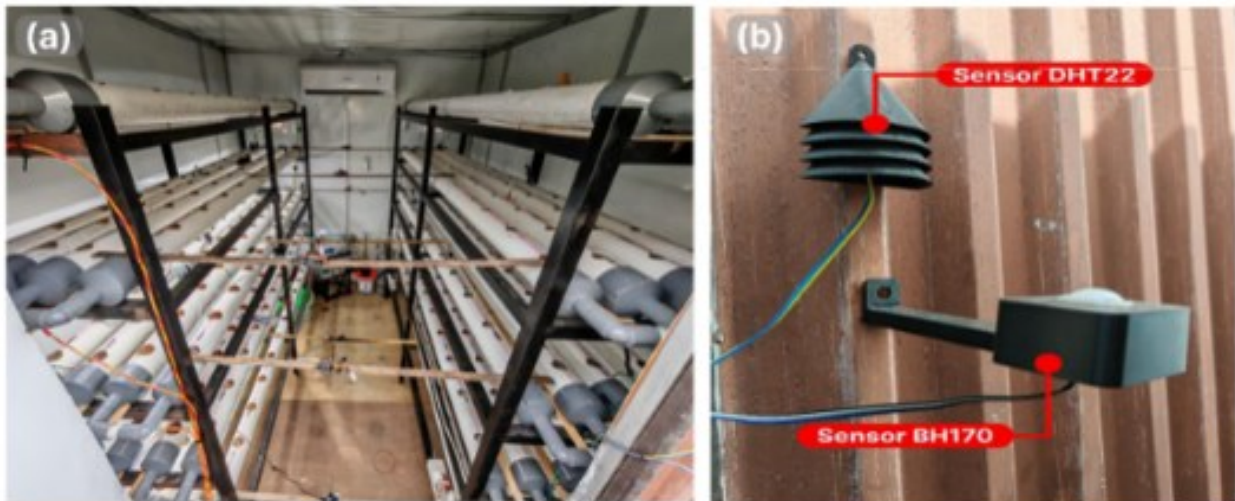


Fig. 1 Indoor-farm implementation: (a) interior of the 10-ft container farm showing the opposing hydroponic racks, central aisle, and end-wall AC unit; and (b) outdoor sensor node consisting of temperature–humidity and light sensors.

A split air-conditioning unit was installed on the end wall to regulate the indoor temperature and relative humidity. The monitored actuators consisted of the AC unit, grow lights, nutrient pump, humidifier, and CO₂ valve. The facility contained 27 nominal indoor sensor nodes and one outdoor node. Each indoor node consisted of an ESP32 microcontroller, a DHT22 temperature–humidity sensor, and a BH1750 light sensor. An MH-Z19C CO₂ sensor was installed at Node 15. At the node level, the ESP32 acquired environmental measurements, performed basic data validation and formatting, and transmitted the resulting records via Wi-Fi using the MQTT protocol. The sensing, processing, and communication functions are summarized in Fig. 2.

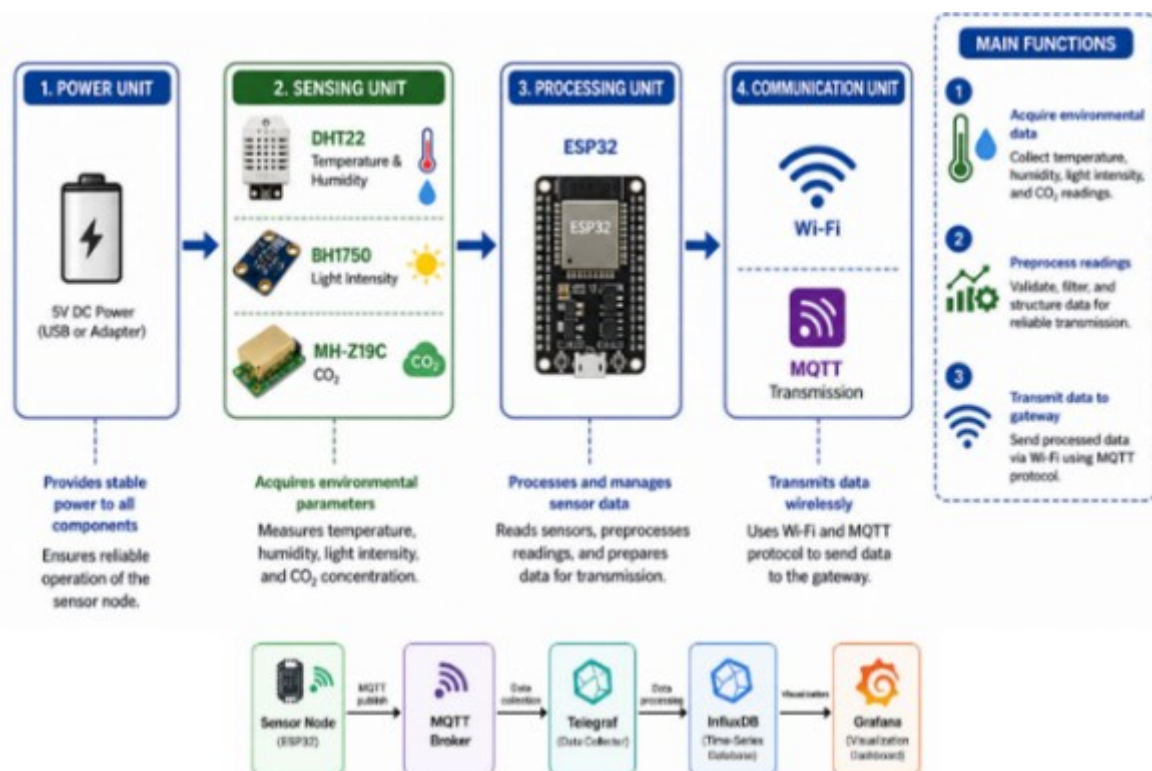


Fig. 2 Wireless sensing and data-management architecture: sensor-node hardware, environmental sensing, ESP32 processing, MQTT transmission, and the data pipeline through Telegraf, Influx DB, and Grafana.

A Jetson Nano gateway received the MQTT messages transmitted by the sensor nodes. Telegraf was used to collect and forward the environmental and actuator data streams to Influx DB, where the measurements were stored as time-series data. Grafana then provided a monitoring dashboard for visualizing sensor measurements and actuator operating conditions. As illustrated in Fig. 2, this data pipeline integrated data acquisition, transmission, storage, and visualization within a single monitoring system. The use of common timestamps allowed environmental measurements from different sensor locations to be synchronized with the recorded operation of the monitored actuators. Therefore, the spatial temperature and relative-humidity conditions could be analyzed based on the actual operating state of the equipment rather than only on predefined operating schedules.

2.2 Physical Implementation and Sensor Placement

The sensor network was arranged in a $3 \times 3 \times 3$ spatial grid to represent the horizontal and vertical conditions inside the container farm. The sensor coordinates were located at $x = 40, 115, \text{ and } 220 \text{ cm}$; $y = 75, 140, \text{ and } 210 \text{ cm}$; and $z = 50, 130, \text{ and } 170 \text{ cm}$. These positions represented three locations along each horizontal direction and three measurement heights corresponding to the lower, middle, and upper parts of the cultivation area. A total of 27 indoor sensor nodes were initially installed. However, Nodes 22, 26, and 27 became inoperative during the observation period due to sensor malfunctions. Therefore, these nodes were excluded from the analysis, leaving 24 valid nodes for the calculation of spatial metrics and IDW interpolation. Because these excluded nodes were located at the corners and edges of the measurement grid, their absence locally affects the spatial coverage quality. Consequently, the IDW estimation near these specific boundary regions carries higher uncertainty, as the interpolation relies more heavily on adjacent interior nodes. The locations of the retained and excluded nodes are shown in Fig. 3.

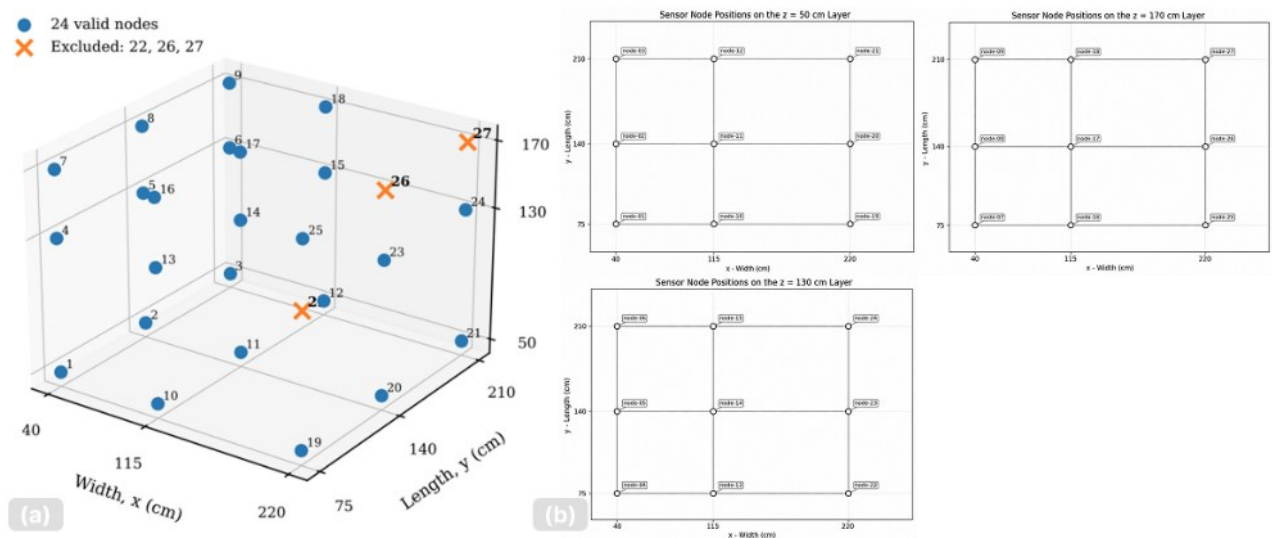


Fig. 3 Node Position Configuration: (a) Three-dimensional sensor placement. Filled markers indicate the 24 valid nodes retained for analysis, while crossed markers indicate Nodes 22, 26, and 27, which were excluded due to operational failure. (b) 2D node positions at heights of 50, 130, and 170 cm..

Before deployment, a one-point intersensor agreement test was conducted to evaluate the consistency of measurements among the sensor nodes. This test was performed over a 24-hour period in a thermally stable, unlit room, using the network's spatial mean as the baseline reference. The temperature measurements produced MAE and RMSE values of 0.370 and 0.536 °C, respectively, while the corresponding relative-humidity values were 2.693 and 3.601 %RH. These results were used to identify sensors with inconsistent measurements before the monitoring period began. The test served only as a screening procedure and was

not intended to establish a full calibration model. Therefore, no calibration correction was applied to the seven-day dataset, and the recorded values were analyzed using the original sensor measurements.

2.3 Data Acquisition, Synchronization, and AC-State Definition

The analysis used seven days of data recorded at 10-min intervals from 24 valid sensor nodes. Temperature, relative humidity, actuator status, and power measurements were synchronized using common timestamps. A total of 982 complete synchronized observations were retained for the spatial analysis, reflecting a minor missing-data proportion of 2.58% (26 out of 1008 nominal time points) caused by intermittent Wi-Fi transmission delays and asynchronous sensor logging. Energy consumption was integrated independently from the valid actuator-power records, representing 165.5 h of monitored operation. The exported AC-status data were obtained from a current-measurement query. Based on the defined operational rule, the AC-state indicator $u_{AC}(t)$ was expressed as:

$$u_{AC}(t) = \{0, \text{if actuator status is OFF}, 1, \text{otherwise}, \quad (1)$$

Therefore, all numerical current readings were classified as AC ON. To prevent misclassification from malformed, missing, or unexpected non-numeric status strings, the AC state was strictly classified as ON only if the numerical power reading explicitly exceeded the standby threshold of 0.3 W. For each actuator a , electrical energy was calculated using rectangular-rule integration over the observed time intervals:

$$E_a = \sum_{k=1}^m \frac{P_a(k)}{1000} \Delta t_k \quad (2)$$

where $P_a(k)$ is the actuator power in watts and Δt_k is the observation interval in hours. Time gaps longer than the regular export interval were treated as missing data and were not extended using the previous power value.

2.4 Spatial Uniformity Metrics

For each complete observation, the spatial mean temperature was calculated as:

$$\underline{T}(t) = \frac{1}{N} \sum_{i=1}^N T_i(t), \quad N = 24. \quad (3)$$

The mean temperatures at the lower and upper measurement planes were denoted by T_{50}^- and T_{170}^- , respectively. The vertical thermal gradient was calculated as :

$$VTG(t) = \frac{T_{170}(t) - T_{50}(t)}{1.2} \quad [^{\circ}C/m], \quad (4)$$

where 1.2 m represents the vertical distance between the 50-cm and 170-cm measurement planes. The vertical humidity gradient was defined as:

$$VHG(t) = \frac{RH_{50}(t) - RH_{170}(t)}{1.2} \quad [\%RH/m]. \quad (5)$$

A positive VTG indicates that the upper layer is warmer than the lower layer, while a positive VHG indicates that relative humidity is higher in the lower layer. Spatial temperature dispersion was quantified using the population standard deviation:

$$\sigma_T(t) = \sqrt{\frac{1}{N} \sum_{i=1}^N [T_i(t) - \bar{T}(t)]^2} \quad (6)$$

and the spatial temperature range:

$$\Delta T(t) = T_i(t) - T_j(t). \quad (7)$$

Lower values of σ_T and ΔT indicate greater spatial temperature uniformity. These dimensional metrics were selected instead of a Celsius-normalized uniformity index.

$$AF_a = \frac{n_{active,a}}{n_{valid,a}} \times 100\% \quad (8)$$

The active fraction of actuator a was calculated as the percentage of valid power records classified as active. An actuator was considered active when its measured power explicitly exceeded a cutoff threshold of 0.3 W, a value applied during data processing to filter out standby power draw and sensor noise.

Table 1 Analysis Configuration and Data Coverage

Item	Configuration
Observation period	9-16 July 2026
Nominal indoor nodes	27
Valid indoor nodes	24
Outdoor nodes	1
Analysis interval	10 min
AC operating cycles	159
IDW parameters	$p = 2, k = 6$

2.5 IDW Mapping and Cross-Validation

Spatial interpolation was used to estimate environmental conditions at locations where no sensor was directly installed. Its performance depends on the spatial arrangement of the sensors, the distance between measurement points, the number of available observations, and the spatial variability of the measured parameter [12]. In this study, the state-averaged temperature and relative-humidity values from the valid sensor nodes were interpolated using three-dimensional Inverse Distance Weighting (IDW) [11]:

$$\hat{Z}(x_0) = \frac{\sum_{i \in N_6} d(x_0, x_i)^{-2} Z(x_i)}{\sum_{i \in N_6} d(x_0, x_i)^{-2}}, \quad (9)$$

where $\hat{Z}(x_0)$ is the estimated value at location x_0 , $Z(x_i)$ is the measured value at sensor location x_i , and $d(x_i)$ is the three-dimensional Euclidean distance between the estimated location and the sensor. The set N_6 denotes the six nearest valid sensor nodes. An inverse-square distance weighting was applied, meaning that sensors located closer to the estimated point had a greater influence than sensors located farther away. The parameters $p = 2$ and $k = 6$ were selected a priori based on standard spatial interpolation practices for confined 3-D grids, ensuring that estimations relied on adjacent measurement planes without excessively smoothing local variations.

The IDW method was used only to visualize the spatial distributions of temperature and relative humidity between measured sensor locations. The principal spatial-uniformity metrics, including VTG, VH_G, σ_T , and ΔT , were calculated directly from the measurements of the 24 valid sensor nodes. Therefore, the statistical evaluation of spatial uniformity did not depend on the interpolated values. Interpolation performance was evaluated using Leave-One-Out Cross-Validation (LOOCV). In each validation step, one sensor node was temporarily excluded, and its value was estimated using the remaining valid nodes with the same IDW configuration. The estimated value was then compared with the actual measurement at the excluded node. This procedure was repeated for each valid sensor location. The resulting interpolation accuracy was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2).

2.6 Statistical Analysis

The seven-day observation period was divided into seven consecutive 24-h blocks to provide comparable daily units for statistical analysis. Within each block, the mean values of VTG, VH_G, σ_T , and ΔT were calculated separately for AC OFF and AC ON conditions. This approach allowed the two operating states to be compared within the same daily period while reducing the influence of unequal numbers of observations between AC OFF and AC ON conditions. Differences between the two AC states were evaluated using a two-sided paired Wilcoxon signed-rank test. This nonparametric test was selected because the analysis involved only seven paired daily blocks and the normality of the paired differences could not be reliably assumed. Spearman rank correlation was then used to examine the relationships between daily AC energy consumption and the mean values of σ_T and ΔT . Because only seven 24-h blocks were available, the statistical results were interpreted as exploratory and were used to identify observed patterns rather than to establish definitive causal relationships.

3. Results and Discussion

3.1 Monitored Energy Use

The five monitored actuators consumed a total of 59.39 kWh during the seven-day observation period. As presented in Table 2 and Fig. 4, the AC unit was the largest energy consumer, accounting for 28.37 kWh or 47.8% of the total monitored actuator energy. The grow lights were the second-largest consumer at 25.32 kWh or 42.6%. The AC operated with a duty cycle of 25.2%. The pump showed an active fraction of 100% because its measured power remained continuously above zero throughout the exported data. Therefore, this value should not be interpreted as a binary commanded duty cycle.

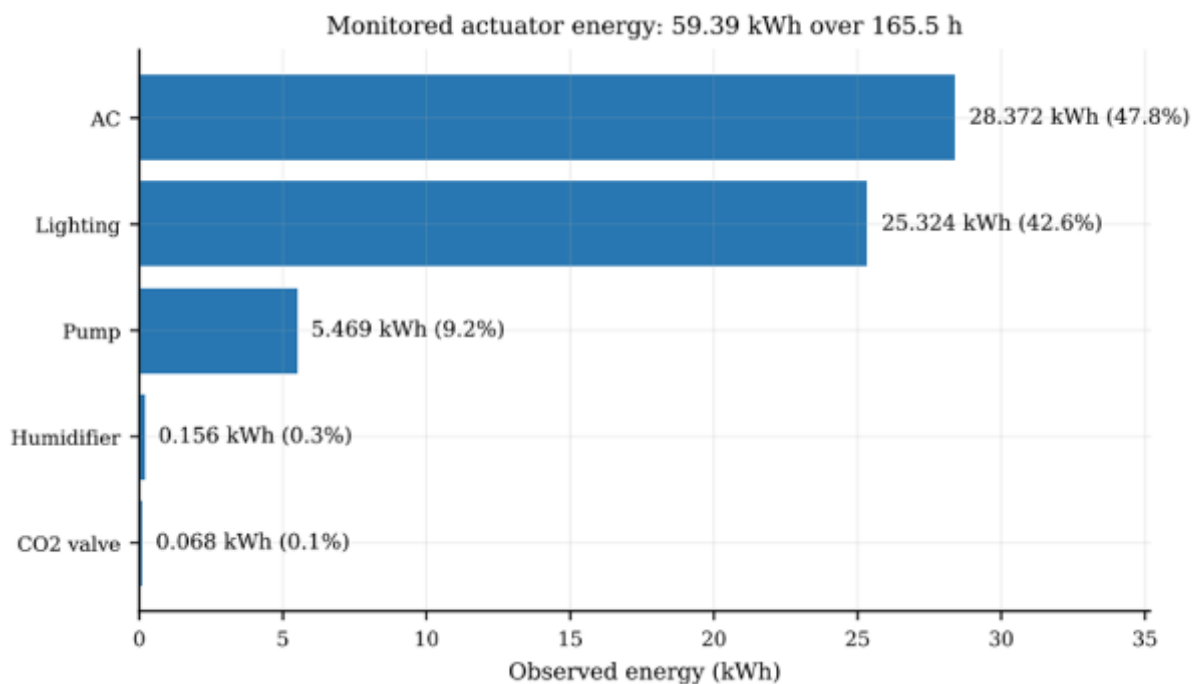


Fig. 4 Actuator energy consumption during the seven-day observation period. Percentage labels indicate the share of total monitored actuator energy.

Table 2 Monitored Actuator Energy And Active Fraction

Actuator	Energy (kWh)	Share (%)	Active fraction (%)
AC	28.37	47.8	25.2
Grow lights	25.32	42.6	66.2
Pump	5.47	9.2	100.0
Humidifier	0.156	0.3	10.3
CO ₂ valve	0.068	0.1	51.2
Total monitored	59.39	100.0	–

The energy profile shows that the AC unit and grow lights dominated the monitored electricity consumption, contributing more than 90% of the total energy use. This indicates that cooling and artificial lighting were the primary electrical loads in the container farm during the observation period. In contrast, the humidifier and CO₂ valve contributed only a small proportion of the total consumption. Although the pump recorded an active fraction of 100%, this value reflects continuously measured power above zero and does not necessarily represent continuous commanded operation. These results establish the AC unit as the main focus for further evaluation of the relationship between energy consumption and spatial temperature uniformity.

3.2 Thermal Impact of Grow Lights and Time of Day

Because grow lights contributed 42.6% of the monitored actuator energy, their operation introduced a substantial internal thermal load. A temporal sub-analysis was conducted to separate the effect of active lighting from the influence of outdoor solar radiation (time of day). During nighttime hours (18:00–05:59) when solar influence was absent, the mean Vertical Thermal Gradient (VTG) was 0.387 °C/m while the grow lights were ON, compared to 0.197 °C/m when the lights were OFF. This confirms that the heat generated by the multilayer lighting configuration directly contributes to vertical stratification.

Table 3 Mean Vertical Thermal Gradient (VTG) by Time of Day and Grow Light Status

Period	Grow Lights Status	Mean VTG (°C/m)
Nighttime (18:00–05:59)	OFF	0.197
	ON	0.387
Daytime (06:00–17:59)	OFF	0.222
	ON	0.931

However, daytime solar radiation acts as a major confounding factor; during daytime hours (06:00–17:59) with lights ON, the VTG escalated to 0.931 °C/m. These results indicate that both artificial lighting and outdoor climate significantly drive thermal stratification, and comparing AC ON/OFF conditions without controlling for these variables limits the ability to isolate the AC's standalone effect.

3.3 Overall Vertical Profile and Spatial Dispersion

Across all complete observations, the mean indoor temperature was 23.88 °C, while the mean relative humidity was 70.82 %RH. The mean temperature increased from 23.58 °C at a height of 50 cm to 24.28 °C at 170 cm, resulting in an overall vertical thermal gradient of 0.583 °C/m. The overall spatial temperature standard deviation was 1.203 °C, while the mean spatial temperature range was 4.574 °C. Table 3 presents the mean temperature and relative-humidity profiles at the three measurement heights. Fig. 5 illustrates the spatial temperature response during representative AC operating cycles.

Table 4 Mean Vertical Environmental Profile

Height (cm)	Temperature (°C)	Relative humidity (%RH)
50	23.58	70.30
130	23.87	71.22
170	24.28	71.01

The vertical profile shows that the upper measurement plane was approximately 0.70 °C warmer than the lower plane, indicating persistent thermal stratification. Relative humidity varied less consistently with height, with the highest mean value observed at 130 cm. The larger overall temperature range further indicates

that horizontal and local variations were greater than the difference between plane-averaged temperatures alone.

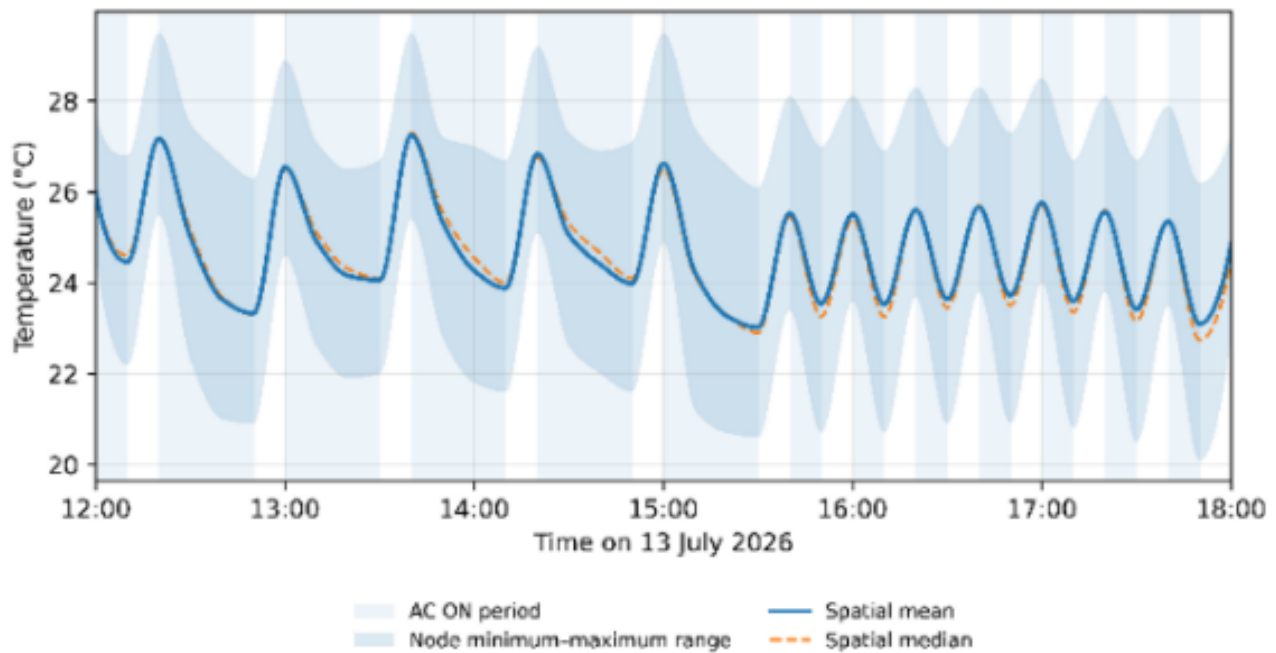


Fig. 5 Indoor spatial temperature response during AC operating cycles on 13 July 2026 from 12:00 to 18:00. Shaded vertical regions indicate AC ON periods. The lines represent the spatial mean and median temperatures, while the shaded envelope represents the minimum-to-maximum temperature range across the 24 valid nodes.

Fig. 5 shows that the spatial mean and median temperatures followed similar changes during the observed AC operating cycles. However, the minimum-to-maximum temperature envelope remained relatively wide, indicating that temperature differences between sensor locations persisted even when the AC was operating. This suggests that changes in the overall indoor temperature were not always accompanied by an equivalent reduction in spatial temperature variation.

3.4 Spatial Maps and IDW Validation

Fig. 6 compares the spatial distributions of temperature and relative humidity under AC OFF and AC ON conditions at measurement heights of 50, 130, and 170 cm. The first two columns use a common temperature scale, while the last two columns use a common relative-humidity scale. These consistent scales enable direct comparison between AC states and measurement heights. Temperatures were generally higher during AC ON periods because the AC was activated under higher thermal-load conditions. Nevertheless, warmer upper layers and local differences between sensor nodes remained visible while the AC was operating. These patterns are consistent with the VTG, spatial standard deviation, and temperature-range results, indicating that AC operation did not fully produce a spatially uniform temperature distribution. Relative humidity was generally lower during AC operation, which may be associated with dehumidification by the cooling system.

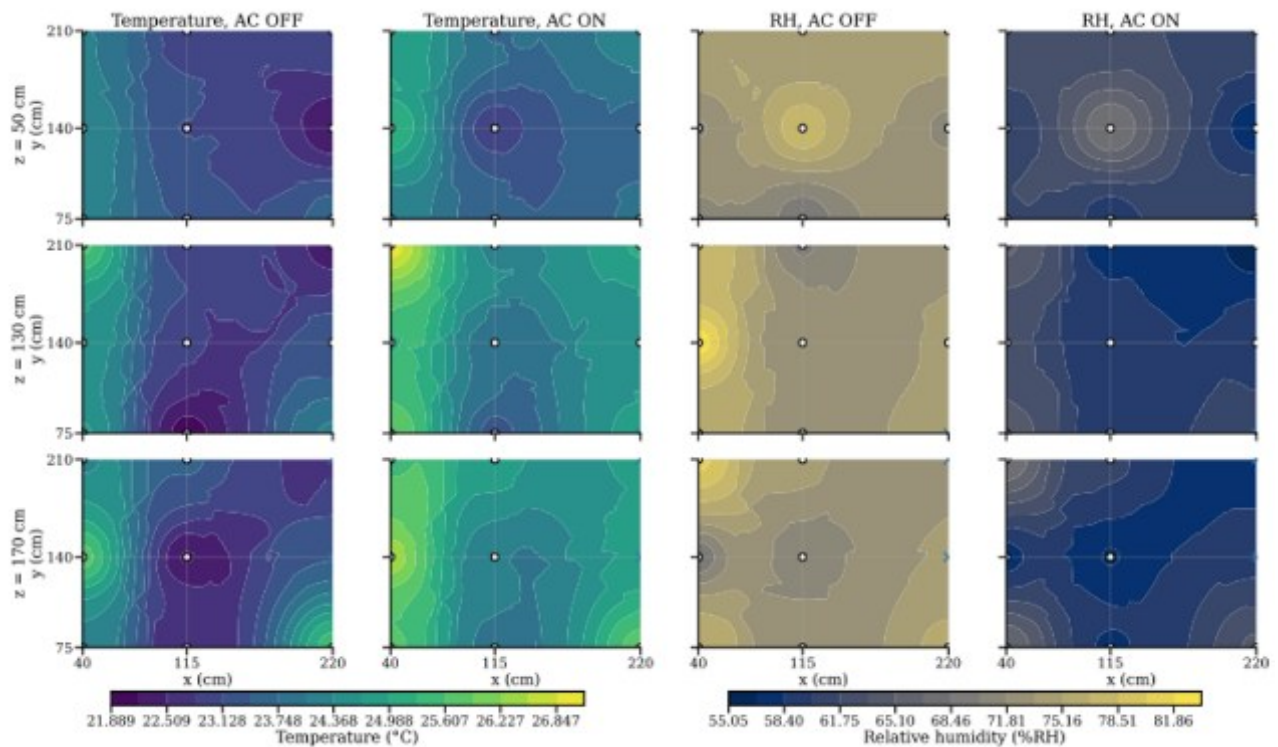


Fig. 6 State-averaged IDW slices at $z = 50, 130$, and 170 cm. The first two columns compare temperature under AC OFF and AC ON conditions, while the last two columns show the corresponding relative-humidity distributions. White circles indicate measured nodes, therefore, evaluating room-average conditions alone may overlook important spatial differences. Red markers indicate excluded nodes, and common scales are used for each variable.

The maps show that the spatial distributions of temperature and relative humidity remained nonuniform across the three measurement heights. During AC ON conditions, the upper layer still contained warmer areas, while lower relative-humidity values appeared across most measurement planes. The persistence of local temperature differences is consistent with incomplete air redistribution within the container. The crossed markers should also be considered when interpreting nearby interpolated areas because those locations were estimated using measurements from the remaining valid nodes.

Table 5 IDW LOOCV Validation Results

Variable	MAE	RMSE	R^2
Temperature ($^{\circ}\text{C}$)	0.455	0.549	0.647
Humidity(%RH)	2.613	3.881	0.405

For temperature, IDW produced an MAE of 0.455°C , an RMSE of 0.549°C , and an R^2 of 0.647. These results indicate that IDW had a moderate ability to represent temperature variations at locations without direct sensor measurements. For relative humidity, the MAE was 2.613 %RH, the RMSE was 3.881 %RH, and the R^2 was 0.405. Therefore, the interpolation represented temperature more reliably than relative humidity. The temperature maps may be used to identify broad spatial patterns, whereas the interpolated relative-humidity patterns should be interpreted more cautiously. Furthermore, given the sensor intersensor agreement uncertainty (MAE of 0.370°C), the minute differences observed in spatial standard deviation (σ_T) between AC OFF and ON states must be interpreted with caution. Propagating this measurement uncertainty indicates that the apparent changes in σ_T are largely inconclusive, suggesting that higher-tolerance sensors

($\pm 0.1^\circ\text{C}$ class) should be considered in future container-farming diagnostic works to capture subtle thermal homogenization effects accurately.

3.5 AC ON/OFF Spatial Assessment

Table 5 presents the spatial metrics calculated for pooled AC OFF and AC ON conditions. The spatial temperature standard deviation was nearly identical between the two states, with values of 1.205°C during AC OFF and 1.197°C during AC ON. The spatial temperature range was slightly larger during AC ON periods, increasing from 4.539 to 4.680°C . Neither dispersion metric showed a consistent paired change across the seven 24-h blocks, with $p = 0.938$ for σ_T and $p = 0.375$ for ΔT .

Table 6 Spatial Metrics by AC Status

Metric	AC OFF	AC ON
VTG ($^\circ\text{C}/\text{m}$)	0.453	0.976
VHG (%RH/m)	-0.791	0.014
σ_T ($^\circ\text{C}$)	1.205	1.197
ΔT ($^\circ\text{C}$)	4.539	4.680
Mean temperature ($^\circ\text{C}$)	23.63	24.64
Mean relative humidity (%RH)	73.99	61.21

In contrast, VTG increased from $0.453^\circ\text{C}/\text{m}$ during AC OFF to $0.976^\circ\text{C}/\text{m}$ during AC ON. This paired difference was consistent across the seven observation blocks and was statistically significant ($p = 0.016$). More importantly, the median paired difference in VTG was $0.523^\circ\text{C}/\text{m}$. This absolute difference is substantially larger than the established sensor measurement uncertainty (MAE of 0.370°C), indicating a physically meaningful effect size where active cooling practically doubled the stratification magnitude. Conversely, the marginal 0.008°C difference in σ_T falls well within the measurement noise, rendering it conclusively insignificant. The mean temperature was also higher during AC ON than during AC OFF, at 24.64 and 23.63°C , respectively.

3.6 Daily Cooling Energy and Spatial Dispersion

Across the seven 24-h observation blocks, AC energy consumption ranged from 1.11 to 5.68 kWh. This analysis examined whether greater cooling-energy consumption was associated with lower spatial temperature dispersion. In Figs. 7 and 8, the bars represent AC energy consumption for each 24-h block, while the lines represent the mean spatial-dispersion metric for the corresponding block. The blocks are ordered from the lowest to the highest AC energy consumption to make the relationship easier to observe.

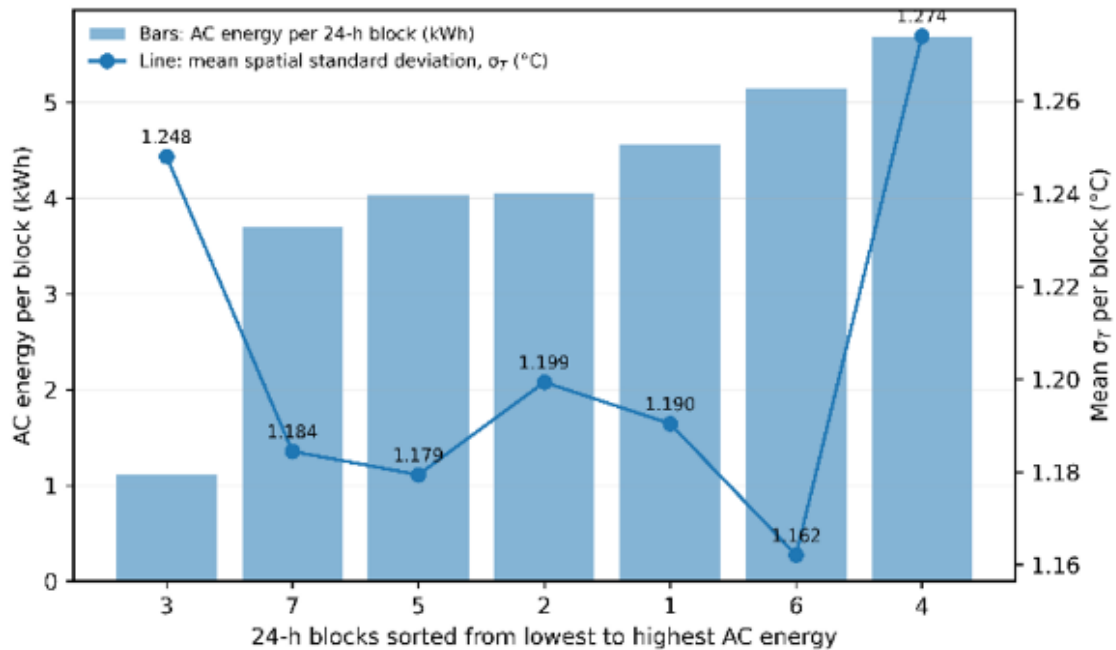


Fig. 7 Daily AC energy and mean spatial temperature standard deviation across seven 24-h blocks. Bars represent AC energy consumption per block, while the line represents the mean spatial standard deviation (σ_T) for the corresponding block. Blocks are ordered from the lowest to the highest AC energy.

Fig. 7 shows that σ_T did not consistently decrease as AC energy consumption increased. Some blocks with relatively high AC energy had low σ_T values, whereas the block with the highest energy consumption had the highest σ_T . Due to the limited sample size of seven daily blocks, formal correlation statistics carry minimal inferential weight. However, the descriptive daily observations visually demonstrate no discernible pattern linking higher AC energy expenditure to an improved (lower) spatial temperature standard deviation.

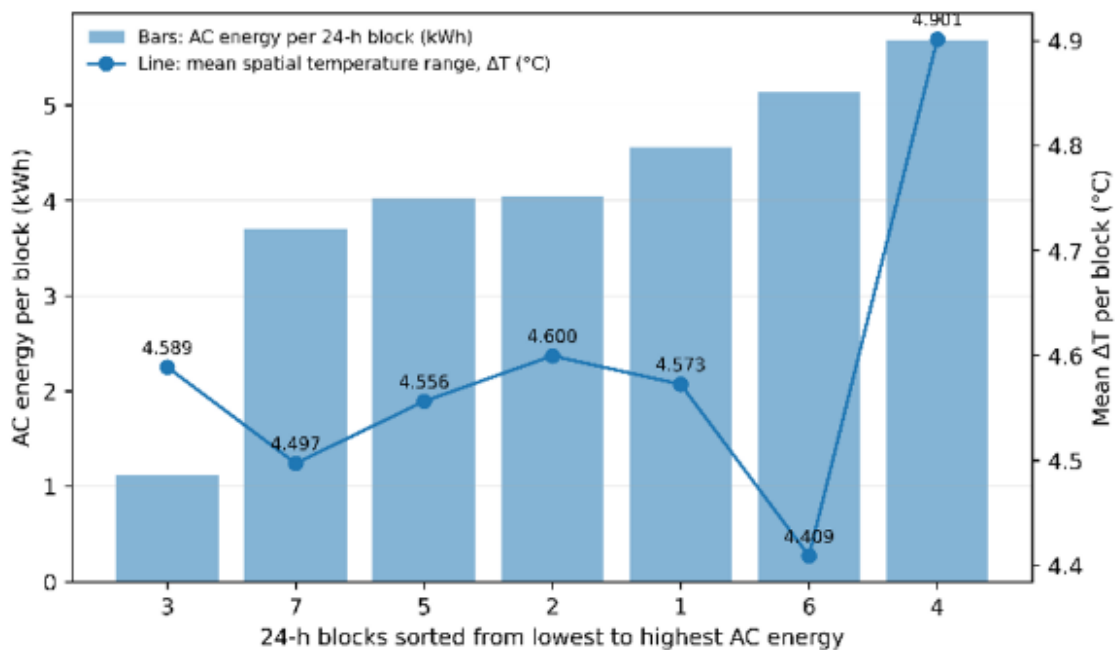


Fig. 8 Daily AC energy and mean spatial temperature range across seven 24-h blocks. Bars represent AC energy consumption per block, while the line represents the mean spatial temperature range (ΔT) for the corresponding block. Blocks are ordered from the lowest to the highest AC energy.

Fig. 8 shows a similar pattern for ΔT . Greater AC energy consumption did not consistently produce a smaller spatial temperature range. The block with the highest energy consumption also had the highest ΔT , whereas several relatively high-energy blocks showed lower temperature ranges. Because the seven-day observation period provides a limited sample size, these correlation results carry no inferential weight. Therefore, this daily energy-dispersion comparison is presented strictly as a methodological illustration for future, longer-term diagnostic assessments (e.g., 30 days or more). Nevertheless, the descriptive daily observations clearly demonstrate that greater cooling-energy consumption did not systematically yield a tighter spatial temperature range under the current experimental conditions.

3.7 Discussion

The AC unit was the largest monitored energy consumer, yet its operation did not produce a clear improvement in spatial temperature uniformity. The values of σ_T were nearly identical under AC OFF and AC ON conditions, while ΔT did not decrease when the AC was active. Daily analysis also showed that greater AC energy consumption was not consistently associated with lower spatial dispersion. The higher mean temperature observed during AC ON periods does not imply that the AC caused indoor warming. The AC operated in response to higher thermal loads. However, because the grow lights ran 66.2% of the time, their significant thermal contribution serves as a major confounding factor that is not explicitly controlled for in the pooled AC ON/OFF comparison. As demonstrated in the earlier temporal sub-analysis, stratifying the spatial metrics by both AC state and grow light state is necessary to fully decouple these variables. However, due to sample size constraints across the 7-day period, a fully stratified multivariable analysis isolating AC operation under constant outdoor and lighting conditions was not feasible. Consequently, the observed spatial differences represent associational findings under mixed operational conditions, rather than isolated causal effects of the AC unit alone. Nevertheless, the persistent vertical gradient**—which nearly doubled from 0.453 to 0.976 $^{\circ}\text{C}/\text{m}$ during active cooling—**and the absence of improvement in σ_T and ΔT indicate that room-level cooling was not accompanied by uniform air distribution.

The physical mechanism behind this exacerbated stratification is likely end-wall downflow reinforcing stratification rather than mixing the air column, an airflow limitation consistent with recent findings in vertical farms [9], [10]. Specifically, the magnitude of the observed VTG (approaching 1.0 °C/m under cooling) is substantially larger than the 0.2–0.5 °C/m gradients typically reported in airflow-optimized vertical farms [9], highlighting the severe microclimate impact of this end-wall downflow limitation. Furthermore, rack geometry, hydroponic channels, and thermal buoyancy may have restricted air mixing between the lower and upper cultivation layers. Based on these findings, simply increasing AC operating time is unlikely to be the most appropriate solution because it may increase energy consumption without improving spatial uniformity. Low-power circulation fans should instead be evaluated as a potential method for improving air mixing and reducing VTG, σ_T , and ΔT . However, their effectiveness should be validated through controlled experiments that account for AC energy, fan energy, air velocity, operating conditions, and plant responses.

4. Conclusion

A wireless sensor network consisting of 27 indoor nodes was deployed in the 10-ft container farm, although only 24 valid nodes were used in the final analysis because three nodes became non-operational. The environmental measurements were synchronized with actuator-energy data to evaluate whether AC energy consumption was associated with spatially uniform indoor conditions. During the seven-day observation period, the AC consumed 28.37 kWh, representing 47.8% of the total monitored actuator energy, with a duty cycle of 25.2%. However, the spatial temperature standard deviation remained approximately 1.2 °C under both AC OFF and AC ON conditions, while the spatial temperature range did not decrease during AC operation. Daily AC energy consumption also showed no consistent relationship with either spatial-dispersion metric. The vertical thermal gradient was greater during AC ON periods, indicating that active cooling did not eliminate temperature stratification between the lower and upper cultivation layers under the observed operating conditions. These findings show that room-level cooling effort and spatial temperature homogenization should be evaluated separately. The main contribution is an energy-aware diagnostic framework that distinguishes cooling effort from spatial temperature homogenization. Based on the observed results, improving active air redistribution appears to be a more relevant engineering variable to investigate than simply increasing AC operating time. Supported by recent airflow optimization studies in vertical farms [10], low-power circulation fans configured to disrupt thermal buoyancy and establish uniform horizontal air velocities across the canopy layers should be prioritized. These localized interventions may therefore be evaluated in future controlled experiments to determine whether they effectively improve air mixing, reduce spatial temperature variation, and maintain acceptable overall energy consumption.

Acknowledgement

The authors would like to thank the Faculty of Informatics and Electrical Engineering, Institut Teknologi Del, Indonesia, for providing the facilities and support required for this research. The authors also acknowledge the contributions of all parties involved in the implementation and data collection activities in the container farm.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

The authors confirm their contributions to the paper as follows: study conception and design: Samuel Abednego Sormin, Raj David Francisco Damanik, and Albert Sagala; system implementation and data collection: Samuel Abednego Sormin and Raj David Francisco Damanik; methodology, data analysis, and visualization: Samuel Abednego Sormin and Raj David Francisco Damanik; supervision and interpretation of

results: Albert Sagala; draft manuscript preparation: Samuel Abednego Sormin and Raj David Francisco Damanik; manuscript review and revision: Samuel Abednego Sormin, Raj David Francisco Damanik, and Albert Sagala. All authors reviewed the results and approved the final version of the manuscript.

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