

Development of an IoT-Based Hydrological Parameter Monitoring System Using an Eco-Hydrology Approach to Support Sustainable Water Resources Management

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Abstract: Reliable, site-specific hydrometeorological observations are essential for supporting eco-hydrological analysis and water resources management. This study developed and evaluated a low-cost Internet of Things (IoT)-based Mini-Automatic Weather Station (Mini-AWS) integrating an ESP-12E/F microcontroller, temperature and humidity sensors, a tipping-bucket rain gauge, local data storage, wireless communication, and a solar-assisted battery system. Field evaluation was conducted during August 2026 using observations from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG). Analysis of 43,967 synchronized temperature and relative humidity pairs yielded a temperature RMSE of 1.066 °C and MAPE of 2.550%. The uncalibrated humidity measurements exhibited an RMSE of 10.881 %RH and a positive measurement bias. A second-order polynomial humidity calibration model was selected using temporally separated training and validation blocks and evaluated on 10,052 internal test observations. Calibration reduced humidity RMSE from 11.500 to 2.848 %RH and MAPE from 17.165% to 3.938%, although residual autocorrelation and heteroscedasticity remained. The correction also reduced the RMSE of AWS-derived Vapor Pressure Deficit (VPD) from 0.3701 to 0.1668 kPa and improved agreement with BMKG-derived operational VPD categories from 45.09% to 81.86%. Initial volumetric calibration of the tipping bucket yielded 0.5084 mm/tip, while 15 additional controlled-flow experiments produced a mean resolution of 0.544 mm/tip; natural-rainfall accuracy was not independently validated. The prototype

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acquired meteorological data during a 31-day deployment using a solar-assisted 2500 mAh Li-ion battery, although battery-voltage accuracy and energy savings were not independently verified. The dashboard incorporated VPD, empirical Ivanov Potential Evapotranspiration (PET), and Rain-Free Days indicators as preliminary eco-hydrological interpretation tools. The calibration and VPD improvements were evaluated offline, while physical implementation of the polynomial correction on the microcontroller remains to be verified. Overall, the Mini-AWS demonstrated promising monitoring performance and improved humidity-derived indicators, subject to further operational and cross-season validation.

Keywords: IoT, Rainfall, Microclimate, Evapotranspiration, Eco-hydrology.

Introduction

Rainfall, air temperature, and relative humidity are essential observations for characterizing local hydrometeorological conditions and interpreting atmosphere–land interactions ([Grossiord et al., 2020](#)). Rainfall provides a major input to the terrestrial water cycle, while temperature and relative humidity influence atmospheric evaporative demand ([Novick et al., 2016](#)). Their combined interpretation through vapor pressure deficit (VPD) can provide additional information about atmospheric drying conditions. Nevertheless, VPD and empirical estimates of potential evapotranspiration (PET) are derived indicators rather than direct measurements of ecosystem water balance, and their reliability depends on the quality of the underlying meteorological observations ([Yuan et al., 2019](#)). In locations with limited monitoring coverage, acquiring continuous and site-specific observations remains challenging. Commercial meteorological instruments may impose procurement, maintenance, and communication costs that constrain the density of observation networks. Low-cost, open-hardware, and Internet of Things (IoT) technologies offer alternatives for localized monitoring, but the practical value of their data depends on documentation of completeness, reference agreement, calibration validity, and operational limitations ([Segovia-Cardozo, Rodríguez-Sinobas, Canales-Ide, et al., 2021](#)). A sensor signal that follows the reference time series closely may still exhibit a systematic measurement bias, which can propagate into derived atmospheric indicators ([Abdelal & Al-Hmoud., 2021](#)). Existing low-cost monitoring studies provide important precedents. ([Segovia-Cardozo et al., 2021](#)) developed an open-hardware hydrological platform with laboratory calibration and field application for soil moisture, rainfall, and water depth. ([Botero-Valencia et al., 2022](#)) presented a solar-assisted, wireless weather station measuring several meteorological variables and compared its observations against reference stations. ([Al-Nabi et al., 2024](#)) developed an ESP32-based solar-powered framework for web-accessible temperature and humidity monitoring. ([Sanz et al., 2024](#)) demonstrated calibrated soil-moisture and water-level networks connected through NB-IoT and a cloud platform. More recently, ([Seyhan and Seyhan., 2026](#)) experimentally

evaluated a portable system for leaf-level VPD under controlled-environment agriculture conditions. These studies establish that low-cost sensing, calibration, cloud communication, and even VPD validation are not new concepts on their own. Their reported application targets and validation designs, however, differ from the present question of how empirical humidity calibration changes the reliability of ambient-air VPD and its operational categories during a single hydrometeorological field deployment.

Table 1 Comparison of selected prior monitoring studies and the present evaluation focus.

Study	Reported contribution and evaluation	Relevance and distinction for this study
Segovia-Cardozo et al. (2021)	Open-hardware hydrological station; calibration of soil-moisture, rainfall, and water-depth sensors; field application.	Validates hydrological sensing, while the present analysis focuses on ambient temperature/RH calibration and its consequences for VPD categories.
Botero-Valencia et al. (2022)	Solar-powered wireless multi-parameter weather station; comparison with reference meteorological stations.	Shows that reference-validated, solar-assisted low-cost AWS already exists; the distinguishing evaluation here is temporal RH model testing linked to VPD error and category agreement.
Al-Nabi et al. (2024)	ESP32-based, solar-supported temperature/RH monitoring with web access.	Demonstrates a comparable IoT architecture; the reported research focus is monitoring functionality rather than evaluating RH correction effects on VPD classification.
Sanz et al. (2024)	Calibrated NB-IoT soil-moisture and water-level network with cloud-based monitoring and field trials.	Demonstrates actual network deployment; the present work is only single-node and instead evaluates meteorological sensor correction and a derived atmospheric indicator.
Seyhan & Seyhan (2026)	Reference evaluation of a low-cost portable leaf-level VPD platform for controlled-environment agriculture.	Establishes prior VPD validation; differs in leaf-level variable, setting, and objective from field-based ambient-air VPD categorization.
Present Mini-AWS	BMKG-aligned one-minute observations; controlled tipping-bucket tests; temporal RH model selection/testing; battery telemetry; offline VPD error and category evaluation.	Contribution is the connected evaluation workflow; limited to one month, one node, and no external PET/firmware-embedded calibration validation.

The comparison highlights a narrower methodological need rather than an absence of low-cost weather-station research: to connect reference-synchronized temperature and relative-humidity observations, temporally separated humidity-model selection and testing, and a quantitative assessment of how sensor correction changes ambient-air VPD errors and category assignments ([Bernardes et al., 2023](#)). This connection is relevant because classification thresholds can amplify seemingly small errors near category boundaries. The present work therefore treats the quality of the derived indicator as an explicit evaluation

outcome, rather than assuming that sensor calibration automatically improves all downstream dashboard information. The research problem addressed is: how can a resource-constrained, IoT-based Mini-Automatic Weather Station (Mini-AWS) be developed and evaluated so that its meteorological observations and derived atmospheric indicators have clearly documented performance and limitations? The prototype integrates an ESP-12E/F, temperature and humidity sensing, a tipping-bucket rain gauge, RTC-based timestamping, local LittleFS storage, wireless telemetry, solar-assisted battery supply, and a Laravel-based dashboard. This hardware–software integration constitutes the experimental platform, not by itself a claim of technological originality. Accordingly, the specific research objectives are to: (i) develop and demonstrate the functions of a single-node Mini-AWS for acquisition, timestamping, buffering, transmission, and dashboard display; (ii) quantify one-minute data availability and agreement of air temperature and relative humidity against a nearby BMKG reference, using complementary error and agreement metrics; (iii) assess controlled-volume tipping-bucket repeatability and evaluate candidate humidity-calibration models through chronological training, validation, and internal testing with residual diagnostics; (iv) characterize battery-voltage observations and acquisition continuity over the 31-day deployment without equating voltage profiles with measured energy efficiency or long-term reliability; and (v) quantify the change in BMKG-referenced ambient-air VPD error and five-category agreement following offline humidity calibration, while presenting Ivanov PET and rain-free days as preliminary dashboard indicators rather than independently validated hydrological outcomes. The principal contribution is therefore an evaluation-oriented workflow linking high-frequency reference comparison, documented data quality, temporally separated empirical humidity calibration, and quantitative reliability assessment of a derived VPD interpretation layer. The study does not claim a new sensing principle, universal calibration model, validated multi-node scalability, physical deployment of the polynomial calibration on the microcontroller, or field accuracy of PET and rainfall under natural events. Its scope is a single Mini-AWS deployment during August 2026, and wider seasonal, ecological, metrological, and operational validation remains necessary.

Research Method

Research Design

The study employed an experimental engineering design approach with prototyping. The stages included hardware and power-supply design, firmware and edge-computing development, tipping-bucket calibration, field validation, humidity calibration, power-management evaluation, and implementation of eco-hydrology indicators on the dashboard.

Mini-AWS System Architecture

The system architecture integrates sensing, edge processing, data buffering, communication, cloud storage, and analytics layers. The AHT20, BMP280, and tipping-bucket sensors generate data processed by the ESP-12E/F. Timestamping is provided by the RTC DS3231. When network connectivity is available, data are transmitted to the cloud server. When connectivity is lost or the battery voltage falls below the defined threshold, data can be stored locally through LittleFS. The cloud and dashboard layers are used for visualization, device status, and eco-hydrology indicators.

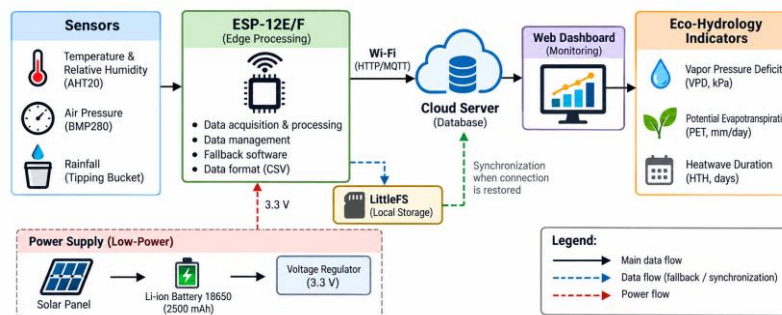


Figure 1 Conceptual architecture of the Mini-AWS

Hardware Design and Low-Power Architecture

The microcontroller used is the ESP-12E/F with a 32-bit architecture and an 80 MHz clock. The minimum system uses a barebone configuration to reduce additional interface components. The adapter board is equipped with 10 k Ω pull-up resistors on RST, GPIO0, and GPIO2. Power-supply stability is enhanced using 100 nF ceramic and 470 μ F electrolytic capacitors across the VCC–GND line. The autonomous power supply uses a single 2500 mAh Li-Ion 18650 battery supported by a solar panel through a TP4056 charging module with DW01A protection. The 3.7–4.2 V battery voltage is stepped down using an HT7333-A LDO. The low-power strategy is implemented through the use of a barebone controller, Modem Sleep, limited Wi-Fi transmission, and Software Fallback when the battery voltage reaches a critical condition (Grossi., 2021; Kanoun et al., 2021).

Table 2 Hardware Specifications.

Component	Model/Configuration	Function
Microcontroller	ESP-12E/F	Data acquisition and edge processing
Temperature & RH	AHT20	Air temperature and relative humidity
Pressure	BMP280	Atmospheric pressure
Rainfall	Tipping bucket + reed switch	Rainfall pulse acquisition
Time	RTC DS3231	Local timestamp
Storage	LittleFS	Local data buffer
Battery	Li-Ion 18650, 2500 mAh	Energy storage
Charging	TP4056 + DW01A	Battery charging/protection
Regulator	HT7333-A	Microcontroller voltage regulation

Sensors and Enclosure

The AHT20 is placed inside a white finned weather shield with natural ventilation to reduce the influence of thermal radiation. The BMP280 is installed in the main enclosure with micro-ventilation. The tipping bucket uses a 120×60 mm or 12×6 cm catchment area, with an area of 72 cm^2 . Mechanical pulses are detected using a Normally Open reed switch and a 5×1 mm neodymium magnet. The RTC DS3231 is used for timestamping. The enclosure is fabricated using a 3D printer to protect the electronic components from rainwater while maintaining sensor functionality.

Software and Software Fallback

The firmware was developed in C++ using the Arduino IDE. Sensor readings are taken every minute. At $V_{\text{bat}} \geq 3.5 \text{ V}$, the system operates in Normal Mode, processes the data, activates Wi-Fi, and sends the payload to the server before returning to energy-saving mode. At $V_{\text{bat}} < 3.5 \text{ V}$, the system enters Fallback Mode and disables Wi-Fi transmission to reduce communication load. The rainISR function on GPIO12 remains active so that tipping-bucket pulses and RTC timestamps can be stored locally in LittleFS. On the server side, the Laravel database uses a combination of `id_perangkat` and `waktu_rtc` as the basis for uniqueness checking to reduce the risk of duplicate records after reboot. The fallback mechanism is positioned as a data-preservation strategy rather than quantitative evidence of the magnitude of energy savings. Battery voltage (V_{bat}) was monitored through the Mini-AWS voltage-measurement circuit and recorded together with the meteorological observations. The recorded values were used to characterize the observed power-supply conditions during field deployment. The firmware design specified a 3.5 V threshold for battery-related operating-mode control. Separately, the Laravel monitoring application used the most recently received voltage reading and telemetry delay to infer the device status, including online, delayed transmission, low-battery indication, and connection loss. These server-side classifications were treated as diagnostic indications rather than direct confirmation of the internal firmware operating mode. The analysis examined the distribution of recorded V_{bat} values, voltage extremes, and observations relative to the configured threshold. Because no simultaneous reference-voltage measurements or controlled fault-injection experiments were performed, the assessment did not quantify absolute V_{bat} measurement accuracy, electrical energy consumption, or fallback recovery performance.

Instrument Calibration and Validation

Tipping-Bucket Calibration

The tipping-bucket rainfall sensor was calibrated using a controlled volumetric method (Segovia-Cardozo et al., 2023). The collector area was 72 cm², corresponding to a 120 × 60 mm catchment opening. A reference volume of 500 mL was applied for each calibration run. To evaluate the consistency of the tipping mechanism under different flow conditions, three outlet diameters (2.5, 3.5, and 5.0 mm) were used, with five repetitions for each configuration, resulting in 15 calibration runs. The timestamped AWS records were used to identify the calibration runs and determine the corresponding number of recorded tips. The recorded tip counts were cross-checked against the manually observed tipping counts. The tipping capacity was calculated as:

$$V_{tip} = \frac{V}{N_{tip}} \quad (1)$$

where V_{tip} is the water volume per tip (mL/tip), V is the reference water volume (500 mL), and N_{tip} is the total number of recorded tips (Segovia-Cardozo, Rodríguez-Sinobas, Díez-Herrero, et al., 2021). The equivalent rainfall resolution was calculated from the collector area as:

$$R_{tip} = \frac{V_{tip}}{A} \times 10 \quad (2)$$

where R_{tip} is the equivalent rainfall depth per tip (mm/tip), and A is the collector area (72 cm²). The standard deviation (SD) and relative standard deviation (RSD) of the tip counts were calculated for each flow configuration to evaluate repeatability (Shedekar et al., 2016).

Temperature and Humidity Validation

Field accuracy validation was conducted through a side-by-side comparison between the developed Mini-AWS and the BMKG reference station during August 2026. The Mini-AWS prototype was installed within a distance of less than 3 meters from the reference instrument. The reference measurements were obtained from an Automated Weather Observing System (AWOS) operated by BMKG. The reference temperature and relative humidity sensor was identified as a Thies Clima Hygro-Thermo Transmitter Compact, model 1.1005.54.780, with the additional instrument identification 264799/4922. According to the instrument information provided by BMKG, the temperature channel had a reported correction of −0.1 °C, measurement uncertainty of 0.15 °C, and resolution of 0.1 °C. The sensor was installed at a height of 1.5 m above ground level and equipped with a radiation shield.

According to the manufacturer's specifications, the sensor incorporates a resistance temperature-measuring element and a capacitive relative-humidity sensor. The manufacturer specifies a relative-humidity accuracy of ± 1.5 %RH within the range of 5–95% RH at temperatures between 10 and 40 °C. This value represents the manufacturer's stated accuracy rather than an instrument-specific calibration uncertainty. For the present comparative analysis, BMKG observations were obtained as timestamped records and synchronized with Mini-AWS observations at one-minute resolution after converting UTC timestamps to Western Indonesian Time (WIB, UTC+7). The original aggregation method used to generate the exported one-minute reference observations requires confirmation from BMKG. Air temperature and relative humidity measurements were evaluated using temporally synchronized one-minute observations. Instrument reading precision was objectively evaluated using two main statistical metrics, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The standard mathematical formulas for the two evaluation metrics are defined as follows ([Hyndman & Koehler., 2006](#)):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_{IoT} - P_{Ref})^2} \quad (3)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{P_{Ref,i} - P_{IoT,i}}{P_{Ref,i}} \right| \quad (4)$$

Here, P_{IoT} denotes the parameter value recorded by the designed IoT edge station, P_{Ref} denotes the actual data value from the metrologically standardized reference instrument, and n represents the total number of observation samples ([Nash & Sutcliffe., 1970](#)). MAPE was used as a relative error metric to describe the practical agreement between the AWS and BMKG measurements. The before–after calibration performance was therefore interpreted using the combined evidence from MAPE, RMSE, NSE, and residual diagnostics.

Data Synchronization and Quality Control

Data completeness and quality control were evaluated using the original AWS and BMKG datasets. AWS timestamps were recorded in Western Indonesian Time (WIB), whereas BMKG timestamps were recorded in Coordinated Universal Time (UTC). BMKG timestamps were converted to WIB (UTC+7) before temporal synchronization. The datasets were normalized to one-minute timestamp resolution. Duplicate AWS observations within the same minute were resolved by averaging the corresponding sensor measurements. AWS and BMKG records were then matched based on their normalized timestamps. Matched observations containing missing temperature or relative humidity reference values were excluded from the statistical

evaluation. Missing AWS measurements were not interpolated. Data completeness was evaluated by comparing the number of unique AWS observation minutes with the theoretical one-minute observation schedule. The number of successfully matched and valid paired observations was determined after temporal synchronization and quality screening.

Humidity Calibration and Temporal Validation

Relative humidity calibration was performed using temporally synchronized and quality-screened observations from the developed Mini-AWS and the BMKG reference station. The paired observations were arranged chronologically and partitioned into three non-overlapping calendar-day blocks for model training, validation, and testing (Roberts et al., 2017). The training period covered 1–17 August 2026, the validation period covered 19–23 August 2026, and the final testing period covered 25–31 August 2026. Observations from 18 and 24 August were excluded to establish 24-hour temporal embargo periods between adjacent partitions. This strategy was applied to reduce temporal proximity and potential information leakage between the datasets (Roberts et al., 2017). Six empirical calibration approaches were evaluated: constant-offset correction, linear regression, second-order polynomial regression, third-order polynomial regression, multivariate linear regression incorporating AWS temperature, and piecewise-linear regression (Bergmeir et al., 2018). Candidate models were fitted using the training dataset and compared using their Root Mean Square Error (RMSE) on the validation dataset. After model selection, the selected model was refitted using the combined training and validation datasets. Its final performance was subsequently assessed using the temporally separated test dataset without further model selection or parameter adjustment (Roberts et al., 2017). Calibration performance was evaluated using RMSE, Mean Absolute Error (MAE), Mean Bias Error (MBE), Mean Absolute Percentage Error (MAPE), and Nash–Sutcliffe Efficiency (NSE) (Nash & Sutcliffe., 1970). Residual autocorrelation was examined using the Durbin–Watson statistic and autocorrelation function (ACF). Heteroscedasticity was evaluated using the Breusch–Pagan test and RMSE stratified by reference relative-humidity intervals (Breusch & Pagan., 1979). Empirical confidence intervals were estimated using moving-block bootstrap resampling with approximately 24-hour blocks to account for temporal dependence among observations (Künsch., 1989). The evaluation was regarded as an internal temporal validation using observations from a single deployment period. The temporal embargo was intended to reduce dependence near partition boundaries but was not assumed to eliminate all serial correlation.

Atmospheric Pressure Measurement

Atmospheric pressure was measured using a BMP280 sensor integrated into the Mini-AWS enclosure. Unlike air temperature and relative humidity, an independent BMKG pressure dataset corresponding to the study location and observation period was not available for this

study. Therefore, a direct statistical accuracy validation of the BMP280 pressure measurement against a BMKG reference instrument could not be performed. Pressure observations were consequently treated as supporting hydrometeorological measurements rather than independently validated ground-truth observations.

Measurement Uncertainty Considerations

Measurement uncertainty was considered by identifying the principal sources affecting each measured parameter. For temperature and relative humidity, the uncertainty sources include sensor-specific offset, local environmental exposure, ventilation, and differences between the prototype and BMKG reference installation. For rainfall, uncertainty is associated primarily with tipping volume variability, controlled water delivery, and residual water effects. Battery-voltage observations are additionally affected by the voltage measurement circuit and changing battery operating conditions. Because the present study was designed primarily as a field performance and prototype validation study, a complete quantitative metrological uncertainty budget was not established for all measurement channels. Instead, empirical agreement metrics (RMSE, MAE, MBE, MAPE, correlation, and NSE) and repeatability measures were used to characterize observed measurement performance. A full uncertainty budget incorporating sensor specifications, reference-instrument uncertainty, calibration-equipment uncertainty, and environmental effects is identified as a requirement for subsequent metrological validation.

Rainfall-Threshold Warning Mechanism

The web dashboard incorporates a rainfall-threshold-based warning mechanism to provide preliminary notification when the accumulated rainfall value reaches a predefined threshold. The mechanism compares the processed rainfall input with the configured threshold and updates the warning status on the dashboard. In the present study, this feature is treated as a prototype decision-support function rather than a validated operational early-warning system. Quantitative evaluation of detection rate, false alarms, missed events, and response time was not performed because the field deployment did not provide a sufficient number of naturally occurring rainfall events with an independent reference record.

Rain-Free Days (HTH) Indicator

Rain-Free Days (HTH; Hari Tanpa Hujan in Indonesian) was implemented as a dashboard indicator representing the elapsed number of calendar days since the last recorded rainfall event. The application identifies the most recent date with a positive daily tipping-bucket count in the rainfall summary database and calculates the elapsed days from that date. When no rainfall event is available in the database, the existing application logic calculates the

elapsed days from the earliest available daily record. This fallback value cannot independently establish the actual number of rain-free days because missing or unvalidated rainfall observations may be interpreted as an absence of rainfall. Accordingly, HTH is treated as a preliminary operational indicator, and its values are not used as validated drought or rainfall-occurrence results in this study. The displayed HTH status categories are application-defined and have not been independently validated against meteorological drought criteria.

Eco-Hydrology Indicators on the Dashboard

The eco-hydrology layer is designed to translate basic meteorological data into indicators of atmospheric conditions and water demand. Temperature and relative humidity are used to derive VPD, while PET is presented as an estimate of potential evaporative demand using the Ivanov method implemented on the dashboard. Rain-Free Days (HTH; Hari Tanpa Hujan) is used as a supporting indicator of rain-free periods when rainfall data are available. VPD is used to represent atmospheric evaporative demand. A low VPD indicates a relatively humid atmosphere and a relatively low ability of the air to draw water from the surface. Conversely, an increase in VPD indicates an increasing vapor-pressure deficit and, conceptually, increasing evaporative demand ([Grossiord et al., 2020](#)). Vapor Pressure Deficit (VPD) was calculated from air temperature and relative humidity using the saturation vapor pressure relationship:

$$VPD = 0.6107 \exp\left(\frac{17.27T}{T + 237.3}\right) \left(1 - \frac{RH}{100}\right)$$

Temperature was expressed in °C, relative humidity in %, and VPD in kPa ([Novick et al., 2016](#)).

The influence of relative humidity calibration on Vapor Pressure Deficit (VPD) was evaluated using the temporally separated internal test dataset. VPD was calculated from air temperature and relative humidity using the saturation vapor pressure relationship. Three VPD series were calculated: (1) reference VPD derived from BMKG temperature and relative humidity, (2) uncalibrated AWS VPD derived from AWS temperature and raw relative humidity, and (3) calibrated AWS VPD derived from AWS temperature and second-order polynomial-calibrated relative humidity. The resulting VPD estimates were compared with BMKG-derived VPD using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE). To evaluate the impact of calibration on the dashboard interpretation layer, VPD values were classified into five operational categories: very low (<0.5 kPa), low (0.5–<1.0 kPa), moderate (1.0–<1.5 kPa), high (1.5–<2.0 kPa), and very high (≥2.0 kPa). Classification agreement was evaluated by comparing the AWS-derived categories before and after calibration against those calculated from the paired BMKG observations. The assessment included overall classification agreement and changes in category assignments.

The BMKG-derived VPD was used as a calculated reference rather than a directly measured atmospheric variable. The category thresholds represented application-defined interpretative boundaries and were not independently validated against crop physiological responses or hydrological outcomes. Potential evapotranspiration (PET) was estimated using the empirical Ivanov formulation because the present Mini-AWS configuration provides air temperature and relative humidity but does not directly measure solar radiation, wind speed, or net radiation (Muhammad et al., 2019). The monthly Ivanov formulation was expressed as:

$$PET = 0.0018(25 + T)^2(100 - RH)$$

where PET is expressed in mm/month, T is mean air temperature (°C), and RH is mean relative humidity (%) (Muhammad et al., 2019). Monthly potential evapotranspiration (PET) was estimated using the empirical Ivanov formulation based on monthly mean air temperature and relative humidity. The dashboard implementation groups available meteorological observations by calendar month and calculates the mean temperature and relative humidity for each month. These monthly means are subsequently used as inputs to the Ivanov equation to produce an empirical estimate expressed in mm/month. The Ivanov method was selected because the Mini-AWS measures air temperature and relative humidity, whereas solar radiation and wind speed are not directly measured by the prototype. Unlike the FAO-56 Penman–Monteith method, which provides a standardized estimation of reference evapotranspiration (ET_o), the Ivanov method was used here as a simplified empirical indicator of potential evaporative demand (Vishwakarma et al., 2022). The current calculation uses available monthly observations and does not independently establish the representativeness of incomplete months. Consequently, PET estimates derived from incomplete monthly records require cautious interpretation. Missing monthly observations should be distinguished from physically meaningful zero evapotranspiration. The resulting estimates were not independently validated against reference evapotranspiration, pan evaporation, or lysimeter measurements.

Software Environment and Reproducibility

Table 3 Software Environment.

Software / Component	Version
Arduino IDE	2.3.10
ESP8266 Arduino Core	3.1.2
AHT20 sensor library	2.0.6
BMP280 sensor library	3.0.0
RTC DS3231 library	2.1.4
Laravel Framework	13.2.0
Livewire	4.2.2

PHP	8.5
Database server	Mysql 8.4.2

The Mini-AWS firmware was developed using the Arduino IDE and the ESP8266 development framework. The monitoring application was implemented using Laravel, Livewire, a MySQL database, and Chart.js. Sensor validation, humidity calibration, residual diagnostics, and confidence interval estimation were performed using a reproducible statistical analysis workflow. The software versions and principal dependencies are summarized in Table 3 to support reproducibility.

Result and Discussion

Prototype Implementation

The Mini-AWS prototype was successfully implemented with the ESP-12E/F as the central acquisition and processing unit. The system integrates the AHT20, BMP280, tipping bucket, RTC DS3231, LittleFS, solar-panel–battery power system, wireless communication, cloud server, and dashboard. This integration enables the system to perform monitoring and local data storage when transmission conditions are not available.

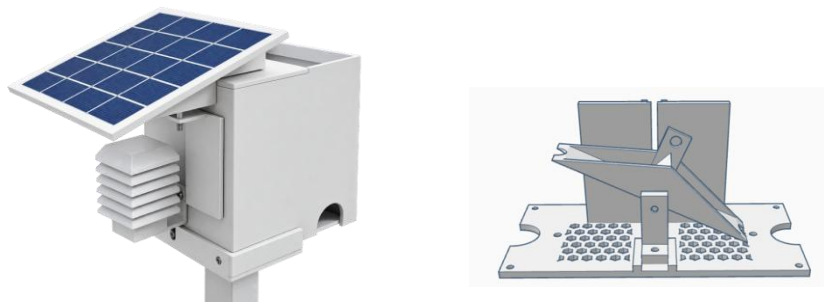


Figure 2 Tipping-Bucket and Mini-AWS Enclosure Design

Tipping-Bucket Calibration Results

Table 4 Tipping-Bucket Calibration Results

Run	Volume (mL)	Tip	Vtip (mL/tip)	Resolution (mm/tip)	Deviation from mean (tips)
1	500	140	3.571	0.4960	+3.4
2	500	138	3.623	0.5032	+1.4
3	500	137	3.650	0.5069	+0.4
4	500	137	3.650	0.5069	+0.4
5	500	131	3.817	0.5301	-5.6
Mean	500	136.6	3.660	0.5084	—

The deviation column represents the difference between the tip count recorded in each calibration run and the mean tip count of 136.6 tips across the five initial repetitions. These deviations are expressed in tips rather than percentages and do not represent measurement errors relative to a certified rainfall reference. The initial volumetric calibration was conducted using five repetitions of a 500 mL reference volume. The average tipping capacity was 3.660 mL/tip, corresponding to a rainfall resolution of 0.5084 mm/tip for the 72 cm² collector area. The standard deviation of the tip counts was 3.36 tips, with an RSD of 2.46%, indicating relatively good repeatability across the five initial repetitions. The resulting 0.5084 mm/tip factor was subsequently used as the operational conversion factor in the firmware and backend during the field deployment. To further evaluate the tipping-bucket response under different controlled flow conditions, an additional calibration experiment was conducted using three outlet diameters (2.5, 3.5, and 5.0 mm). Each configuration was tested five times using a fixed reference volume of 500 mL, resulting in 15 additional calibration runs.

Table 5 Individual tipping-bucket calibration runs

Run	Outlet diameter (mm)	Volume (mL)	AWS tips	mL/tip	Resolution (mm/tip)
1	5,0	500	128	3,906	0,543
2	5,0	500	124	4,032	0,560
3	5,0	500	128	3,906	0,543
4	5,0	500	126	3,968	0,551
5	5,0	500	123	4,065	0,565
6	2,5	500	124	4,032	0,560
7	2,5	500	132	3,788	0,526
8	2,5	500	129	3,876	0,538
9	2,5	500	131	3,817	0,530
10	2,5	500	131	3,817	0,530
11	3,5	500	133	3,759	0,522
12	3,5	500	132	3,788	0,526
13	3,5	500	121	4,132	0,574
14	3,5	500	125	4,000	0,556
15	3,5	500	131	3,817	0,530

Table 6 Additional controlled-flow calibration of the tipping-bucket rainfall sensor

Flow config.	Outlet (mm)	n	Mean tips	SD (tips)	RSD (%)	Mean capacity (mL/tip)	Mean resolution (mm/tip)
Small	2,5	5	129,40	3,21	2,48	3,866	0,537
Medium	3,5	5	128,40	5,18	4,03	3,899	0,542
Large	5	5	125,80	2,28	1,81	3,976	0,552
Overall	—	15	127,87	3,81	2,98	3,914	0,544

The timestamped raw AWS records were also examined to verify the electronic recording of the tipping-bucket pulses. During the calibration experiment, the rainfall conversion factor was temporarily set to 1; therefore, the rainfall field in the raw AWS log represented the number of tipping-bucket pulses rather than rainfall depth in millimeters. The raw AWS records were consistent with the manually observed tipping counts for all 15 calibration runs. For example, Run 1 consisted of 123 tips recorded at 05:29:32 and 5 tips at 05:30:32, giving a total of 128 tips, which was identical to the manually observed count. Across the three controlled flow configurations, the mean resolutions were 0.537, 0.542, and 0.552 mm/tip for the 2.5, 3.5, and 5.0 mm outlet configurations, respectively. The overall mean resolution was 0.544 mm/tip, with an RSD of 2.98% across the 15 additional runs. The relatively small differences among the three configurations indicate a reasonably consistent tipping response under the tested controlled flow conditions (Segovia-Cardozo et al., 2023). The slightly higher resolution obtained in the additional calibration compared with the initial value of 0.5084 mm/tip suggests that the estimated tipping capacity may vary with experimental configuration and flow conditions. Therefore, the additional experiment is interpreted as an expanded calibration assessment rather than a retrospective replacement of the conversion factor used during the field deployment. Although the controlled-flow experiment provided additional evidence of tipping-bucket repeatability under different flow configurations, it does not replace validation under natural rainfall conditions. A direct comparison with an independent reference rain gauge during natural rainfall was not available during the study period because of prolonged dry conditions. Consequently, the present results should be interpreted as controlled volumetric and flow-condition calibration rather than full field accuracy validation of rainfall measurements (Colli et al., 2014; Vasvári., 2005).

BMKG Data Synchronization

Table 7 Data availability and completeness

Indicator	Observations
Expected AWS observations (August 2026)	44,640
Raw AWS records	44,400
Unique AWS minute timestamps	44,398
Duplicate AWS minute bins	2
Missing AWS minute slots	242
Raw BMKG records	44,639
Theoretical overlapping minutes	44,220
Matched AWS–BMKG observations	43,977
Excluded invalid pairs	10
Valid paired observations	43,967
Maximum consecutive missing AWS interval	4 minutes

The data completeness assessment identified 44,400 raw AWS observations, corresponding to 44,398 unique minute timestamps after resolving two duplicate minute bins. Relative to the theoretical monthly schedule of 44,640 one-minute observations, 242 observation minutes were missing, resulting in a timestamp-based data completeness of approximately 99.46%.

The BMKG dataset contained 44,639 observations. Following UTC-to-WIB conversion, the theoretical overlapping observation window between the AWS and BMKG datasets comprised 44,220 minutes. Timestamp matching yielded 43,977 paired observations. Quality screening subsequently excluded 10 pairs containing missing reference temperature or relative humidity values, resulting in 43,967 valid paired observations. The final dataset represented 98.49% of the theoretical AWS monthly observation schedule and was used for the initial sensor performance assessment. These findings indicate high data availability during the observation period, although missing observations and temporal limitations were retained as considerations in the interpretation of measurement performance. The longest consecutive gap in the normalized AWS observation schedule was four minutes. Missing AWS observations were not interpolated, and invalid paired observations were excluded before the statistical evaluation.

Temperature and Humidity Validation against BMKG

The measurement performance of the developed Mini-AWS was evaluated through a side-by-side comparison with the BMKG reference instrument. The evaluation compared 43,967 temporally synchronized data pairs (1-minute recording resolution, observation period from August 1 to August 31, 2026). The BMKG reference data recorded in UTC were aligned to Western Indonesia Time (WIB / UTC+7). The compared microclimate parameters included

Air Temperature (TA_MG) and Relative Humidity (RH_MG). The quantitative statistical evaluation followed standard metrology formulas for Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), as presented in Table 8.

Table 8 Statistical Evaluation of IoT AWS Data versus BMKG Reference Station (Ground Truth).

Parameter	N	RMSE	MAE	MBE	MAPE	r	R ²	NSE
Temperature	43,967	1.066 °C	0.719 °C	+0.686 °C	2.550%	0.982	0.964	0.912
Humidity	43,967	10.881 %	10.110 %	+10.065 %	15.652%	0.977	0.955	0.341
Rainfall	0	—	—	—	—	—	—	—

Temperature Sensor Performance

Based on 43,967 valid data pairs, the mean BMKG temperature was 27.218 °C and the AWS temperature was 27.903 °C. RMSE was 1.066 °C, MAE 0.719 °C, MBE +0.686 °C, MAPE 2.550%, Pearson r 0.982, R² 0.964, and NSE 0.912. The high correlation indicates very strong temporal agreement. The positive MBE indicates a systematic positive bias of approximately 0.69 °C. Because the study did not independently measure radiation, ventilation, or sensor-level thermal conditions, the physical cause of this bias cannot be isolated. Differences in local exposure, ventilation, sensor placement, and sensor-specific offset are considered possible contributors. The daily temperature pattern in the graph was also consistent between the two instruments. Thus, the temperature sensor demonstrated good agreement in representing temporal temperature variations, although its remaining positive measurement bias should be considered when interpreting absolute temperature values.

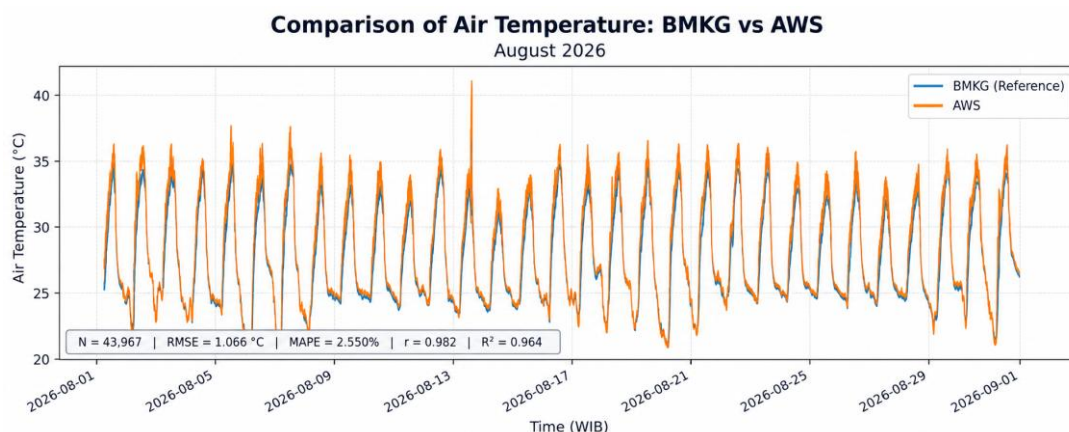


Figure 3 Comparison of BMKG reference and Mini-AWS air temperature observations during August 2026.

Humidity Sensor Performance Before Calibration

The mean BMKG RH was 64.399 %RH and the AWS RH was 74.464 %RH. RMSE was 10.881 %RH, MAE 10.110 %RH, MBE +10.065 %RH, MAPE 15.652%, r 0.977, R² 0.955, and NSE 0.341.

These results show that high temporal correlation is not identical to high absolute accuracy. The sensor was able to track changes in RH but exhibited substantial positive bias. The bias increased from approximately +7.62 %RH at 30–40% to +15.53 %RH at 80–90%, indicating that a single offset was inadequate.

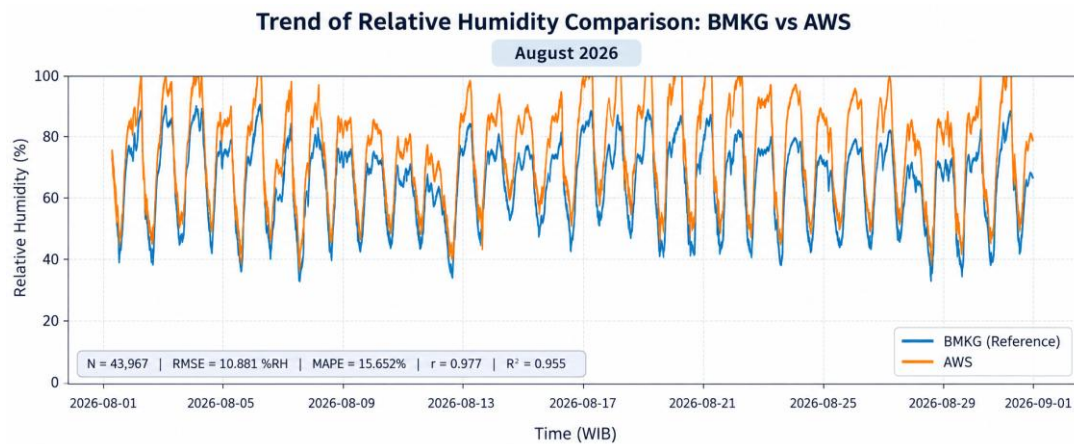


Figure 4 Comparative trend of BMKG and AWS relative humidity during August 2026

Humidity Sensor Calibration

The synchronization and quality-screening procedures yielded 43,967 valid paired observations for relative humidity calibration. Following chronological partitioning and the application of temporal embargo periods, 24,017 observations were assigned to training, 7,063 observations to validation, and 10,052 observations to final testing. The remaining 2,835 observations were excluded because they belonged to the temporal embargo periods. The comparison of six empirical calibration approaches showed that second-order polynomial regression achieved the lowest validation RMSE of 3.788 %RH, followed by piecewise-linear regression (3.807 %RH) and linear regression (4.103 %RH). Therefore, second-order polynomial regression was selected as the baseline calibration approach for subsequent evaluation. After model selection, the polynomial coefficients were re-estimated using the combined training and validation datasets. The resulting calibration equation was:

$$RH_{cal} = -13.851688 + 1.324447(RH_{AWS}) - 0.003436777(RH_{AWS}^2)$$

The polynomial calibration model was developed and evaluated offline using the synchronized AWS–BMKG dataset. Its numerical implementation was subsequently checked using a C++ function intended for the ESP-12E/F microcontroller. However, physical deployment of the polynomial correction in the operational firmware was not verified during the reported field observation period. Therefore, the calibrated humidity and derived VPD performance presented in this study represent offline evaluation results rather than independently verified edge-calibrated telemetry. The final internal temporal test dataset comprised 10,052 paired observations from 25–31 August 2026. Before calibration, the relative humidity sensor

produced an RMSE of 11.500 %RH, MAE of 10.805 %RH, MBE of +10.747 %RH, MAPE of 17.165%, and NSE of 0.201. After applying the second-order polynomial correction, RMSE decreased to 2.848 %RH, MAE to 2.469 %RH, MBE to +1.354 %RH, and MAPE to 3.938%, while NSE increased to 0.951. The relative RMSE reduction was 75.23%.

These results demonstrate substantial improvement in measurement agreement within the temporally separated test period. However, the remaining positive bias indicates that the calibration did not completely eliminate systematic measurement error.

Table 9 Performance of Relative Humidity Calibration on the Temporal Test Dataset

Metric	Before calibration	After calibration
Number of observations	10,052	10,052
RMSE (%RH)	11.500	2.848
MAE (%RH)	10.805	2.469
MBE (%RH)	+10.747	+1.354
MAPE (%)	17.165	3.938
NSE	0.201	0.951

Residual Autocorrelation Analysis

Residual autocorrelation analysis indicated strong temporal dependence after calibration. The Durbin–Watson statistic was 0.045, while the autocorrelation function showed coefficients of 0.971 at a one-minute lag, 0.683 at a 60-minute lag, and 0.624 at a 1,440-minute lag. The persistence of positive autocorrelation indicates that successive residuals were not statistically independent. Therefore, conventional uncertainty estimates assuming independent observations may not adequately represent the variability of model performance. Using moving-block bootstrap resampling with approximately 24-hour blocks, the exploratory 95% confidence interval for the calibrated test RMSE was 2.564–3.185 %RH. The corresponding confidence interval for relative RMSE reduction was 72.32–77.87%. These results support the improvement in measurement agreement while demonstrating the persistence of temporal error dependence. Because the final test period covered approximately seven days, the bootstrap intervals should be interpreted as exploratory estimates rather than evidence of long-term calibration stability.

Residual Heteroscedasticity Analysis

The Breusch–Pagan test indicated statistically significant heteroscedasticity ($p < 0.001$), demonstrating that the residual variance was not constant across the evaluated observations.

The stratified error analysis showed that calibration performance varied across reference relative humidity intervals. The calibrated RMSE was approximately 1.73 %RH within the 30–50%RH range and increased to approximately 3.33 %RH within the 60–70%RH range. These findings indicate that although second-order polynomial regression substantially reduced the

overall measurement error, calibration performance remained dependent on the observed humidity conditions. Consequently, the proposed polynomial calibration should be considered a baseline empirical correction model rather than a universally applicable calibration function. Further evaluation across different seasonal and environmental conditions is necessary to establish its broader applicability.

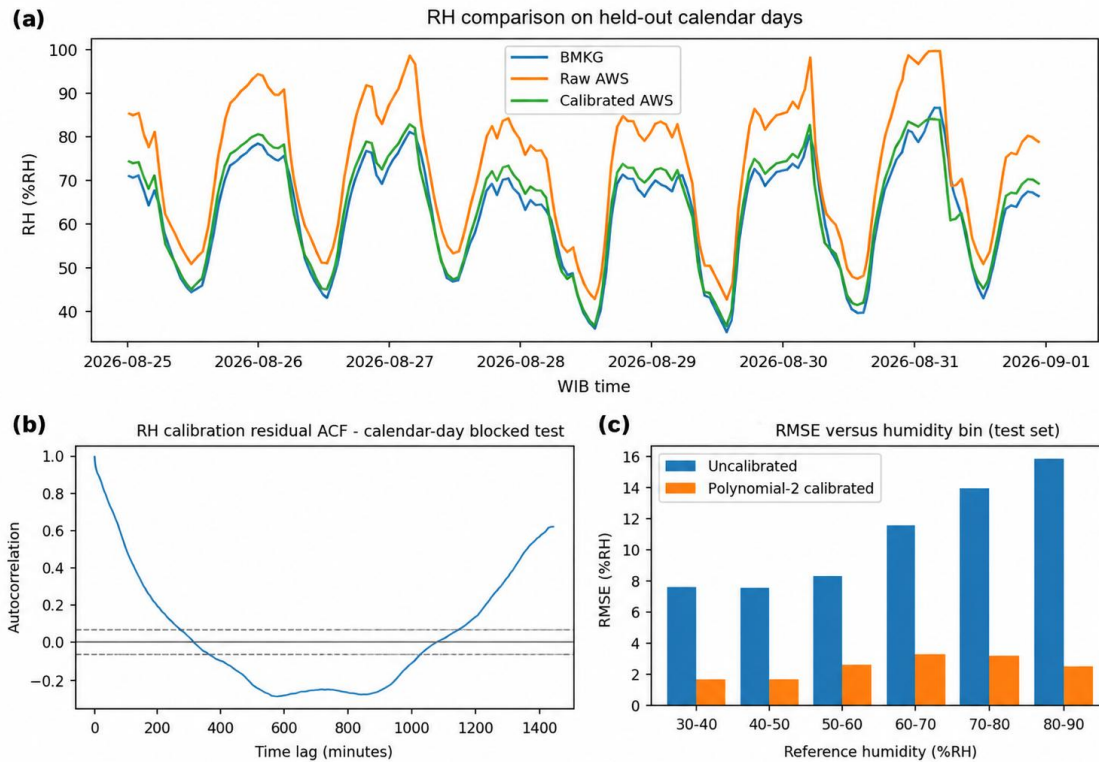


Figure 5 Evaluation of relative humidity calibration on the temporally separated internal test dataset ($n = 10,052$; 25–31 August 2026, WIB): (a) comparison of BMKG reference humidity with raw and calibrated AWS observations; (b) autocorrelation function of post-calibration residuals; and (c) RMSE before and after calibration across reference relative humidity intervals.

Atmospheric Pressure Measurement

The BMP280 provided continuous atmospheric pressure measurements during the field deployment. However, quantitative accuracy validation could not be conducted because corresponding atmospheric pressure observations from BMKG were not available for the study period and location. Consequently, the pressure data are presented as supporting observations within the Mini-AWS system rather than as independently validated reference-quality measurements. The pressure parameter was retained in the system because it provides additional atmospheric information and demonstrates the capability of the proposed Mini-AWS to acquire multiple hydrometeorological variables. Nevertheless, the absence of an independent reference dataset limits the interpretation of the pressure measurements in terms of absolute accuracy.

Power-Supply and Energy Evaluation

Table 10 Battery Analysis Results

Vbat Parameter	Result
Number of records	44,400
Mean	4.177 V
Minimum	2.780 V
Maximum	4.338 V
Vbat $\geq$ 3.5 V	44,398 (99.9955%)
Vbat < 3.5 V	2 (0.0045%)
Battery capacity	1 $\times$ 18650; 2500 mAh
Additional source	Solar panel
Field observation period	1–31 August 2026 (31 days)

Battery voltage (Vbat) was monitored through the system voltage-measurement circuit and recorded at the same one-minute acquisition interval as the environmental parameters. The 3.5 V threshold was used as a software control threshold for switching between Normal and Fallback operation. In this study, Vbat was evaluated primarily as an operational indicator of the power-supply condition rather than as a metrologically calibrated voltage measurement. No independent reference-voltage measurement was performed during the August 2026 deployment; therefore, the absolute voltage accuracy of the Vbat channel was not quantified.

During the 31-day observation period in August 2026, the Mini-AWS recorded 44,400 battery-voltage observations, with a mean recorded voltage of 4.177 V, a minimum of 2.780 V, and a maximum of 4.338 V. Of these observations, 44,398 (99.9955%) were at or above the configured 3.5 V control threshold, while two observations were below this threshold.

Further examination identified repeated recorded voltages exceeding 4.2 V, as well as two isolated low-voltage readings of approximately 2.79 V and 2.78 V that differed abruptly from neighboring observations. These findings indicate potential measurement-channel uncertainty or transient operating conditions that cannot be distinguished using the available telemetry alone. The values above 4.2 V should not be interpreted as confirmed battery overcharging, nor should the isolated low-voltage records be considered verified battery-depletion events. The Vbat measurement channel was not independently calibrated against a reference voltmeter during the deployment. The prototype used a single 2500 mAh Li-Ion 18650 battery supported by a solar-panel charging system. The low-power strategy consisted of limited Wi-Fi transmission, Modem Sleep, and a Software Fallback mode that disables Wi-Fi transmission when Vbat falls below 3.5 V. In the present study, power performance was evaluated operationally from the recorded battery-voltage profile and observed operating duration. Direct current and power measurements were not performed for the individual operating modes. Therefore, the study does not report quantitative energy consumption, energy savings, or mode-specific power efficiency. The prototype remained operational during

the 31-day observation period in August 2026. The recorded Vbat profile showed that 44,398 of 44,400 observations (99.9955%) remained at or above the 3.5 V fallback threshold. This operational result indicates that the solar-assisted battery system was able to sustain prototype operation during the tested period. However, because current and power were not directly measured, the observed voltage profile cannot be converted into a quantitative energy-consumption or energy-saving estimate. The contribution of individual operating modes, including Wi-Fi transmission, Modem Sleep, and Fallback, therefore remains to be quantified in future experiments.

Software Fallback and Data Preservation

The Software Fallback mechanism was implemented as a data-preservation strategy for critical power or communication conditions. During Normal Mode ($V_{bat} \geq 3.5$ V), the system performs sensor acquisition and attempts wireless transmission. When Vbat falls below 3.5 V, Wi-Fi transmission is disabled while sensor acquisition, the rainISR interrupt, RTC timestamping, and LittleFS local storage remain active. The server-side database uses the combination of device identifier (`id_perangkat`) and RTC timestamp (`waktu_rtc`) to reduce the risk of duplicate records after reconnection or reboot. The present field deployment provided operational observations of the battery threshold and system behavior, but it did not include a dedicated, controlled fault-injection campaign covering repeated communication failures, forced power-critical conditions, data recovery, and quantified packet/data loss. Therefore, the Fallback mechanism is evaluated in this study primarily as an implemented data-preservation function rather than as a fully quantified fault-tolerance test. The implemented Fallback mechanism prioritizes local data preservation when the battery voltage falls below the 3.5 V threshold or when communication is unavailable. During the August 2026 deployment, two Vbat observations below 3.5 V were recorded, at approximately 2.79 and 2.78 V. The firmware architecture was designed to disable Wi-Fi transmission while maintaining local acquisition and LittleFS storage during this condition. The database-side uniqueness rule based on `id_perangkat` and `waktu_rtc` was also implemented to reduce the possibility of duplicate records following reboot or subsequent data synchronization. These observations demonstrate that the required fallback logic and data-preservation architecture were implemented. However, because a dedicated fault-injection and recovery experiment was not conducted, the present results do not quantify data-loss probability, recovery time, or the exact amount of energy saved by Fallback operation.

Integration of Eco-Hydrology Indicators into the Dashboard

The cloud-server dashboard interface was developed using the Laravel 13 framework and Livewire 4, integrated with the Chart.js charting library. The web dashboard can be accessed at: <https://hidrologi.eko-teknik.my.id/>

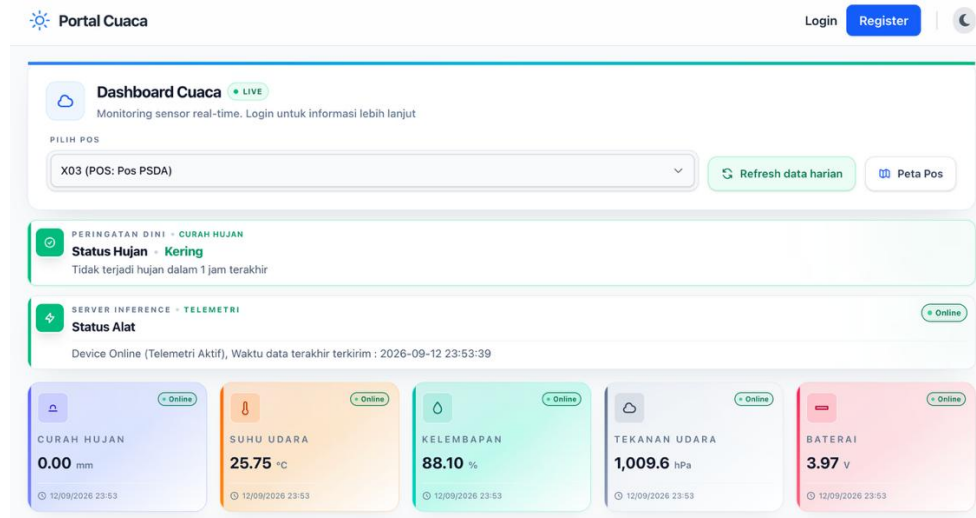


Figure 6 Web dashboard view (observation-station selection section)

The system is designed to accommodate data from multiple observation stations. Users can select a specific observation station whose data they want to display. After selection, the system presents information on rainfall status, device condition, and meteorological parameters including rainfall, air temperature, humidity, and atmospheric pressure, as shown in Figure 6. The implemented server architecture supports device-specific identification through `id_perangkat`, while the combination of device identifier and RTC timestamp provides a mechanism for distinguishing records from different observation nodes. The dashboard also includes an observation-station selection interface, demonstrating that the software layer was structured for multiple stations. However, the present field experiment involved only one Mini-AWS node. Consequently, the study demonstrates multi-node architectural readiness, but does not experimentally establish scalability under simultaneous multi-node operation. Performance under multiple concurrent nodes, including communication load, database throughput, synchronization, and data integrity, requires dedicated multi-node testing.

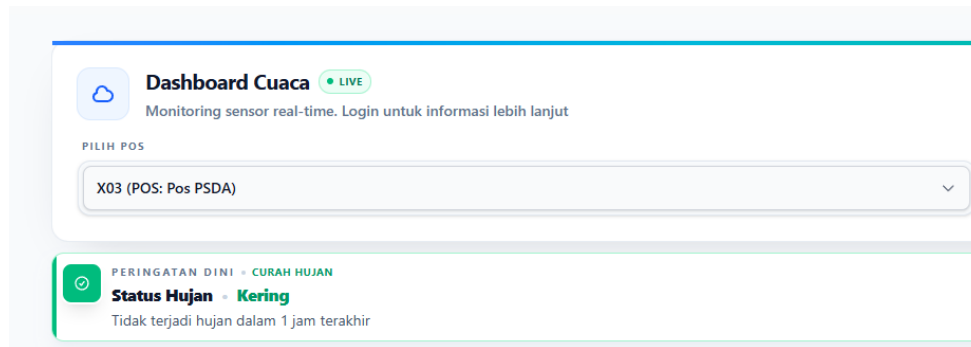


Figure 7. Rainfall-Threshold Warning Function.

The dashboard implements a rainfall-threshold-based warning feature that converts processed rainfall input into a warning status when the configured threshold is reached. The function demonstrates the implementation of the decision logic and dashboard notification pathway. However, its operational performance was not quantitatively validated in the present study because the field observation period did not provide sufficient naturally occurring rainfall events with an independent reference record. Therefore, the warning feature should be interpreted as a prototype notification mechanism rather than a validated early-warning system. Future validation should use multiple natural rainfall events and evaluate detection rate, false-alarm rate, missed-event rate, and response time against an independent reference gauge. Furthermore, the system development is not focused only on presenting physical data such as temperature, humidity, atmospheric pressure, and rainfall, but also includes an eco-hydrology-based interpretation layer to support more comprehensive environmental analysis.

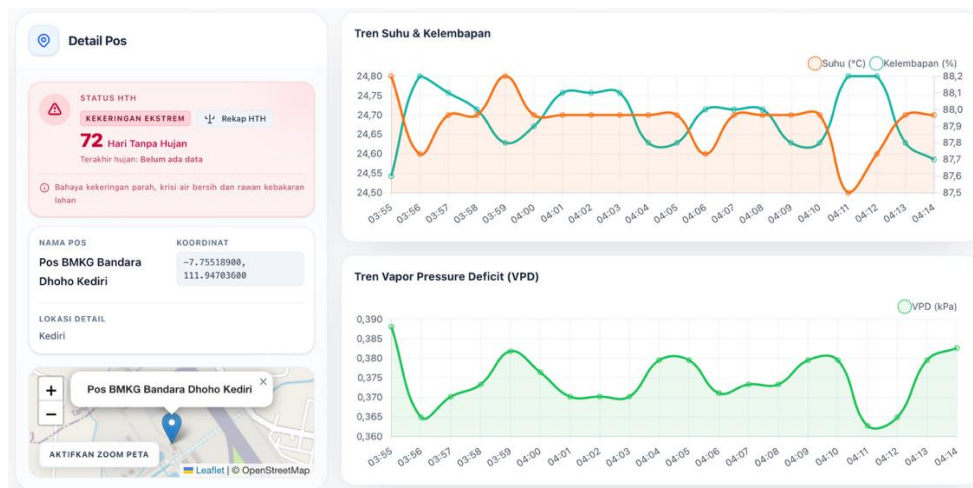


Figure 8 Web dashboard view (HTH, temperature and humidity trends, and VPD section)

Figure 8 also shows the Rain-Free Days (HTH) indicator. However, because the AWS rainfall column in the August 2026 dataset contains no numerical values, the HTH indicator displayed on the dashboard was not used as a quantitative result in this study. This is important to prevent drought interpretation based on unvalidated rainfall input.

Conceptually, this integration forms an information chain: microclimate observation → VPD/PET → evaporative-demand interpretation → supporting information for water management (Grossiord et al., 2020). The system does not yet perform complete watershed water-balance modeling because it does not include components such as soil moisture, infiltration, runoff, groundwater storage, and vegetation-cover dynamics. Therefore, the term eco-hydrology in this study is used to describe an interpretation layer of the relationship between atmospheric conditions and water demand, rather than a claim that the entire ecosystem water balance has been modeled.

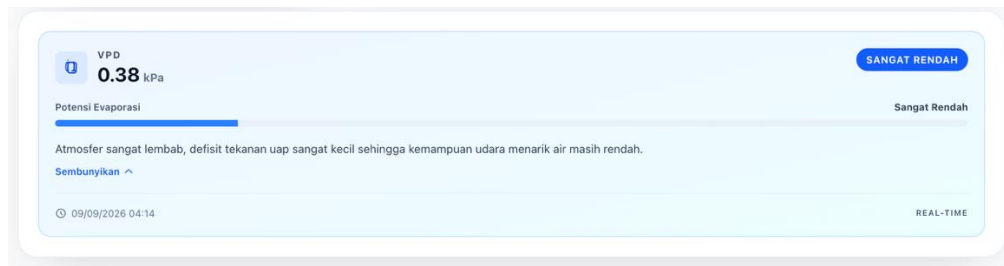


Figure 9. Web dashboard view (VPD value interpretation)

In the dashboard view shown in Figure 9, a VPD of 0.38 kPa is displayed as a very low condition, with a description indicating that the atmosphere is very humid and the ability of the air to draw water remains low. The calculated VPD represents a derived atmospheric-demand indicator whose uncertainty depends primarily on temperature and relative-humidity measurement errors. From an eco-hydrological perspective, low VPD indicates relatively low atmospheric evaporative demand at the observation time. Thus, VPD provides process context that cannot be obtained from temperature or RH values alone.

Table 1. Evaluation of Derived VPD and Operational Classification Agreement

Metric	Before RH calibration	After RH calibration
Test observations	10,052	10,052
VPD RMSE (kPa)	0.3701	0.1668
VPD MAE (kPa)	0.3413	0.1212
VPD MBE (kPa)	-0.3227	+0.0183
Correct classifications	4,532	8,229
Classification agreement (%)	45.09	81.86

The effect of relative humidity calibration on derived VPD was evaluated using 10,052 temporally separated paired observations from 25–31 August 2026. BMKG-derived VPD, calculated from reference temperature and relative humidity, was used as the comparison baseline. Before humidity calibration, AWS-derived VPD produced an RMSE of 0.3701 kPa, MAE of 0.3413 kPa, and MBE of -0.3227 kPa. After applying the second-order polynomial humidity calibration, RMSE decreased to 0.1668 kPa and MAE decreased to 0.1212 kPa, while

MBE changed to +0.0183 kPa. The operational VPD classification agreement with BMKG-derived categories increased from 45.09% (4,532 of 10,052 observations) before calibration to 81.86% (8,229 of 10,052 observations) after calibration, representing an improvement of 36.78 percentage points. A total of 4,356 observations changed from incorrectly classified to correctly classified categories after calibration, whereas 659 observations changed from correct to incorrect classifications. The improvement therefore represents a substantial overall gain rather than an improvement for every individual observation.

Classification discrepancies remained particularly relevant for observations close to category boundaries. Furthermore, the categories were defined as operational atmospheric-demand interpretations and were not independently validated against actual evapotranspiration, crop water stress, or watershed hydrological responses.



Figure 10. Web dashboard view (PET value interpretation)

The integration of the Ivanov method enabled the Mini-AWS dashboard to display empirical monthly PET estimates derived from recorded air temperature and relative humidity. This functionality extends the monitoring system beyond the presentation of raw meteorological observations by providing an additional indicator of potential evaporative demand. However, the Ivanov estimates were not validated against independent evapotranspiration observations or FAO-56 Penman–Monteith estimates. The calculation also depends on the representativeness and completeness of the monthly temperature and humidity observations.

Consequently, the dashboard PET output should be interpreted as a preliminary empirical indicator rather than a validated measurement of actual evapotranspiration or standardized reference evapotranspiration (ETo). Furthermore, because the polynomial relative-humidity calibration has not yet been physically integrated into the deployed firmware, the improvement observed in offline VPD analysis should not be assumed to have already

improved operational PET estimates. Additional evaluation using complete monthly datasets and independent evapotranspiration reference methods is necessary before the PET estimates are employed for quantitative irrigation scheduling or watershed water-balance assessment.

The dashboard functions are documented through the interface screenshots presented in Figures 6–10 and the quantitative VPD evaluation results reported in Table 11. These materials provide a record of the implemented monitoring and interpretation functions beyond the availability of the live website. The corresponding calibration and evaluation procedures are documented to support reproducibility.

Conclusions

This study developed and evaluated an IoT-based Mini-Automatic Weather Station (Mini-AWS) integrating hydrometeorological sensing, edge processing, local data storage, wireless telemetry, and eco-hydrological indicators. During the August 2026 field deployment, the system produced 43,967 valid paired observations for comparison with BMKG temperature and relative humidity measurements. The temperature sensor demonstrated good agreement with the reference observations, with an RMSE of 1.066 °C, MAPE of 2.550%, and NSE of 0.912, although a positive bias of +0.686 °C remained. The uncalibrated humidity measurements exhibited substantial positive bias, with an RMSE of 10.881 %RH. Using temporally separated training, validation, and test datasets, second-order polynomial calibration reduced humidity RMSE from 11.500 to 2.848 %RH and MAPE from 17.165% to 3.938% on the 10,052-observation internal test dataset, corresponding to a 75.23% reduction in RMSE. Nevertheless, strong residual autocorrelation and significant heteroscedasticity indicate that the calibration model requires further validation across different environmental and seasonal conditions. The initial tipping-bucket volumetric calibration yielded a resolution of 0.5084 mm/tip, while 15 additional controlled-flow experiments using three outlet configurations produced an overall mean resolution of 0.544 mm/tip. These results demonstrated repeatability under controlled conditions but did not establish measurement accuracy during natural rainfall events. The Mini-AWS also acquired meteorological observations during a 31-day deployment using a single 2500 mAh Li-ion 18650 battery supported by solar charging. Although 44,398 of 44,400 recorded battery-voltage observations were at or above the configured 3.5 V threshold, the presence of anomalous voltage readings and the absence of independent voltage calibration limit conclusions regarding absolute Vbat accuracy. Furthermore, the energy-saving contribution and reliability of the Software Fallback mechanism were not quantitatively validated. The integration of eco-hydrological indicators extended the Mini-AWS beyond conventional meteorological data presentation. On the internal temporal test dataset, humidity calibration reduced the RMSE

of AWS-derived VPD against BMKG-derived VPD from 0.3701 to 0.1668 kPa and increased agreement across five operational VPD categories from 45.09% to 81.86%. These findings demonstrate that improved relative humidity measurements can enhance the consistency of derived atmospheric-demand indicators. However, the reported improvement was obtained through offline analysis, and physical integration of the polynomial correction into the ESP-12E/F firmware remains to be verified. The empirical Ivanov PET estimates and Rain-Free Days indicators provide preliminary supporting information for eco-hydrological interpretation but were not independently validated against evapotranspiration measurements or hydrological outcomes. Overall, the developed Mini-AWS provides a promising platform for localized hydrometeorological monitoring and preliminary eco-hydrological analysis. Future research should prioritize natural-rainfall validation, cross-season sensor calibration, verification of embedded calibration and telemetry performance, independent battery-voltage and energy-consumption measurements, and validation of derived eco-hydrological indicators using additional environmental observations.

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