

Review

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Posted Date: 27 February 2026

doi: 10.20944/preprints202602.1866.v1

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Review

Cost-Effective TinyML-Ready Design and Field Deployment of a Solar-Powered Environmental Monitoring Data Collector Using LTE-M Communication

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Abstract

Environmental monitoring is essential for smart agriculture, renewable energy assessment, and climate-aware farm management. However, deploying autonomous sensing platforms in rural environments remains challenging due to energy constraints, communication reliability, and real-time processing requirements. This paper presents a modular, solar-powered environmental monitoring platform integrating LTE-M communication and TinyML-enabled edge sensing. The proposed system adopts a dual-microcontroller architecture, combining an Arduino Nano 33 BLE for real-time sensor acquisition and edge processing with an Arduino MKR NB 1500 dedicated to low-power wide-area communication. The platform integrates temperature, humidity, atmospheric pressure, rainfall, wind, and light sensors within a scalable framework. Two monitoring stations were deployed in rural regions of Romania to evaluate communication robustness, sensing stability, and energy autonomy. Field results demonstrate reliable LTE-M connectivity (4,306 RSSI samples; mean -75.51 dBm) and strong agreement with a regional weather station, with mean deviations of -0.71°C (temperature), 4.98% (humidity), and a stable pressure offset of -9.58 hPa attributable to altitude differences. Despite a total system cost of €315, the platform achieves measurement performance comparable to professional meteorological stations while maintaining long-term solar-powered operation. The proposed architecture provides a scalable and cost-effective solution for distributed smart agriculture and environmental monitoring applications.

Keywords: NB-IoT; LTE-M; Cat-M1; TinyML; environmental monitoring; IoT weather station; smart agriculture; renewable energy sensing; solar-powered IoT; edge computing

1. Introduction

Smart, data-driven agriculture has become essential for improving crop productivity, resource efficiency, and climate resilience [1–3]. Continuous monitoring of environmental parameters such as temperature, humidity, rainfall, solar radiation, wind speed, and wind direction enables farmers to optimize irrigation schedules, detect crop stress conditions, improve yield prediction, and reduce operational costs. Environmental sensing also supports renewable energy resource evaluation and smart city environmental monitoring, where accurate meteorological data assists solar and wind energy planning, microclimate modeling, and urban climate management.

Traditional environmental monitoring stations are typically expensive and difficult to deploy across large agricultural or rural regions. Installation, calibration, and maintenance costs limit scalability, particularly in distributed farming environments where localized sensing is required. Many commercial weather monitoring systems exceed acquisition costs of several thousand euros (€5000+),

restricting widespread adoption in data-driven agriculture and highlighting the need for affordable monitoring platforms with comparable sensing capabilities and modular extensibility.

Recent advancements in Internet of Things (IoT) technologies have enabled the development of low-cost, distributed environmental monitoring platforms [4,5] capable of real-time data collection. Among available IoT communication technologies, Narrowband Internet of Things (NB-IoT) such as LTE-M have emerged as promising solutions for low-power, long-range communication in rural environments. NB-IoT and LTE-M have emerged as promising LPWAN technologies for rural IoT deployments due to extended coverage and low energy consumption [6,7]. These technologies provide improved coverage, enhanced scalability, and reduced energy consumption compared to traditional cellular communication systems, making them particularly suitable for remote environmental monitoring applications.

In parallel, the emergence of Tiny Machine Learning (TinyML) enables intelligent data processing directly on microcontroller-based embedded systems. The emergence of TinyML enables intelligent inference directly on resource-constrained microcontrollers [8,9]. Edge-based processing allows local data filtering, anomaly detection, adaptive sampling, and event-driven sensing, reducing communication overhead and improving system responsiveness. Such capabilities are particularly valuable in agricultural monitoring scenarios where continuous sensing generates large volumes of data that may not require constant cloud transmission.

Despite recent progress in IoT environmental monitoring systems, several challenges remain. These include ensuring long-term autonomous operation through renewable energy harvesting, integrating heterogeneous sensor modules within a unified architecture, achieving reliable communication in rural environments with variable signal coverage, and enabling intelligent edge-based processing while maintaining low power consumption. Energy harvesting using solar power has been widely adopted to extend the operational lifetime of wireless environmental sensor networks [10,11]. Many existing monitoring platforms focus on single-domain applications and lack flexibility for multi-domain sensing and modular expansion.

To address these challenges, this paper proposes a modular, solar-powered environmental monitoring platform integrating LTE-M/NB-IoT communication and TinyML-enabled real-time sensing. The system adopts a dual-microcontroller architecture that separates high-frequency sensor acquisition and edge intelligence from long-range wireless communication tasks.

Specifically, the Arduino Nano 33 BLE is responsible for real-time sensor interfacing, interrupt-driven acquisition of mechanical sensing components, and future TinyML-based inference tasks. Its higher computational capability (64 MHz CPU), extended SRAM, and larger flash memory enable local preprocessing, adaptive sampling strategies, and edge analytics. In contrast, the Arduino MKR NB 1500 is dedicated to LTE-M communication and cloud data transmission, ensuring reliable low-power wide-area connectivity in rural environments.

This functional separation improves system scalability, enhances energy efficiency by isolating communication bursts from sensing logic, and increases robustness by reducing cross-dependencies between computation and transmission subsystems. The dual-microcontroller architecture, along with the primary hardware characteristics and communication roles of each module, is illustrated in Figure 1.

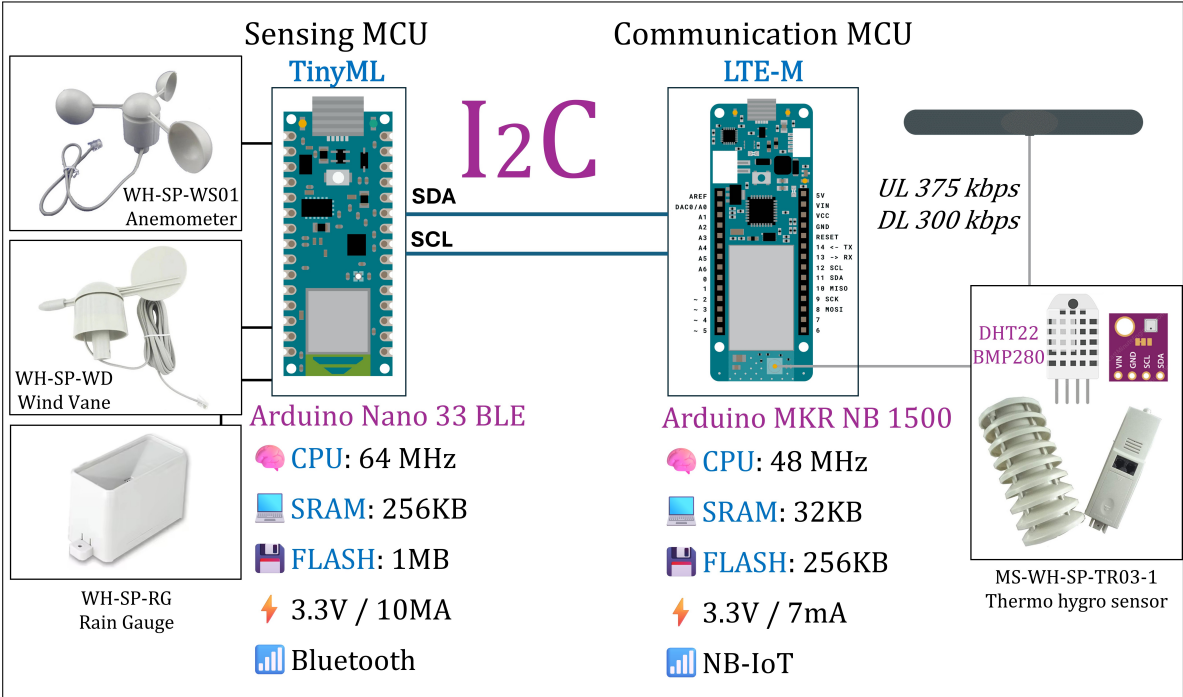


Figure 1. Dual-microcontroller architecture of the proposed environmental monitoring platform. The Arduino Nano 33 BLE performs real-time sensor acquisition and TinyML-based edge processing, while the Arduino MKR NB 1500 provides LTE-M/NB-IoT communication for reliable long-range cloud connectivity.

Beyond architectural modularity, the proposed system was designed with strong emphasis on real-world deployability and long-term autonomy. The integration of solar energy harvesting, LiFePO₄ battery storage, heterogeneous environmental sensing modules, and LTE-M communication enables fully autonomous operation in geographically dispersed agricultural areas. Accurate solar radiation forecasting using machine learning has become an active research area due to its relevance in renewable energy planning [12]. Particular attention was given to communication robustness under varying cellular coverage conditions, sensing stability under environmental exposure, and energy-aware system operation.

To validate the proposed architecture under practical operating conditions, field deployments were conducted in two geographically distinct regions characterized by different cellular coverage profiles and environmental conditions. The deployments were intentionally selected to evaluate communication reliability and energy autonomy under heterogeneous rural scenarios. One monitoring station was installed in Sănandrei, Timiș County, representing a suburban environment with stable LTE-M network coverage, while the second station was deployed in Rogoz de Beliu, Arad County, representing a remote rural environment with limited cellular signal availability.

The main contributions of this paper are summarized as follows:

- Proposal and implementation of a dual-microcontroller, solar-powered environmental monitoring architecture integrating LTE-M/NB-IoT communication and TinyML-enabled edge intelligence.
- Development of a low-energy sensing platform enabling long-term autonomous deployment in rural agricultural environments.
- Integration of heterogeneous environmental sensors within a unified real-time sensing and edge-processing framework.
- Experimental field validation in geographically distinct deployment regions with different cellular coverage characteristics.
- Performance evaluation in terms of communication reliability, sensing stability, and energy autonomy.



Figure 2. Field deployment of the proposed solar-powered environmental monitoring platform in Sânnandrei, Timiș County. The installation illustrates real-world integration of the sensing platform within an agricultural environment characterized by stable LTE-M network coverage.

The remainder of this paper is organized as follows. Section 2 reviews related work in IoT-based environmental monitoring systems and smart agriculture sensing platforms. Section 3 presents the system architecture and hardware design. Section 4 describes the communication framework and software implementation. Section 5 presents experimental deployment results and performance evaluation. Section 6 concludes the paper and outlines future research directions.

2. Related Work

2.1. IoT-Based Weather Stations and Environmental Data Collectors

Low-cost IoT weather stations have been increasingly studied for environmental monitoring and climate-aware agriculture. Recent systematic reviews highlight the growing adoption of affordable hardware platforms, modular sensor integration, and scalable communication protocols for resource-constrained agricultural environments [13,14]. These platforms aim to provide continuous environmental monitoring while reducing deployment costs compared to traditional meteorological systems.

Several implementations have focused on low-cost microcontroller-based weather monitoring systems. For instance, Khan et al. [15] proposed a weather monitoring platform based on ESP32 microcontrollers and ESP-NOW communication, capable of measuring temperature, humidity, rainfall, wind speed, and light intensity. Their work emphasizes affordability and low-power communication for distributed sensing environments. Similarly, Jasso-Reyes et al. [16] presented a modular IoT meteorological station architecture, demonstrating the feasibility of integrating multiple environmental sensors into portable and scalable monitoring platforms.

Broader research efforts have examined the role of IoT sensing in smart agriculture ecosystems. Eyasin et al. [17] introduced IoT-based multi-sensor crop monitoring solutions aimed at improving crop productivity through continuous environmental data acquisition and analysis. Furthermore, Zhurakovskiy et al. [18] proposed a machine learning-based environmental monitoring framework

capable of performing real-time data analysis and environmental forecasting, highlighting the growing integration of predictive analytics into environmental sensing systems.

From a communication perspective, Low-Power Wide-Area Network (LPWAN) technologies such as NB-IoT and LTE-M have gained increasing attention for agricultural and rural IoT deployments. Zhao et al. [19] investigated NB-IoT and 5G dual-channel communication architectures for autonomous agricultural machinery, demonstrating the potential of cellular LPWAN technologies for large-scale field operations. Additionally, real-world experimental evaluations of NB-IoT energy consumption [20,21] provide detailed insights into power profiles, transmission states, and device-level energy trade-offs. More recently, Trabelsi et al. [22] analyzed NB-IoT performance characteristics and delay-sensitive traffic scheduling, emphasizing the importance of communication optimization in cellular IoT systems.

Despite these advancements, several limitations remain in existing IoT weather monitoring systems. Many low-cost platforms rely on single microcontroller architectures, where sensing, processing, and communication tasks share computational resources. This architectural design may limit scalability when integrating advanced edge intelligence while simultaneously maintaining reliable long-range communication. Although several studies investigate cost-effective hardware, energy-efficient sensing, or cloud-based analytics, fewer works explicitly address the integration of TinyML-capable edge processing with cellular LPWAN technologies such as NB-IoT or LTE-M within modular, solar-powered environmental monitoring platforms.

The proposed system differentiates itself by combining:

- A dual-microcontroller architecture separating real-time sensing and edge intelligence from communication tasks,
- LTE-M/NB-IoT connectivity validated under real rural deployment conditions,
- Solar-powered autonomous operation,
- TinyML-ready hardware resources for future adaptive communication and sensing strategies.

By addressing sensing reliability, communication robustness, and architectural modularity simultaneously, the proposed platform contributes toward scalable and intelligent environmental monitoring systems suitable for precision agriculture and renewable energy assessment.

2.2. NB-IoT Communication for Environmental Monitoring Systems

Narrowband Internet of Things (NB-IoT) is a low-power wide-area network (LPWAN) technology standardized by the 3rd Generation Partnership Project (3GPP) to support massive machine-type communication in IoT applications. NB-IoT operates within licensed cellular frequency bands and provides extended coverage, high connection density, and improved energy efficiency compared to traditional short-range wireless communication technologies.

NB-IoT has attracted increasing attention in agricultural and environmental monitoring applications due to its capability to support reliable long-range communication in rural and geographically distributed environments. Zhao et al. [19] demonstrated the integration of NB-IoT and 5G communication channels in an IoT-based platform for autonomous agricultural machinery, highlighting the suitability of NB-IoT for large-scale agricultural sensing and monitoring systems requiring reliable connectivity and cloud-based data processing.

Energy efficiency is a critical factor in autonomous environmental monitoring deployments. Several studies have analyzed the power consumption characteristics of NB-IoT communication modules under real deployment conditions. Lukic et al. [20] performed an in-depth real-world evaluation of NB-IoT module energy consumption, demonstrating that optimized transmission scheduling and power management techniques significantly improve device lifetime in battery-powered IoT sensing platforms. Similarly, Michelinakis et al. [21] conducted empirical measurements of NB-IoT device energy consumption and provided detailed insights into communication energy profiles, highlighting the importance of optimizing data transmission intervals for long-term autonomous sensing systems.

Compared to alternative LPWAN technologies such as LoRa and Sigfox, NB-IoT benefits from operating within existing cellular infrastructure, enabling improved security, quality of service, and network scalability. These characteristics make NB-IoT particularly suitable for mission-critical environmental sensing applications requiring reliable bidirectional communication and centralized cloud integration.

Despite these advantages, the integration of NB-IoT communication within modular and low-cost environmental monitoring platforms remains an active research area. Several existing sensing systems rely on single microcontroller architectures and prioritize communication reliability over distributed intelligent processing capabilities. Furthermore, although previous studies have extensively analyzed NB-IoT communication performance and energy consumption, fewer works investigate its integration with TinyML-based edge processing within solar-powered and modular sensing architectures designed for long-term field deployment.

Motivated by these limitations, this work proposes an environmental monitoring platform that integrates NB-IoT communication with TinyML-enabled edge processing using a dual-microcontroller architecture. The proposed system evaluates NB-IoT communication reliability under heterogeneous signal coverage conditions while supporting real-time intelligent sensing in distributed agricultural monitoring environments.

3. Materials and Methods

3.1. General Architecture of the Environmental Data Collector

The proposed environmental data collector is designed as a modular, solar-powered IoT monitoring platform capable of supporting real-time environmental sensing, edge processing, and long-range wireless communication. The system integrates heterogeneous sensing modules, embedded computation, cellular communication, and autonomous energy management into a unified architecture suitable for remote agricultural and environmental deployments. The design philosophy emphasizes scalability, energy efficiency, and functional decoupling between sensing, processing, and transmission tasks in order to ensure long-term reliable operation under outdoor conditions.

Figure 3 illustrates the overall system-level architecture and its physical decomposition. From an integration perspective, the platform can be structured into three tightly coupled yet functionally distinct layers: (i) a mechanical sensing layer mounted on a supporting pillar, (ii) an embedded processing and communication layer enclosed within a weatherproof housing, and (iii) an autonomous power management layer based on photovoltaic energy harvesting and battery storage.

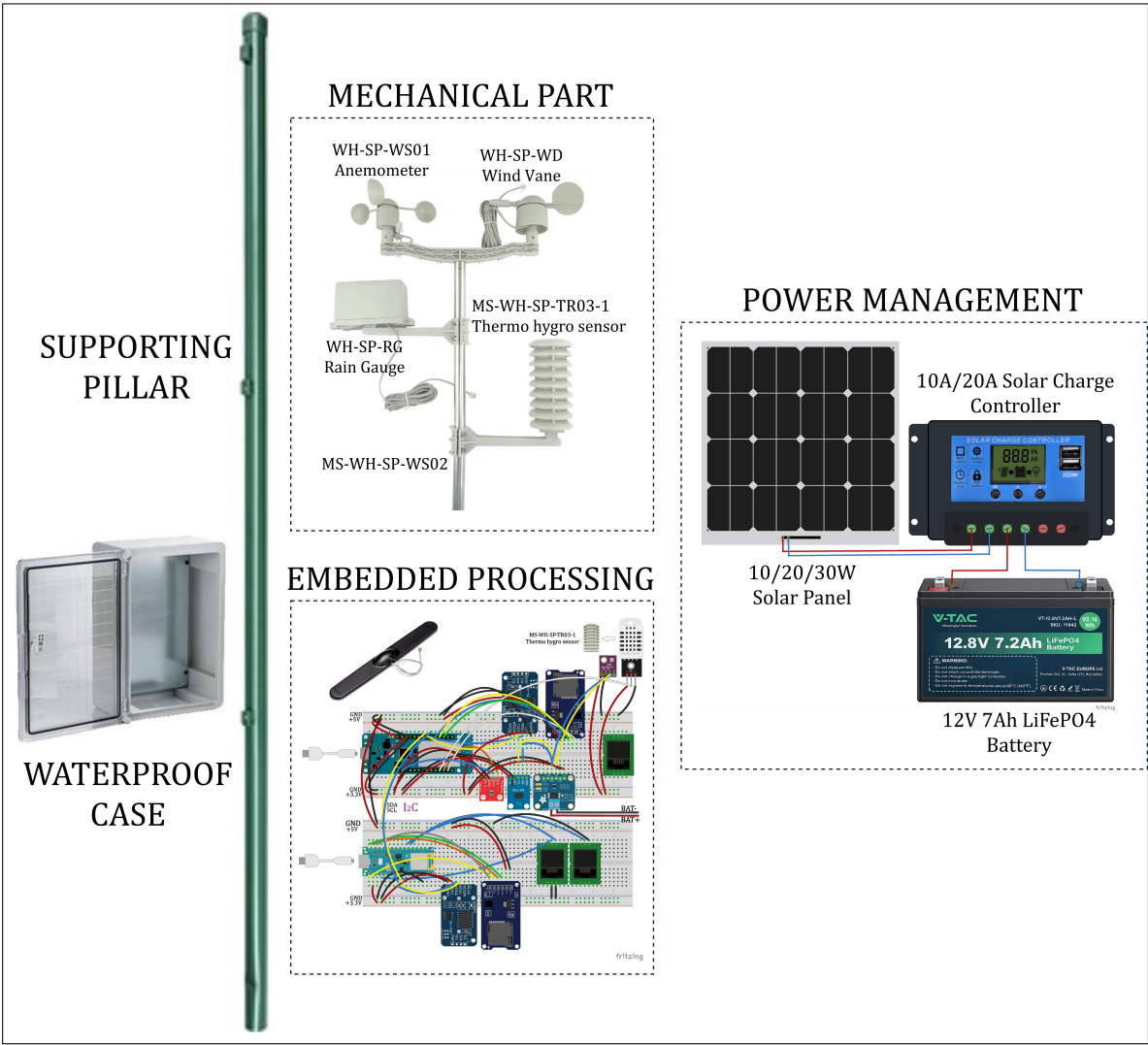


Figure 3. General system-level architecture of the proposed solar-powered environmental data collector. The platform integrates: (i) a mechanical sensing assembly (anemometer, wind vane, rain gauge, thermo-hygro module) mounted on a supporting pillar; (ii) a waterproof enclosure housing the dual-microcontroller hardware prototype (Arduino Nano 33 BLE for real-time sensing and TinyML-ready edge processing, Arduino MKR NB 1500 for LTE-M/NB-IoT communication); and (iii) a solar energy management subsystem composed of a 10–30 W photovoltaic panel, PWM charge controller, and 12 V LiFePO₄ battery. The architecture highlights the modular separation between mechanical sensing, embedded processing, communication, and autonomous power management.

The mechanical sensing layer comprises the meteorological instruments responsible for direct environmental interaction, including wind speed, wind direction, rainfall, temperature, and humidity measurement modules. These components are positioned at elevated height on a dedicated supporting structure to ensure unobstructed airflow exposure and representative microclimate measurements. Mechanical isolation from the electronics enclosure minimizes vibration coupling and reduces thermal interference between sensing elements and embedded circuitry.

The embedded processing layer houses the dual-microcontroller architecture within an IP-rated waterproof enclosure. This layer performs interrupt-driven acquisition of mechanical sensor signals, digital interfacing with solid-state sensors, local preprocessing, and LTE-M/NB-IoT data transmission. Physical separation of the sensing assembly from the electronics enclosure enhances maintainability, protects sensitive components from environmental exposure, and simplifies system diagnostics and upgrades.

The autonomous power management layer ensures energy independence through a photovoltaic panel, charge regulation circuitry, and LiFePO₄ battery storage. This subsystem is dimensioned to support multi-day autonomy under reduced solar irradiance conditions while maintaining sufficient energy reserves for communication bursts and edge computation tasks. The separation of energy management from sensing and processing layers allows independent optimization of power budgeting and communication scheduling strategies.

This layered decomposition improves modularity, simplifies maintenance, and enables independent optimization of sensing, computation, communication, and energy subsystems. Furthermore, the architecture supports straightforward sensor replacement, subsystem scaling, and future integration of additional edge intelligence capabilities without requiring structural redesign of the entire platform.

3.1.1. Mechanical Sensing Layer

The mechanical sensing components were adapted from commercially available weather station modules compatible with the MS-WH-SP-WS02 platform. These components include an anemometer for wind speed measurement, a wind vane for directional sensing, a tipping-bucket rain gauge for precipitation detection, and a thermo-hygro sensor module for temperature and humidity monitoring. The sensors are externally mounted on a rigid supporting pillar to ensure unobstructed exposure to ambient environmental conditions.

Although commercial modules were used in the current deployment, the proposed platform is designed as a hardware-agnostic solution. Sensing elements may be replaced with equivalent commercial devices or custom-designed mechanical assemblies without requiring architectural modification. This flexibility enables future integration of locally manufactured or 3D-printed sensor structures to reduce system cost and improve accessibility.

The anemometer and rain gauge generate pulse-based signals proportional to wind speed and rainfall events, respectively, while the wind vane provides directional information via discrete resistive or analog output states. These sensors rely on interrupt-driven signal generation, requiring accurate detection of high-frequency pulse transitions to ensure measurement reliability under rapidly changing environmental conditions.

3.1.2. Embedded Processing and Communication Layer

Real-time acquisition of mechanical sensor signals is handled by the Arduino Nano 33 BLE microcontroller. The Nano 33 BLE was selected due to its reliable interrupt handling capabilities, sufficient computational performance, and low-power operating characteristics. The microcontroller continuously monitors sensor interrupt lines to ensure that all mechanical events are captured without data loss.

Although the Nano 33 BLE provides enhanced Flash memory, SRAM capacity, and processing frequency compared to traditional ultra-low-power microcontrollers, the present deployment phase primarily focuses on robust data acquisition and preprocessing. The available computational headroom is reserved for future integration of TinyML-based edge intelligence algorithms, including predictive energy management and adaptive sensing strategies.

Long-range communication and cloud connectivity are managed by the Arduino MKR NB 1500 module, which supports LTE-M/NB-IoT communication. The NB-IoT interface enables reliable low-power wide-area network (LPWAN) connectivity, allowing sensor data transmission even in rural or geographically isolated environments characterized by limited cellular coverage. The communication subsystem supports bidirectional connectivity for remote device monitoring, configuration updates, and firmware management.

The dual-microcontroller architecture physically separates sensing and edge-processing tasks from communication functions. This separation enhances system scalability, improves energy efficiency by isolating high-consumption communication events, and provides computational flexibility for future intelligent processing extensions.

3.1.3. Autonomous Power Management Layer

The power subsystem ensures long-term autonomous operation through solar energy harvesting and battery storage. The architecture integrates a photovoltaic panel with configurable power ratings (10–30 W), a PWM solar charge controller for battery regulation, and a 12 V LiFePO₄ battery used as the primary energy storage unit.

This configuration enables sustained operation without external power infrastructure, supporting deployment in remote agricultural environments. The charge controller manages battery charging cycles, prevents overcharging and deep discharge conditions, and provides regulated power distribution to the embedded processing modules.

Detailed electrical modeling, battery dimensioning strategy, winter energy risk analysis, and charging stress evaluation are presented in Section 3.3.

3.1.4. System Integration and Deployment Considerations

All electronic components are housed inside an IP-rated waterproof enclosure designed to protect against environmental exposure while maintaining thermal stability. The enclosure supports modular integration of sensing, processing, and communication modules and allows convenient maintenance access during field deployment.

In the current implementation phase, the primary objective is long-term environmental and system performance data collection, including battery state monitoring and communication reliability assessment. The collected datasets provide the foundation for future development of edge intelligence models aimed at optimizing energy consumption, adaptive sampling strategies, and communication scheduling.

The modular architecture enables flexible adaptation of the platform to multiple application domains, including precision agriculture, distributed environmental monitoring, renewable energy assessment, and future AI-native edge sensing applications.

3.2. Sensor Modules Integration and Prototype Wiring Architecture

To validate the proposed environmental monitoring platform under real operating conditions, a low-fidelity hardware prototype was developed and deployed directly in field monitoring locations (Figure 4). The prototype integrates sensing modules, microcontroller units, and communication interfaces while preserving sufficient hardware flexibility to support iterative system refinement and component replacement when necessary. This deployment strategy enables evaluation of signal integrity, communication reliability, and real-time data acquisition performance under actual environmental conditions, while allowing rapid adaptation of sensing and power management configurations based on field observations.

Figure 4 presents the detailed wiring layout of the sensing subsystem and microcontroller interconnections implemented using breadboard-based prototyping. The design enables rapid testing, modular sensor replacement, and flexible expansion of sensing capabilities.

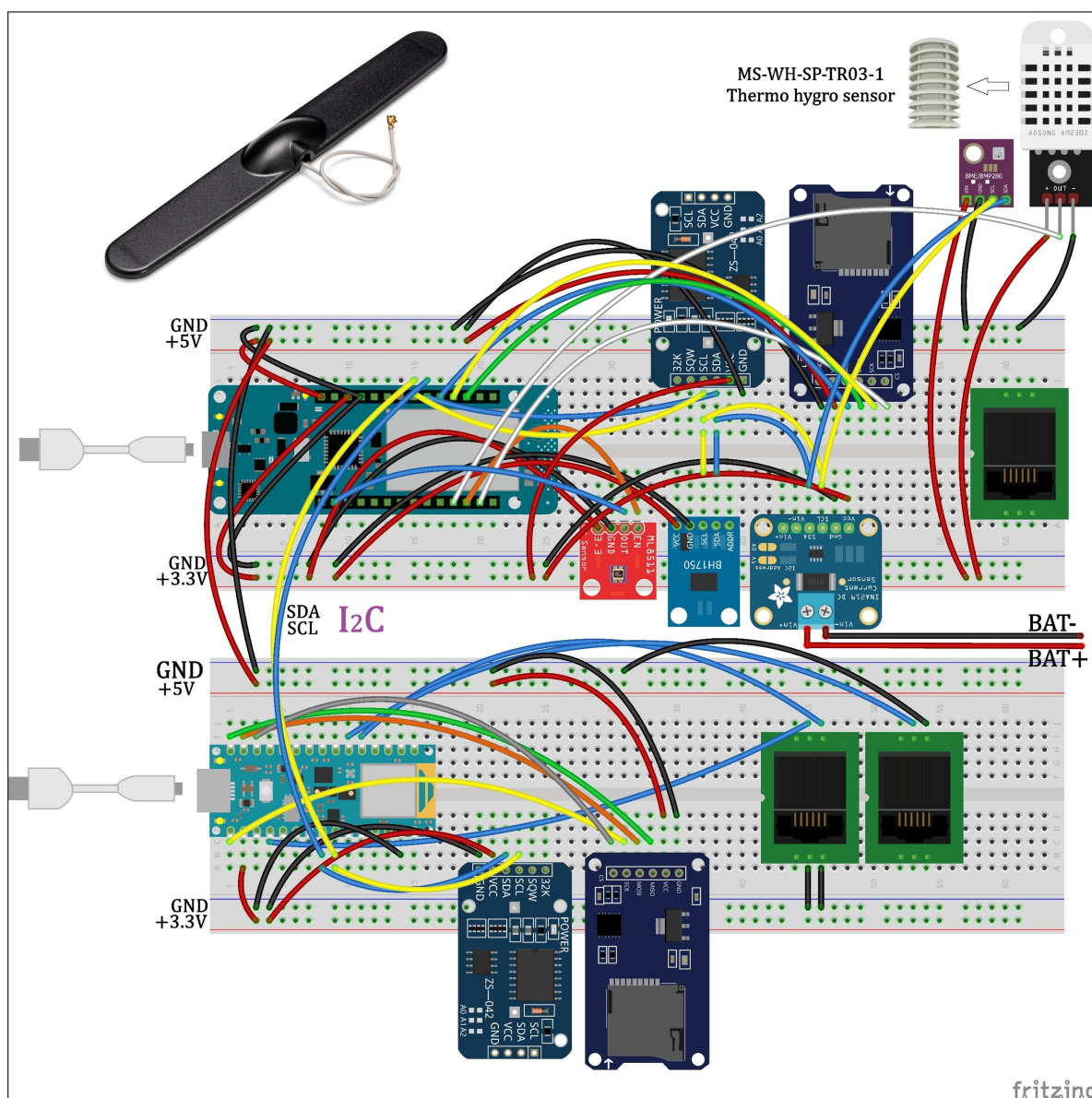


Figure 4. Low-fidelity prototype wiring architecture of the embedded processing unit. The breadboard-based implementation integrates environmental sensor modules, dual microcontroller units, RJ11/RJ12 connectors for mechanical meteorological sensors, and USB-powered interfaces connected to the solar charge controller.

The sensing subsystem integrates multiple environmental monitoring modules, including temperature, humidity, atmospheric pressure, and inertial sensing units connected through standard digital communication interfaces such as I²C and SPI. Additional mechanical meteorological sensors, including the anemometer, wind vane, and tipping-bucket rain gauge, are interfaced using dedicated RJ11/RJ12 connectors. These connectors provide a standardized and reliable interface between the data collector and externally mounted mechanical sensing elements. In the proposed configuration, three RJ11/RJ12 connectors are employed to support wind speed measurement, wind direction sensing, and rainfall detection.

The mechanical sensors generate pulse-based or resistive signals that are routed through the RJ connectors and processed by the Arduino Nano 33 BLE microcontroller using interrupt-driven acquisition routines. This configuration ensures accurate event counting and directional sensing while minimizing signal loss or timing inaccuracies associated with mechanical switching components.

The dual-microcontroller architecture is physically implemented on the prototype breadboard platform, where both the Arduino Nano 33 BLE and the Arduino MKR NB 1500 modules are mounted and interconnected with the sensing modules. The Nano 33 BLE performs real-time sensing and

preprocessing, while the MKR NB 1500 manages NB-IoT (LTE-M) communication and cloud data transmission.

Power distribution for the microcontrollers is provided through USB interfaces connected to the solar charge controller. Two USB output ports from the charge controller are used to supply regulated power independently to each microcontroller unit. This approach simplifies power routing, enhances modularity, and supports independent debugging and firmware updates for each processing unit during development.

The breadboard-based wiring architecture provides a flexible and accessible testing platform that allows rapid prototyping and sensor substitution without requiring printed circuit board fabrication. Although the prototype design is not optimized for long-term outdoor deployment, it enables comprehensive validation of sensing reliability, interrupt handling performance, and communication workflows prior to integration into the final weatherproof enclosure.

The modular wiring strategy also supports future system scalability, allowing additional sensing modules or custom-designed connectors to be integrated with minimal hardware modification.

3.2.1. LTE-M/Cat-M1 Communication Using Arduino MKR NB 1500

Long-range communication and cloud connectivity are implemented using the Arduino MKR NB 1500 platform, which integrates a u-blox SARA-R4 LTE modem supporting LTE-M (Cat-M1) and NB-IoT (NB1) standards. The board was selected due to its compatibility with low-power wide-area cellular communication, secure TCP/IP support, and seamless integration within Arduino-based embedded architectures.

Figure 5 presents the electrical characteristics and communication capabilities of the MKR NB 1500 module used in the proposed system.

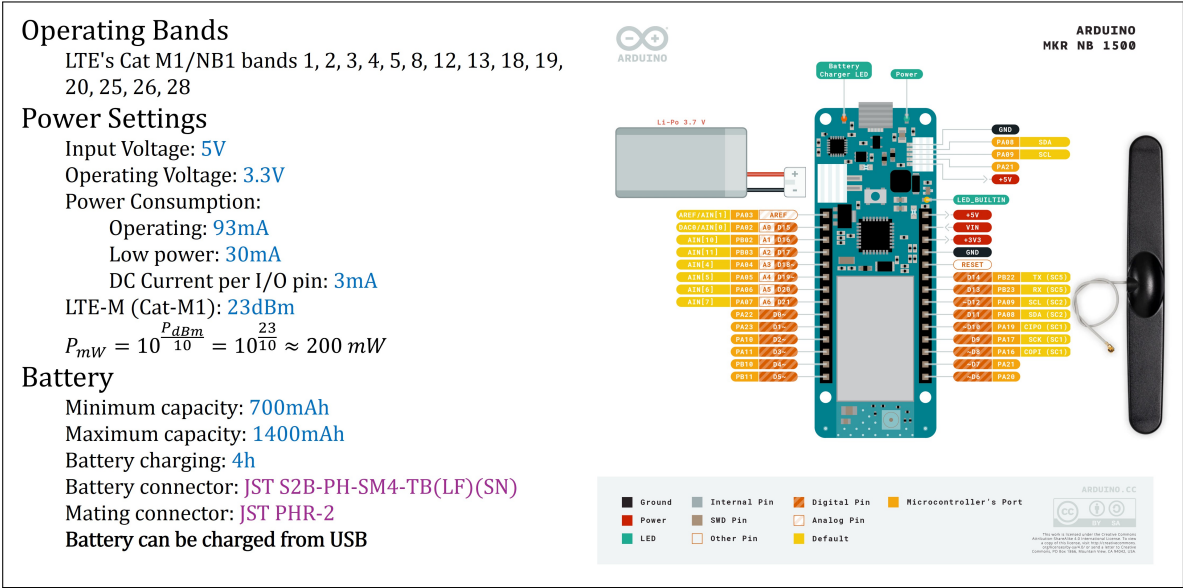
Transmission Power Characteristics. The integrated u-blox SARA-R4 modem operates in 3GPP Power Class 3 with a maximum transmission power shown in Equation 1.

$$P_{TX,max} = 23 \text{ dBm} \quad (1)$$

The equivalent linear power is presented in Equation 2.

$$P_{mW} = 10^{\frac{23}{10}} \approx 200 \text{ mW} \quad (2)$$

Unlike LoRa-based modules, transmission power in LTE-M systems is not manually configured at the application level. Instead, it is dynamically controlled by the cellular network according to 3GPP uplink power control mechanisms. The modem adjusts its transmission power based on signal quality indicators such as RSRP and RSSI, link budget requirements, and network scheduling constraints. This adaptive behavior improves link robustness under heterogeneous rural coverage conditions while maintaining regulatory compliance.



This auxiliary buffering strategy improves communication reliability and complements the main solar-powered LiFePO₄ storage system described in Section 3.3.

Communication Workflow in the Dual-MCU Architecture. Within the proposed dual-microcontroller architecture, the MKR NB 1500 is exclusively responsible for LTE-M communication. The Arduino Nano 33 BLE performs real-time sensor acquisition and preprocessing, after which aggregated timestamped environmental measurements are transferred via I2C to the MKR NB 1500 for transmission.

Communication sessions are scheduled by the RTC module. During each transmission cycle, the modem:

- Wakes from low-power state,
- Establishes LTE-M connectivity,
- Uploads environmental data to the remote cloud platform,
- Returns to low-power mode.

This duty-cycled communication strategy minimizes active modem time, reduces average energy consumption, and supports long-term autonomous operation under solar-powered conditions.

Rationale for LTE-M Selection. LTE-M was selected over alternative LPWAN technologies such as LoRa due to:

- Operation in licensed cellular spectrum,
- Higher receiver sensitivity and improved link budget,
- Native infrastructure support without private gateways,
- Bidirectional communication and QoS control,
- Seamless integration with existing cellular networks.

These characteristics are particularly advantageous in distributed agricultural deployments where reliable wide-area connectivity is required without additional gateway infrastructure. The integration of LTE-M communication within a modular solar-powered architecture enables scalable environmental monitoring while preserving energy autonomy and network robustness under variable rural coverage conditions.

3.2.2. Real-Time Clock Integration and Time-Synchronized Data Acquisition

Accurate time synchronization is essential for environmental monitoring systems that operate under low-power constraints and require periodic data acquisition and transmission. To ensure reliable timestamping and deterministic wake scheduling, the proposed platform integrates a DS3231 Real-Time Clock (RTC) module connected via the I²C communication interface.

Figure 6 illustrates the hardware configuration and addressing capabilities of the DS3231 RTC module used in the proposed system. The module provides stable local timekeeping with a typical drift of approximately ± 2 ppm (corresponding to approximately ± 63 seconds per year). While this level of accuracy is adequate for maintaining short-term sampling consistency, cumulative drift may become significant during long-term autonomous deployments, particularly in distributed multi-node monitoring scenarios where strict temporal alignment between stations is required.

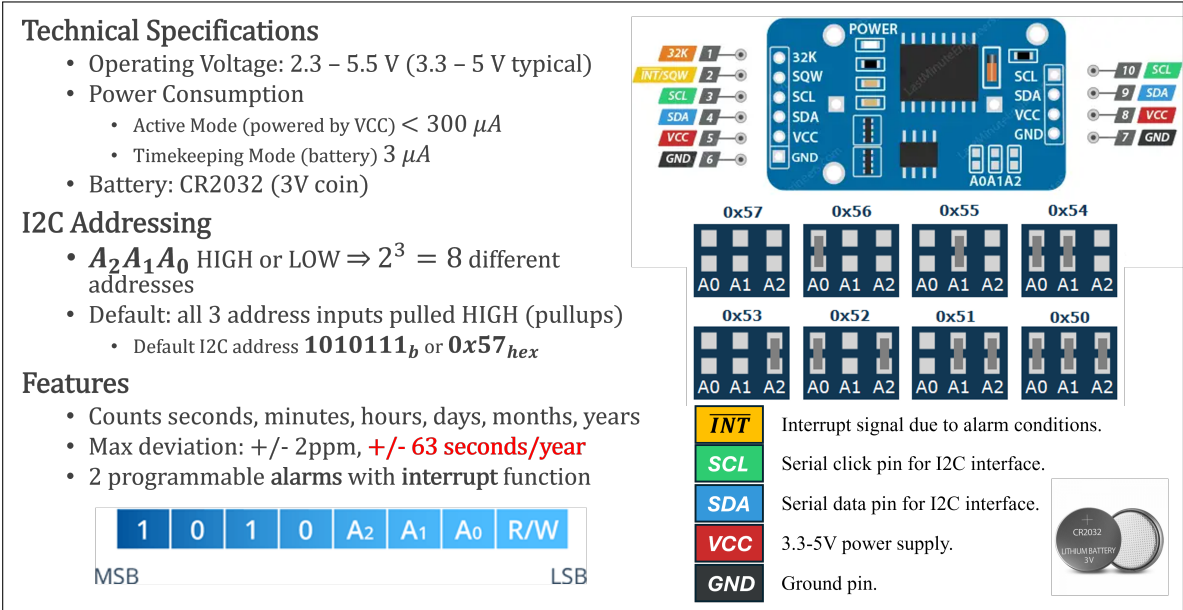


Figure 6. DS3231 real-time clock module used for time synchronization and wake scheduling. The module supports I²C communication, programmable alarms, battery-backed timekeeping, and configurable addressing options.

The RTC supports programmable alarms, interrupt generation, and battery-backed timekeeping using an external CR2032 coin-cell battery, enabling continuous time tracking during power interruptions. In the proposed architecture, the DS3231 operates as the primary local timekeeper, while higher-precision long-term synchronization is achieved through periodic external calibration, as described in the following subsection.

In the proposed architecture, the RTC module is interfaced with the Arduino MKR NB 1500 and Arduino Nano 33 BLE microcontrollers through the I²C bus using the default address configuration. The RTC provides precise timestamps for environmental measurements, communication scheduling, and data logging operations. Time synchronization is initially established during device initialization, either by synchronizing the RTC with the system compilation time or by maintaining previously stored time information preserved by the RTC backup battery.

The RTC module plays a critical role in enabling energy-efficient operation by supporting deterministic wake-up scheduling. Instead of relying on internal microcontroller timers, which may accumulate drift during extended sleep intervals, the system periodically queries the RTC to determine the exact time and calculate the required sleep duration until the next acquisition interval. The monitoring platform supports configurable sampling intervals, typically ranging from one minute during testing phases to 15-minute intervals during field deployment.

To ensure consistent sampling alignment, a first-boot synchronization mechanism is implemented. Upon system initialization, the device enters a synchronization phase in which data acquisition is delayed until the next scheduled interval boundary. This approach guarantees that all subsequent measurements are collected at fixed time slots, simplifying time-series data analysis and improving interoperability with external data processing systems.

During each wake cycle, the microcontroller retrieves the current timestamp from the RTC, performs environmental data acquisition from connected sensors, and stores the measurement results locally using an SD card storage module. When network connectivity is enabled, the timestamped measurements are transmitted to a remote cloud server using NB-IoT (LTE-M) communication. After completing data acquisition and transmission tasks, the system enters a low-power sleep mode until the next scheduled acquisition interval determined by the RTC.

The integration of the RTC module ensures reliable long-term timekeeping, enables deterministic sampling intervals, and supports aggressive power-saving strategies. This time-synchronized

operation is essential for maintaining data consistency across distributed monitoring stations and for enabling future deployment of edge intelligence algorithms that rely on temporally aligned environmental datasets.

3.2.3. Atomic Time Synchronization Using DCF77 Radio Clock

Although the DS3231 RTC module provides stable local timekeeping, cumulative drift may occur during long-term autonomous deployments, potentially reaching approximately ± 63 seconds per year. For distributed environmental monitoring platforms that rely on synchronized multi-station datasets, long-term timing drift can introduce temporal inconsistencies in recorded environmental parameters. To address this limitation, the proposed monitoring platform integrates an external atomic time synchronization mechanism based on the DCF77 radio time signal.

The DCF77 system is a longwave radio time transmission service operating at 77.5 kHz and broadcast from Germany. The signal is derived from atomic clock references and provides highly accurate time synchronization across large geographical areas of Europe. The DCF77 receiver module periodically decodes amplitude-modulated time signals, enabling the monitoring platform to obtain absolute time references independent of local oscillator drift.

Figure 7 illustrates the integration of the DCF77 atomic clock receiver with the Arduino microcontroller and the DS3231 RTC module. The DCF77 receiver is connected using a dedicated digital input line that captures pulse-width encoded time information transmitted by the radio signal. Arduino processes the received time frame, validates signal integrity, and updates the RTC module when synchronization criteria are satisfied.

In the proposed architecture, the RTC module serves as the primary local timekeeping unit, while the DCF77 receiver operates as a periodic calibration source. This hierarchical time synchronization strategy minimizes energy consumption by avoiding continuous radio signal decoding, which can be power-intensive. Instead, DCF77 synchronization is performed at configurable intervals or during system initialization phases to correct accumulated RTC drift.

Upon successful decoding of a valid DCF77 time frame, the microcontroller compares the received atomic reference time with the current RTC timestamp. If the time deviation exceeds a predefined correction threshold, the RTC is adjusted to the corrected atomic time reference. This approach ensures long-term temporal stability while preserving the low-power operational characteristics of the monitoring platform.

The combined use of RTC-based local timekeeping and periodic atomic synchronization enables the monitoring system to maintain accurate timestamping over extended deployment durations. This capability is particularly important for applications requiring high temporal alignment, such as multi-node environmental sensing, renewable energy resource analysis, and time-series machine learning model training.

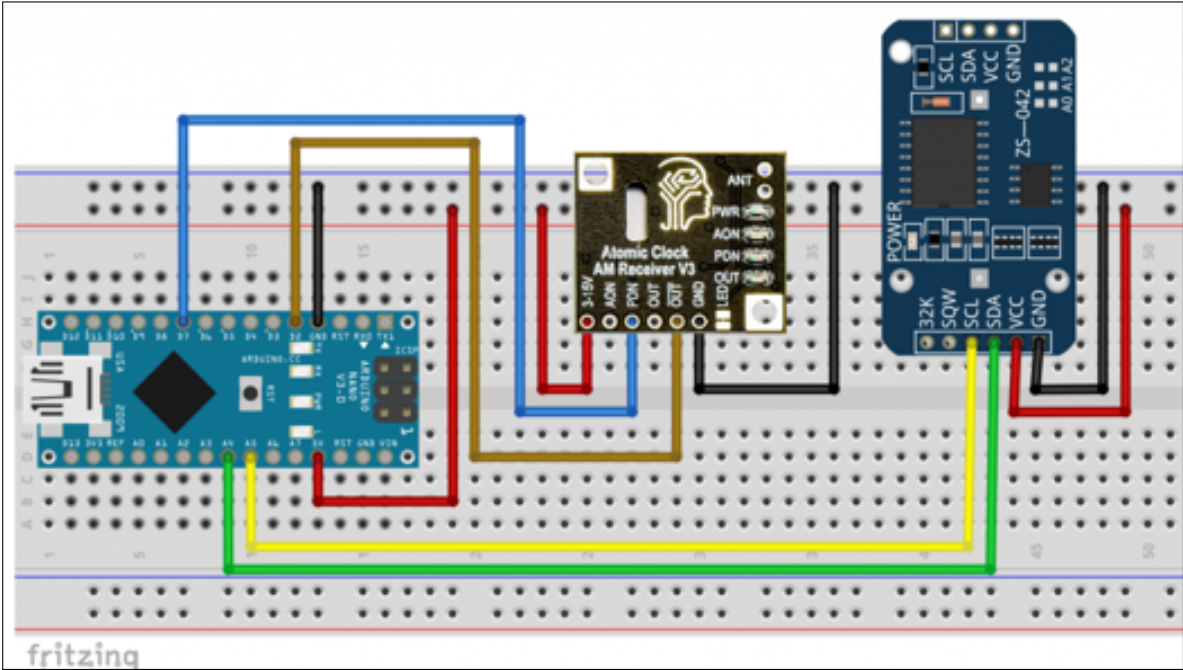


Figure 7. Integration of the DCF77 atomic clock receiver with the Arduino microcontroller and DS3231 RTC module. The DCF77 receiver provides periodic atomic time synchronization, while the RTC module maintains continuous local timekeeping for low-power operation.

Furthermore, the DCF77 integration enhances system resilience by providing an external reference independent of cellular network availability or satellite-based positioning systems. This feature supports reliable time synchronization in rural and remote monitoring locations where GNSS reception or continuous network connectivity may be limited.

3.2.4. Temperature and Humidity Sensing: DHT22 Selection Rationale

Accurate temperature and relative humidity measurements are essential for long-term environmental monitoring, microclimate analysis, and energy-aware agricultural management. Sensor precision directly impacts downstream analytics, including anomaly detection, crop stress modeling, and predictive environmental forecasting. In the proposed sensing architecture, the DHT22 digital temperature and humidity sensor was selected instead of the lower-cost DHT11 due to its extended measurement range, improved accuracy, higher resolution, and enhanced long-term stability, making it more suitable for outdoor autonomous deployments.

Figure 8 presents the pin configuration of both DHT11 and DHT22 sensors. Both devices share an identical four-pin layout (VCC, DATA, NC, GND) and operate using a single-wire digital communication protocol that transmits 40-bit data frames containing temperature and humidity information. This electrical and protocol compatibility enables seamless hardware replacement without requiring modifications to the microcontroller firmware logic. Consequently, system scalability and sensor upgrades can be implemented with minimal architectural impact.

The quantitative performance differences between the two sensors are summarized in Figure 9. The DHT22 provides a significantly extended temperature measurement range of -40°C to 80°C compared to 0°C to 50°C for the DHT11, which is critical for year-round outdoor agricultural deployments where winter sub-zero conditions and summer heat extremes may occur. Similarly, the humidity measurement range is expanded to 0–100% RH versus 20–90% RH, allowing reliable operation in highly humid or near-saturation environments such as greenhouses or early morning field conditions.

Accuracy improvements are also substantial: the DHT22 specifies $\pm 0.5^{\circ}\text{C}$ temperature accuracy and approximately $\pm 2\%$ RH humidity accuracy under nominal conditions, compared to $\pm 1^{\circ}\text{C}$ and $\pm 4\%$ RH for the DHT11. Reduced measurement uncertainty directly enhances the reliability of

long-term time-series datasets and improves the robustness of machine learning models trained on environmental variables.

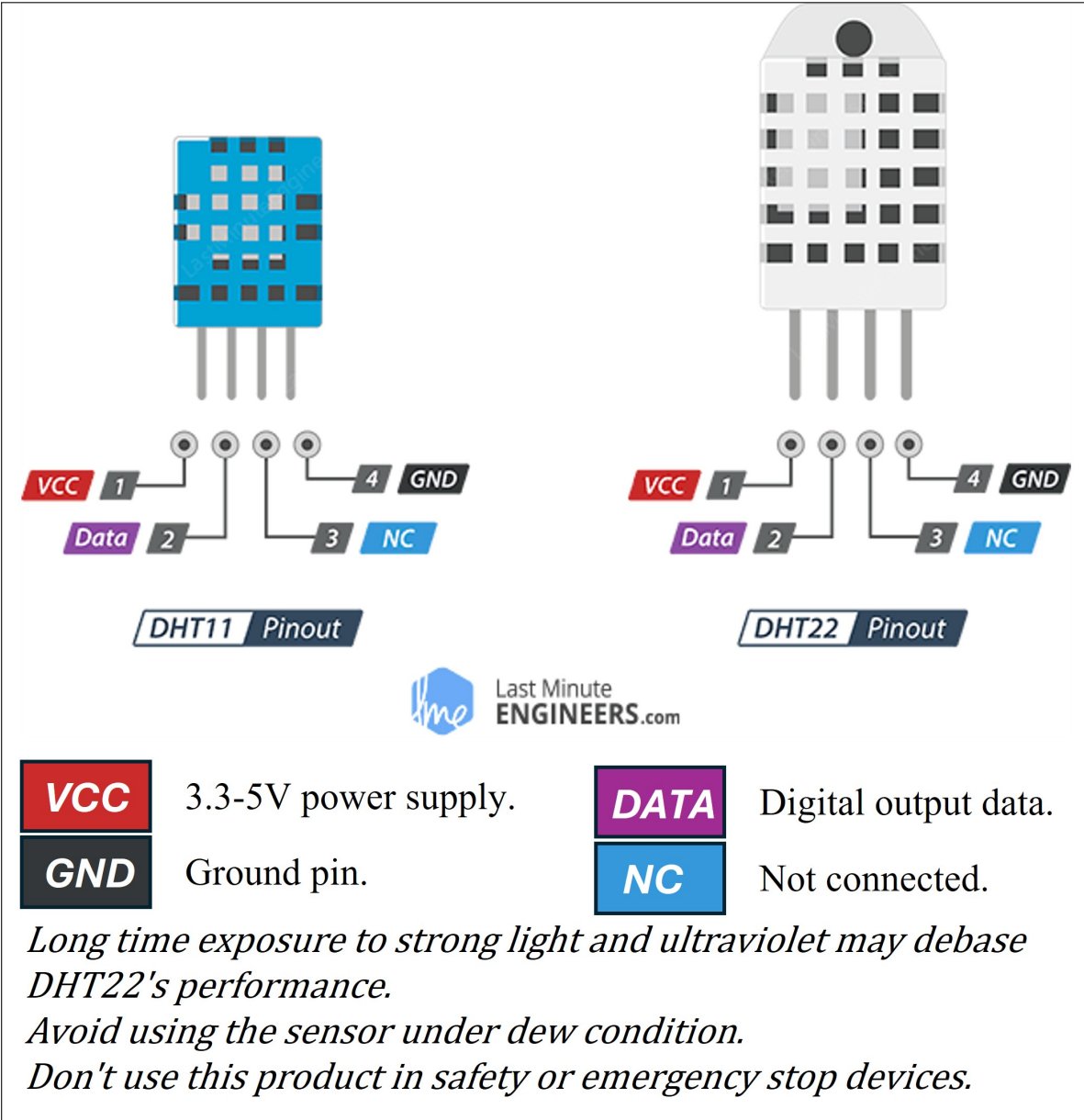


Figure 8. Pin configuration of DHT11 and DHT22 sensors. Both sensors share identical pin assignments and single-wire digital communication interfaces, enabling straightforward replacement at hardware level (figures adapted from lastminuteengineers.com).

Resolution differences further justify the selection. The DHT22 provides 0.1°C and 0.1% RH resolution, whereas the DHT11 is limited to 1°C and 1% RH increments. Higher resolution reduces quantization artifacts, improves sensitivity to subtle environmental fluctuations, and enables more precise detection of microclimate variations.

Long-term stability characteristics also favor the DHT22, which exhibits lower annual humidity drift compared to the DHT11 (see Figure 9). Improved stability reduces recalibration frequency and supports long-duration autonomous deployments powered by renewable energy sources, aligning with the design goals of the proposed monitoring platform.

Icon	Attribute	DHT11	DHT22
	Temperature Range	0°C to +50°C	-40°C to +80°C
	Temperature Accuracy	$\pm 1^{\circ}\text{C}$ (0°C) $\pm 2^{\circ}\text{C}$ (50°C)	$< \pm 0.5^{\circ}\text{C}$
	Temperature Resolution	1°C	0.1°C
	Humidity Range	20% RH to 90% RH	0% RH to 100% RH (-40°C to 80°C)
	Humidity Accuracy	$\pm 4\%$ (25°C) $\pm 5\%$ (0°C to 50°C)	$\pm 2\%$ to $\pm 5\%$ (25°C) $\pm 5\%$ (0°C to 50°C)
	Humidity Resolution	1% RH	0.1% RH
	Voltage Range	3.0V – 5.5V	3.3V – 6.0V
	Current Consumption	0.5mA – 2.5mA (measuring) 0.1mA – 0.15mA (standby)	1mA – 1.5mA (measuring) 0.04mA – 0.05mA (standby)
	Long Term Stability	$\pm 1\%$ RH/year	$\pm 0.5\%$ RH/year
	Sensing Period	~4ms	~5ms
	Collection/Sensing Period	>6s	>2s
	Price	1-2 €	5-10 €

Figure 9. Technical comparison between the DHT11 and DHT22 temperature and humidity sensors. The figure summarizes key specifications including measurement range, accuracy, resolution, operating voltage, current consumption, long-term stability, sensing interval, and cost. The comparison highlights the improved accuracy, wider humidity range, finer resolution, and better long-term stability of the DHT22, justifying its selection for the proposed environmental monitoring platform.

Figure 10 illustrates the actual wiring configuration implemented in the hardware prototype. The DHT22 module is powered directly from the 3.3 V rail of the Arduino Nano 33 BLE, ensuring full logic-level compatibility without additional voltage regulation. The DATA pin is connected to a dedicated GPIO pin (D2 in the current implementation), configured for bidirectional communication according to the DHT timing protocol.

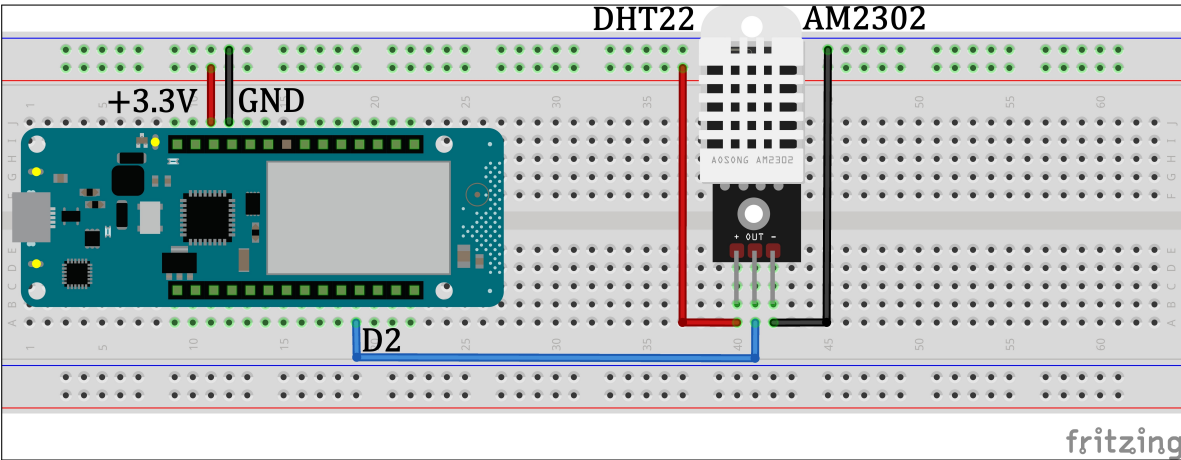


Figure 10. Breadboard implementation of the DHT22 sensor within the hardware prototype (designed with Fritzing). The sensor is powered from the 3.3 V rail, and the digital DATA line is connected to GPIO pin D2 of the Arduino Nano 33 BLE. The wiring shown corresponds to the actual configuration used during system validation.

The wiring configuration shown in Figure 10 corresponds to the deployed field prototype used for validation. A pull-up resistor on the DATA line (integrated within the DHT22 module variant used in this study) ensures signal stability and reliable digital communication over short interconnection distances. The minimal three-wire interface reduces parasitic effects, simplifies sensor replacement, and supports the modular design philosophy of the overall monitoring platform.

Although the DHT22 has a slightly longer minimum sampling interval (>2 s) than the DHT11 (1 s), this limitation is irrelevant within the proposed architecture, where acquisition intervals are scheduled in the order of minutes. The improved performance characteristics justify the marginal increase in cost and make the DHT22 more suitable for long-term outdoor environmental deployments.

3.2.5. Atmospheric Pressure Sensing: Selection of the BMP280 Module

Accurate atmospheric pressure measurement is essential for altitude estimation, weather trend analysis, and environmental modeling in distributed monitoring systems. In the proposed architecture, the BMP280 digital barometric pressure sensor was selected instead of the earlier BMP180 due to its improved accuracy, higher resolution, and enhanced temperature compensation performance.

Figure 11 presents the pin configuration of both BMP180 and BMP280 modules. Both sensors support I²C communication via SDA and SCL lines, enabling integration within the shared I²C bus of the sensing subsystem. The BMP280 additionally supports configurable I²C addresses (0x76 or 0x77), allowing flexible bus configuration in multi-sensor environments.

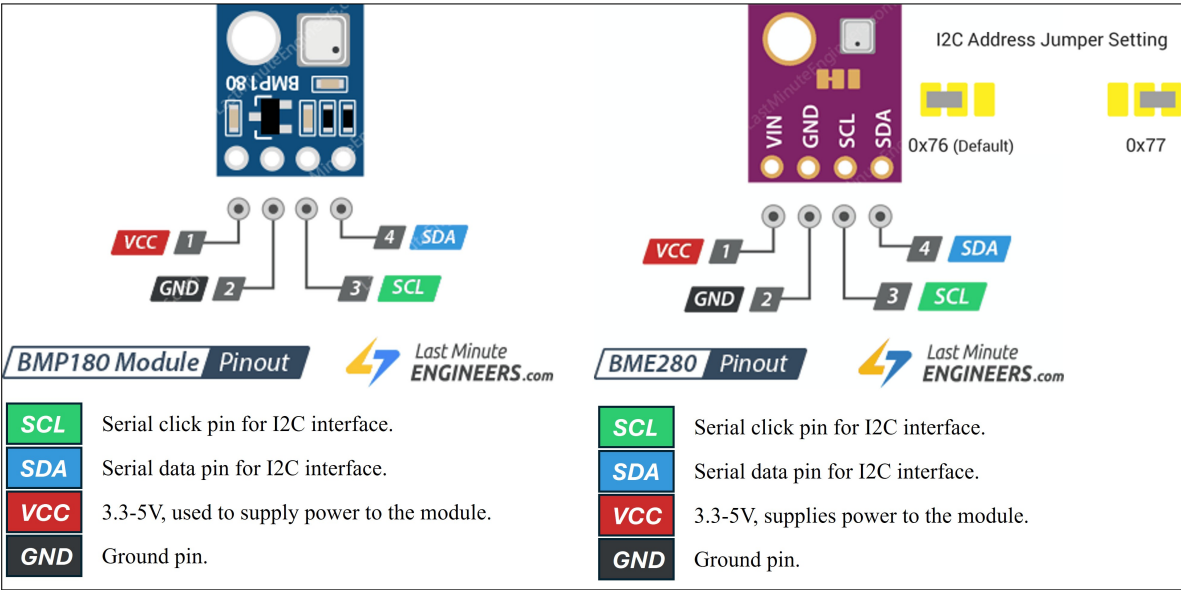


Figure 11. Pin configuration of BMP180 and BMP280 pressure sensor modules. Both devices support I²C communication and operate at low voltage levels compatible with embedded microcontroller platforms (figures adapted from lastminuteengineers.com).

Figure 12 provides a detailed performance comparison between BMP180 and BMP280 sensors. Although both modules operate within the same pressure range (300–1100 hPa), the BMP280 offers improved absolute pressure accuracy (± 1 hPa) compared to the BMP180 (± 2 hPa). This improvement is significant for altitude estimation and atmospheric trend monitoring applications.

Although the BMP180 supports ultra-high-resolution oversampling modes capable of achieving internal pressure resolution on the order of 0.01 hPa, its absolute pressure accuracy remains ± 2 hPa. In contrast, the BMP280 provides improved absolute accuracy (± 1 hPa) and enhanced temperature compensation stability. For long-term environmental monitoring, absolute accuracy and thermal stability are more critical than raw digital resolution, particularly when evaluating atmospheric trends over extended periods.

Icon	Attribute	BMP 180	BMP 280
	Pressure Range 	300 – 1100 hPa	300 – 1100 hPa (-500 to +9000 m)
	Pressure Relative Accuracy 	± 0.12 hPa (± 1 m) (950 – 1050 hPa @25°C-40°C)	± 0.12 hPa (± 1 m) (700 – 900 hPa @ 25°C-40°C)
	Pressure Absolute Accuracy 	± 2.0 hPa (± 4.5 hPa) (300 – 1100 hPa @0°C-65°C)	± 1 hPa (950– 1050 hPa @ 0°C-40°C)
	Pressure Resolution 	1.0 (0.01) hPa	0.16 hPa
	Temperature Range 	-40°C to +85°C	-40°C to +85°C
	Temperature Accuracy 	$\pm 1^{\circ}\text{C}$ (0 to 65°C) $\pm 1.5^{\circ}\text{C}$ (-40°C to 0°C)	$\pm 0.5^{\circ}\text{C}$ (@ 25°C) $\pm 1^{\circ}\text{C}$ (0°C to 65°C)
	Temperature Resolution 	0.1°C	0.01°C
	Voltage Range	3.3V – 5.5V	1.7V – 3.6V
	Current Consumption	0.6 mA	0.7-1.1 mA
	Long Term Stability	± 1 hPa/year	± 1 hPa/year
	Price 	1-2 €	2-7 €

*The temperature measurement is used internally to calibrate the pressure and humidity sensors.
The maximum measurable humidity decreases at extremely high and low temperatures.*

Figure 12. Performance comparison between BMP180 and BMP280 barometric pressure sensors, including pressure accuracy, resolution, temperature performance, voltage range, current consumption, and long-term stability. The improved resolution and accuracy of the BMP280 motivate its selection for the proposed monitoring platform.

Furthermore, effective measurement performance is influenced not only by digital resolution but also by noise characteristics and temperature-dependent compensation algorithms. The BMP280 incorporates improved internal filtering and calibration mechanisms, resulting in more stable pressure readings under varying environmental conditions.

Temperature measurement performance is also superior in the BMP280, providing improved accuracy and finer resolution. Since internal temperature compensation directly affects pressure calculation stability, enhanced temperature precision contributes to more reliable pressure readings under varying environmental conditions.

Although the BMP280 exhibits slightly higher active current consumption compared to the BMP180, the difference remains negligible within the overall energy budget of the solar-powered monitoring platform.

In addition to pressure measurement, the BMP280 integrates an internal temperature sensor used primarily for pressure compensation. While the device provides temperature readings with typical accuracy of approximately $\pm 0.5^{\circ}\text{C}$ (at 25°C), its primary design objective is barometric sensing rather than ambient temperature monitoring. In comparison, the DHT22 sensor employed in the sensing subsystem provides calibrated temperature and humidity measurements with comparable or superior temperature stability across the environmental range of interest.

Within the proposed architecture, temperature data from the DHT22 is therefore considered the primary ambient temperature reference, while the BMP280 temperature output is used for internal compensation and redundancy verification. This multi-sensor approach enhances robustness and enables cross-validation between independent sensing elements.

3.3. Wind Direction and Wind Speed Sensing Methodology

Wind measurements in the proposed platform are performed using the WH-SP-WD wind vane and the WH-SP-WS01 anemometer, which operate on complementary mechanical and electrical principles. Both sensors are physically mounted on the same mechanical assembly and electrically interconnected through a shared RJ11/RJ12 cable interface.

3.3.1. Wind Vane Operation Principle

The WH-SP-WD wind direction sensor operates using a mechanical magnet-based switching mechanism. Internally, the device contains eight reed switches, each connected to a resistor with a distinct resistance value. As the wind vane rotates, an embedded magnet activates one or two reed switches depending on the blade position. This design allows up to 16 discrete angular positions to be detected, corresponding to the principal and intermediate compass directions.

Each angular position produces a specific equivalent resistance value. When combined with an external fixed resistor (10 kΩ in the reference configuration), the wind vane forms a voltage divider circuit. The resulting output voltage is proportional to the selected resistance and can be measured using an analog-to-digital converter (ADC). In the proposed implementation, the analog output of the wind vane is directly connected to an analog input pin of the Arduino Nano 33 BLE, which samples the voltage and maps it to the corresponding wind direction angle.

Figure 13 illustrates the directional mapping and RJ11 routing configuration used in the sensor assembly. The diagram highlights the discrete directional sectors and the shared cable architecture.

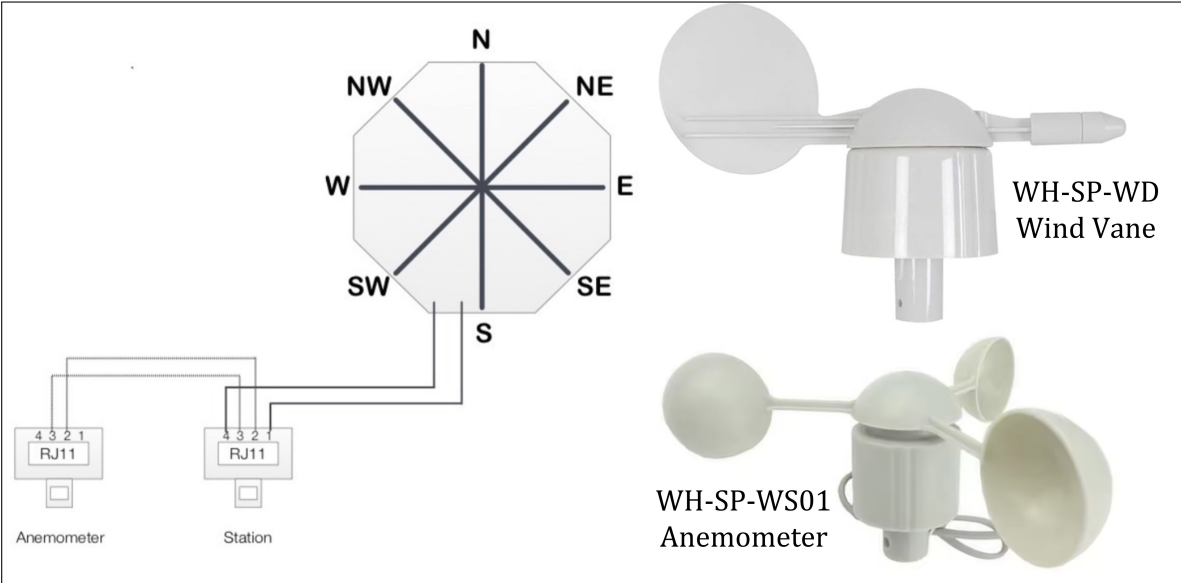


Figure 13. Wind vane directional sectors and RJ11 routing configuration. The sensor contains eight magnetically actuated switches connected to distinct resistors, allowing discrete angular detection through resistance-based voltage division. The anemometer signal is routed through the wind vane assembly via the same cable interface.

3.3.2. Anemometer Pulse-Based Measurement

The WH-SP-WS01 anemometer measures wind speed using a mechanical cup assembly coupled with a magnetic reed switch. Each full or partial rotation of the cup mechanism generates a pulse as the magnet passes the reed contact. The pulse frequency is directly proportional to wind speed.

The anemometer is electrically integrated into the wind vane module through a specially fitted connector. The RJ11/RJ12 cable connecting the wind vane to the embedded processing unit carries both:

- the analog wind direction signal (resistive voltage divider output), and
- the digital pulse signal generated by the anemometer.

In the proposed hardware configuration, only the two central conductors of the RJ11/RJ12 cable are used for the anemometer signal, while the remaining conductors serve the wind vane resistive network. The anemometer pulse line is connected to a digital interrupt-capable input of the Arduino Nano 33 BLE. Interrupt-driven counting ensures that high-frequency pulse events are captured accurately without polling overhead.

Wind speed is calculated by counting pulse transitions over a predefined time interval and applying the manufacturer-provided conversion factor between pulse frequency and linear wind velocity. This interrupt-based acquisition approach ensures reliable measurement even under rapidly changing wind conditions.

3.3.3. Integrated Signal Acquisition Strategy

The combined routing of wind direction and wind speed through a single cable simplifies mechanical assembly and reduces wiring complexity on the supporting pillar. At the embedded processing layer, the Arduino Nano 33 BLE performs simultaneous analog sampling (for wind direction) and interrupt-driven pulse counting (for wind speed).

This dual acquisition strategy allows:

- real-time wind direction estimation via ADC conversion and lookup mapping,
- precise wind speed measurement through edge-triggered pulse counting,
- minimal power consumption by avoiding continuous polling, and
- scalable integration within the broader TinyML-enabled edge processing framework.

The separation of mechanical sensing from embedded electronics, combined with interrupt-driven acquisition, enhances reliability, reduces signal noise, and ensures stable long-term operation under outdoor environmental conditions.

3.4. Rain Gauge Wiring and Measurement Configuration

Precipitation measurement is performed using the WH-SP-RG tipping-bucket rain gauge. The sensor operates on a self-emptying mechanical principle in which collected rainwater fills one side of a calibrated bucket. When a predefined volume threshold is reached, the bucket tips, empties, and simultaneously actuates an internal magnetic reed switch. This event generates a short-duration electrical pulse corresponding to a fixed rainfall increment.

As illustrated in Figure 14, the rain gauge provides a pulse-based output via an RJ11 connector. The internal reed switch is connected to the two middle pins of the RJ11 plug, forming a normally-open contact. When the bucket tips, the contact momentarily closes, generating a digital pulse detectable by a microcontroller.

In the proposed architecture, the two central conductors of the RJ11 cable are connected to an interrupt-capable digital input pin of the Arduino Nano 33 BLE. One conductor is referenced to ground, while the second is connected to the input configured with an internal pull-up resistor. Under idle conditions, the input remains in a logic HIGH state. During a tipping event, the reed switch closes and pulls the line to ground, producing a falling-edge interrupt.

This interrupt-driven configuration enables accurate pulse detection without continuous polling, reducing computational load and minimizing energy consumption in the solar-powered system.

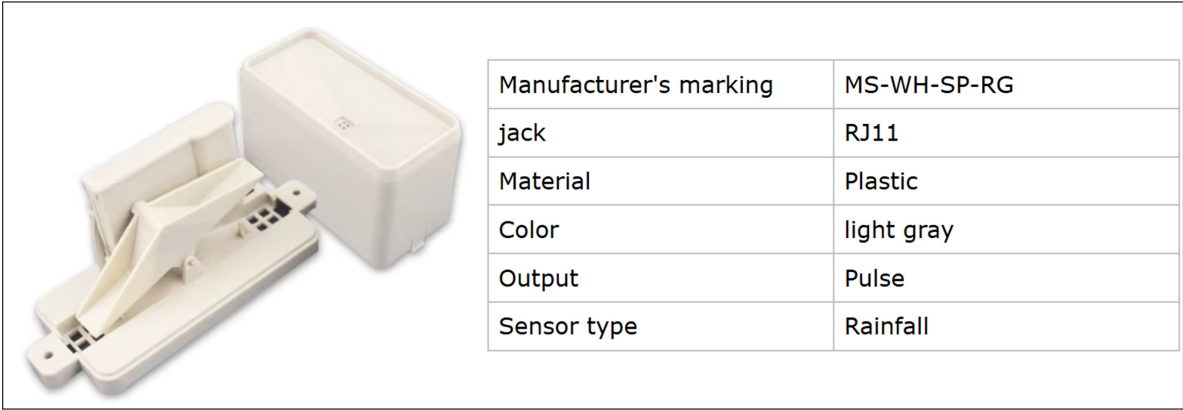


Figure 14. WH-SP-RG tipping-bucket rain gauge used in the proposed environmental monitoring platform. The device provides a reed-switch pulse output through an RJ11 connector, where each tipping event corresponds to approximately 0.2794 mm of accumulated rainfall.

3.4.1. Rainfall Computation Model

Each tipping event corresponds to approximately 0.2794 mm of precipitation according to the manufacturer specification. Let N denote the number of detected pulses within a measurement interval. The accumulated rainfall R (in millimeters) is computed as:

$$R = N \times 0.2794 \text{ mm}$$

(3)

Rainfall intensity (mm/h) is estimated by counting pulses within a defined temporal window and extrapolating to an hourly rate. Cumulative precipitation is obtained by summing incremental measurements over longer observation periods.

The simplicity of the reed-switch pulse interface enhances robustness and long-term reliability under outdoor conditions. Since the output is purely digital, no analog calibration or signal conditioning circuitry is required, making the sensor particularly suitable for low-power IoT deployments.

3.5. Power Management Module

3.5.1. High-Level Design

Long-term autonomous operation represents a critical requirement for distributed environmental monitoring systems deployed in rural or remote locations. To support energy-independent operation, the proposed monitoring platform integrates a solar-powered energy harvesting subsystem combined with battery-based energy storage and charge management circuitry.

The power management architecture of the proposed system is illustrated in Figure 15. The subsystem consists of a photovoltaic solar panel, a solar charge controller, and a rechargeable lithium iron phosphate (LiFePO₄) battery. The solar panel, with selectable power ratings of 10 W, 20 W, or 30 W depending on deployment conditions, converts solar radiation into electrical energy. The generated energy is regulated by a 20 A solar charge controller responsible for managing battery charging cycles, preventing overcharging and deep discharge conditions, and stabilizing power delivery to the sensing and communication modules.

Energy storage is provided by a 12 V LiFePO₄ battery with a nominal capacity of 7.s Ah. LiFePO₄ battery technology was selected due to its improved thermal stability, extended lifecycle, and enhanced safety compared to conventional lithium-ion battery technologies. The battery supplies regulated power to both the Arduino Nano 33 BLE sensing module and the Arduino MKR NB 1500 communication module via USB, ensuring continuous system operation during low solar irradiance periods and nighttime conditions.

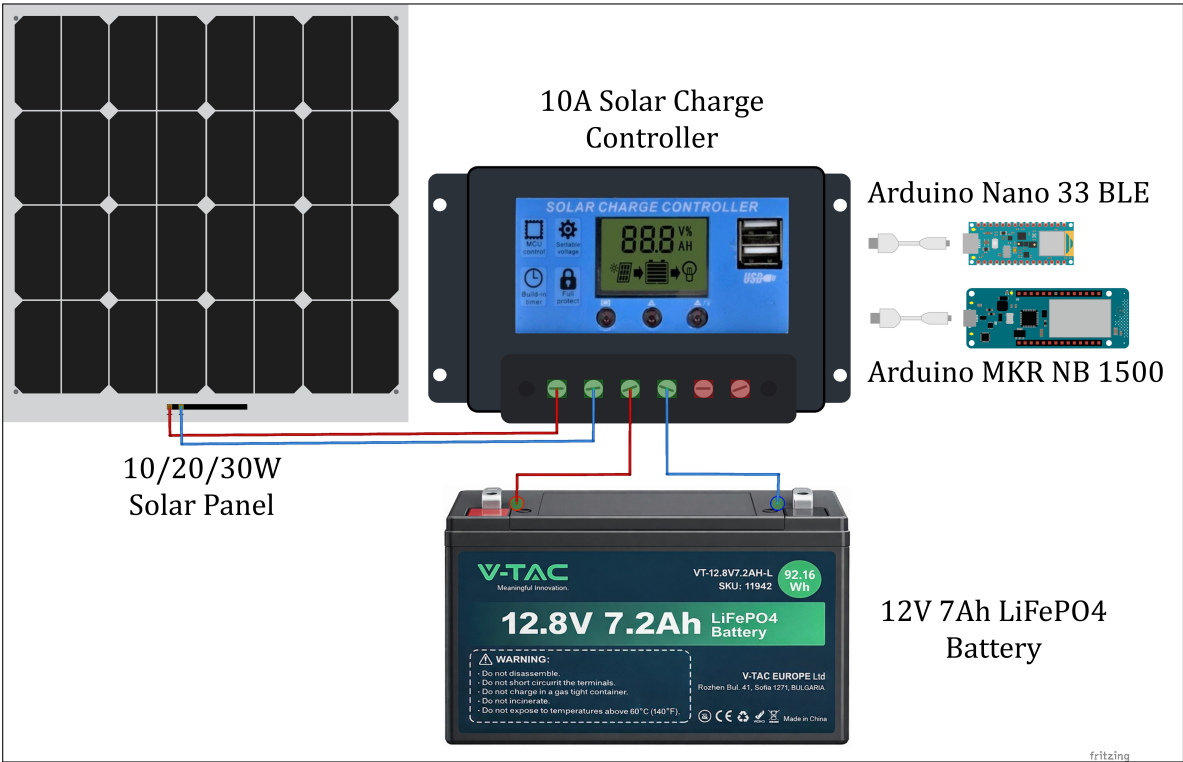


Figure 15. Power management architecture of the proposed monitoring platform. The subsystem integrates a photovoltaic solar panel, charge controller, and LiFePO₄ battery to provide autonomous energy supply for sensing and NB-IoT communication modules.

The power management design prioritizes energy efficiency by enabling low-power operation modes in both microcontroller modules and optimizing data transmission intervals. This approach reduces overall system power consumption while maintaining reliable environmental data acquisition and communication performance. The modular design of the energy subsystem also allows adaptation of solar panel capacity and battery size depending on geographical deployment conditions and seasonal solar radiation availability.

The implemented power management architecture enables long-term autonomous deployment of the environmental monitoring platform while supporting scalable sensing and communication requirements in distributed agricultural and environmental monitoring scenarios.

3.5.2. Winter Energy Risk Analysis and Battery Dimensioning

Although the selected LiFePO₄ battery capacity may appear oversized relative to the average system power consumption, energy storage sizing is primarily influenced by worst-case seasonal operating conditions. In temperate continental climates like Romania, winter operation introduces significant risks related to reduced solar irradiance and sub-zero ambient temperatures, which may affect both solar energy harvesting and battery charging performance.

To evaluate these risks, a machine learning-based temperature prediction model was developed using historical meteorological data for the deployment region. The model estimates hourly ambient temperature trends during winter months, allowing the identification of prolonged freezing periods that may impact system energy availability.

Figure 16 presents the predicted hourly temperature evolution during the winter period between December and February for one of the monitoring locations. The shaded red regions indicate periods where ambient temperature drops below 0°C. During these intervals, LiFePO₄ batteries may experience reduced charging efficiency or charging restrictions due to internal battery protection mechanisms designed to prevent degradation and ensure safe operation.

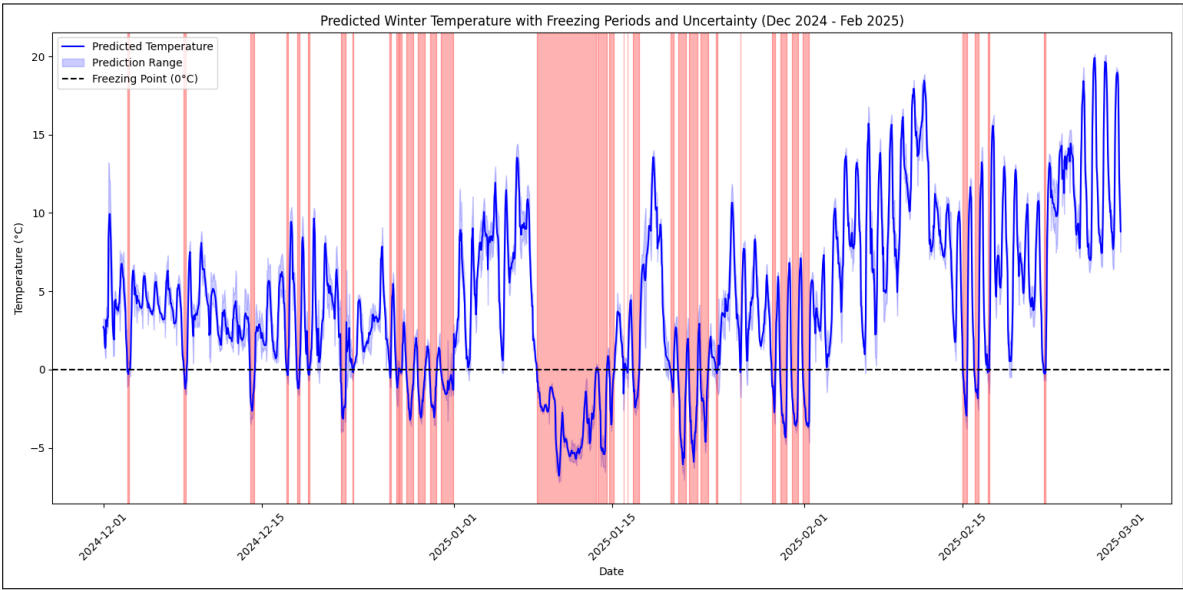


Figure 16. Machine learning-based hourly winter temperature prediction for one deployment location between December 2024 and February 2025. The blue curve represents predicted hourly temperature, while shaded red regions indicate sub-zero temperature intervals where battery charging efficiency may be reduced or temporarily disable due to battery protection constraints.

Extended freezing periods may coincide with reduced solar radiation levels, particularly during overcast weather, snow accumulation on photovoltaic panels, or short daylight intervals typical for winter months. Snow and frost formation may partially or completely obstruct solar panel surfaces, further reducing energy harvesting efficiency. These combined environmental factors increase the probability of prolonged low-energy input conditions. Consequently, sufficient battery capacity is required to maintain uninterrupted system operation during these periods of limited solar energy availability.

It should be noted that the internal temperature within the device enclosure may remain slightly higher than the external ambient temperature due to thermal insulation and heat generated by electronic components. Additionally, advanced battery management strategies, such as temperature-controlled charging protection or low-temperature battery heaters, may further mitigate cold-weather charging limitations.

In addition to temperature-related charging limitations, solar radiation availability during winter months was also evaluated to assess seasonal energy harvesting constraints. Historical solar radiation data and predictive modeling were used to estimate hourly solar irradiance levels during winter deployment periods.

Figure 17 illustrates the predicted hourly solar radiation levels between December 2025 and March 2026 during daylight hours (06:00–18:00). The dashed line represents the median solar radiation level across the analyzed period. The results indicate significant variability in solar irradiance, with extended intervals characterized by low radiation levels caused by overcast weather conditions, reduced solar elevation angles, and shorter daylight durations typical for winter months.

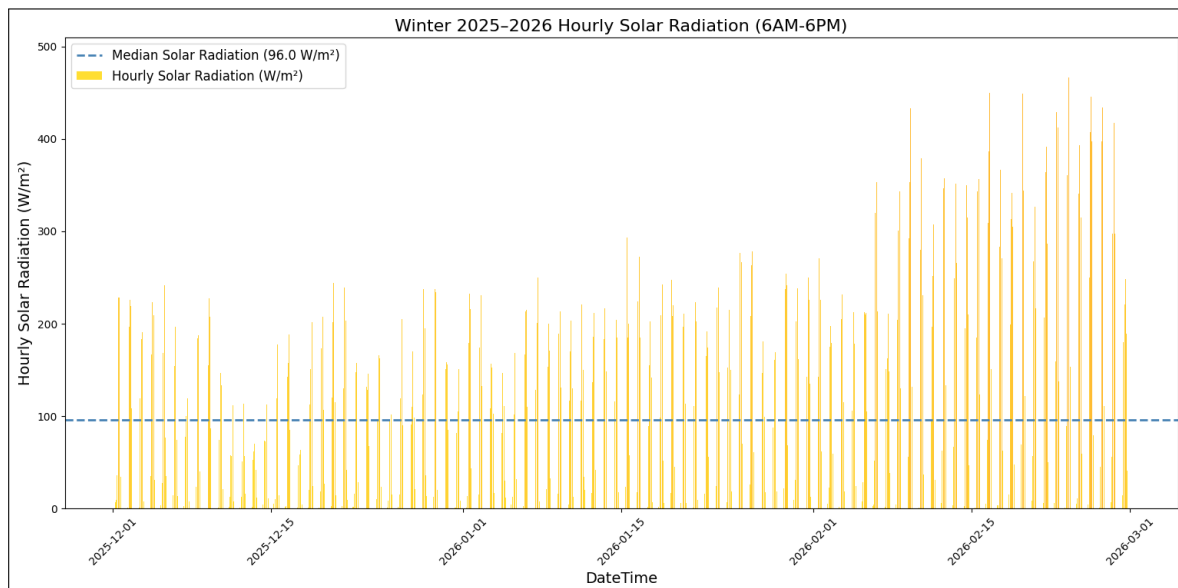


Figure 17. Predicted hourly solar radiation levels during winter months (December 2025 – March 2026) for one deployment location. The dashed line represents the median solar radiation level. The results highlight significant variability and prolonged low-irradiance intervals that may limit photovoltaic energy harvesting during winter operation (see Appendix A.1).

The analysis demonstrates that solar energy harvesting during winter may be highly intermittent and insufficient to fully sustain continuous system operation without adequate energy storage capacity. These findings further justify the selection of a higher-capacity battery to ensure reliable system performance during prolonged periods of reduced solar input.

The combined evaluation of temperature constraints and seasonal solar radiation variability enables risk-aware battery dimensioning and supports reliable long-term autonomous operation of the environmental monitoring platform under challenging winter environmental conditions.

3.5.3. Charge Regulation and Power Distribution

To regulate charging and ensure stable power delivery, the platform employs a 10 A PWM solar charge controller in a 12 V battery system. The current rating (10 A) represents the controller's maximum supported battery-side charge current, i.e., the upper bound of charging current delivered to the battery under peak photovoltaic (PV) input conditions.

For PWM controllers, the PV array is effectively operated close to the battery charging voltage during the bulk charging phase. Therefore, the maximum supported PV power can be approximated as

$$P_{\max} \approx I_{\max} \cdot V_{\text{chg}}, \quad (4)$$

where $I_{\max}$ is the controller current rating and V_{chg} is the battery charging voltage. For LiFePO₄ batteries, a typical charging voltage is $V_{\text{chg}} \approx 14.2$ V (depending on battery management system constraints and charging profile). With $I_{\max} = 10$ A, the theoretical upper PV power limit is

$$P_{\max} \approx 10 \cdot 14.2 \approx 142 \text{ W}. \quad (5)$$

In practice, conversion losses, temperature effects, and irradiance variability reduce available power; thus, PV sizing below this limit is recommended for robust operation.

Given a PV rated power P_{PV} , the idealized battery charge current during bulk charging can be estimated as

$$I_{\text{chg}} \approx \min\left(\frac{P_{\text{PV}}}{V_{\text{chg}}}, I_{\max}\right). \quad (6)$$

For the PV modules supported by the proposed platform (10/20/30 W), the expected peak charging currents are approximately:

$$I_{\text{chg}}(10\text{W}) \approx \frac{10}{14.2} \approx 0.70 \text{ A}, \quad (7)$$

$$I_{\text{chg}}(20\text{W}) \approx \frac{20}{14.2} \approx 1.41 \text{ A}, \quad (8)$$

$$I_{\text{chg}}(30\text{W}) \approx \frac{30}{14.2} \approx 2.11 \text{ A}, \quad (9)$$

which remain well below the 10 A controller limit.

In addition to controller limits, battery charging stress is commonly expressed using the C-rate, defined as

$$C_{\text{rate}} = \frac{I_{\text{chg}}}{C_{\text{Ah}}}, \quad (10)$$

where I_{chg} is the battery charge current and C_{Ah} is the nominal battery capacity in ampere-hours. Higher C-rates generally imply faster charging but may increase thermal and electrochemical stress depending on the battery chemistry and battery management system (BMS) constraints.

To illustrate the influence of battery capacity on charge stress under worst-case controller output, Figure 18 shows the theoretical C-rate if the controller were to deliver its full rated current ($I_{\text{max}} = 10 \text{ A}$). For small battery capacities, the implied C-rate increases rapidly, motivating the use of moderate charge currents and/or sufficiently sized storage for long-term outdoor deployments.

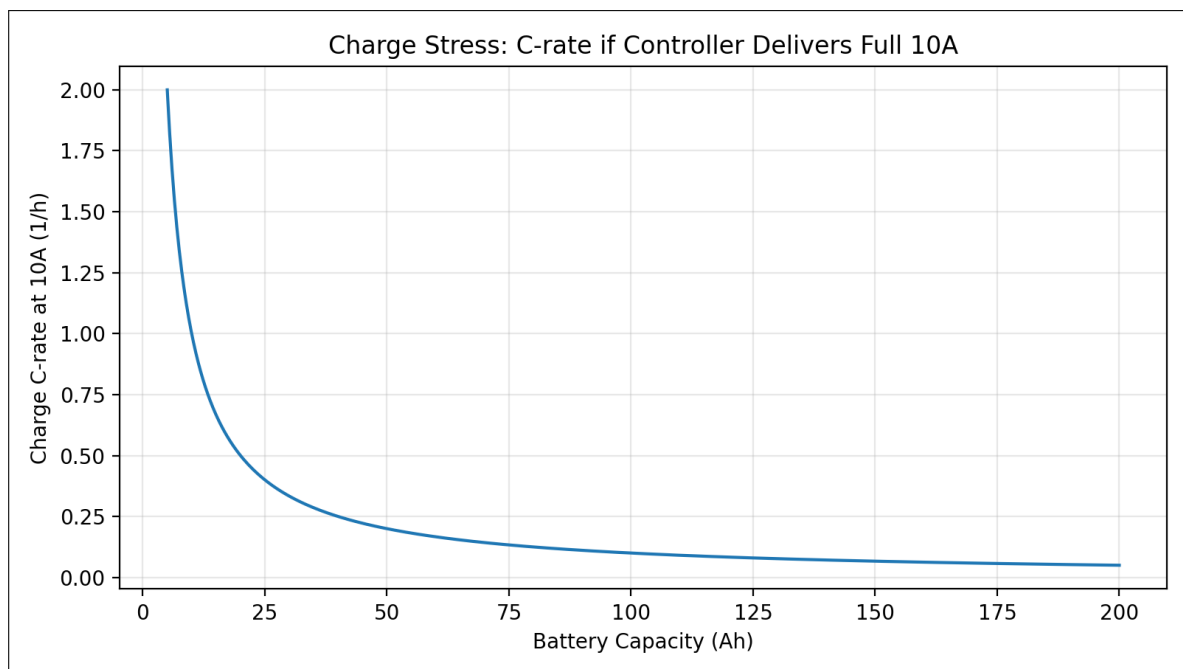


Figure 18. Charge stress expressed as C-rate if the PWM charge controller delivers its full rated current ($I_{\text{max}} = 10 \text{ A}$). Smaller battery capacities correspond to higher implied C-rates.

A joint feasibility view relating PV sizing and battery capacity is presented in Figure 19. The figure maps the implied C-rate under ideal peak irradiance as a function of PV rated power and battery capacity (up to 50 Ah), while the vertical boundary indicates the maximum PV power beyond which the 10 A controller current limit would be exceeded under idealized conditions. In practice, winter irradiance variability, panel temperature effects, and conversion losses reduce effective charge current; however, the map provides a conservative design guideline for selecting PV and battery combinations that remain within controller limits and avoid excessive charge stress.

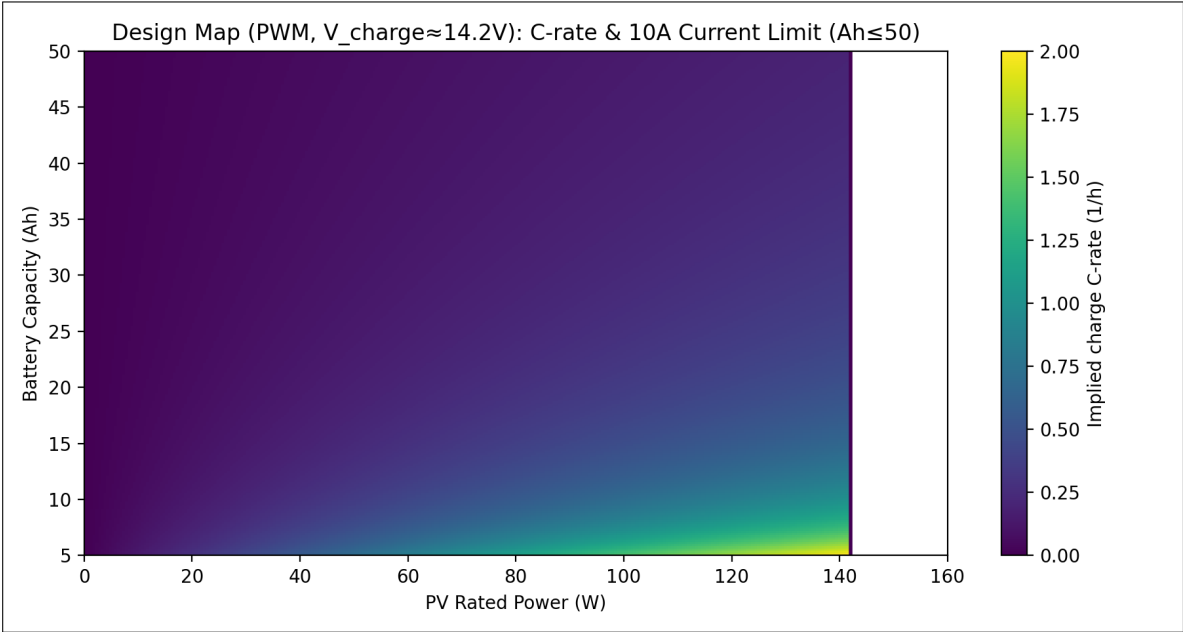


Figure 19. Design map for a 10 A PWM controller in a 12 V LiFePO₄ system ($V_{\text{chg}} \approx 14.2$ V), showing implied charging C-rate as a function of PV rated power and battery capacity (up to 50 Ah). The boundary indicates the theoretical PV power above which the controller charge current limit (10 A) would be exceeded under ideal peak conditions.

For the proposed system configuration, the selected PV modules (10–30 W) generate peak charging currents between approximately 0.7 A and 2.1 A. When combined with the selected 12 V 7.2 Ah LiFePO₄ battery, the resulting charge stress corresponds to an approximate C-rate of $C_{\text{rate}} \approx 2.1/7.2 \approx 0.29\text{C}$ under ideal peak charging conditions. This charging level remains well within the typical recommended operating range for LiFePO₄ batteries, ensuring safe and reliable battery operation.

These results confirm that battery stress is primarily governed by effective charging current rather than photovoltaic power alone. Proper controller current limiting and conservative PV sizing represent essential design strategies for protecting low-capacity LiFePO₄ batteries in autonomous solar-powered IoT deployments.

Finally, PV module voltage constraints must satisfy the controller’s PV input voltage limit (maximum open-circuit voltage, $V_{\text{OC,max}}$), as specified by the manufacturer. In 12 V PWM systems, “12 V nominal” PV panels (typically $V_{\text{mp}} \approx 17\text{--}18$ V) are commonly used to ensure effective charging at V_{chg} while maintaining safe voltage margins under cold-weather increases in V_{OC} .

3.6. Cloud Database Architecture and Data Management

To support scalable storage, device management, and real-time data visualization, a relational database was deployed in the cloud using MySQL and administered via phpMyAdmin. The database schema was designed to ensure referential integrity, efficient time-series querying, and multi-user device management. The entity-relationship (ER) structure of the system is illustrated in Figure 20.

Users Table. The users table stores authentication and role information for dashboard access. Each user record contains a unique id, username, email, a password_hash and a role field (admin or user). Indexes on username and email ensure efficient login queries. This design supports multi-user management of deployed monitoring devices.

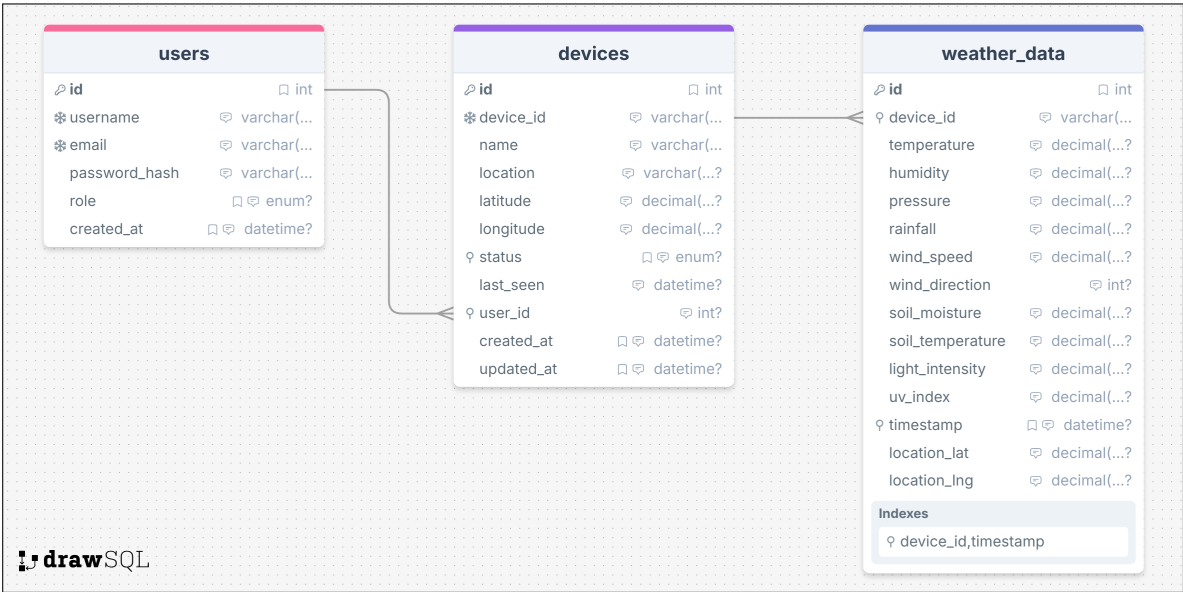


Figure 20. Entity-relationship diagram of the cloud database deployed in MySQL. The schema includes three main entities: `users`, `devices`, and `weather_data`, with foreign-key constraints ensuring referential integrity between device ownership and time-series measurements.

Devices Table. The `devices` table maintains metadata for each deployed weather station. Each device is identified by a globally unique `device_id` (UUID string), along with descriptive fields such as `name`, `location`, GPS coordinates (`latitude`, `longitude`), operational status, and `last_seen` timestamp.

A foreign key constraint links `devices.user_id` to `users.id`, implementing a one-to-many relationship where a single user can manage multiple devices. The `ON DELETE SET NULL` rule ensures that devices remain stored even if a user account is removed, preserving historical data consistency.

Weather Data Table (Time-Series Core). The `weather_data` table represents the central time-series storage component of the system. Each record corresponds to a single measurement timestamp and contains:

- Atmospheric variables: temperature, humidity, pressure
- Precipitation and wind parameters: rainfall, wind speed, wind direction
- Soil measurements: soil moisture, soil temperature
- Solar-related parameters: light intensity, UV index
- GPS coordinates at measurement time

Each measurement is linked to a specific device via a foreign key constraint referencing `devices.device_id`. The `ON DELETE CASCADE` rule ensures that removing a device automatically removes its associated measurements, preventing orphaned records.

To optimize analytical and dashboard queries, composite indexing was implemented:

- `INDEX (device_id, timestamp)` for fast retrieval of time-series data per device
- `INDEX (timestamp)` for chronological queries

This structure enables efficient filtering for operations such as:

- Retrieving the latest data point per device
- Aggregating daily or monthly statistics
- Exporting winter datasets for machine learning pipelines

Design Rationale. The relational design was selected over a NoSQL approach due to:

- Strong referential integrity requirements between users, devices, and measurements
- Structured meteorological schema with consistent measurement types
- Efficient indexing for time-series queries

- Compatibility with phpMyAdmin and shared-hosting cloud environments

By separating device metadata from high-frequency measurement data, the system ensures scalability for long-term deployments while maintaining efficient query performance. The schema supports both real-time monitoring and historical data extraction for downstream analytics and Machine Learning model training.

Furthermore, the designed relational database schema is fully integrated with a cloud-based web application that enables real-time data access, visualization, device management, and AI-driven analytics. As illustrated in Figures A2, A3, A4, the platform provides a centralized *Dashboard* for system-level monitoring, a *Weather Data* module for structured tabular access to time-series measurements, and a *Data Collectors* interface for managing field-deployed devices, including their operational status, connectivity metrics (e.g., RSSI), and last communication timestamps.

In addition, dedicated analytics modules such as *Weather Insights*, *Agricultural Insights*, and *Green Energy Insights* enable the integration and deployment of Machine Learning algorithms for predictive modeling, anomaly detection, and domain-specific decision support. Detailed implementation aspects of the web application architecture, user management, device orchestration mechanisms, and interface components are provided in Appendix B. This modular cloud architecture ensures seamless interaction between edge devices, centralized storage, and AI services, thereby supporting scalable deployment of intelligent environmental monitoring systems across multiple industries.

4. Results

4.1. NB-IoT Signal Strength Evaluation in Field Deployment

To evaluate the communication reliability of the proposed environmental monitoring platform, field measurements of Received Signal Strength Indicator (RSSI) levels were collected during Data Collector deployment in Sânnandrei, Timiș County, Romania.

Figure 21 presents the statistical distribution of NB-IoT RSSI measurements recorded by the deployed monitoring node. A total of 4,306 signal strength readings were collected during routine environmental data transmissions. The measured RSSI values ranged from -93 dBm to -57 dBm, with an average RSSI of -75.51 dBm and a median RSSI of -77 dBm.

The histogram distribution indicates that the majority of RSSI measurements fall within the interval between -85 dBm and -71 dBm. Approximately 36.9% of the measurements were concentrated within the -80 dBm to -76 dBm range, while 23.8% of the samples were recorded between -75 dBm and -71 dBm. These signal strength intervals correspond to good to excellent NB-IoT connectivity levels according to commonly accepted cellular signal quality classifications.

Lower signal strength intervals, categorized as fair or weak communication conditions (below -90 dBm), were rarely observed, representing less than 1% of the total measurements. No measurements were recorded within the very poor signal strength range below -113 dBm, indicating stable network coverage at the deployment location.

The observed RSSI distribution confirms that the NB-IoT connectivity provides sufficient link reliability for periodic environmental data transmission using low-power communication intervals. Stable signal conditions also reduce retransmission overhead, contributing to improved energy efficiency of the solar-powered monitoring system.

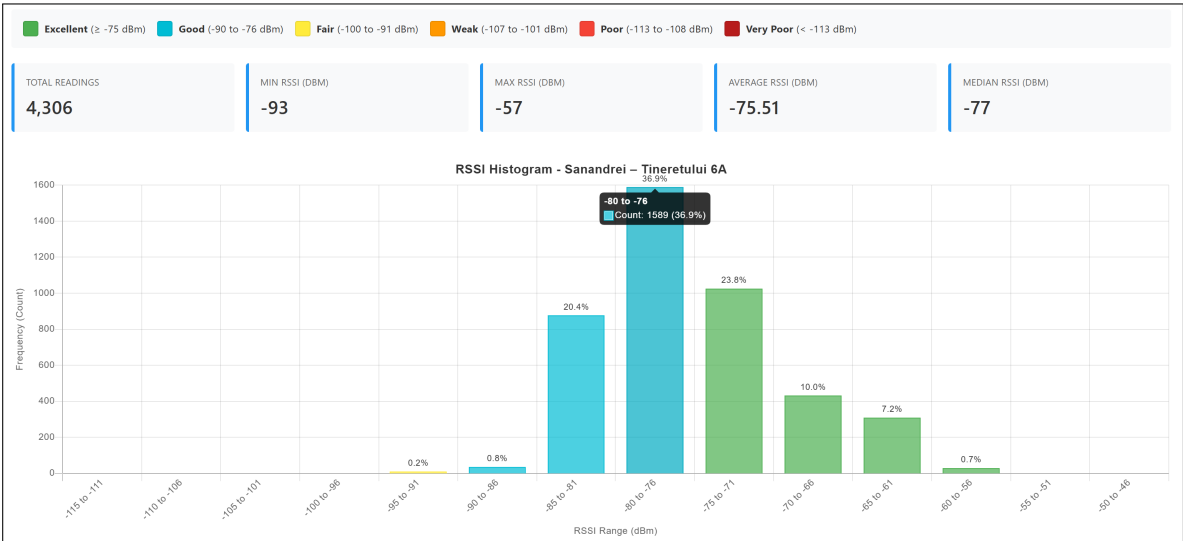


Figure 21. Distribution of NB-IoT (Orange LTE-M) RSSI measurements collected during field deployment in Sănandrei, Timiș County, Romania. The histogram shows signal strength frequency distribution and statistical indicators including minimum, maximum, average, and median RSSI values.

Furthermore, the collected RSSI dataset provides valuable insights for future adaptive communication strategies. Signal strength statistics can be used to dynamically adjust transmission intervals, optimize modem power states, or support machine learning-based communication scheduling to further extend battery autonomy during adverse environmental or network conditions.

4.2. Microclimate Analysis: Comparison with Regional Weather Station Data

To validate the performance of the IoT data collector and assess microclimate variations, the measurements from the backyard installation (2 m altitude) were compared with data from the official weather station in Sanandrei (10 m altitude) for the period from January 16 to January 31, 2026. The weather station data, obtained from Visual Crossing, represents standard meteorological measurements at 10 m height, while the data collector captures local microclimate conditions at 2 m elevation within a residential backyard environment characterized by surrounding houses, trees, and garden vegetation.

During this observation period, the temperature, humidity, and pressure sensors were positioned outside the data collector enclosure, directly exposed to ambient air at 2 m altitude. This sensor placement represents an improvement over earlier configurations where sensors were housed inside the collector case with only a ventilation hole, as direct exposure ensures more accurate measurement of ambient conditions and better agreement with standard meteorological measurements.

Hourly data points were extracted from the 15-minute interval collector dataset (filtering for measurements where minute equals zero) and matched with corresponding hourly weather station observations. This temporal alignment enabled direct comparison of temperature, relative humidity, and atmospheric pressure between the two measurement locations.

4.2.1. Temperature Comparison

Figure 22 presents the temperature comparison between the backyard data collector and the weather station. The analysis reveals a mean temperature difference of -0.71°C (collector minus station), with a standard deviation of 1.05°C, indicating that the backyard location was, on average, slightly cooler than the regional weather station. The temperature differences ranged from -3.90°C to 4.10°C, demonstrating temporal variability in the microclimate conditions.

The observed variations can be attributed to several microclimate factors:

- (1) the lower measurement height (2 m vs. 10 m) which places the sensor closer to the ground surface, potentially experiencing stronger radiative cooling effects during nighttime and reduced solar heating during daytime;

- (2) the sheltered location among buildings and vegetation, which may create localized cooling effects through shading and reduced wind exposure;
- (3) the proximity to ground-level heat sources and sinks, including soil thermal properties and vegetation evapotranspiration.

Despite these local variations, the temperature measurements from the backyard data collector demonstrate a strong temporal correlation with the regional weather station data, following the same diurnal and synoptic patterns. The collector’s temperature profile closely tracks the weather station’s temperature evolution throughout the observation period, confirming that the device accurately captures the underlying meteorological trends. The observed differences, which remain within the standard deviation range of -3.90°C to 4.10°C , can be attributed to local microclimate factors such as shading from surrounding structures, ground-level thermal effects, and reduced wind exposure, rather than systematic measurement errors. This alignment validates the data collector’s capability to monitor local environmental conditions while maintaining consistency with regional weather patterns.

4.2.2. Humidity Comparison

The relative humidity comparison, shown in Figure 23, demonstrates a mean difference of 4.98% (collector minus station), with a standard deviation of 5.95% and a range from -10.99% to 24.45%. The positive mean difference indicates that the backyard location was, on average, more humid than the weather station measurements. The variability in humidity differences reflects the complex interactions between local vegetation, soil moisture, and micro-scale atmospheric processes.

The higher average humidity at the backyard location may result from several factors:

- (1) reduced air circulation due to the sheltered positioning among buildings and vegetation, which may trap moisture near the ground;
- (2) local evapotranspiration patterns from garden vegetation that may create micro-scale humidity gradients;
- (3) the influence of surrounding structures which may affect local air circulation and moisture distribution.

The range of differences (over 35 percentage points) highlights the importance of microclimate monitoring, as local conditions can deviate significantly from regional averages, particularly in heterogeneous environments with mixed land cover.

The solid blue line in Figure 22 represents measurements from the IoT data collector with sensors directly exposed to ambient air, while the dashed red line shows data from the official weather station. The collector’s temperature profile closely tracks the weather station’s temporal patterns, demonstrating excellent agreement (mean difference: -0.71°C , $\sigma = 1.05^{\circ}\text{C}$) with local microclimate variations resulting in differences within the range of -3.90°C to 4.10°C .

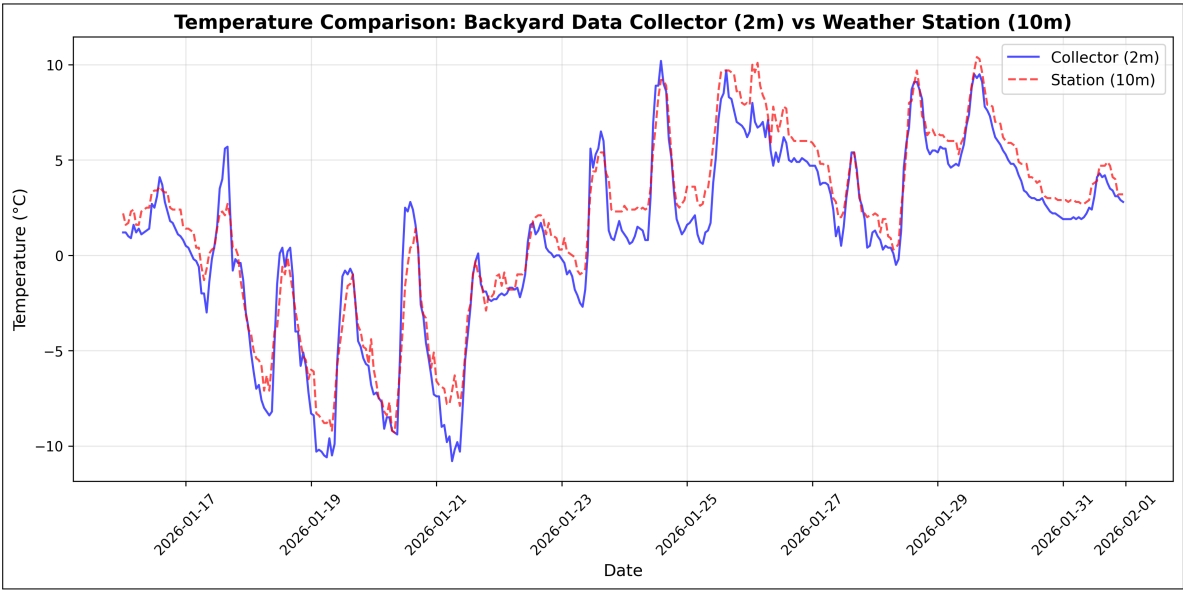


Figure 22. Temperature comparison between the data collector (2 m altitude) and the regional weather station (10 m altitude) in Sanandrei, Romania, from January 16 to 31, 2026.

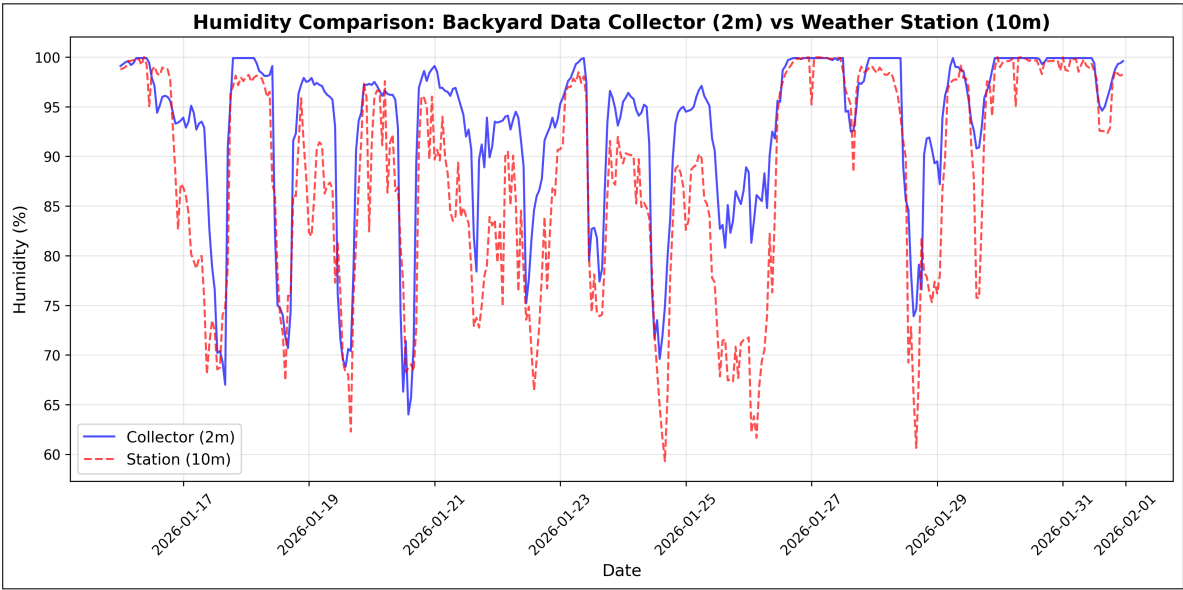


Figure 23. Relative humidity comparison between the data collector (2 m altitude) and the regional weather station (10 m altitude) in Sanandrei, Romania, from January 16 to 31, 2026.

The solid blue line in Figure 23 represents measurements from the IoT data collector with sensors directly exposed to ambient air, while the dashed red line shows data from the official weather station. The mean difference of 4.98% (collector minus station) with a standard deviation of 5.95% reflects local microclimate influences from surrounding vegetation and built structures, with the improved sensor placement ensuring accurate measurement of ambient conditions.

4.2.3. Pressure Comparison

Figure 24 illustrates the atmospheric pressure comparison between the two measurement locations. The analysis shows a consistent negative pressure difference with a mean of -9.58 hPa (standard deviation: 0.28 hPa), ranging from -10.38 hPa to -8.93 hPa. This systematic offset is primarily attributed to the 8 m altitude difference between the two sensors (2 m vs. 10 m), as atmospheric pressure decreases with elevation according to the barometric formula.

The solid blue line in Figure 24 represents measurements from the IoT data collector with sensors directly exposed to ambient air, while the dashed red line shows data from the official weather station. The consistent offset of approximately -9.58 hPa is primarily attributed to the 8 m altitude difference between the two measurement locations, with minimal temporal variation ($\sigma = 0.28\text{ hPa}$) confirming both sensor calibration accuracy and the effectiveness of direct sensor exposure.

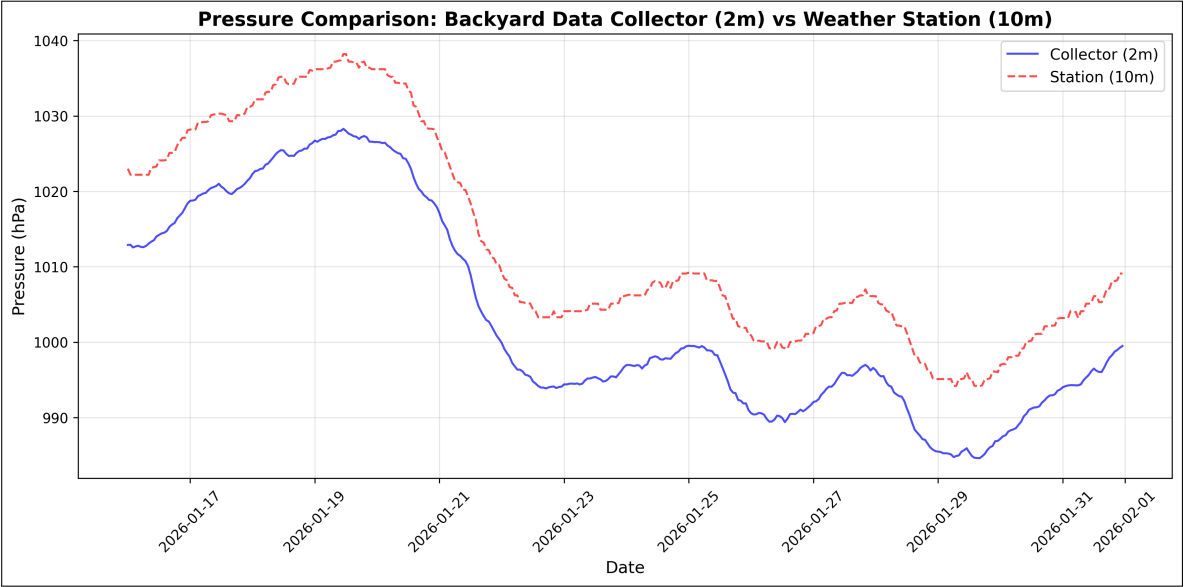


Figure 24. Atmospheric pressure comparison between the data collector (2 m altitude) and the regional weather station (10 m altitude) in Sanandrei, Romania, from January 16 to 31, 2026.

The small standard deviation (0.28 hPa) indicates that the pressure difference remained remarkably stable throughout the observation period, confirming that the offset is predominantly due to the altitude difference rather than measurement error or local pressure anomalies. This consistency validates the pressure sensor calibration and demonstrates that, when corrected for altitude, the data collector provides reliable atmospheric pressure measurements that align with regional weather station data.

4.3. Cost-Effective Sensor Performance and Validation

A key objective of this research was to demonstrate that accurate microclimate monitoring can be achieved using low-cost, commercially available sensors. The hardware components selected for the IoT data collector represent the most economical options available on the market, with a total system cost of $\text{€}315.00$ (Table 1). Despite the minimal investment, the validation results demonstrate that these budget sensors provide measurements of exceptional quality that closely match those from professional weather station equipment.

The pressure sensor performance provides particularly compelling evidence of the system’s accuracy. As shown in Figure 24, the atmospheric pressure measurements from the data collector follow the weather station’s pressure patterns with remarkable precision. The temporal evolution of pressure, including subtle variations and minor fluctuations, is captured with such fidelity that the two datasets appear nearly indistinguishable when overlaid, differing only by the consistent altitude-related offset of approximately -9.58 hPa ($\sigma = 0.28\text{ hPa}$). This exceptional agreement validates that even the most economical pressure sensors (BMP280, $\text{€}7.00$) can deliver professional-grade measurements when properly calibrated and positioned.

Similarly, the temperature and humidity sensors (DHT22, $\text{€}12.00$) demonstrate excellent performance, with mean differences of -0.71°C ($\sigma = 1.05^{\circ}\text{C}$) and 4.98% ($\sigma = 5.95\%$) respectively, compared to the regional weather station. These small differences are primarily attributable to genuine microclimate variations between the 2 m backyard location and the 10 m weather station height, rather than

sensor limitations. The strong temporal correlation observed across all parameters confirms that the low-cost sensor suite accurately captures both diurnal patterns and synoptic-scale weather variations.

The validation results demonstrate that cost-effective sensor solutions can achieve measurement quality comparable to professional meteorological equipment, making distributed microclimate monitoring economically viable for agricultural applications. This finding is particularly significant for precision agriculture, where the deployment of multiple monitoring stations across fields requires affordable yet reliable sensing technology.

Table 1. Hardware cost breakdown of the proposed AI-ready NB-IoT data collector.

Item	Description	Price
MCU & COMM		
Arduino Nano 33 BLE	EdgeAI-capable light-weight sensor controller	€31.00
MKR NB 1500	NB-IoT Data transmission module	€80.00
Dipole Pentaband Antenna	MKR NB 1500 Antenna	€6.00
SENSORS		
Weather station	Mechanical part	€50.00
Thermo/hygro sensor	Thermo hygro sensor case	€20.00
DHT22	Temperature & humidity	€12.00
BMP280	Barometric pressure sensor	€7.00
POWER MANAGEMENT		
30W Solar Panel	Breckner Germany, 440×425×45 mm	€12.00
Solar Charge Controller	12/24V, 20A, 2× USB ports	€5.00
2× LiFePo4 Battery 7Ah	V-TAC SKU-11942 12.8V 7.2Ah	€30.00
CASINGS		
Distribution Panel	Starke ST01411 30×20×13 cm IP65	€11.00
Battery Case	Starke ST01438 30×40×17 cm IP65	€35.00
Sonoff case	UV & light sensors	€5.00
WIRING & CONNECTORS		
Cable RJ12 6P6C	1× Cable Rj12 6 wires for DHT22 & BMP280	€3.00
Connector PIC-ICSP	2× OLIMEX-ICSP, OLIMEX-ICSP-mini and MICROCHIP-RJ11	€8.00
Total		€315.00

5. Limitations

5.1. Limitations of Temperature and Humidity Measurement

Although the DHT22 sensor provides a cost-effective solution for environmental monitoring, several limitations must be considered in long-term autonomous deployments.

5.1.1. Humidity Long-Term Drift

According to the manufacturer specifications, the DHT22 exhibits a long-term humidity stability of approximately ±0.5%RH per year. Assuming a conservative worst-case linear accumulation model, the total humidity error after *N* years can be approximated as:

$$E_{N,RH} = E_{0,RH} + N \cdot D_{RH}$$

(11)

where *E*_{0,RH} represents the initial accuracy (typically ±2%RH at 25°C) and *D*_{RH} = 0.5%RH/year denotes the annual drift.

After five years, the worst-case accumulated humidity error becomes:

$$E_{5,RH} = \pm(2\% + 5 \times 0.5\%) = \pm4.5\%RH$$

(12)

Such cumulative deviation may influence long-term humidity trend analysis, irrigation control thresholds, and disease prediction models that rely on precise relative humidity estimation.

5.1.2. Estimated Temperature Long-Term Drift

The DHT22 datasheet does not explicitly specify long-term temperature stability. However, considering its initial temperature accuracy of approximately $\pm 0.5^{\circ}\text{C}$ and its sensor grade, a conservative engineering approximation assumes a temperature drift on the order of:

$$D_T \approx 0.05^{\circ}\text{C}/\text{year} \tag{13}$$

Under a worst-case linear accumulation assumption:

$$E_{5,T} = \pm(0.5^{\circ}\text{C} + 5 \times 0.05^{\circ}\text{C}) = \pm 0.75^{\circ}\text{C} \tag{14}$$

Although sub-degree drift remains acceptable for general environmental monitoring, gradual bias accumulation may affect multi-year datasets used for machine learning model training, particularly in applications sensitive to subtle temperature variations.

5.1.3. Implications for Long-Term Environmental Monitoring

In extended deployments, cumulative sensor drift may lead to:

- gradual offset bias in humidity and temperature records,
- artificial long-term trend distortion,
- reduced precision in threshold-based control strategies,
- decreased robustness of ML models trained on absolute measurements.

For applications primarily relying on relative changes or short-term dynamics, the DHT22 remains suitable for cost-effective monitoring. Nevertheless, periodic cross-validation with reference meteorological data or software-based drift compensation strategies should be considered in multi-year intelligent sensing systems.

Figure 25 illustrates the projected long-term degradation of temperature and humidity accuracy for the DHT22 sensor over a five-year deployment period under a conservative linear drift assumption. The temperature accuracy is assumed to degrade from an initial $\pm 0.5^{\circ}\text{C}$ to approximately $\pm 0.75^{\circ}\text{C}$ after five years, based on an estimated drift of $\pm 0.05^{\circ}\text{C}/\text{year}$. Similarly, humidity accuracy is assumed to degrade from an initial $\pm 2\%\text{RH}$ to approximately $\pm 4.5\%\text{RH}$ after five years, based on the specified long-term stability of $\pm 0.5\%\text{RH}/\text{year}$.

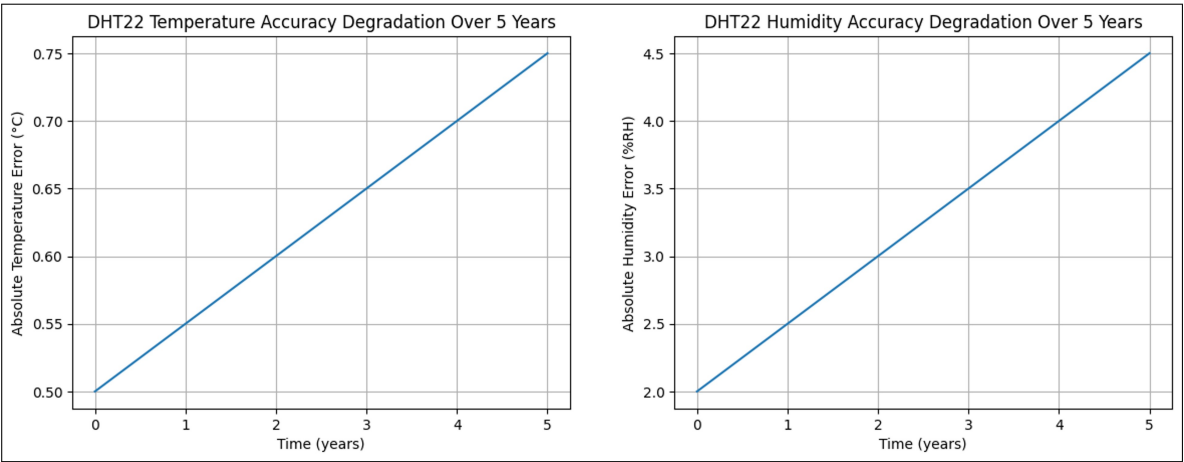


Figure 25. Projected five-year linear accuracy degradation of the DHT22 sensor. Left: Temperature absolute error growth from $\pm 0.5^{\circ}\text{C}$ to $\pm 0.75^{\circ}\text{C}$ assuming $\pm 0.05^{\circ}\text{C}/\text{year}$ drift. Right: Humidity absolute error growth from $\pm 2\%\text{RH}$ to $\pm 4.5\%\text{RH}$ assuming $\pm 0.5\%\text{RH}/\text{year}$ drift. The plots illustrate the potential long-term uncertainty accumulation in autonomous multi-year deployments.

5.2. Limitations of Atmospheric Pressure Measurement

Although the BMP280 sensor provides reliable and cost-effective barometric pressure measurements suitable for environmental monitoring, several accuracy and long-term stability considerations must be acknowledged.

According to the manufacturer specifications (Figure 12), the absolute pressure accuracy of the BMP280 varies depending on the pressure and temperature operating range. Within the 700–900 hPa interval at 25–40°C, the typical accuracy is approximately ± 0.12 hPa (equivalent to approximately ± 1 m altitude). However, within the 950–1050 hPa range at 0–40°C, corresponding to typical sea-level atmospheric conditions, the accuracy decreases to approximately ± 1 hPa. This error margin corresponds to an altitude uncertainty of approximately ± 8 – ± 9 m when applying the barometric formula.

While such deviations are acceptable for short-term meteorological trend monitoring, they may introduce bias when high-precision altitude normalization or pressure-gradient analysis is required. In particular, when comparing measurements across distributed nodes deployed at slightly different elevations, accumulated systematic offsets could impact cross-station consistency if not properly calibrated.

In addition to instantaneous accuracy limits, the BMP280 exhibits a specified long-term stability of approximately ± 1 hPa per year. This drift corresponds to a gradual altitude-equivalent deviation of roughly ± 8 m per year. For short-term environmental monitoring, this drift is generally negligible. However, in long-term deployments extending across multiple years, cumulative drift may introduce systematic bias into historical datasets.

Such drift can be particularly relevant for machine learning applications. Supervised learning models trained on multi-season pressure data may implicitly learn sensor-specific offsets rather than purely atmospheric dynamics. In distributed deployments, heterogeneous drift behavior across multiple nodes could lead to model inconsistencies if pressure values are used as direct predictive features. Therefore, periodic recalibration against a trusted reference (e.g., nearby meteorological stations or known altitude correction models) is recommended.

Furthermore, temperature-dependent accuracy variation may influence pressure readings during seasonal transitions. Although the BMP280 incorporates internal temperature compensation, residual thermal effects can still contribute to small deviations, especially under rapid ambient temperature changes or enclosure-induced thermal gradients.

To mitigate these limitations in future deployments, several strategies can be adopted:

- Periodic cross-calibration using regional meteorological reference data.
- Altitude normalization using standardized barometric correction models.
- Drift-aware preprocessing pipelines before ML training.
- Feature engineering strategies that emphasize pressure gradients rather than absolute values.

While the BMP280 provides a cost-effective and sufficiently accurate solution for trend-based environmental monitoring, future system iterations should investigate higher-accuracy barometric sensors with improved long-term stability characteristics. Sensors offering lower absolute pressure error margins and reduced annual drift may enhance reliability in multi-year deployments and distributed sensing networks. Additionally, the integration of automatic or semi-automatic calibration strategies, such as periodic cross-referencing with regional meteorological stations, GNSS-assisted altitude normalization, or adaptive model-based offset correction, could further mitigate long-term drift effects. Such enhancements would be particularly beneficial for Machine Learning applications, where cumulative systematic bias may influence model training and long-horizon prediction performance.

Although the BMP280 sensor provides cost-effective and stable short-term barometric pressure measurements, long-term accuracy degradation must be considered in multi-year deployments. According to the manufacturer's specifications, the absolute pressure accuracy varies depending on the pressure and temperature range. In the 700–900 hPa interval at 25–40°C, the typical accuracy is approximately ± 0.12 hPa, while in the 950–1050 hPa range at 0–40°C, corresponding to typical

sea-level conditions, the accuracy decreases to approximately ± 1 hPa. In addition, the specified long-term stability is approximately ± 1 hPa per year.

5.2.1. Worst-Case Linear Drift Model

Assuming a conservative worst-case scenario in which long-term drift accumulates linearly over time, the total absolute pressure error after N years can be approximated as:

$$E_{N,\text{worst}} = E_0 + N \cdot D \quad (15)$$

where E_0 represents the initial absolute accuracy (hPa) and D denotes the annual drift (hPa/year).

For $E_0 = \pm 1$ hPa and $D = \pm 1$ hPa/year, the worst-case accumulated error after five years becomes:

$$E_{5,\text{worst}} = \pm(1 + 5) = \pm 6 \text{ hPa} \quad (16)$$

Using the barometric approximation near sea level, where 1 hPa corresponds to approximately 8–9 m of altitude variation, this translates into an altitude-equivalent uncertainty of approximately ± 48 – ± 54 m after five years.

5.2.2. Stochastic Drift Model

In practice, long-term sensor drift may not accumulate strictly linearly but instead behave as a bounded random process. Assuming drift follows a random-walk model, the expected accumulated deviation can be approximated as:

$$E_{N,\text{typ}} \approx E_0 + D\sqrt{N} \quad (17)$$

For $N = 5$ years and $D = 1$ hPa/year:

$$E_{5,\text{typ}} \approx \pm(1 + \sqrt{5}) \approx \pm 3.24 \text{ hPa} \quad (18)$$

This corresponds to an altitude-equivalent deviation of approximately ± 26 – ± 29 m.

Figure 26 visualizes both models over a 5-year horizon for $E_0 = 1$ hPa and $D = 1$ hPa/year. The left panel shows the expected growth of absolute pressure error, while the right panel expresses the same degradation as a relative error percentage normalized by a representative sea-level reference pressure $P_{\text{ref}} = 1013$ hPa. Under the worst-case model, the error reaches ± 6 hPa after five years (approximately 0.59%), whereas the stochastic model yields an expected error of ± 3.24 hPa (approximately 0.32%). Although these relative deviations remain below 1%, they represent systematic offsets that can bias long-horizon learning if raw absolute pressure is used without correction.

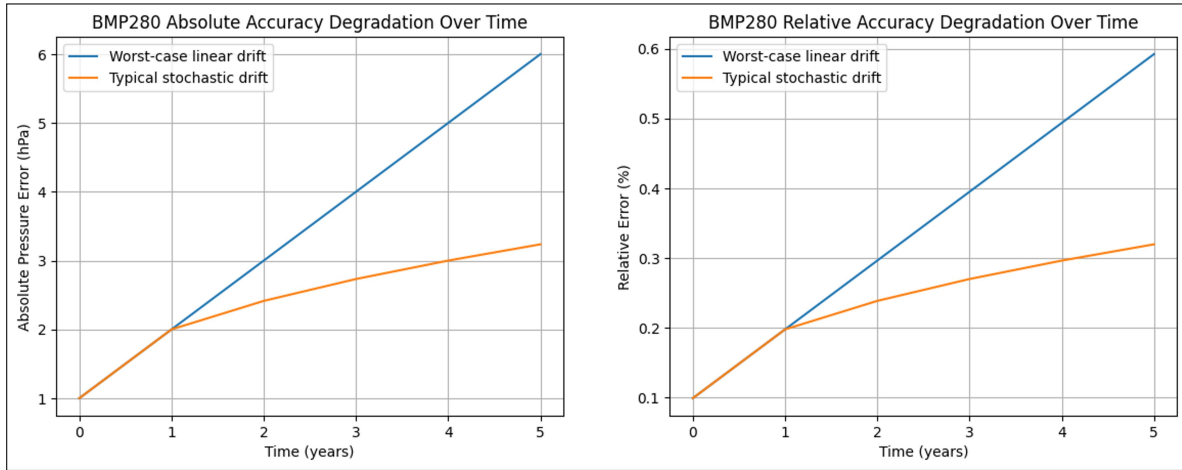


Figure 26. Simulated degradation of BMP280 pressure accuracy over time using two drift models ($E_0 = 1$ hPa, $D = 1$ hPa/year). **Left:** absolute pressure error growth (hPa). **Right:** relative error percentage normalized by $P_{\text{ref}} = 1013$ hPa. The plots highlight that multi-year deployments may experience gradual baseline shifts, which can impact Machine Learning models if absolute pressure is used directly as an input feature.

To reduce drift-induced bias in future TinyML tasks, pressure features should preferentially be expressed in drift-robust forms, such as temporal differences:

$$\Delta P(t) = P(t) - P(t - \Delta t) \quad (19)$$

or trend estimators computed over fixed windows:

$$S(t) = \frac{P(t) - P(t - T)}{T} \quad (20)$$

These formulations largely cancel long-term baseline shifts and emphasize meteorologically meaningful dynamics. For multi-year deployments and multi-node learning scenarios, future work should also evaluate higher-grade barometric sensors with improved long-term stability or implement periodic calibration and adaptive offset correction strategies.

6. Discussion

The validation results demonstrate that the proposed IoT data collector achieves exceptional measurement accuracy using the most economical sensors available on the market, with a total hardware cost of only €315.00 (Table 1). The comparison between the backyard data collector and the regional weather station reveals distinct microclimate characteristics at the 2 m measurement height, while simultaneously validating the performance of low-cost sensor technology.

The sensors, directly exposed to ambient air at 2 m altitude, provide accurate measurements that closely track regional weather patterns. The mean temperature difference of -0.71°C ($\sigma = 1.05^\circ\text{C}$) demonstrates excellent agreement with the weather station, with remaining differences attributable to genuine microclimate variations rather than measurement artifacts. The humidity measurements show a positive mean difference (4.98%, $\sigma = 5.95\%$), reflecting the influence of local vegetation and built structures on moisture distribution. The relatively small differences observed across all parameters validate the sensor performance and confirm that direct exposure to ambient conditions provides reliable microclimate monitoring.

The pressure sensor performance provides particularly compelling evidence of the system's accuracy. As shown in Figure 24, the atmospheric pressure measurements from the data collector follow the weather station's pressure patterns with remarkable precision. The temporal evolution of pressure, including subtle variations and minor fluctuations, is captured with such fidelity that the two datasets appear nearly indistinguishable when overlaid, differing only by the consistent altitude-related

offset of approximately -9.58 hPa ($\sigma = 0.28$ hPa). This exceptional agreement validates that even the most economical pressure sensors (BMP280, €7.00) can deliver professional-grade measurements when properly calibrated and positioned. Similarly, the temperature and humidity sensors (DHT22, €12.00) demonstrate excellent performance, with the strong temporal correlation observed across all parameters confirming that the low-cost sensor suite accurately captures both diurnal patterns and synoptic-scale weather variations.

These findings underscore the value of distributed microclimate monitoring systems for agricultural applications, where local environmental conditions at crop level (typically 1–2 m height) may differ substantially from standard meteorological measurements taken at 10 m height. The ability to capture these microclimate variations is particularly important for precision agriculture, where management decisions benefit from site-specific environmental data rather than regional averages. The validation results demonstrate that cost-effective sensor solutions can achieve measurement quality comparable to professional meteorological equipment, making distributed microclimate monitoring economically viable for large-scale agricultural deployment. This finding is particularly significant for precision agriculture, where the deployment of multiple monitoring stations across fields requires affordable yet reliable sensing technology.

The combination of low cost, high accuracy, and reliable performance positions the proposed system as an accessible solution for farmers and agricultural researchers seeking to implement distributed environmental monitoring networks. The demonstrated capability to achieve professional-grade measurements with budget sensors opens new possibilities for widespread adoption of precision agriculture technologies, particularly in resource-constrained agricultural regions where cost-effectiveness is paramount.

7. Conclusions

This paper presented the design, implementation, and field validation of a modular, solar-powered environmental monitoring platform integrating LTE-M/NB-IoT communication and TinyML-enabled edge processing. The proposed architecture combines a dual-microcontroller approach, where the Arduino Nano 33 BLE performs real-time sensor acquisition and local processing, while the Arduino MKR NB 1500 ensures reliable long-range communication. This separation of sensing, edge intelligence, and communication enhances modularity, energy efficiency, and scalability.

Field deployment in two distinct environments in Romania demonstrated stable LTE-M connectivity, with RSSI measurements ranging from -93 dBm to -57 dBm and an average signal strength of -75.51 dBm, confirming reliable rural communication performance. Microclimate validation against an official regional weather station showed strong temporal correlation for temperature, humidity, and pressure measurements. The observed differences were primarily attributed to local environmental conditions and altitude variations rather than sensor inaccuracies. In particular, the atmospheric pressure comparison revealed a consistent altitude-related offset of -9.58 hPa with minimal variance ($\sigma = 0.28$ hPa), validating sensor stability and calibration.

The results confirm that low-cost, commercially available sensors such as the DHT22 and BMP280 can achieve measurement performance comparable to professional meteorological stations when properly integrated and calibrated. With a total hardware cost of approximately €315, the proposed platform demonstrates that distributed microclimate monitoring can be economically viable for precision agriculture applications.

Beyond sensing, the integration of TinyML capabilities enables local data filtering and event-driven processing, reducing transmission overhead and improving energy efficiency in solar-powered deployments. The modular architecture further allows adaptation to additional sensing domains, renewable energy assessment, and smart city environmental monitoring.

Future work will focus on adaptive communication scheduling based on signal quality indicators, extended multi-season deployment analysis, integration of additional energy-aware machine learning

models, and large-scale distributed deployment across agricultural regions to support data-driven farm management at scale.

8. Future Work and Next Steps

The dual-microcontroller architecture adopted in this work opens significant opportunities for extending the platform beyond conventional environmental monitoring toward intelligent, adaptive edge-based decision systems. The separation between sensing and communication functions provides a foundation for distributed learning, adaptive communication strategies, and energy-aware system optimization.

8.1. Large-Scale Data Collection and Dataset Expansion

The next development phase will focus on extended multi-season data acquisition across diverse environmental conditions. Continuous logging of meteorological parameters, communication metrics (RSSI, RSRP, transmission latency), battery voltage levels, and solar charging behavior will enable the construction of a comprehensive multi-domain dataset. Such a dataset will support supervised and self-supervised learning approaches for communication optimization, anomaly detection, and predictive energy management.

Scaling the deployment to multiple nodes across heterogeneous rural environments will further enable spatial analysis of microclimate variability and cellular signal dynamics, forming the basis for distributed learning strategies and federated edge intelligence.

8.2. Adaptive LTE-M Communication via TinyML

A primary objective of future research is the implementation of adaptive LTE-M communication control using TinyML models deployed on the Arduino Nano 33 BLE. Instead of relying on fixed transmission intervals, the edge node will dynamically adjust communication parameters based on:

- Signal strength indicators (RSSI, RSRP)
- Battery state-of-charge and charging rate
- Solar energy availability forecasts
- Environmental event detection (e.g., rainfall, wind spikes)
- Network stability statistics

Machine learning models trained offline using collected datasets will be quantized and deployed on the Nano 33 BLE to enable real-time inference. The model outputs may control:

- Transmission interval adaptation
- Modem power state selection
- Data aggregation strategies
- Event-triggered communication

This adaptive mechanism aims to minimize energy consumption while maintaining data reliability and quality of service.

8.3. Migration Toward High-Precision Humidity and Temperature Sensing

Although the current implementation employs the DHT22 sensor for temperature and relative humidity monitoring, future system iterations may benefit from migration toward higher-precision digital sensing platforms such as the Sensirion SHT45 (Figure 27).

Icon	Attribute	DHT11	DHT22	SHT45
	Temperature Range	0°C to +50°C	-40°C to +80°C	-40°C to +125°C
	Temperature Accuracy	±1°C (0°C) ±2°C (50°C)	< ±0.5°C	±0.1°C
	Temperature Resolution	1°C	0.1°C	0.01°C
	Humidity Range	20% RH to 90% RH	0% RH to 100% RH (-40°C to 80°C)	0% RH to 100% RH
	Humidity Accuracy	±4% (25°C) ±5% (0°C to 50°C)	±2% to ±5% (25°C) ±5% (0°C to 50°C)	±1% RH (±0.5% long-term production)
	Humidity Resolution	1% RH	0.1% RH	0.01% RH
	Voltage Range	3.0V – 5.5V	3.3V – 6.0V	1.1V – 3.6V
	Current Consumption	0.5mA – 2.5mA (measuring) 0.1mA – 0.15mA (standby)	1mA – 1.5mA (measuring) 0.04mA – 0.05mA (standby)	0.3mA – 0.5mA (measuring) 0.08uA – 3.4mA (standby)
	Long Term Stability	±1%RH/y	±0.5%RH/y	<0.2%RH/y, <0.03°C/y
	Sensing Period	~4ms	~5ms	~1.8-8ms
	Collection/Sensing Period	>6s	>2s	>2s
	Price	1-2 €	5-10 €	17 €

Figure 27. Comparison of DHT11, DHT22, and SHT45 temperature and humidity sensor specifications (information taken from the datasheets).

The DHT22 provides acceptable performance for low-cost environmental monitoring, offering ±0.5°C temperature accuracy and ±2–5% RH humidity accuracy, with a long-term drift of approximately ±0.5%RH/year. However, several limitations affect its suitability for precision agriculture and long-term autonomous deployments:

- Limited humidity stability over time
- Slow single-wire communication protocol
- Relatively high measurement current (1–1.5 mA)
- Moderate resolution (0.1°C, 0.1% RH)

In contrast, the SHT45 represents a next-generation CMOSens[®] platform offering substantial improvements:

- Temperature accuracy: ±0.1°C
- Humidity accuracy: ±1% RH
- Resolution: 0.01°C and 0.01% RH
- Long-term drift: < 0.2%RH/year, < 0.03°C/year
- Standby current: 0.08 μA
- Fast I²C digital interface with CRC integrity

8.3.1. Expected Impact of Migration

Replacing the DHT22 with SHT45 would:

1. Improve measurement fidelity by reducing systematic temperature error from ±0.5°C to ±0.1°C, enhancing evapotranspiration modeling and microclimate monitoring.
2. Increase long-term deployment stability by lowering humidity drift (< 0.2%RH/year).
3. Reduce power consumption due to ultra-low standby current, improving autonomous solar-battery operation.
4. Enable higher sampling rates (millisecond-scale measurement times).
5. Improve communication robustness through I²C with CRC validation.

Despite the higher unit cost compared to DHT22, the improved accuracy, stability, and energy efficiency make the SHT45 a strong candidate for research-grade and precision agriculture deployments.

8.4. Migration Toward Higher-Accuracy Barometric Sensors

Although the BMP280 sensor provides an excellent balance between cost and performance for distributed environmental monitoring, future iterations of the platform will investigate the integration of higher-accuracy pressure sensors, such as the BMP388. Figure 28 summarizes the comparative characteristics of BMP180, BMP280, and BMP388 modules.

The BMP388 offers improved metrological performance, including enhanced absolute and relative pressure accuracy as well as superior long-term stability. While the BMP280 specifies an absolute accuracy of approximately ± 1 hPa (950–1050 hPa @ 0–40°C) and a long-term stability of ± 1 hPa/year, the BMP388 reduces the absolute accuracy error to approximately ± 0.5 hPa and improves long-term stability to approximately ± 0.33 hPa/year. Over multi-year deployments, this reduction in drift could significantly limit cumulative bias, particularly in applications involving altitude estimation, pressure-based weather pattern classification, or long-term machine learning model training.

In addition to improved stability, the BMP388 provides higher pressure and temperature resolution, which may enhance the detection of subtle atmospheric variations. Although the module cost is moderately higher (approximately €12–14 compared to €2–7 for BMP280), the performance-to-cost ratio remains highly favorable, especially for deployments targeting long-term autonomous operation with minimal recalibration.

Icon	Attribute	 BMP 180	 BMP 280	 BMP 388
	Pressure Range	300 – 1100 hPa	300 – 1100 hPa (-500 to +9000 m)	300 – 1250 hPa (-500 to +9000 m)
	Pressure Relative Accuracy	± 0.12 hPa (± 1 m) (950 – 1050 hPa @ 25°C-40°C)	± 0.12 hPa (± 1 m) (700 – 900 hPa @ 25°C-40°C)	± 0.08 hPa (± 66 cm) (900 – 1100 hPa @ 25°C-40°C)
	Pressure Absolute Accuracy	± 2.0 hPa (± 4.5 hPa) (300 – 1100 hPa @ 0°C-65°C)	± 1 hPa (950 – 1050 hPa @ 0°C-40°C)	± 0.5 hPa (300 – 1100 hPa @ -20°C-40°C)
	Pressure Resolution	1.0 (0.01) hPa	0.0018 hPa	0.0066 hPa (0.00085 hPa)
	Temperature Range	-40°C to +85°C	-40°C to +85°C	-40°C to +85°C
	Temperature Accuracy	$\pm 1^\circ\text{C}$ (0 to 65°C) $\pm 1.5^\circ\text{C}$ (-40°C to 0°C)	$\pm 0.5^\circ\text{C}$ (@ 25°C) $\pm 1^\circ\text{C}$ (0°C to 65°C)	$\pm 0.3^\circ\text{C}$ (@ 25°C) $\pm 0.5^\circ\text{C}$ (0°C to 65°C)
	Temperature Resolution	0.1°C	0.01°C	0.005°C (0.00015 °C)
	Voltage Range	3.3V – 5.5V	1.7V – 3.6V	1.65V – 3.6V
	Current Consumption	0.6 mA	0.7 - 1.1 mA	0.7 - 0.8 mA
	Long Term Stability	± 1 hPa/year	± 1 hPa/year	± 0.33 hPa/year
	Price	1-2 €	2-7 €	12-14 €

The temperature measurement is used internally to calibrate the pressure and humidity sensors.
The maximum measurable humidity decreases at extremely high and low temperatures.

Figure 28. Comparative specifications of BMP180, BMP280, and BMP388 barometric pressure sensors. The figure summarizes pressure range, relative and absolute accuracy, resolution, temperature characteristics, supply voltage, current consumption, long-term stability, and approximate market price. The BMP388 demonstrates improved absolute accuracy (± 0.5 hPa), enhanced relative accuracy (± 0.08 hPa), and superior long-term stability (± 0.33 hPa/year) compared to BMP280 and BMP180, making it a strong candidate for multi-year autonomous environmental monitoring deployments.

Future research will evaluate the trade-offs between sensor cost, long-term drift behavior, and machine learning model robustness. Experimental campaigns will be conducted to quantify whether the improved stability of the BMP388 translates into measurable gains in predictive accuracy for pressure-based ML models, adaptive communication strategies, and energy optimization algorithms implemented on the Arduino Nano 33 BLE platform.

Figure 29 illustrates the projected long-term degradation of both absolute and relative pressure accuracy for the BMP280 and BMP388 sensors over a five-year deployment horizon. Two drift models

are considered: a conservative worst-case linear accumulation model and a stochastic random-walk model representing more typical long-term behavior.

As shown in Figure 29(a), the BMP280 may reach an absolute error of approximately ± 6 hPa after five years under worst-case linear drift assumptions, while the BMP388 remains below approximately ± 2.2 hPa under the same conditions. Under the random-walk model, the expected degradation is significantly lower for both sensors, yet the BMP388 consistently demonstrates improved long-term stability.

Figure 29(b) presents the corresponding relative error evolution (expressed as percentage of nominal atmospheric pressure near 1000 hPa). The BMP388 maintains substantially lower long-term relative deviation, which is particularly relevant for machine learning applications that rely on multi-year consistency of environmental features.

These results highlight the potential benefits of adopting higher-stability pressure sensors in future long-term, ML-driven environmental monitoring deployments.

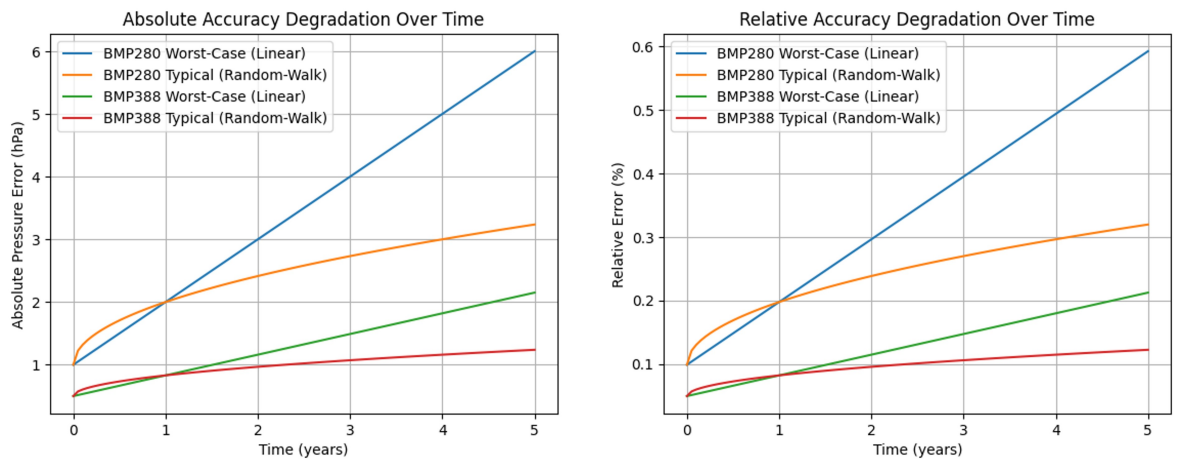


Figure 29. Projected long-term degradation of pressure measurement accuracy for BMP280 and BMP388 sensors over a five-year deployment period. (a) Absolute pressure error evolution (hPa) under worst-case linear drift and stochastic random-walk models. (b) Corresponding relative error expressed as percentage of nominal atmospheric pressure (1000 hPa). The results highlight the improved long-term stability of the BMP388 compared to the BMP280, particularly in extended autonomous environmental monitoring scenarios.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BMS	Battery Management System
Cat-M1	LTE Category M1 (LTE-M)
CR2032	20 mm diameter, 3.2 mm thickness lithium coin cell battery
DCF77	German longwave atomic time signal (77.5 kHz)
GPIO	General Purpose Input/Output
I2C	Inter-Integrated Circuit
IoT	Internet of Things
LiFePO ₄	Lithium Iron Phosphate Battery
Li-Po	Lithium Polymer Battery
LPWAN	Low Power Wide Area Network
LTE-M	Long Term Evolution for Machines
MCU	Microcontroller Unit
NB-IoT	Narrowband Internet of Things
PWM	Pulse Width Modulation
PV	Photovoltaic
QoS	Quality of Service
RJ11/RJ12	Registered Jack 11/12 Connector
RSSI	Received Signal Strength Indicator
RTC	Real-Time Clock
SD	Secure Digital (memory card)
SPI	Serial Peripheral Interface
SRAM	Static Random-Access Memory
TinyML	Tiny Machine Learning

Appendix A Winter Solar Radiation Prediction

Appendix A.1 Sanandrei Winter Solar Radiation Dataset and Splitting Strategy

This appendix describes the Sanandrei dataset used to train and evaluate the winter-time solar radiation prediction model. The dataset was built from a multi-year historical weather time series (CSV format) containing hourly records with a unified timestamp column (datetime) and meteorological variables. In this study, the prediction target is solarradiation, while the input feature set includes calendar context and weather predictors: dayofyear, hour, temp, feelslike, dew, windgust, windspeed, winddir, and visibility. To focus on the winter solar resource, we filtered the dataset to the winter months {December, January, February} and further restricted samples to daytime hours between 06:00 and 18:00 (inclusive). After filtering, samples were sorted chronologically to preserve the natural temporal ordering of the time series. Solar-derived missing values (when present in the source file) were conservatively imputed with zero for solarradiation, solarenergy, and uvindex, reflecting the fact that these variables may be absent or null during night-time or data gaps, while the remaining required predictors were validated and rows containing NaNs in the used columns were removed.

Appendix A.2 Chronological Train/Validation/Test Split

To avoid temporal leakage and to emulate real deployment conditions (training on past seasons to predict future seasons), the dataset was split strictly by year, using a chronological hold-out strategy. Specifically, the training set includes winter daytime data from 2019–2023, the validation set uses the subsequent year 2024, and the test set uses the most recent year 2025. This corresponds to a 5-year / 1-year / 1-year partition, illustrated in Figure A1. Under this configuration, the split represents approximately 66.67% training data and 16.67% each for validation and testing (assuming comparable winter daytime sampling density across years). This design supports robust hyperparameter tuning on the validation year (2024) while providing an unbiased performance estimate on a strictly unseen future year (2025).

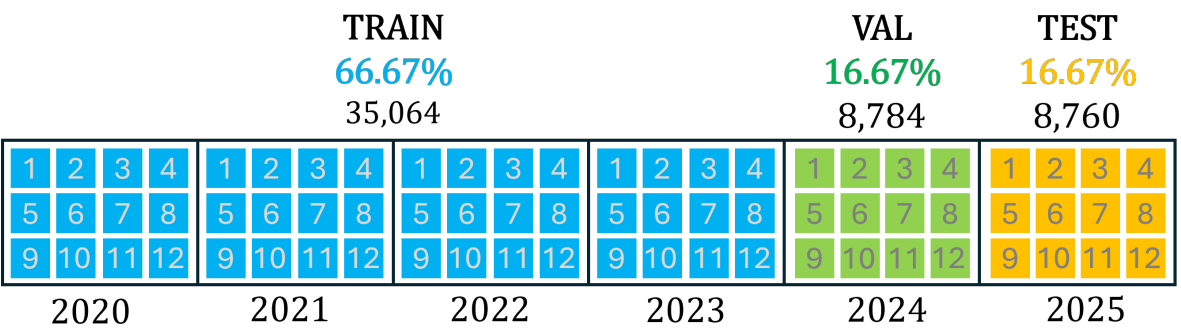


Figure A1. Chronological dataset splitting strategy used for winter daytime solar radiation forecasting in S  nandrei. Winter daytime samples are partitioned by year into training (2019–2023, 66.67%), validation (2024, 16.67%), and testing (2025, 16.67%) subsets to prevent temporal leakage and to evaluate generalization on a future year.

Appendix A.3 Normalization and Sliding-Window Sequence Construction

After the year-based split, feature scaling was applied using min–max normalization. Importantly, scalers were *fit on the training subset only* and then applied to validation and test subsets, ensuring that no statistical information from 2024 or 2025 is used during training-time preprocessing. Formally, let $\mathbf{x}_t \in \mathbb{R}^d$ be the feature vector at time t and y_t the solar radiation target; min–max scaling maps each feature dimension to $[0, 1]$ using training-set extrema.

To model temporal dependencies, the normalized time series was transformed into supervised learning samples using a sliding-window strategy. With a sequence length of $SEQ_LEN = 24$, each input tensor is constructed from the previous 24 time steps:

$$\mathbf{X}_t = [\mathbf{x}_{t-24}, \mathbf{x}_{t-23}, \dots, \mathbf{x}_{t-1}] \in \mathbb{R}^{24 \times d}, \quad \mathbf{y}_t = y_t.$$

This procedure is applied independently within the training, validation, and test subsets (without crossing year boundaries), producing three sequence datasets used to train and evaluate various ML models.

Appendix A.3.1 Analysis of Random Forest Configurations and Performance

This section analyzes the performance of the Random Forest (RF) models under three different temporal filtering strategies: (i) winter daytime only, (ii) winter full-day, and (iii) all-year daytime. The objective was to evaluate how seasonal filtering and diurnal constraints influence model generalization and predictive stability.

1) Winter Daytime Model (December–February, 06:00–18:00).

As shown in Table A1, the relatively high training score compared to validation indicates moderate overfitting. Restricting the dataset to daylight hours reduces noise from nighttime zero-radiation values but also significantly reduces sample size and variability. The use of a deeper tree structure (Table A2, $max_depth = 20$) contributes to stronger fitting on the training set but slightly weaker validation generalization.

Table A1. Performance comparison of the three best-performing Random Forest configurations under different temporal filtering strategies.

Metric	Winter Daytime	Winter Full Day	All-Year Daytime
R^2_{train}	0.9733	0.9781	0.9890
R^2_{val}	0.7951	0.8261	0.9121
R^2_{test}	0.8415	0.8420	0.9059

Table A2. Comparison of best-performing Random Forest architectures across temporal filtering strategies.

Parameter	Winter Daytime	Winter Full Day	All-Year Daytime
n_estimators	50	25	100
max_depth	20	None	None
min_samples_split	5	5	5
min_samples_leaf	1	1	1
max_features	log2	sqrt	sqrt

2) Winter Full-Day Model (December–February, 00:00–23:00).

Interestingly, despite including zero-radiation nighttime values, this configuration achieved lower MAE and RMSE on validation. The trees were allowed to grow without depth restriction ($max_depth=$ None), but the reduced number of estimators (25) acted as implicit regularization. The improvement suggests that including full daily patterns may help the model better learn transition dynamics (sunrise/sunset behavior).

3) All-Year Daytime Model (Full Year, 06:00–18:00).

The all-year daytime configuration achieved the strongest overall performance. This significant improvement is primarily due to:

- Larger dataset size
- Increased seasonal variability
- Broader solar radiation patterns

Although the validation RMSE appears higher than the winter-only full-day case, this must be interpreted relative to the increased dynamic range of solar radiation across all seasons. The higher R^2 values confirm superior generalization capability.

Comparative Discussion.

Several important insights emerge:

1. Expanding the temporal coverage (all-year) substantially improves generalization.
2. Including nighttime winter data reduces validation error compared to winter daytime-only filtering.
3. Hyperparameter differences (e.g., number of trees and tree depth) significantly impact overfitting behavior.
4. Shallower ensembles (fewer trees or no depth constraint with fewer estimators) may generalize better under limited seasonal data.

These findings demonstrate that dataset design and temporal filtering strategies influence performance as much as hyperparameter tuning. The difference between $R^2_{val} = 0.795$ and $R^2_{val} = 0.826$ under the same seasonal restriction highlights that architectural tuning alone can produce measurable improvements, even when the underlying dataset remains unchanged.

Appendix A.3.2 Comparison of Random Forest Architectures

The comparison in Table A2 shows that the best-performing configuration for the largest dataset (all-year) required a higher number of trees, while winter-restricted datasets performed optimally with fewer estimators. This suggests that ensemble capacity should scale proportionally with dataset diversity and seasonal variability.

Appendix B Cloud Web Application Architecture

Appendix B.1 Overview

To support scalable data management, device orchestration, and AI-driven analytics, a cloud-based web application was developed and deployed alongside the environmental monitoring infrastructure (Figure A2). The platform acts as an intermediary layer between edge devices (Arduino-based data collectors), the centralized MySQL database hosted in the cloud, and end-users accessing the system through a browser interface.

The web application was implemented using a PHP–MySQL backend architecture and deployed via a cloud hosting environment with phpMyAdmin database administration. The system enables secure authentication, real-time visualization of measurements, device lifecycle management, alert handling, and integration of Machine Learning inference modules.

Appendix B.2 System Architecture

The cloud platform follows a three-tier architecture:

1. **Edge Layer** – Solar-powered environmental data collectors transmitting measurements via LTE-M/NB-IoT to the cloud API.
2. **Backend Layer** – REST-based PHP services interfacing with a MySQL relational database.
3. **Frontend Layer** – Responsive dashboard for visualization, analytics, and device management.

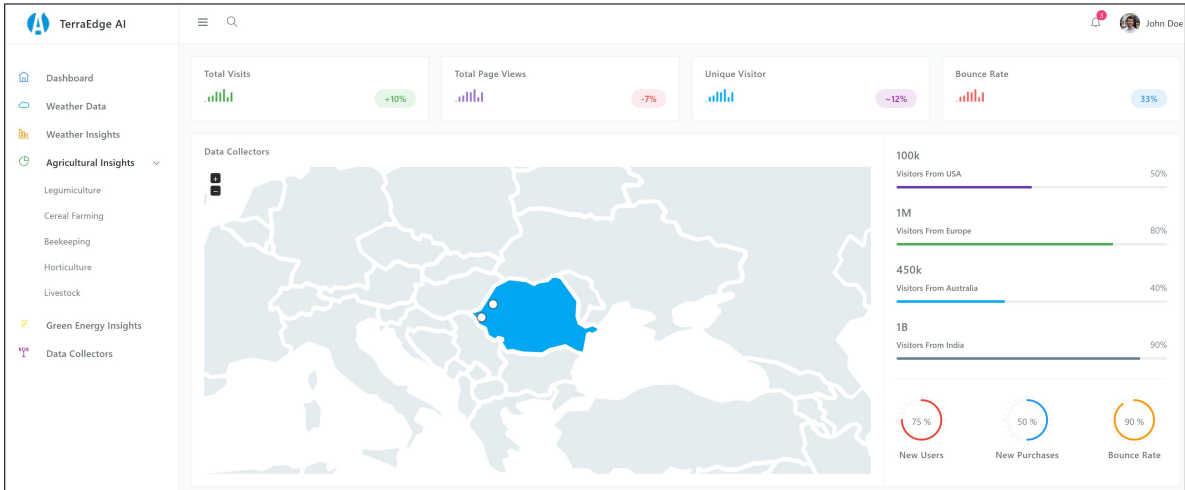


Figure A2. Cloud Dashboard interface of the EdgeAI Management platform showing system-wide monitoring and device management features, including geographic visualization of deployed data collectors, high-level performance indicators, and navigation modules for Weather, Agricultural, and Green Energy Insights.

Incoming measurements are transmitted by each device using a unique `device_id` identifier. The backend validates, stores, and indexes time-series data in the `weather_data` table, enabling efficient chronological retrieval and filtering.

Appendix B.3 User and Device Management

The platform supports role-based access control through the `users` table, allowing both administrative and standard user roles. Administrators can:

- Register and manage devices
- Assign devices to specific users
- Monitor connectivity and operational status
- Review alerts and system notifications

The `Data Collectors` interface allows monitoring of deployed devices, including:

- Device name and geographic location
- GPS coordinates
- Operational status (active, inactive, maintenance)
- Last communication timestamp
- RSSI statistics and connectivity quality

This structure ensures traceability and accountability for each field-deployed node.

Appendix B.4 Weather Data Visualization

The `Weather Data` module provides structured access to time-series measurements (see Figure A3). Users can:

- Filter data by device
- Sort by timestamp
- Search specific intervals
- Inspect temperature, humidity, pressure, rainfall, wind, soil, and radiation parameters

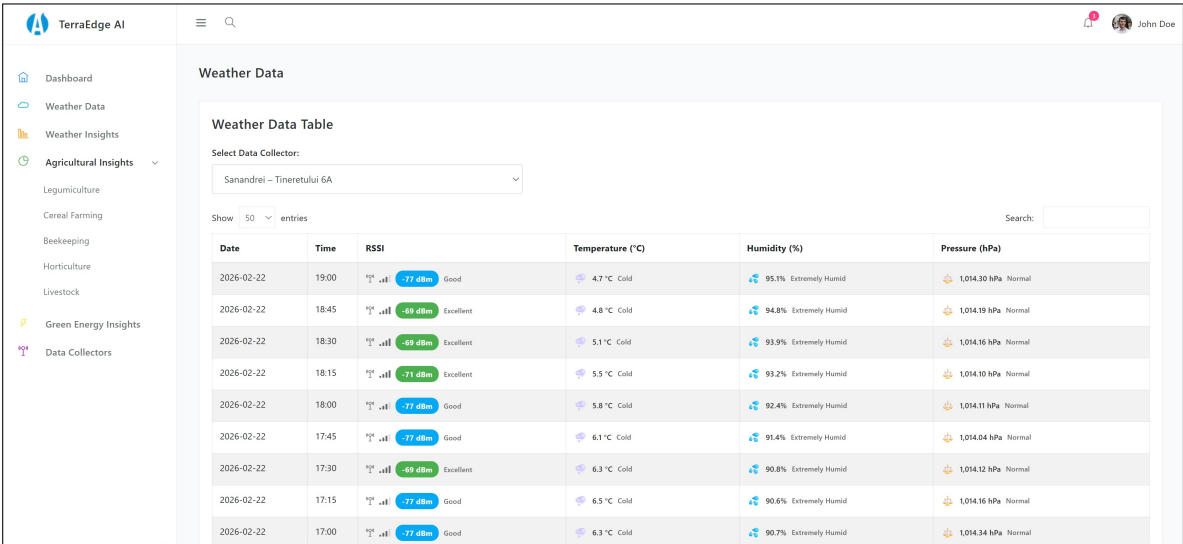


Figure A3. Weather Data module of the EdgeAI cloud platform showing structured time-series measurements, device selection interface, and tabular visualization of environmental parameters (temperature, humidity, pressure, and RSSI).

Measurements are displayed with contextual interpretation (e.g., “Cold”, “Extremely Humid”, “Normal Pressure”) to enhance usability for non-technical stakeholders.

Efficient database indexing on (device_id, timestamp) ensures optimized query performance even for multi-year datasets.

Appendix B.5 Dashboard and System Monitoring

The main *Dashboard* page (Figure A2) provides system-level insights, including:

- Total readings and device activity
- Connectivity statistics (RSSI distribution)
- Geographic visualization of deployed stations (Sanandrei, Timis county RO; Rogoz de Beliu, Arad county RO)
- Summary indicators and performance metrics

This centralized overview allows rapid assessment of network health and spatial distribution of devices.

Appendix B.6 AI Integration and Insight Modules

The cloud platform integrates predictive and analytical Machine Learning modules under dedicated sections (Figure A4):

- **Weather Insights** – Time-series forecasting (e.g., temperature prediction with uncertainty bands)
- **Agricultural Insights** – Soil moisture prediction, irrigation advisory support, crop stress indicators
- **Green Energy Insights** – Solar radiation prediction, energy yield estimation, hybrid renewable modeling

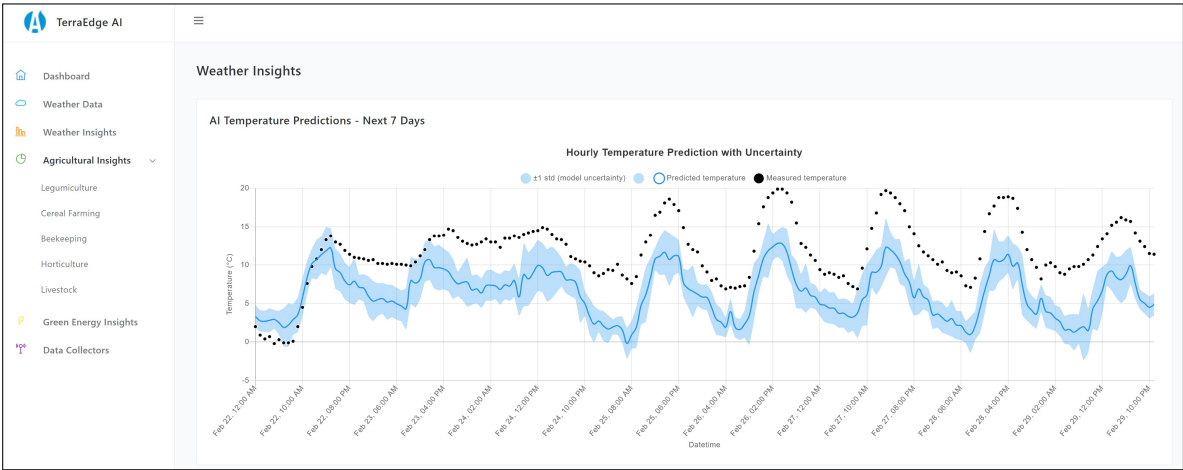


Figure A4. Weather Insights module illustrating AI-based temperature forecasting with uncertainty estimation. The plot presents predicted temperature values, measured observations, and confidence intervals (± 1 standard deviation), enabling interpretability and reliability assessment of the deployed Machine Learning model.

Machine Learning models can be executed either:

1. Directly in the cloud (high-capacity inference),
2. Or partially at the edge (TinyML-based inference on Arduino Nano 33 BLE).

The cloud dashboard serves as the visualization and orchestration interface for these AI outputs.

Appendix B.7 Scalability and Multi-Industry Applicability

The modular database design and API-driven backend enable horizontal scalability. Additional sensor types, new device categories, or industry-specific analytics modules can be incorporated without redesigning the core schema.

The platform architecture supports applications in:

- Precision agriculture
- Renewable energy optimization
- Environmental monitoring
- Smart farming and IoT ecosystems

Appendix B.8 Summary

The cloud dashboard constitutes a critical component of the overall environmental monitoring architecture. It bridges edge intelligence and centralized analytics, enabling data acquisition, storage, visualization, and Machine Learning integration within a unified, scalable ecosystem.

This integrated design supports both research-oriented experimentation and practical deployment across agricultural, environmental, and renewable energy domains.

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