

Article

Development of Low-Power Forest Fire Water Bucket Liquid Level and Fire Situation Monitoring Device

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Abstract

A portable and integrated monitoring device was developed to digitally assess both water levels and surrounding fire-related conditions in forest firefighting water buckets using multi-sensor fusion. The system integrates a hydrostatic liquid-level sensor with temperature–humidity and smoke sensors. Validation was performed through field-oriented experiments conducted under semi-controlled conditions. Water-level measurements were collected over a three-month period under simulated forest conditions and benchmarked against conventional steel-ruler readings. Early-stage fire monitoring experiments were carried out using dry wood and leaf litter under varying wind speeds, wind directions, and representative extreme weather conditions. The device achieved a mean water-level bias of -0.60% , a root-mean-square error of 0.64% , and an overall accuracy of 99.36% . Fire monitoring reached a maximum detection distance of 7.30 m under calm conditions and extended to 16.50 m under strong downwind conditions, with performance decreasing toward crosswind directions. Stable operation was observed during periods of strong winds associated with typhoon events, as well as prolonged high-temperature exposure. The primary novelty of this work lies in the conceptualization of a Collaborative Forest Resource–Hazard Monitoring Architecture. Unlike traditional isolated sensors, our proposed framework utilizes a dual-domain decision-making model that simultaneously assesses water-bucket storage stability and micro-scale fire threats. By implementing a robust ‘sensing–logic–alert’ framework tailored for rugged environments, this study offers a new methodological reference for the intelligent management of forest firefighting resources.

Keywords: forest fire bucket; fire monitoring; field monitoring equipment; liquid level monitoring



Academic Editor: José Aranha

Received: 22 December 2025

Revised: 13 January 2026

Accepted: 15 January 2026

Published: 16 January 2026

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1. Introduction

According to the Global Forest Resources Assessment 2020 released by the Food and Agriculture Organization of the United Nations, the average annual area affected by forest fires worldwide reached 15.2 million hectares between 2015 and 2020, accounting for 32.7% of the net global forest area loss during the same period [1,2]. In China, statistics from the Ministry of Emergency Management indicate that, in 2021, wildfire incidents attributed to insufficient fire-fighting water supply resulted in an average 4.2-fold expansion of burned areas once fires became uncontrolled. A similar pattern was observed during the 2021

wildfire on Evia Island, Greece, where manual patrol intervals of up to 48 h caused the critical early ignition stage to be missed [3]; as a result, the fire spread at a rate of approximately 200 m per minute, ultimately affecting 126,000 hectares. These events collectively underscore the critical importance of maintaining adequate water levels in firefighting water buckets and achieving real-time fire monitoring in forested environments [4,5]. While current research often treats forest fire monitoring and the monitoring of firefighting water resources as separate domains, this study provides a valuable complement to the field by developing an integrated terminal. The device primarily ensures the operational readiness of water buckets through precise level monitoring, while simultaneously incorporating fire monitoring to enhance early warning capabilities. This integrated approach bridges the functional gap between resource management and environmental sensing, offering a more holistic solution for forest fire mitigation.

In practice, firefighting water buckets frequently suffer from insufficient water levels. This is often caused by agricultural water extraction, natural leakage, or structural damage. Moreover, conventional firefighting operations rely heavily on manual inspections by a limited number of forest rangers. These rangers must cover extensive areas, making the process both time-consuming and labor-intensive. Early-stage fires are also difficult to detect promptly through manual patrols. Such delays often lead to uncontrolled fire spread and low operational efficiency [6–8]. Consequently, there is a pressing need for portable, digitalized monitoring solutions. These systems must be capable of continuously assessing both water availability and surrounding fire conditions. Effective solutions should automatically acquire multi-sensor data with high accuracy. They must also identify abnormal conditions and provide timely alerts. Therefore, developing low-power monitoring devices for water buckets is of significant importance. Such technology is essential for the effective protection of forest resources.

In recent years, substantial progress has been made in both liquid-level and fire monitoring technologies. For liquid-level measurement, several representative approaches exist. These include high-precision microwave resonance sensors with resistive energy-dissipation structures [9,10]. Other methods utilize capacitive sensors, such as the TE MS45 series (TE Connectivity Measurement Specialties, Hampton, VA, USA) [11,12], or externally heated MgB₂-based sensors for liquid hydrogen [13–15]. Despite their high accuracy, these instruments are typically expensive. They also exhibit limited adaptability, which restricts their widespread deployment in rugged terrains. Alternative solutions have also been explored. These include float-based mechanical sensors like the Honeywell FLS-S10 (Honeywell Sensing and Safety Technologies, Golden Valley, MN, USA) [16] and ultrasonic sensors such as the SensComp 600 (SensComp Inc., Livonia, MI, USA) [17]. Additionally, polymer optical fiber (POF) liquid-level sensors have gained international popularity [18,19]. However, these options are often unsuitable for forest environments. They typically suffer from poor outdoor robustness or excessively high power consumption [20].

Fire monitoring technologies have evolved significantly in recent years. Representative methods include satellite-based remote sensing systems, such as the Visible Infrared Imaging Radiometer Suite (VIIRS) [21,22] and the MODIS global fire monitoring system [23]. Additionally, cooperative monitoring using unmanned aerial vehicle (UAV) swarms has gained prominence [24]. Ground-based sensor networks are also widely used. These include LoRa systems [25,26] and distributed laser-based fire monitoring systems [27,28].

Despite these advancements, existing approaches face common limitations. Satellite systems often have long monitoring cycles. UAV-based swarms frequently suffer from high power consumption and limited flight endurance [29]. Furthermore, ground-based laser systems involve high deployment costs and significant maintenance requirements [30,31]. These factors combined constrain the applicability of such technologies in long-term, large-

scale forest monitoring scenarios. To address these specific challenges, the proposed system moves beyond general integration by tackling the precision and power constraints of traditional sensors [32,33]. Specifically, it overcomes the limitations of manual inspection and single-parameter reliability through a multi-sensor fusion mechanism—combining hydrostatic pressure, smoke, and thermo-hygrometric data—within a low-power 4G-based framework. This mechanism enables the device to perform autonomous, long-term monitoring while ensuring that water-level tracking is both real-time and resilient to environmental noise.

In summary, substantial challenges remain despite notable advances in liquid-level and fire monitoring research. To address these gaps, this work proposes a multi-sensor monitoring system. The system integrates a hydrostatic liquid-level sensor with complementary fire-related sensors. The approach employs an innovative low-power design strategy and a dedicated data processing framework. The primary novelty of this work lies in the conceptualization of a Collaborative Forest Resource–Hazard Monitoring Architecture. Unlike traditional isolated sensors, our proposed framework utilizes a dual-domain data processing model that simultaneously evaluates water-bucket storage stability and micro-scale fire threats. By implementing a low-power sensing–logic–alert framework tailored for rugged environments, this study offers a new methodological reference for the intelligent management of forest firefighting resources.

2. Device and System Design

2.1. Electromechanical Structure Design

The mechanical structure of the device was designed and simulated using SketchUp (v2024), as illustrated in Figure 1. The core components included a plastic enclosure, a hydrostatic liquid-level sensor, and a battery. The enclosure was fabricated from ABS engineering plastic, selected for its high compressive strength, toughness, and corrosion resistance. A polyurethane waterproof sealing ring was embedded along the inner cross-section of the enclosure lid to enhance sealing performance. After sensor installation, silicone potting was applied with reserved openings, and desiccant packs were placed inside the enclosure to further improve water and moisture resistance.

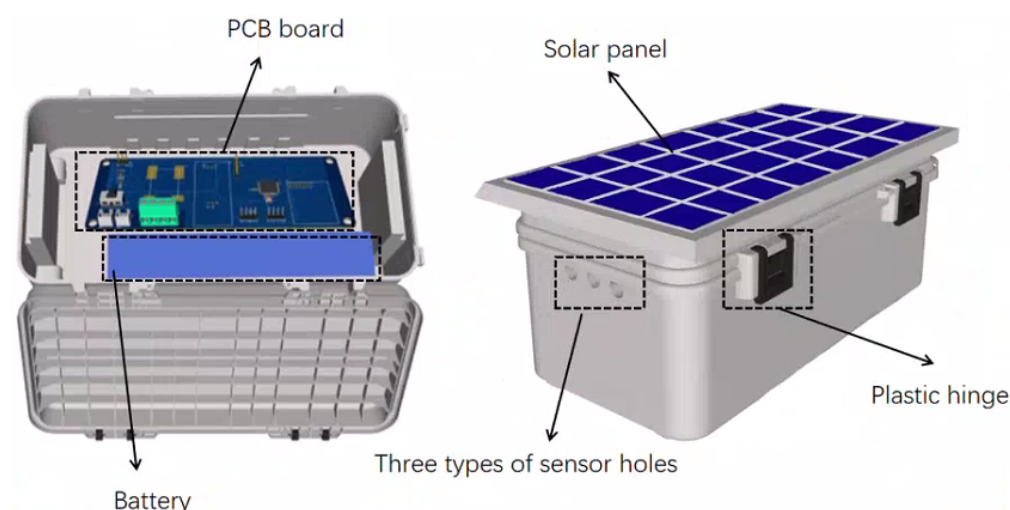


Figure 1. Mechanical structure diagram.

The overall dimensions of the device were 210 mm × 130 mm × 110 mm. Three mounting ports were reserved on the side panel for sensor integration, while the top surface was designed to accommodate a solar panel. This configuration balanced portability with sufficient internal space for component integration. The total cost of the equipment is approximately 300 yuan.

2.2. Circuit Design

The circuit architecture of the device is illustrated in Figure 2 and consists of four core modules: the main control unit, the power management unit, the sensing unit, and the communication and timing unit.

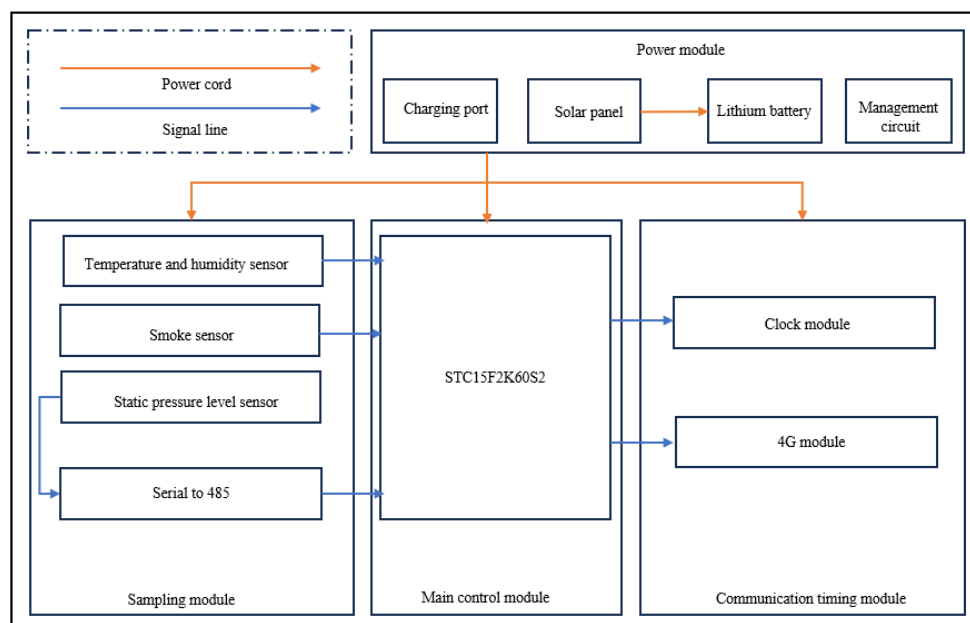


Figure 2. Circuit structure framework diagram.

The main control unit was built around an STC15-series microcontroller (STC15F2K60S2) (STC Micro Technology Co., Ltd., Shenzhen, China) and its peripheral circuitry, which coordinated the operation of all modules and performed data acquisition and processing. The power management unit comprised a charging interface, a solar panel, a lithium battery, and a dedicated management circuit. The solar panel directly charged the lithium battery, while the management circuit integrated step-up/step-down voltage regulation, battery capacity management, and overcurrent protection to ensure power adaptability and operational safety.

The sensing unit included a hydrostatic liquid-level sensor for monitoring the water level of firefighting buckets, selected for its high accuracy, strong outdoor adaptability, and cost effectiveness, as well as an SHT30 temperature–humidity sensor (Sensirion AG, Stäfa, Switzerland) and an SGP30 (Sensirion AG, Stäfa, Switzerland) TVOC/ $e\text{CO}_2$ (For forest fire monitoring, these $e\text{CO}_2$ and TVOC fluctuations serve as critical indicators of early-stage pyrolysis, offering a reliable proxy for air quality changes) sensor. The latter two sensors featured low power consumption and supported the I²C communication protocol, thereby reducing code redundancy and simplifying system integration.

In the communication and timing unit, the liquid-level sensor output was transmitted to the microcontroller via an RS-485 interface converted from a serial signal. A real-time clock module periodically awakened the microcontroller from low-power sleep mode to initiate data acquisition, while a 4G communication module enabled bidirectional data exchange with a remote server. Considering the multi-node application scenarios, each device's 4G module has a unique identification code. After transmitting data to the server, it is possible to observe from the server which device sent the data. This supports the parallel deployment of multiple devices from the system architecture perspective.

Low-power operation was achieved by controlling sensor power supply through MOS switches and managing the microcontroller sleep–wake cycles via the timing module. This strategy simplified the circuit structure, facilitated fault diagnosis, and eased subsequent

firmware maintenance. Combined with the solar panel mounted on the top of the enclosure, the system adopted an “internal power throttling plus external energy harvesting” approach, ensuring long-term endurance for outdoor deployment.

The forest firefighting water-bucket water-level monitoring device developed in this study employed a two-layer printed circuit board (PCB). Based on the design principles of the aforementioned modules, electronic components were arranged and routed in a rational manner, and the resulting PCB layout is shown in Figure 3.

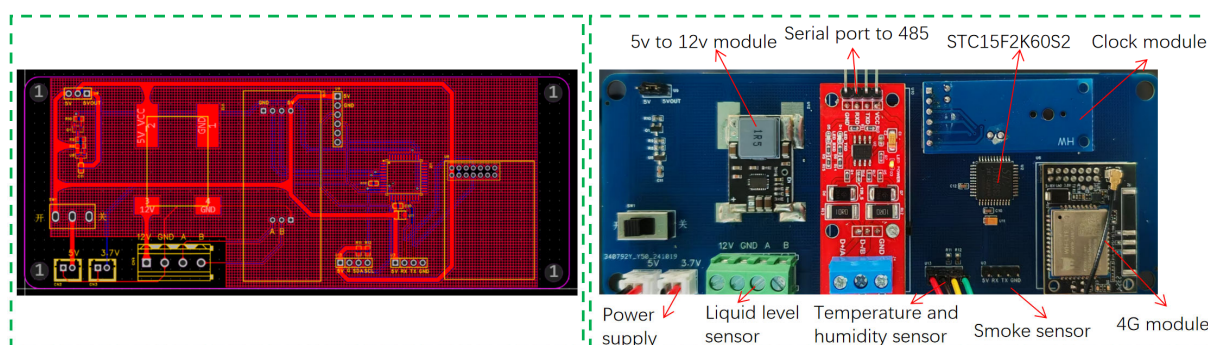


Figure 3. PCB layout.

2.3. Software Design

The software for the front-end monitoring device focuses on water-level and fire detection in firefighting buckets. The system architecture follows a hierarchical structure. As illustrated in Figure 4, it comprises five layers: the object, physical, hardware, data, and software layers. The software layer includes two main components. First, a data acquisition program runs on the STC15 MCU. This program was developed in C using the Keil platform (v5.24.2). Second, a data management program operates on the upper computer. The upper-computer software utilizes a PC-based Vue + C# architecture with a separated front-end and back-end. Additionally, a mobile client was developed using the WeChat Mini Program toolkit (v1.06.2306020). Figure 5 provides screenshots of the upper-computer interface on this mobile client.

Upon deployment, each device was assigned a unique identifier to obtain the corresponding bucket’s geographical location, environmental parameters, and sensor data. After comparative analysis, the results were visualized and combined with multiple indicators—including temperature, humidity, TVOC/ $e\text{CO}_2$ concentrations, geographical information, weather conditions, and holidays—to assess fire risk levels (Table 1). To enhance the system’s decision-support capability, we integrated socio-cultural risk factors, such as the Qingming Festival, into the monitoring logic as temporal weighting variables. Specifically, these periods are characterized by a significant increase in human activity and traditional fire-related practices in forest areas. In our system, these calendar-based variables are not merely descriptive but act as dynamic threshold adjusters. During identified high-risk dates, the system can be configured to increase the sampling frequency of the SGP30 and temperature sensors, or lower the alarm threshold for TVOC/ $e\text{CO}_2$ fluctuations. This integration transforms the device from a passive sensor node into a context-aware decision-support tool, bridging the gap between quantitative environmental sensing and qualitative risk assessment.

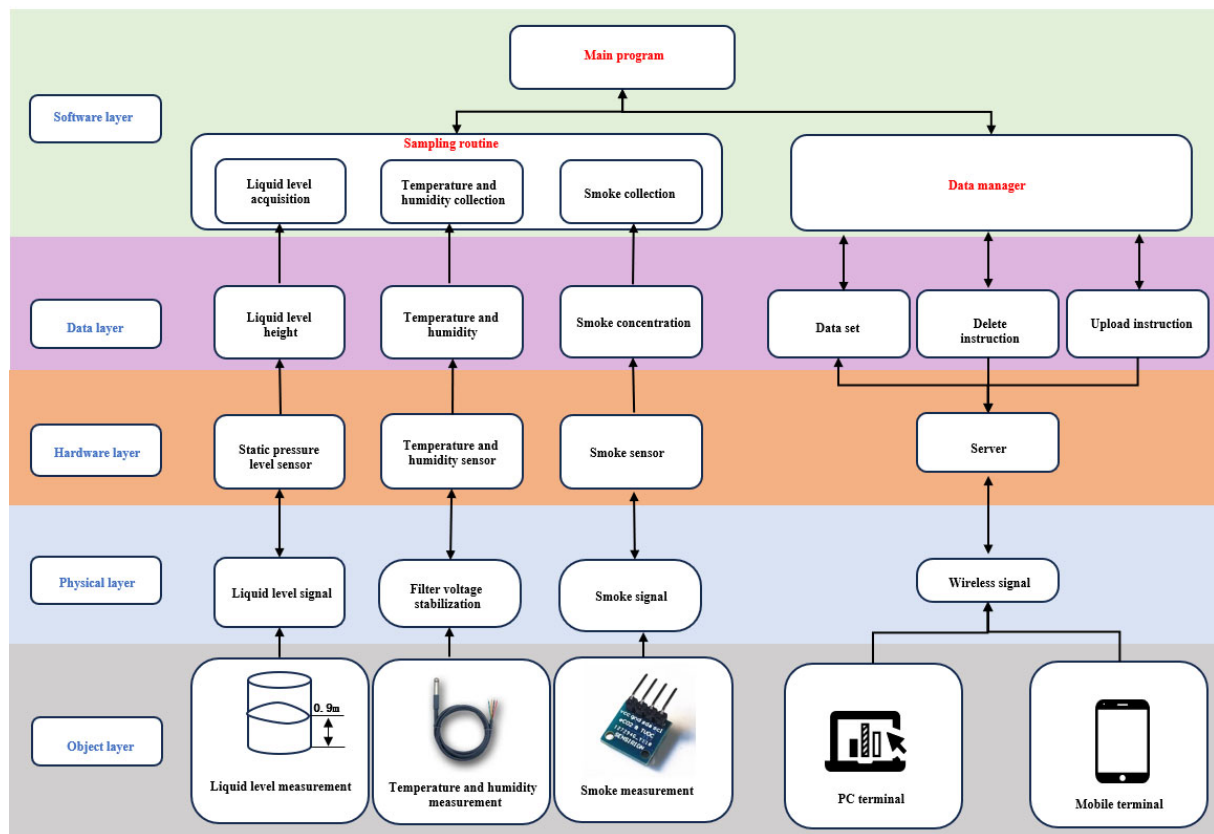


Figure 4. Overall flowchart of the system.

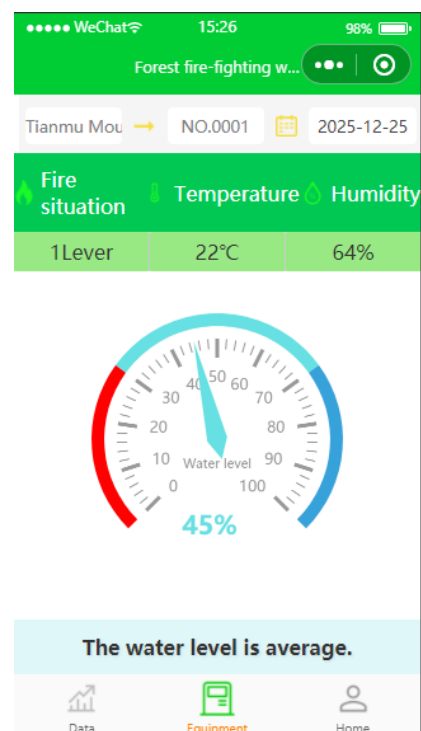


Figure 5. The upper computer diagram of the mini-program terminal.

Table 1. Monitoring Index Definition Table.

Index Classification	Indicator Name	Definition/Description	Data Source	Unit/Scope	Threshold Reference
Environmental parameters	Temperature	Ambient temperature	Sht30 sensor	°C	≥40 °C
Environmental parameters	Humidity	Relative humidity of air	Sht30 sensor	%	<30%
Environmental parameters	TVOC/eCO ₂ concentration	Air TVOC/eCO ₂ concentration	Sgp30 sensor	PPB/PPM	>480 PPM
Geographic information	Surrounding environment	Are there any areas of human activity around	Make on-site records when installing the equipment	Classification (tombs/farmlands/forests, etc.)	Grave/Farmland
Weather condition	Weather type	Current weather conditions	Meteorological Bureau api	Classification (Sunny/Rainy/Windy, etc.)	Sunny/Strong wind
Time	Holidays	Is it a holiday at present	Real-time api	Categories (Qingming/Mid-Autumn/New Year’s Eve, etc.)	Qingming Festival/Mid-Autumn Festival/New Year’s Eve

To provide a more intuitive representation of water levels, three quantitative categories were defined: “Low” (<30%), “Moderate” (30%–70%), and “Healthy” (>70%), facilitating straightforward assessment.

2.4. Principle of Liquid Level Sensor

The hydrostatic liquid-level sensor converted water pressure into an electrical current using a high-precision, high-sensitivity pressure transducer. The output current was subsequently processed through an amplification circuit and an analog-to-digital (A/D) converter to generate a digital signal, which was transmitted to external circuitry via an RS-485 communication module. A photograph of the hydrostatic liquid-level sensor with RS-485 output is shown in Figure 6. The sensor circuitry included a pressure transducer, an amplification stage, and a microprocessor, as illustrated in Figure 7.



Figure 6. Picture of the static pressure liquid level sensor.

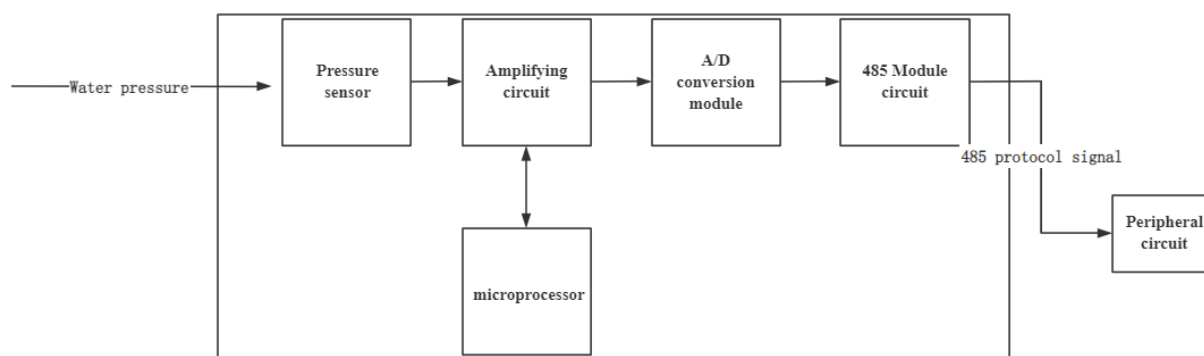


Figure 7. Circuit structure diagram of static pressure type liquid level sensor.

The operating principle of a conventional pressure-type water-level gauge involves positioning a pressure sensor at a certain depth below the water surface and determining the water level by measuring the hydrostatic pressure of the liquid. As illustrated in Figure 8, P represents the total pressure, P_A the atmospheric pressure, ρ the water density, and g the gravitational acceleration. The water level H , defined as the height difference between the sensor and the water surface, can be expressed as:

$$H(\rho, g, P, P_A) = \frac{P - P_A}{(\rho g)} \quad (1)$$

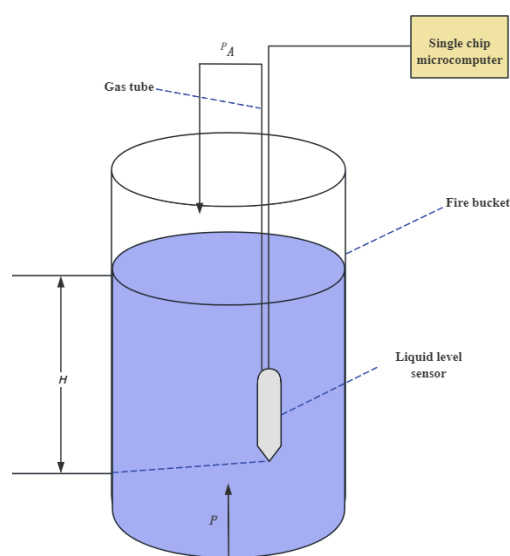


Figure 8. Measurement principle diagram of static pressure type liquid level sensor.

In the hydrostatic liquid-level sensor used in this study, an additional vent tube was integrated within the cable (Figure 8) to eliminate the influence of atmospheric pressure P_A , simplifying the water-level calculation to:

$$H(\rho, g, P) \approx \frac{P}{\rho_0 g_0} \left(1 - \frac{\Delta \rho}{\rho_0} - \frac{\Delta g}{g_0} + \frac{\Delta \rho \Delta g}{\rho_0 g_0} \right) \quad (2)$$

However, the output of the pressure sensor may not be perfectly linear, and a deviation exists between the measured pressure P and the true pressure. This deviation can be approximated using a polynomial model, as expressed in Equation (3). When the coefficients k_1 and k_2 are sufficiently small, the correction term can be linearized with respect to water level. By neglecting the second-order term $k_2 P^2$, the formula simplifies to Equation (4). To account for measurement offsets, the sensors were first calibrated under

an empty-bucket condition (i.e., with no water) to establish a zero-reference level, and the initial readings were recorded. In addition to the empty-bucket calibration, the linearity of the hydrostatic pressure sensor was validated across the effective measurement range of 0–80 cm (considering the maximum bucket height of 90 cm). Based on the physical principle $P = \rho gh$, the relationship between liquid depth and pressure is inherently linear under stable environmental conditions. To confirm this, we performed a multi-point verification by recording sensor outputs at 20 cm increments (0, 20, 40, 60, and 80 cm). This ensures that the measurement accuracy is maintained consistently throughout the operational range of the firefighting water bucket.

$$H = \frac{P}{(\rho g)} - \frac{k_1 P}{(\rho g)} - \frac{k_2 P^2}{(\rho g)} \quad (3)$$

$$H \approx \frac{P}{(\rho g)} (1 - k_1) \quad (4)$$

3. Experimental Method

3.1. The Overall Framework of the Experimental Design

The experiments were conducted on the rear campus of Zhejiang A&F University, Lin'an District, Hangzhou, Zhejiang Province, China (30°15' N, 119°43' E). This location closely resembled typical deployment sites for forest firefighting water buckets, which are generally placed in densely forested yet relatively flat areas with convenient access for water retrieval or frequent personnel activity in high-fire-risk zones.

For the water-level monitoring experiment, one self-developed low-power forest firefighting water-bucket monitoring device was used, along with a semi-sealed white PE bucket (diameter 600 mm, total height 900 mm, capacity 198 L) and a conventional steel ruler (range: 0–1 m). The measurement procedure is illustrated in Figure 9.



Figure 9. Field measurement map. (a) Steel ruler. (b) Equipment.

For the smoke range monitoring experiment, the same low-power monitoring device was employed in conjunction with an anemometer, several high-power electric fans, and a quantity of dry firewood and fallen leaves and twigs to simulate early-stage fire conditions.

3.2. Experimental Design of Long-Term Performance and Influencing Factors of Liquid Level Monitoring

The self-developed monitoring device was placed in the test bucket as shown in Figure 9. Data acquisition was programmed to occur three times daily—at 06:00, 12:00, and 18:00—for a period of three months (from 14 November 2024 to 14 February 2025). All

collected data were uploaded to the PC-based upper-computer software (v2024) for storage and statistical analysis.

Concurrently, water levels were measured using a conventional steel ruler at 12:00 and 18:00 each day over the same three-month period. For accuracy evaluation, only device measurements temporally aligned with the steel-ruler measurements (i.e., at 12:00 and 18:00) were selected for comparison. Device data recorded at 06:00 were used exclusively for continuous monitoring analysis and were not included in the comparative accuracy assessment. Based on the temporally aligned data, daily average water-level values were calculated, and comparative analysis was performed to evaluate measurement consistency and accuracy.

3.3. Experimental Design for Smoke Range Monitoring

Experiments were conducted under calm, sunny conditions. Multiple high-power electric fans were arranged in a row laterally at a distance of 7 m upwind from the fire source to simulate natural forest winds (commonly 1–5 m/s). Fan speed settings and placement distances were calibrated using an anemometer. Three wind-speed levels were defined: low (1–2 m/s), medium (3–4 m/s), and high (5 m/s), in addition to a no-wind condition.

Approximately 1 kg of dry firewood and 500 g of fallen twigs and leaves were used as fuel, and the fire source was confined to an area of 0.5 m². Each fire was allowed to burn for 30 s to simulate an early-stage wildfire before measurements were taken. Multiple experimental replicates were performed for each wind-speed condition, with a fresh fire prepared for each replicate.

The fire source was defined as the origin (0,0), with the upwind direction designated as $-x$ and the monitoring device placed along the $+x$ axis. Measurements were taken along radial directions at 0° (downwind), 30°, 60°, 90°, 120°, 150°, and 180° (upwind), starting from 1 m and increasing incrementally until no significant TVOC or $e\text{CO}_2$ variation was detected. For each combination of wind speed and direction, the maximum effective detection distance was recorded. All measurements were repeated multiple times, and the results were averaged to obtain representative values.

3.4. Experimental Design for the Stability of Equipment in Extreme Weather Conditions

The operational stability of the device under representative environmental stress conditions was examined between 23 July 2025 and 1 August 2025, a period encompassing the days before and after the landfall of Typhoon “Zhujiecao.” During this period, the device was continuously deployed in an outdoor environment, and observational measurements were conducted daily at 14:00, corresponding to the peak ambient temperature of the day. Recorded parameters included internal and external temperature and humidity, device battery level, data transmission performance, and overall structural integrity. These observations were used to qualitatively examine the device’s operational stability under combined high-temperature, strong-wind, and heavy-rain conditions encountered in a practical outdoor setting, rather than under fully controlled extreme-weather test protocols.

4. Research Results

4.1. Evaluation of Liquid Level Measurement Results

Let D_i denote the daily average water-level values measured by the developed device, and M_i the corresponding reference values obtained using a conventional steel ruler, with n representing the total number of measurement days. The following Equations (5)–(8)

were employed to calculate the bias (BIAS), relative bias (relBIAS), root-mean-square error (RMSE), and relative root-mean-square error (relRMSE) of the device measurements.

$$\text{BIAS} = \frac{1}{n} \sum_{i=1}^n (D_i - M_i) \quad (5)$$

$$\text{relBIAS} = \frac{1}{n} \sum_{i=1}^n \left(\frac{D_i}{M_i} - 1 \right) \times 100\% \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (D_i - M_i)^2} \quad (7)$$

$$\text{relRMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{D_i}{M_i} - 1 \right)^2} \times 100\% \quad (8)$$

The average water-level values D_i measured by the device were compared with the corresponding averages M_i obtained using a conventional steel ruler. The results indicated that, relative to the steel-ruler measurements, the overall bias (BIAS) was -3.06 mm (-0.60%), the root-mean-square error (RMSE) was 3.28 mm (0.64%), and the coefficient of determination (R^2) was 0.986 , yielding an overall measurement accuracy of 99.36% . The data acquired by the device were therefore largely consistent with those obtained by the traditional steel ruler. A linear fit between D_i and M_i is shown in Figure 10.

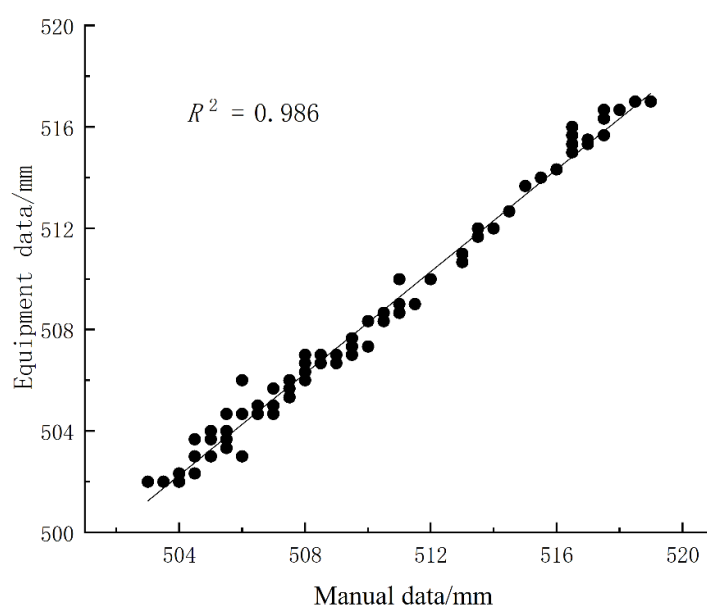


Figure 10. The linear fitting graph of D_i and M_i .

4.2. Analysis of Factors Influencing Liquid Level

The data collected over the three-month period were processed to calculate daily averages. Daily mean values of temperature, humidity, and precipitation were compared with the corresponding daily average water levels. The results are presented in Figure 11.

From Figure 11, it is apparent that the average water level decreased by 11.33 mm between 14 November 2024 and 25 December 2024, whereas from 26 December 2024 to 14 February 2025, the decrease was 5.67 mm. The decline during the earlier period was notably greater than that in the later period. Examination of the temperature–water-level relationship indicates that the average daily temperatures prior to 26 December were mostly above 10 °C, with a relatively rapid cooling trend, while the average temperatures after 26 December remained around 10 °C with minimal variation. Analysis of the humidity and

precipitation data shows that sudden increases in either parameter led to slight increases or delayed decreases in water level in the following days.

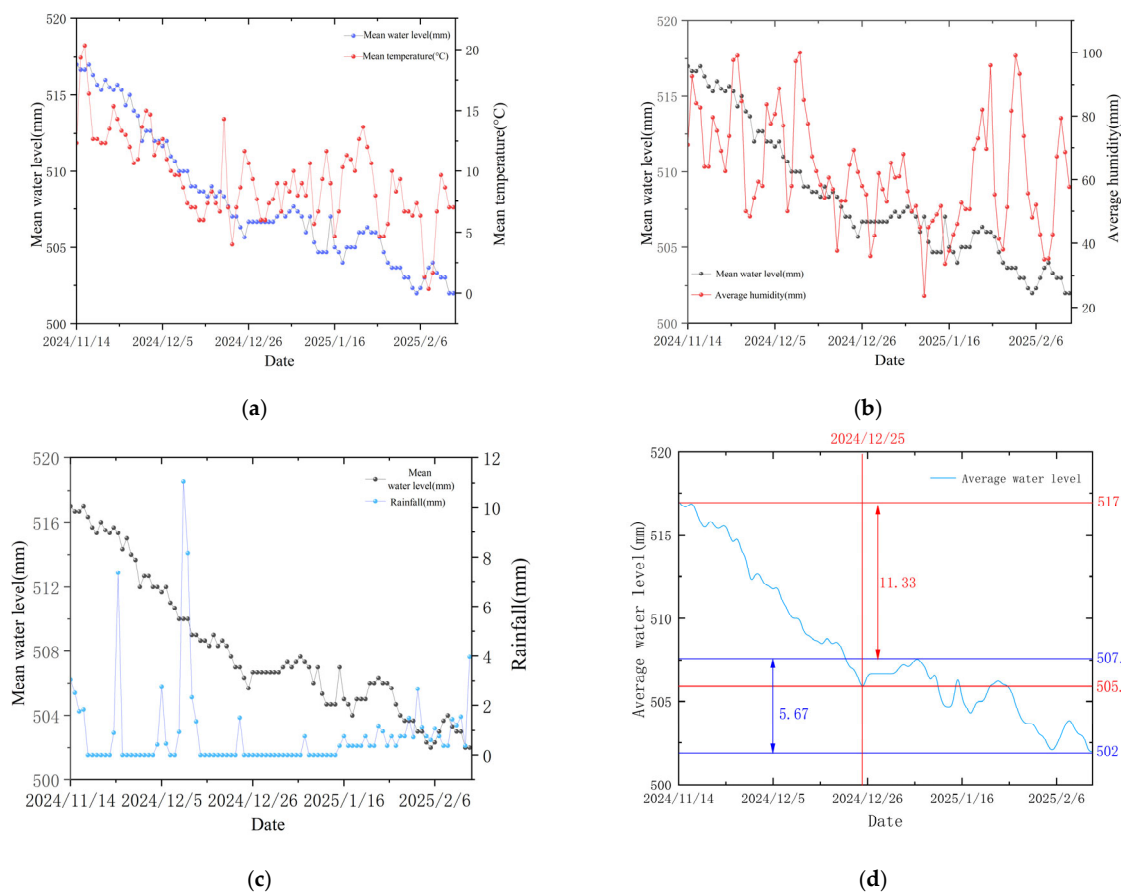


Figure 11. A chart showing the impact of various types of data on water levels. (a) The influence of temperature. (b) The influence of humidity. (c) The influence of rainfall. (d) Average water level change chart.

4.3. Analysis of Smoke Range Monitoring Results

Under identical fuel and fire-source dimensions, the data obtained for different combinations of wind speed and direction were processed to calculate the average detection distances for no wind, low wind (1–2 m/s), medium wind (3–4 m/s), and high wind (5 m/s) at the corresponding angles. Comparisons of smoke-monitoring ranges under varying wind conditions are summarized in Table 2.

Table 2. Comparison of smoke monitoring ranges from different angles under different wind speeds.

Wind Speed	0°	30°	60°	90°	120°	150°	180°
No wind	7.30	7.30	7.30	7.30	7.30	7.30	7.30
Low wind speed	9.40	9.05	7.90	6.55	5.75	4.55	4.30
Medium wind speed	14.55	13.45	9.90	5.85	3.85	2.15	1.50
High wind speed	16.50	15.50	11.90	5.30	2.80	0.90	0.30

Low wind speed (1–2 m/s), Medium wind speed (3–4 m/s), High wind speed (5 m/s).

The results indicate that, within typical forest wind speeds, higher wind speeds enhanced smoke dispersion in the downwind direction (0–60°), extending the effective detection distance of the device. In lateral wind directions (60–120°), smoke was dispersed horizontally, with faster winds causing greater downwind dilution. In the upwind direction (120–180°), smoke propagation was obstructed, and the degree of obstruction increased

with wind speed. The coordinate plots of smoke monitoring ranges under different wind speeds are shown in Figure 12.

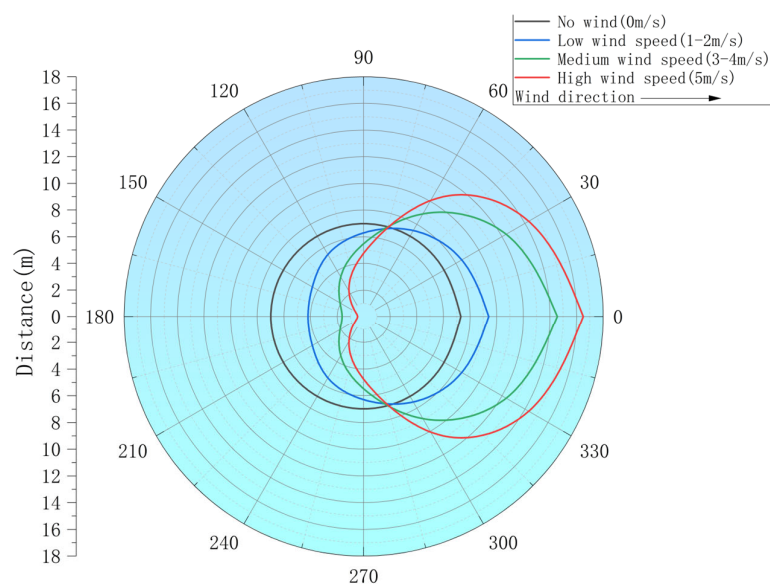


Figure 12. Monitoring coordinate map of smoke range under different wind speeds.

4.4. Analysis of Equipment Stability Results in Extreme Weather

The experimental data collected over the ten days before and after the typhoon were processed, and the monitoring results for temperature, humidity, battery level, data transmission stability, and device integrity are summarized in Table 3. Analysis indicated that, whether under high temperatures of 38 °C or during extreme conditions such as typhoon-induced rain and wind, the internal humidity of the device remained within a healthy range, and the overall sealing integrity was maintained with no water ingress observed. Data transmission occurred consistently as scheduled, while the battery level exhibited a gradual, stable decline. These results demonstrate that the device maintained robust stability and reliability under complex environmental conditions.

Table 3. A comparison of various data ten days before and after the typhoon.

Date	Weather	Temperature	Humidity	Humidity Inside the Equipment	Battery Power	Whether the Data Is Sent on Time	Equipment Integrity
23 July	Sunny day	36 °C	65%	58%	79%	YES	ST1
24 July	Sunny day	38 °C	59%	51%	78%	YES	ST1
25 July	light rain	31 °C	85%	67%	78%	YES	ST2
26 July	Moderate rain	28 °C	94%	73%	76%	YES	ST3
27 July	light rain	32 °C	82%	65%	76%	YES	ST2
28 July	Cloudy	31 °C	90%	71%	74%	YES	ST2
29 July	light rain	32 °C	72%	61%	74%	YES	ST2
30 July	rainstorm	24 °C	99%	76%	74%	YES	ST3
31 July	Cloudy	27 °C	94%	72%	73%	YES	ST2
1 August	Cloudy	31 °C	79%	63%	73%	YES	ST1

ST1: The shell is dry and there is no water seepage inside. ST2: The shell is damp but there is no water seepage inside. ST3: Water accumulates on the outer shell, but there is no seepage inside.

4.5. Equipment Power Consumption Testing and Analysis

The device was powered by a 20,000 mAh, 5 V lithium battery. It entered active operation for five minutes each day to perform water-level and fire-detection measurements,

with each data transmission lasting 15 s, while remaining in a low-power mode for the remainder of the day. During active operation, the device exhibited an average voltage of 5.10 V and an average current of 62.89 mA, corresponding to an average power of 0.32 W as calculated from $P = V \times I$. In low-power mode, the average power was 0.03 W.

Based on these values, the daily energy consumption in low-power mode was 0.684 Wh, and in active mode 0.384 Wh, yielding a total daily consumption of 1.068 Wh. Given the battery capacity, the theoretical operation time without recharging was approximately 93 days (battery capacity/daily consumption).

The solar panel mounted on top of the device measured $0.13 \text{ m} \times 0.21 \text{ m}$. Assuming an average of 4 effective sunlight hours per day and accounting for 80% practical efficiency, the daily energy harvested was approximately 15.7 Wh, allowing the battery to be fully recharged in 6.8 days. Even under continuous lack of sunlight, the device could operate autonomously for three months. When sunlight was restored mid-cycle, the battery could be fully recharged within 6–7 days. The power consumption waveform during a single active operation, measured by a power meter, is shown in Figure 13.

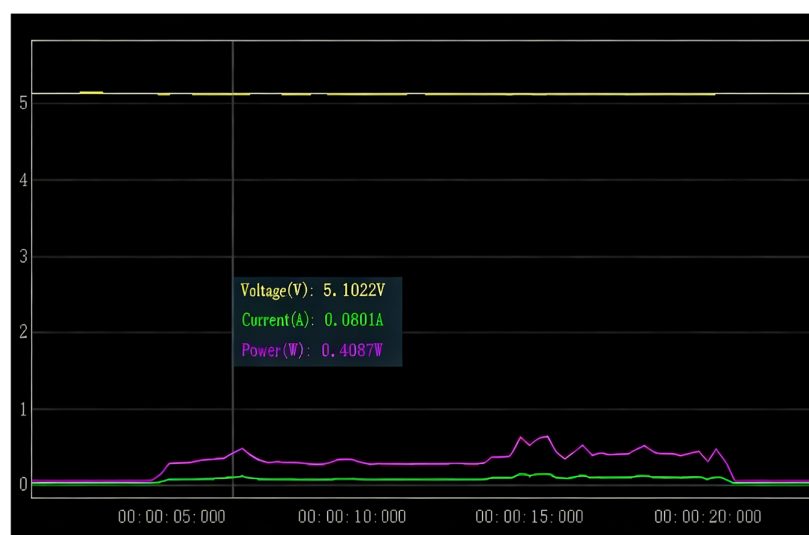


Figure 13. Waveform diagram of energy consumption during the first operation of the equipment.

5. Discussion

This study developed an integrated IoT monitoring device that achieves high-precision water-level sensing and early-stage fire detection. Over a three-month field deployment, the device maintained high stability, yielding an RMSE of 3.28 mm (0.64%) and an overall accuracy of 99.36%. These results indicate that the hydrostatic pressure-based sensing approach is highly reliable for long-term forest resource management. The high R^2 value (0.986) further confirms that the device can accurately track dynamic water-level fluctuations caused by natural evaporation or agricultural extraction, providing a solid data foundation for firefighting preparedness.

Compared with recent studies on liquid-level monitoring, the results of this research are highly competitive. For instance, Wang and Zhang [11] reported an error margin of approximately 1.5%–3.0% using capacitive array sensors, which, while precise, are sensitive to the dielectric constant changes in contaminated water. In contrast, our device maintains a lower BIAS of -0.60% , demonstrating superior robustness against water quality variations. Furthermore, while ultrasonic solutions such as those evaluated by Guan et al. [28] provide non-contact measurement, they often suffer from signal scattering in dense forest canopies and exhibit higher power consumption. Our hydrostatic approach overcomes these limitations by offering a passive sensing mechanism that is both energy-

efficient and physically robust. Compared to float-type sensors (e.g., Honeywell FLS-S10), which are prone to mechanical jamming by forest debris, the integrated electromechanical design of our system ensures a significantly lower maintenance frequency, making it more suitable for large-scale, unattended deployment.

In terms of fire monitoring, the multi-sensor fusion strategy (Temperature, $e\text{CO}_2$, TVOC) provides a critical localized complement to large-scale systems. Mainstream satellite-based monitoring, such as VIIRS and MODIS [21–23], typically operates on update cycles of several hours and can be obscured by cloud cover or thick forest canopies. Our device, however, offers real-time, ground-level sensing with a detection range of up to 16.50 m under downwind conditions. By integrating fire monitoring directly with firefighting water buckets, the system ensures the immediate availability of suppression resources once elevated fire risk is identified. This coupling of hazard sensing and resource monitoring enables rangers to rapidly assess on-site conditions and make informed, location-based operational decisions. Compared with systems that focus solely on fire detection or environmental sensing, the proposed approach represents a shift toward integrated resource–hazard awareness, offering a more practical and scalable solution for long-term forest fire prevention and management.

Limitations and Future Prospects

Although the proposed device demonstrated good performance in preliminary validation, several limitations remain that need to be addressed in future research:

- (1) Analysis of the relationship model between sensor data and festivals: In future research, we aim to further refine the system’s decision-making intelligence by developing a more robust socio-physical coupling model. Specifically, qualitative variables such as seasonal fire risk levels and regional festival-related human activities will be quantified using fuzzy logic or Bayesian networks.
- (2) Verify the accuracy of different water levels: future research will focus on more rigorous and standardized calibration procedures.
- (3) Regarding the issues of IoT security and sensor drift: Although the proposed system demonstrates stable performance under the evaluated experimental conditions, several aspects related to long-term deployment and system security were not the primary focus of the present study. Specifically, IoT cybersecurity, potential data loss during wireless transmission, and long-term sensor drift were not investigated in detail. In the current implementation, data transmission follows standard communication protocols without advanced encryption or intrusion detection mechanisms. In addition, while short- and medium-term measurements indicate stable sensor behavior, long-term drift compensation and automated recalibration strategies remain to be explored. These aspects will be addressed in future work to further improve system reliability for large-scale and long-term forest deployment.
- (4) AI or predictive models: Another limitation of the current prototype is the absence of advanced Artificial Intelligence (AI) or Machine Learning (ML) predictive models. Currently, the device relies on a multi-sensor fusion logic with fixed thresholds to ensure minimal power consumption and real-time responsiveness on edge hardware. While this approach is effective for basic detection, it may lack the robustness required to distinguish complex environmental interference from true fire signals in diverse terrains. Future research will explore the integration of Lightweight AI or predictive algorithms at the gateway level.
- (5) Extended validation of applicability: The generalization of the system to diverse forest regions with varying climatic and topographic conditions remains a key area for future validation. Currently, the device was tested under semi-controlled conditions that mirror subtropical climates; however, its performance in extreme environments—

such as high-latitude regions with sub-zero winters or arid zones with intense solar radiation—requires further assessment of battery resilience and sensor drift.

- (6) Analysis of false positives and false negatives of the sensor: False negatives (FN) typically occur during the smoldering stage or under strong crosswind conditions, where smoke particles may fail to reach the sensors effectively. In our experiments, delayed responses or non-triggers were recorded at distances exceeding 10 m under extreme crosswind directions, representing a potential FN risk. Due to limitations such as time and venue, the analysis of false positives and false negatives of the sensors was not conducted. Subsequent experiments in this regard will be carried out to enhance the accuracy of the equipment.
- (7) The authenticity of the forest fire situation: Validation under real forest fire conditions was not conducted in this study due to safety, ethical, and regulatory constraints associated with uncontrolled wildfire experiments. While such experiments cannot fully replicate the complexity of real forest fires, they provide a practical and widely adopted approach for preliminary system validation. Field validation during real wildfire events, in collaboration with forestry or emergency management authorities, will be pursued in future work to further assess system performance under realistic fire scenarios.
- (8) Energy Limitation Analysis: The energy sustainability model was primarily validated under relatively ideal solar conditions. In real-world forest deployments, factors such as winter seasons, canopy shading, and persistent cloudy weather can significantly reduce the photovoltaic charging efficiency. Future work will involve long-term energy harvesting stress tests under dense canopy coverage and extreme low-temperature conditions to refine the power-balance model and ensure autonomous operation throughout all four seasons.
- (9) The limitations of fire monitoring: The current fire monitoring module of the equipment still has some drawbacks such as a limited monitoring range and insufficient sensor data. Even when used for multi-point monitoring in forests, there are still significant monitoring blind areas. We will make improvements in this aspect in the future.

Overall, the device combines multi-parameter monitoring capability with low power consumption and integrated system design and demonstrates performance suitable for forest firefighting monitoring under the tested conditions.

6. Conclusions

The multi-sensor, low-power forest firefighting water-bucket monitoring device proposed in this study enables integrated functions of automatic monitoring, data uploading, and database analysis. By combining water-level monitoring of firefighting buckets with forest fire monitoring, the system simplifies the workload of forest personnel while ensuring data accuracy, effectively addressing the limitations of existing field-deployed water-bucket monitoring equipment. The device is easy to operate, provides precise measurements, and consumes minimal power, making it well-suited for use in complex outdoor environments and offering broad prospects for forest monitoring applications.

However, certain limitations remain. The device's operational endurance could be further improved, and its waterproofing performance requires enhancement to better withstand more extreme and variable field conditions.

Author Contributions: Conceptualization, S.C. and X.L.; methodology, L.S. and X.Z.; software, S.C.; validation, S.H., C.D. and H.L.; formal analysis, D.W.; investigation, G.J.; resources, H.L.; data curation, H.L.; writing—original draft preparation, X.L. and S.C.; writing—review and editing, S.C.

and X.L.; visualization, S.C.; supervision, X.L.; project administration, C.D.; funding acquisition, X.L. and S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (32301585), the National Innovation Park for Forestry and Grass Equipments (2024YG15), and the Natural Science Foundation of Zhejiang Province (Grant No. LQN25C160004).

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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