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One-Year Field Evaluation of a Low-Cost Arduino-Based Tipping-Bucket Rain Gauge in Central Mexico

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ABSTRACT

Accurate and cost-effective rainfall monitoring remains a challenge in regions with sparse station networks. This study developed and tested a low-cost rainfall monitoring device based on an Arduino Mega 2560 coupled with two tipping-bucket rain gauges (WH-SP-RG™ MISOL). The device was deployed for one year (July 2024–June 2025) at the Colegio de Postgraduados, Texcoco, Mexico, to evaluate its reliability under natural rainfall conditions. Calibration with controlled water applications showed that each tipping event represented 0.288 mm of rainfall, closely matching the manufacturer's specification of 0.2794 mm per tip. A difference of 8.6% was detected between tips counted manually and those recorded by the Arduino, indicating a slight tendency of the raw Arduino signal to overcount tipping events. Rainfall events were classified into light, moderate, and high intensities, and statistical analyses were conducted using non-parametric methods. Results showed strong agreement between the two gauges, with cumulative totals differing by only 11.8% during the study period. Differences between gauges were minimal for light (1.95%) and moderate rainfall (2.6%), but increased for high-intensity events (7.81%), suggesting greater variability under heavy rainfall conditions. Excluding single-tip events, no significant differences were found between sensors under the same rainfall intensity. Overall, the results demonstrate that low-cost Arduino-based rain gauges, when carefully leveled and calibrated, can provide reliable rainfall measurements consistent with ranges reported in the literature. The prototype operated successfully for an entire year, confirming its potential as a valuable and accessible tool for hydrological monitoring in resource-limited settings.

Keywords: Arduino, Rainfall, Factory Calibration.

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1 Introduction

Accurate and high spatiotemporal resolution rainfall observations are essential in many applications [1]. Several methods are available to measure rainfall, including traditional rain gauges and non-catching type gauges. The latter represent an emerging class of in situ precipitation measurement instruments; however, rigorous testing and calibration are more challenging for these instruments than for traditional gauges [2]. Furthermore, dedicated hardware is often very expensive and requires additional software to control its behavior [3].

In Mexico, the National Meteorological Service (Servicio Meteorológico Nacional, SMN; smn.conagua.gob.mx) operates 203 automatic stations that record meteorological variables, including precipitation, distributed over a territory of 1.96 million km² [4]. This limited density highlights the need for easy-to-use and low-cost instruments capable of recording rainfall with greater spatial coverage.

Some studies have already conducted accuracy tests by employing low-cost and open-source I/O boards such as those in the Arduino family [3]. Due to their precision, acceptable performance [5] and ease of use, tipping-bucket rain gauges (TBRs) remain one of the most widely used instruments for rainfall monitoring [6]. These gauges allow rainfall to be stored in predetermined accumulation intervals such as 15-minute, hourly, or daily totals [7].

Building upon this context, the present study developed a low-cost device capable of measuring and storing rainfall using a tipping-bucket gauge. The device was deployed at a single site to evaluate its performance and to detect small differences in measurement between closely positioned sensors.

2 Materials and methods

The experiment was conducted at the facilities of Colegio de Postgraduados, Campus Montecillo (Texcoco, Mexico). The purpose was to test the functionality and data reliability of a low-cost tipping-bucket rain gauge prototype under real-world conditions over a period of nearly one year (July 23, 2024 to June 23, 2025). Rain gauges were mounted on the rooftop of a two-level structure, positioned 1.5 meters apart, at the geographic coordinates 19.500013° N, 98.884627° W.

2.1 Design and Assembly of the Prototype

The rainfall monitoring device was built using an Arduino Mega 2560, responsible for logging data and storing it on a microSD card. The system included a DS1302TM real-time clock (RTC) module for timestamping rainfall events, an MLMSDTM microSD module for data storage, and a WH-SP-RG™ MISOL digital rain gauge, which operates via pulses generated by a tipping bucket mechanism. A 3.5-inch TFT display was included to allow on-site visualization of rainfall events. All components were housed in a custom 3D-printed enclosure, designed in AutoCAD and printed using an Ender 3 V2 printer. Power was supplied via a Steren™ adjustable power adapter set at 6V. Standard RJ11 connectors were used for the rain gauge input, and 2.5mm DC male-female connectors were used for the power line.

The total cost of the rainfall monitoring device was approximately USD 100, including the Arduino Mega 2560 board (USD 15), the WH-SP-RG™ MISOL digital rain gauge (USD 30), a 3.5-inch TFT display (USD 20), a microSD module

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(USD 5), a DS1302 RTC module (USD 3), an adjustable Steren™ power adapter (USD 12), and connectors (USD 5). The 3D-printed enclosure added approximately USD 10 in PLA material costs. This makes the device significantly more affordable than commercial rainfall monitoring systems, which generally range from several hundred to several thousand USD, depending on their configuration and software support.

2.2 Rainfall Logging and Data Structure

Rainfall was recorded each time a pulse was detected by the sensor, using the INPUT_PULLUP configuration in the Arduino IDE. Each tipping event, corresponding to an on–off–on sequence (one click), was interpreted as 0.2794 mm of precipitation [8]. To avoid duplicate entries caused by debounce errors, data were only recorded when a pulse occurred at least one second after the previous one. Each rainfall event was saved in .txt format with comma-separated values in the following structure: date (dd.mm.yyyy), time (hh:mm:ss), rainfall value, and units. Although repeating values and units in each line may seem redundant, this format was intentionally chosen to ensure the file was universally interpretable by users unfamiliar with the system.

2.3 Sensor leveling considerations for accurate rain gauge calibration

To ensure the accuracy of the tipping bucket mechanism, proper leveling of the rain gauge is critical. During a preliminary test with 1 L of water applied at a constant flow rate, variations in the total number of tipping events were recorded by the Arduino board, despite similar median time intervals between tips (Fig. 1). In this test, the rain gauge was intentionally left unlevelled to evaluate the impact of slight inclinations.

Results showed that even minor tilts caused considerable variability in the number of tipping events, likely due to imbalance in the bucket's rotation axis. In some cases, the internal plastic wall of the sensor housing appeared to obstruct the free movement of the tipping mechanism, requiring more water to trigger each tip. Additionally, discrepancies in the response time between both sides of the bucket were noted, introducing noise in the data.

These findings were confirmed during calibration trials using 1000 mL, where a slight tilt caused delays in tipping, associated with added resistance due to friction and imbalance. This highlights the importance of meticulous leveling in every installation. Consequently, during the final calibration with 200 mL, special care was taken to ensure perfect leveling, which resulted in minimal variation across replicates.

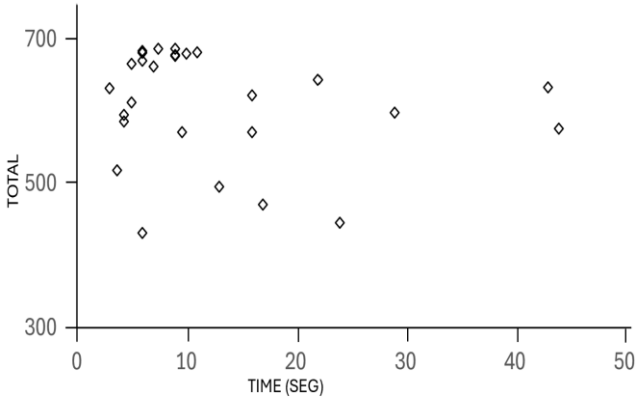

Fig. 1 Tipping event totals measured by Arduino from the rain gauge under different time intervals and inclinations.

2.4 Calibration of the Rain Gauge

The calibration process began by identifying the highest recorded daily rainfall during the study period (from July 23, 2024, to June 23, 2025), which was 30 mm. To reproduce this amount under controlled conditions, it was necessary to convert this rainfall depth into a corresponding water volume, based on the catchment area of the tipping-bucket rain gauge.

The WH-SP-RG™ MISOL digital rain gauge specifies a resolution of 0.2794 mm per tip. To determine the internal catchment area, a scaled top-view photograph of the sensor inlet was digitized and traced in AutoCAD.

The internal area was delineated by selecting a contour line located at the midpoint of the wall thickness surrounding the rain gauge inlet (see Fig. 2). This process yielded an estimated internal area of 58.4014 cm². The contour was chosen under the assumption that a raindrop falling exactly on this midpoint would split evenly, with half entering the gauge and half falling outside. Therefore, this boundary was considered a reasonable approximation of the effective catchment area.

Fig. 2 Top view of the internal catchment area (red line) of the WH-SP-RG™ MISOL rain gauge inlet, defined at the midpoint of the wall thickness under the assumption that a raindrop falling on this point would split evenly inside and outside the gauge.

Using this area, the volume of water required to trigger one tip was calculated as the product of the catchment area and the specified tip height of 0.2794 mm per tip. This resulted in a theoretical volume of approximately 1.6317 cm³ per tip, which, assuming a water density of 1 g/cm³, equals 1.6317 mL. Consequently, to simulate a 30 mm rainfall event, a total of approximately 175.2 mL of water would be required.

To ensure sufficient volume and allow for slight measurement errors or evaporation losses, 200 mL of water was selected as the calibration volume. This amount slightly exceeds the equivalent of 30 mm of rainfall over the catchment area and ensures that multiple tips would be registered during calibration.

The rain gauge was carefully leveled, and 200 mL of water were measured using a 1 L graduated cylinder. This volume was then transferred into a capped plastic bottle. Water was applied to the rain gauge by gently tilting the bottle to release a controlled flow, allowing the internal tipping bucket to move at specific intervals. Initially, water was dispensed so that one tip occurred every 2 seconds. The same process was repeated for tipping intervals of 4, 5, 6, 7, 8, and 10 seconds.

During each run, the total number of tipping events was recorded manually by listening to the audible clicks of the tipping mechanism, and simultaneously by the Arduino-based data logger. The data collected included the time interval between each tip, the total tipping events counted manually (referred to as OB for "observed"), and those recorded by the Arduino (referred to as AR), as shown in Fig. 3.

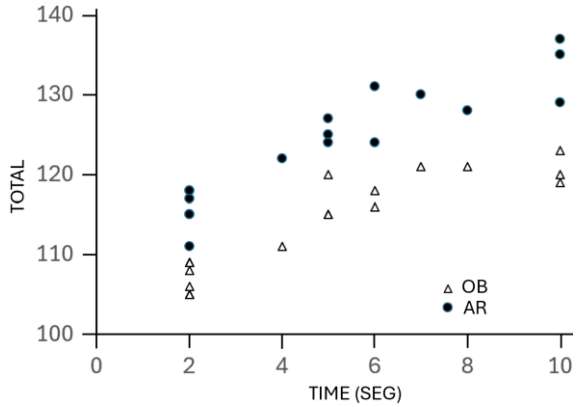

Fig. 3 Total number of rain gauge tipping events (TOTAL) detected manually (OB) and by Arduino (AR) under different water application intervals (TIME)

To estimate the average number of tipping events corresponding to 200 mL of water under steady conditions, only the tests where tips occurred every 5 seconds or more were used. This subset was chosen because these intervals produced consistent and stable readings. From these data (10 total repetitions detected manually), the required sample size to estimate the mean tipping count with 95% confidence was calculated following Montgomery and Runger's methodology. Based on an estimated standard deviation of 3 tips and an accepted error margin of ±2 tips, the minimum required sample size was approximately 8. As 10 repetitions were conducted, this requirement was satisfied.

The average number of tipping events recorded across those repetitions was 118.8, corresponding to 200 mL of water. This indicates that each tipping event represented approximately 1.68 mL of water. Given the previously calculated internal catchment area of 58.4014 cm², this volume per tip would be equivalent to a rainfall depth of approximately 0.288 mm per tip. The experimentally derived value of 0.288 mm per tip differed from the manufacturer's specification (0.2794 mm per tip) by approximately 3%. Such differences are expected due to uncertainties in manual water application and small mechanical tolerances of tipping-bucket mechanisms. Because the manufacturer's value represents the standardized calibration of the sensor under controlled conditions and is commonly used in previous studies employing the same model, this value was adopted for subsequent rainfall calculations. Given the small magnitude of the difference, using either value would have only a minor effect on the final rainfall estimates.

In addition, the average number of tipping events recorded manually across repetitions with inter-tip times greater than 5 s was 118.8, whereas the Arduino recorded an average of 129.0 events for the same 200 mL water applications. Taking the manual count as the closest reference to the actual number of physical bucket tips, this difference indicates that the Arduino system overcounted events by approximately 8.6%. This overcounting was most likely associated with contact bounce or rapid signal transitions in the tipping-bucket switch, which occasionally generated spurious pulse registrations despite the debounce criterion implemented in the code. Therefore, if uncorrected, the raw Arduino signal would slightly overestimate rainfall.

According to the World Meteorological Organization [9], rainfall intensity is classified as follows: Light (0.1–2.5 mm/h), Moderate (2.6–7.5 mm/h), Heavy (7.6–50 mm/h), Very Heavy (50.1–100 mm/h), and Torrential (>100 mm/h). Assuming a tipping interval of 5 seconds, which corresponds to the minimum interval at which the sensor consistently produced accurate tipping counts during calibration, each tip would represent approximately 0.288 mm of rainfall. At this rate (0.288 mm every 5 seconds), the maximum intensity measurable by the rain gauge would be approximately 207.6 mm/h. This was calculated by extrapolating the per-tip volume over an hour.

For intervals shorter than 5 seconds between tipping events, the total number of tips recorded was consistently lower than expected. This suggests that the sensor may become saturated or face mechanical limitations when processing higher frequency inputs, likely due to the rebound or oscillation time of the internal tipping bucket mechanism. As a result, calibration was established exclusively for flow rates that produce tipping intervals longer than 5 seconds, which correspond to intensities below 207 mm/h. This upper limit still encompasses the expected range of extreme natural rainfall events at the study site and ensures reliable operation within the gauge's functional range.

2.5 Precipitation Data Structuring and Event Detection

The precipitation data used in this study were collected from two rain gauges, referred to as Left and Right, which automatically logged rainfall between July 23, 2024 and June 23, 2025. Raw data were stored in plain text format (.txt), with each record containing date, time, rainfall amount, and measurement units.

For data processing, the records were imported into Microsoft Excel and converted into a continuous datetime format to facilitate temporal analysis. Rainfall events were identified using a custom data-processing workflow in which consecutive records were grouped into the same event when the time interval between them was shorter than 30 minutes. When the interval exceeded this threshold, a new rainfall event was defined.

After event identification, the start and end times of each rainfall event were automatically determined, and the resulting event dataset was used for further analysis and visualization.

2.6 Rainfall Event Visualization

Following the classification of precipitation events, the next step involved the preparation of the data for visual representation. The goal was to generate a graphical timeline that clearly displayed the start and end of each rainfall event throughout the monitoring period.

Using the EventMarkers column, the rows labeled as start and end were filtered separately. For each start label, the corresponding day and start time were extracted and stored together in a new column, creating a coordinate that marked the beginning of an event. This was done in Column B of the Excel sheet. Similarly, the day and time corresponding to the end of each event were extracted and stored in Column F.

To simplify plotting, these start and end coordinates were interleaved into a single column. This was accomplished with a VBA macro named "IntercalateRowBF", which combined the two lists in an alternating pattern. The result was that the first value from the start list appeared at the top, followed by the corresponding value from the end list, then the next start value, then the next end value, and so on. This output was placed in Column J and allowed for the structured pairing of event boundaries.

For visualization in a CAD environment such as AutoCAD, the interleaved coordinates were transformed into polyline command sequences using another macro called "GeneratePlineColumnN". This macro generated text blocks following the syntax required by the pline command in AutoCAD. Each block began with the word "pline", followed by two consecutive coordinates (start and end), and ended with an empty line. These blocks were written into Column N of the

Excel sheet, enabling the user to copy and paste them directly into AutoCAD to create line segments representing the rainfall events.

The final graphical output consisted of a series of horizontal lines that visually represented the timing and duration of rainfall events. This visual approach provided an intuitive understanding of the distribution of precipitation over time and allowed for easy identification of clustered or isolated events.

2.7 Daily Rainfall Visualization

To complement the timeline of individual rainfall events, an additional graphical element was added to display the total daily precipitation above the event segments. The approach used to generate this visual component followed a similar structure to that described for the rainfall events.

In this case, each plotted line represented the total rainfall accumulated on a specific day. For each day with recorded precipitation, two coordinate points were defined. The initial coordinate was always set at (day of occurrence, 0), and the final coordinate was (day of occurrence, total rainfall for that day). These coordinates formed vertical line segments representing the daily rainfall totals, which were overlaid on the main timeline to provide context and scale to the distribution of rainfall throughout the study period.

2.8 Statistical Analysis

To evaluate the differences between rainfall events measured by both rain gauges, the data were organized into a single table where each row represented a corresponding event. For each event, the total rainfall, event duration, and rainfall intensity were obtained for both sensors. Scatterplots were prepared to visualize the agreement between sensors. Rainfall data were organized into six treatments to enable comparison between the two rain gauges across three categories of rainfall intensity: light, moderate, and high. For each variable analyzed (rainfall intensity, total rainfall per event, and event duration), the treatments were defined as follows: 1.1 (left sensor – light), 1.2 (right sensor – light), 1.3 (left sensor – moderate), 1.4 (right sensor – moderate), 1.5 (left sensor – high), and 1.6 (right sensor – high). Each treatment was thus characterized by the distribution of rainfall events recorded under comparable conditions by the left and right gauges.

Single-tip events (i.e., events comprised of a single bucket tip) were excluded from the treatment-based analyses (intensity, total per event, and duration) because (i) they represent minimal rainfall amounts near the resolution limit of the tipping mechanism and are therefore highly sensitive to timing noise and mechanical/electronic uncertainty, and (ii) approximately half of them did not occur simultaneously at both gauges, preventing reliable one-to-one pairing for event-level comparisons. Importantly, these events were still accounted for in the computation of total accumulated rainfall over the study period.

Box-and-whisker plots were used to visualize the distribution of each treatment. To evaluate statistical assumptions, homogeneity of variances was tested with Levene's test (leveneTest, car package) [10], and normality was assessed with the Shapiro–Wilk test (shapiro.test, base R). As assumptions of normality and homoscedasticity were not consistently satisfied, non-parametric methods were used.

For pairwise comparisons of left vs. right sensors within the same rainfall intensity category, the Mann–Whitney U test (Wilcoxon rank-sum; wilcox.test) was applied. For simultaneous comparison across all six treatments, the Kruskal–Wallis test (kruskal.test) was employed as a non-parametric alternative to one-way ANOVA. When significant differences were detected, post hoc multiple comparisons were carried out with Bonferroni-adjusted pairwise tests (pairwise.wilcox.test) and with the HSD test (HSD.test, agricolae package) [11]. Groupings from multiple comparisons were visualized directly on the boxplots using the cld function from the multcomp package [12].

All statistical analyses and visualizations were performed in R version 4.2.2 [13]. The main libraries employed were: car, agricolae, multcomp, ggplot2 [14], and base R functions (boxplot, shapiro.test, wilcox.test, kruskal.test).

3 Results

The rainfall dataset was visualized as shown in Fig. 4, where vertical lines and dots represent the occurrence of rainfall events on an hourly basis throughout the study period. In addition, daily rainfall totals are displayed for the entire observation period. The upper panels correspond to the right rain gauge, while the lower panels correspond to the left rain gauge. This visualization allows simultaneous inspection of both the temporal distribution of rainfall events and the daily accumulation patterns recorded by each instrument.

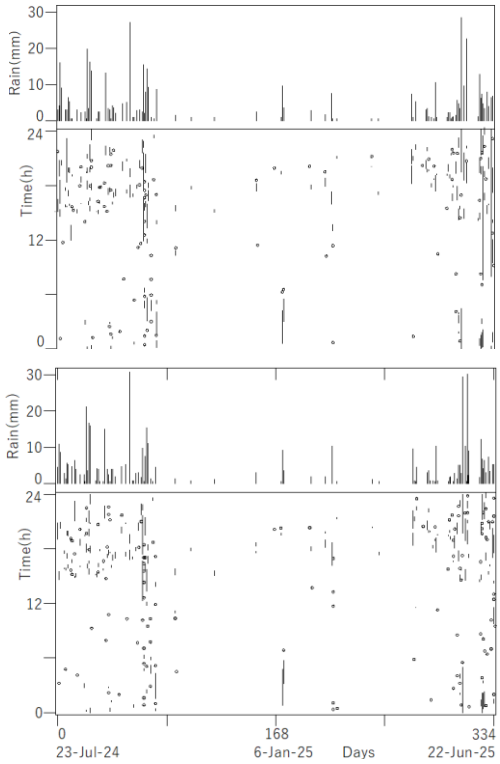

Fig. 4 Rainfall event timing and daily accumulation detected by the right (top) and left (bottom) rain gauges.

In addition, rainfall totals, event durations, and rainfall intensities were compared between sensors using scatterplots, as shown in Fig. 5. The left panel of the figure illustrates the comparison of total rainfall per event, the central panel presents event duration, and the right panel displays rainfall intensity, each contrasting measurements obtained from the left and right rain gauges. This visualization provides a direct assessment of agreement between the two instruments across the three main rainfall descriptors.

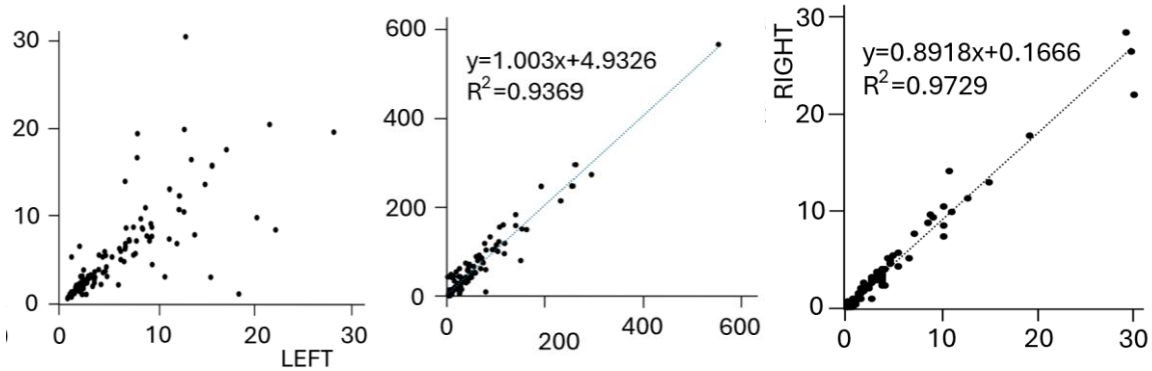

Fig. 5 Scatterplots of rainfall totals in mm (left side), event durations in minutes (center), and rainfall intensities in mm h-1 (right side) recorded by the left (LEFT) and right (RIGHT) rain gauges.

Statistical Analysis of Rainfall Intensity. Box-and-whisker plots of rainfall intensities recorded by both rain gauges under light, moderate, and high rainfall events are presented in Fig. 6. Levene's test for homogeneity of variances across all six treatments (1.1–1.6) indicated significant differences ($p = 3.79 \times 10^{-15}$), confirming heteroscedasticity among the groups. Pairwise Levene's tests, however, showed that variance was homogeneous between gauges within the same rainfall category: light (1.1 vs. 1.2, p = 0.0663), moderate (1.3 vs. 1.4, p = 0.2464), and high (1.5 vs. 1.6, p = 0.3682).

Normality of distributions was evaluated using the Shapiro–Wilk test, which did not hold for any of the treatments (1.1: p = 0.0174; 1.2: $p = 2.73 \times 10^{-7}$; 1.3: p = 0.0016; 1.4: $p = 5.94 \times 10^{-5}$; 1.5: p = 0.0002; 1.6: p = 0.0102). Consequently, non-parametric tests were applied.

Pairwise comparisons between gauges for the same rainfall category were performed with the Mann–Whitney U test. No significant differences were found between light (1.1 vs. 1.2, p = 0.4063), moderate (1.3 vs. 1.4, p = 0.2389), or high rainfall events (1.5 vs. 1.6, p = 0.0837).

Finally, the Kruskal–Wallis test across all six treatments (1.1–1.6) revealed significant differences in distributions, as reflected by the letter groupings shown in Fig. 6.

Statistical Analysis of Total Rainfall. Box-and-whisker plots of total rainfall per event for both sensors and rainfall categories are shown in Fig. 7. Levene's test across all six treatments (1.1–1.6) indicated significant differences in variances (p = 0.0305), suggesting heterogeneity among groups. However, pairwise Levene's tests revealed that variances were homogeneous between gauges for light and moderate rainfall events (1.1-1.4, p = 0.3075) and between the two sensors under high rainfall events (1.5 vs. 1.6, p = 0.8045).

Because the assumptions of homogeneity and normality were not satisfied, the Kruskal–Wallis test was applied across all treatments. The analysis revealed significant differences among treatments, as reflected by the letter groupings above the boxplots in Fig. 7.

Statistical Analysis of Rainfall Event Duration. Box-and-whisker plots of event duration for both sensors and rainfall categories are presented in Fig. 8. Levene's test across all six treatments (1.1–1.6) indicated significant differences in variances (p = 0.0036), showing heterogeneity among groups. However, pairwise Levene's tests suggested homogeneity of variances between the two sensors within moderate rainfall events (1.3 -1.6, p = 0.1636) and within light rainfall events (1.1 vs. 1.2, p = 0.6937).

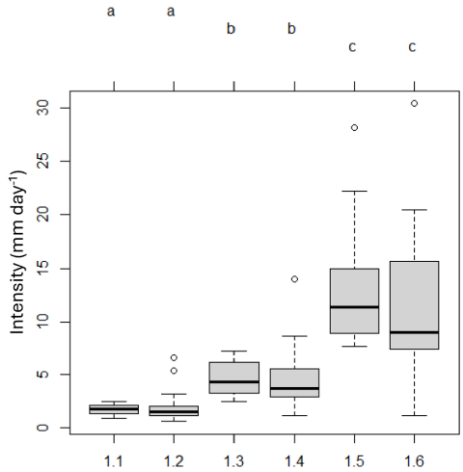

Fig. 6 Box-and-whisker plots of rainfall intensity for six treatments: 1.1 (left sensor – light rain), 1.2 (right sensor – light rain), 1.3 (left sensor – moderate rain), 1.4 (right sensor – moderate rain), 1.5 (left sensor – high rain), and 1.6 (right sensor – high rain), with significant differences among treatments indicated by the letter groupings above the boxes.

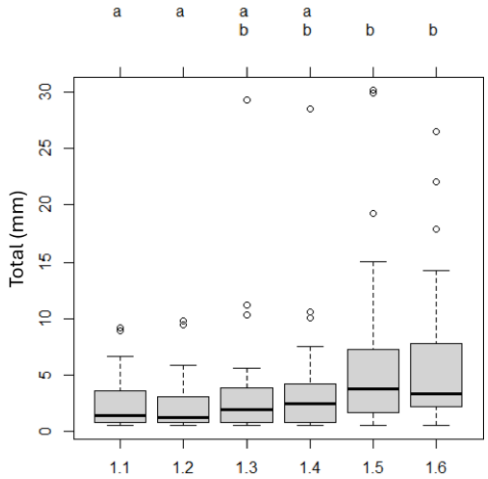

Fig. 7 Box-and-whisker plots of total rainfall per event for six treatments: 1.1 (left sensor – light rain), 1.2 (right sensor – light rain), 1.3 (left sensor – moderate rain), 1.4 (right sensor – moderate rain), 1.5 (left sensor – high rain), and 1.6 (right sensor – high rain), with significant differences among treatments indicated by the letter groupings above the boxes.

Since assumptions of homogeneity and normality were not met, the Kruskal–Wallis test was applied to all treatments, revealing significant differences in distributions. Post hoc multiple comparisons using Bonferroni adjustments further identified which treatments differed significantly, as reflected by the letter groupings shown above the boxplots in Fig. 8.

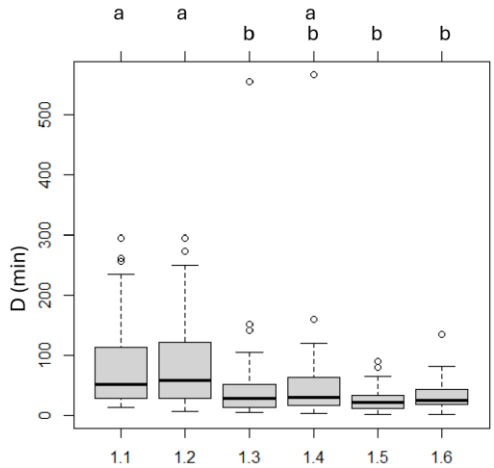

Fig. 8 Box-and-whisker plots of rainfall duration per event (D) for six treatments: 1.1 (left sensor – light rain), 1.2 (right sensor – light rain), 1.3 (left sensor – moderate rain), 1.4 (right sensor – moderate rain), 1.5 (left sensor – high rain), and 1.6 (right sensor – high rain), with significant differences among treatments indicated by the letter groupings above the boxes.

When comparing totals by treatment, differences between sensors were minimal for light rainfall events (1.1 vs. 1.2: 101.98 vs. 100.03 mm) and moderate for medium-intensity events (1.3 vs. 1.4: 142.77 vs. 139.14 mm), but increased substantially for high-intensity events (1.5 vs. 1.6: 227.43 vs. 210.95 mm). This pattern indicates that discrepancies between sensors tended to grow as rainfall intensity increased.

In total, light, moderate, and high rainfall events accounted for 472.19 mm at the left sensor and 450.11 mm at the right sensor. Furthermore, single-tip events were excluded from the treatment classification, representing 132 cases (61.19 mm) for the left sensor and 57 cases (23.19 mm) for the right sensor. Including these events, the total rainfall accumulated during the study period was 533.37 mm for the left gauge and 473.30 mm for the right gauge, resulting in an overall difference of approximately 11.8%. Notably, six larger events (0.56 to 8.94 mm, totaling 22.91 mm) were recorded only by the left gauge and not by the right gauge. These missing records are unlikely to be related to the mechanical saturation discussed in the calibration section, since the rainfall amounts were relatively small and well within the operational range of the tipping bucket. A more plausible explanation is a temporary obstruction or disturbance affecting the tipping mechanism or the signal acquisition system of the right gauge. During field inspections, small biological debris (e.g., spider webs) was occasionally observed inside the device housing, which may interfere with the proper operation of the system. After cleaning the device, normal operation resumed, suggesting that minor environmental obstructions can temporarily affect the measurements.

4 Discussion

In Fig. 5, the scatterplots of rainfall totals per event indicate a coefficient of determination (R^2) of 0.9729 and a slope of 0.8918. Similar results were reported by Urban and Strug [15], who found R^2 values ranging from 0.9043 to 0.9938 and slopes between 0.7782 and 0.9777 when comparing daily precipitation sums between the Hellmann rain gauge and different types of automatic gauges. This strong agreement is also consistent with the calibration performed in the present study, where the difference between the average number of tips counted manually for inter-tip times greater than 5 seconds (118.8) and those recorded by the Arduino (129.0) indicated an error of 8.6%. The raw Arduino signal showed a slight tendency to overcount bucket tips, which would lead to rainfall overestimation if not filtered during data processing.

The comparison of rainfall totals and event durations between the two gauges showed very strong agreement, with cumulative totals differing by only 11.8% over the study period. Comparable discrepancies have been reported in other studies. For instance, Liu et al. [16] found differences in rainfall amounts among six different instruments ranging from 0% to 27.7%. Similarly, Urban and Strug [15] reported differences of 5–14% between gauges located less than 5 m apart. The 11.8% difference observed in this study is therefore within the range reported in previous investigations.

Regarding the single-tip events, there was a large difference between the two rain gauges, with 132 cases (61.19 mm) recorded by the left sensor and 57 cases (23.19 mm) by the right sensor. This discrepancy can be explained by the findings of Padron et al. [17], who compared tipping-bucket gauges with resolutions of 0.254 mm, 0.2 mm, and 0.1 mm, and found that underestimation was greater at lower resolutions, particularly for low-intensity events. They also noted that rainfall intensities below 2 mm h^{-1} cannot be measured accurately. As a general conclusion, Padron et al. [17] attributed the larger error for lower intensities to intrinsic gauge characteristics affecting wetting and evaporation losses.

From Fig. 6, Fig. 7, and Fig. 8, it can be observed that as rainfall intensity increased, the total rainfall per event also increased while event duration decreased, with clear statistical differences among treatments. Additionally, no significant differences were found between the left and right sensors under the same rainfall intensity (i.e., pairs 1.1–1.2, 1.3–1.4, and 1.5–1.6). This indicates that, excluding the single-tip events, both sensors performed consistently under the same conditions. However, the differences between sensors tended to grow at higher rainfall intensities. Specifically, for light rain, the difference between left and right sensors was 1.95% (101.98 vs. 100.03 mm); for moderate rain, 2.6% (142.77 vs. 139.14 mm); and for high rain, 7.81% (227.43 vs. 210.95 mm). This suggests that at the microscale, total rainfall measurements may vary more substantially under high-intensity conditions.

Finally, the low-cost rainfall measurement device developed for this study functioned reliably throughout the evaluation period (July 23, 2024 to June 23, 2025). Similar results have been reported by other researchers who found that Arduino-based systems can measure rainfall adequately [18],[19] and accurately [20],[21].

5 Conclusions

This study demonstrated that a low-cost Arduino-based device coupled with tipping-bucket rain gauges operated reliably over a one-year period. The two sensors showed very similar behavior, with cumulative rainfall differing by only 11.8% during the study, a discrepancy well within the ranges reported in the literature. At the treatment level, differences between gauges were minimal under light and moderate rainfall, but increased under high-intensity events, suggesting that sensor variability tends to grow as rainfall intensity increases.

Single-tip events, which represented small, non-coincident records, were excluded to avoid noise and improve the

robustness of the comparisons. Statistical analyses confirmed that, apart from these events, no significant differences were detected between gauges operating under the same rainfall conditions.

Calibration tests further supported the robustness of the device. The average number of tipping events per 200 mL of water corresponded closely to the manufacturer's specified resolution (0.2794 mm per tip). In addition, the difference between the average number of tips counted manually for inter-tip times greater than 5 s (118.8) and those recorded by the Arduino (129.0) indicated a discrepancy of approximately 8.6%, reflecting a slight tendency of the raw Arduino signal to overcount tipping events. If unfiltered, this behavior would lead to a small overestimation of rainfall. Therefore, the calibration results overall support the reliability of the rainfall measurements obtained.

Overall, the findings indicate that low-cost rain gauges, when properly deployed and carefully leveled, and analyzed, can provide reliable rainfall measurements, offering a valuable and accessible tool for hydrological monitoring in resource-limited settings.

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Author Contributions

A. Quevedo-Nolasco: Conceptualization, Methodology, Resources, Writing – Review & Editing, Supervision; **G. J. Aguado-Rodríguez:** Formal Analysis, Software, Data Curation, Writing – Original Draft, Visualization.

Conflicts of Interest Statement

The authors declare no competing financial or non-financial interests, nor any personal relationships, that could influence the work reported herein.

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Generative AI Statement

Generative AI (ChatGPT, GPT-5) was used to assist in English language revision, to draft example code snippets, and to create preliminary visualizations of diagrams later developed manually by the authors. All analyses, figures, and interpretations were verified and finalized by the authors. No AI-generated data or results are presented as original work.

Data Availability Statement

Data will be made available upon reasonable request.

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