frontiers | Frontiers in Earth Science

TYPE Original Research
PUBLISHED 06 February 2026
DOI 10.3389/feart.2026.1721642

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OPEN ACCESS

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RECEIVED 09 October 2025
REVISED 03 December 2025
ACCEPTED 05 January 2026
PUBLISHED 06 February 2026

CITATION
Mitze F, Jacobs SR, Breuer L, Zeballos JC, Codalli F, Shagega FP and Weeser B (2026) Validation of analog sensor measurements in hydrometeorological participatory monitoring in various tropical countries.
Front. Earth Sci. 14:1721642.
doi: 10.3389/feart.2026.1721642

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Validation of analog sensor measurements in hydrometeorological participatory monitoring in various tropical countries

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As remote tropical mountain regions often lack open data and traditional methods of collecting hydrometeorological data are not always feasible, this study validates an alternative participatory monitoring approach for collecting hydrometeorological data in mountainous regions in Ecuador, Honduras and Tanzania. Volunteers used analog low-cost sensors to measure air temperature, relative humidity, rainfall and water level. The measurements were validated with photos taken alongside the measurements. Data from selected stations were additionally validated against automatic sensor data using different metrics, such as the mean absolute error (MAE). In addition, errors made by frequent and non-frequent participants were compared, assessing the performance of these two target groups. In the period between May 2023 and May 2025 a total of 2,982 observations were received, whereby the majority were submitted by frequent participants (84.4%). A comparison between frequent and non-frequent users showed that the former measured with higher accuracy. The comparison with automatic sensor data showed a correlation for all parameters ranging from 0.42 to 0.96. The best results in terms of accuracy were achieved for air temperature (MAE: 0.74 °C–1.65 °C) and water level (MAE: 0.04–0.08 m). On the other hand, a high deviation was found for relative humidity (MAE: 16.76%–31.69%). This deviation was corrected by applying linear regression, resulting in moderate deviation (MAE: 5.45%–9.50%). Rainfall had a MAE ranging from 2.55 to 3.10 mm. This was mainly attributed to the low measurement frequency and the limited capacity of the rain gauges. Overall, the study showed ambivalent results, where analog thermometers and water level gauges can be considered the most promising alternatives to automatic sensor measurements. However, the hygrometers only provided moderate measurement quality, while the rain gauges used were too small to cover all rainfall in the periods analyzed.

KEYWORDS

air temperature, citizen science, rainfall, relative humidity, water level

1 Introduction

The Sustainable Development Goal 6 (SDG 6), of the United Nations 2030 Agenda for Sustainable Development, is aimed at ensuring availability and sustainable management of water and sanitation for all until 2030 (United Nations, 2015). In 2022, approximately 2.2 billion people worldwide lacked access to safely managed drinking water, and around half of the global population faced severe water scarcity (United Nations Department of Economic and Social Affairs, 2024). These figures highlight the urgent need for sustainable water management strategies, which are essential now and will become increasingly critical in the future. The majority of critically affected people live in the so-called "Global South" (United Nations, 2022), where climate change already has significant impacts, especially on vulnerable populations (Sen Roy, 2018; Ngcamu, 2023).

Strategies to cope with climate change impacts on water resources require reliable hydrometeorological data like rainfall, air temperature or water levels. Such data are commonly recorded by automatic weather and gauging stations, but these are costly and complex to maintain. The global distribution of gauging and precipitation monitoring stations is highly disproportionate and is decreasing (Kidd et al., 2017; Ruhi et al., 2018; Krabbenhoft et al., 2022). This particularly affects remote regions in the Global South, often because of the lack of financial resources (Buytaert et al., 2014; Fankhauser and McDermott, 2014; Ruhi et al., 2018). Satellite-based monitoring becomes increasingly relevant due to the possibility of obtaining information where ground observations are complex or not possible. While satellite remote sensing products, for instance for precipitation (Sun et al., 2018; Tang et al., 2020) or land surface temperatures (Li et al., 2023), have improved over the last decades, the spatial and temporal resolution remain limiting factors (Levizzani and Cattani, 2019; Marra et al., 2019; Mao et al., 2021). Especially orographic precipitation in mountainous areas remains complex to sense (Kimani et al., 2017; Barros and Arulraj, 2020; Hemp and Hemp, 2024). Collecting water level data in smaller rivers with satellite-based products is challenging or even not possible due to the spatial resolution and accuracy (Musa et al., 2015; Grimaldi et al., 2016; Bandini et al., 2017). Therefore, it is important to explore suitable, cost-effective alternatives to ground observations.

One possible approach is the integration of the general public into the scientific process, which is commonly known as citizen science (Dickinson et al., 2012; Buytaert et al., 2014). A sub-category of this is called participatory monitoring (PM), in which volunteers only participate in order to collect data and information (Danielsen et al., 2009). Various projects have demonstrated PM potentials with different approaches for measuring water level, precipitation and other hydrometeorological parameters (Buytaert et al., 2014; Weeser et al., 2018; Davids et al., 2019a; Arienzo et al., 2021; Scheller et al., 2024). While most PM projects have focused on North America or Europe, fewer have been implemented in countries in the Global South (Buytaert et al., 2014; Njue et al., 2019).

In this study, the data collection of the HydroCrowd project is validated. Here, hydrometeorological observations were collected using a novel PM approach in remote mountainous regions in Ecuador, Honduras and Tanzania. A network of weather and water monitoring stations equipped with analog low-cost sensors was installed in these areas. The approach combines different elements of various PM projects, such as rainfall monitoring like in the CoCoRaHS (Reges et al., 2016) and Smartphones4Water (Davids et al., 2019a) project, or water level monitoring and smartphone based data transmission previously demonstrated in the CrowdWater (Seibert et al., 2022) project. To obtain an even more comprehensive suite of hydrometeorological parameters, the monitoring is extended to also include air temperature, relative humidity and turbidity. At weather stations, participants measured air temperature, relative humidity and rainfall. At water stations at rivers, the water level and turbidity of the river water were measured. Similar to CoCoRaHS, but unlike Smartphones4Water, we used standardized, commercially available rain gauges for rainfall collection. Unlike CrowdWater, we used physical rather than virtual water level gauges. While local community members (from here on referred to as frequent participants) were targeted as possible participants in Honduras, the main focus in Ecuador and Tanzania was on local and international tourists (non-frequent participants), respectively. For validation purposes, participants were asked to upload photos of the sensors when sending their observation which could be done using the projects smartphone application or the web interface. Additionally, selected stations were equipped with automatic sensors to test the accuracy of the analog sensors. The data collection approach is visualized in Figure 1.

The main objective of this study was to validate the project's participatory approach for collecting hydrometeorological data. The results of this analysis can be used to inform future projects about the suitability of PM approaches for hydrometeorological monitoring in similar contexts, depending on the project purpose and associated data accuracy requirements. The following research questions were addressed in this study.

1. How well can frequent and non-frequent participants measure hydrometeorological parameters using simple analog sensors?
2. How good are the analog sensor measurements by participants compared to automatic sensors in terms of accuracy?

2 Materials and methods

2.1 Study areas

For the project, study areas in three different tropical mountain settings in Ecuador (ECU), Honduras (HND) and Tanzania (TNZ) were selected, with the majority of the stations located in protected national parks. The areas differ in dominating land use and local climatological conditions and are described in the following sections.

2.1.1 Ecuador

Three sites in the province of Azuay, Southern Ecuador (ECU), were selected as study areas (Figure 2). The first site is located in the Andean Páramo ecosystem in the North-Eastern part of the Cajas National Park [3,144–4,429 m above sea level (a.s.l.)] (Pesántez et al., 2018; Arcusa et al., 2020).

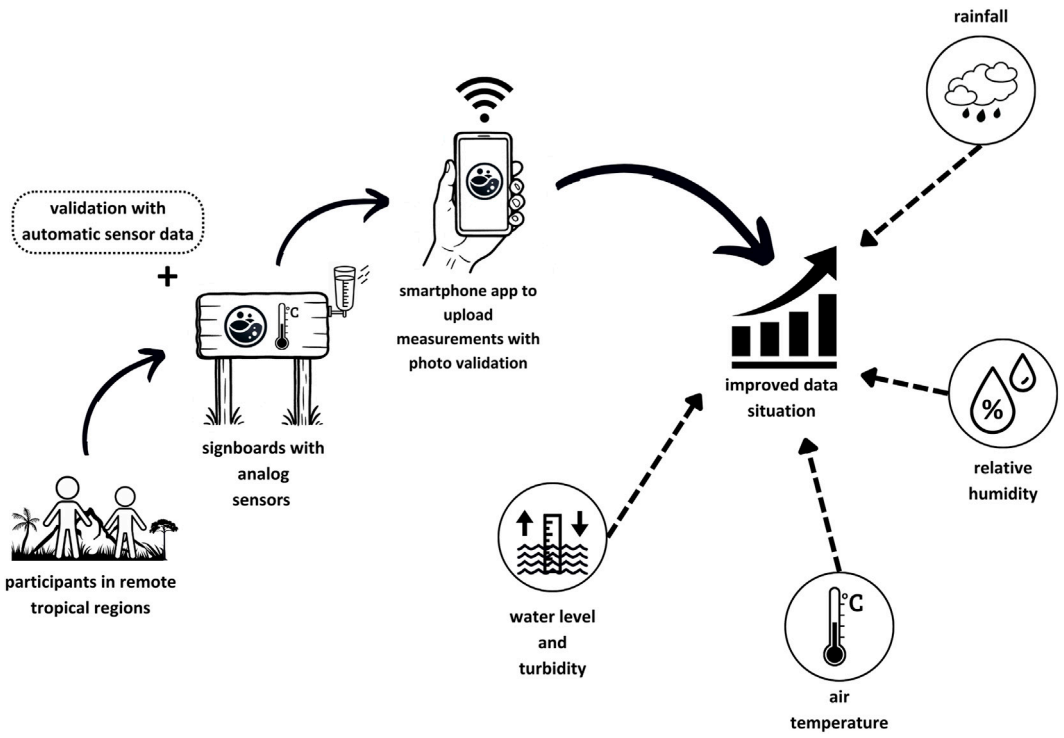


FIGURE 1
Schematic overview of the participatory monitoring approach used in HydroCrowd.

The climate in the area is influenced by various atmospheric mechanisms, including the Intertropical Convergence Zone and the El Niño-Southern Oscillation and the Pacific Decadal Oscillation (Poveda et al., 2006; Morán-Tejeda et al., 2016). The climate of the region is typically classified as a tropical high-mountain climate, characterized by minimal seasonal variation attributable to its equatorial location with daytime temperature between 12 °C–18 °C and nighttime temperatures that can drop down to −8 °C (Hansen et al., 2003; Buytaert et al., 2006). Various studies characterized an annual precipitation between 1,000 and 1,300 mm (Buytaert et al., 2006; Celleri et al., 2007; Padrón et al., 2020). The landscape is dominated by tussock grass, low shrubs and glacial lakes and a small share of pine forest and pasture on Holocene Andosols and Histosols (Buytaert et al., 2006; Harden, 2006; Carrillo-Rojas et al., 2016; Bandowe et al., 2018). The city of Cuenca, the second study site, is the third largest city of the country with a population of approx. 596,000 (Instituto Nacional de Estadística y Censos, 2022). It is located in a basin around 30 km east to the Cajas National Park, with an altitude spanning between 2,350 and 2,550 m a.s.l. (Gianoli and Bhatnagar, 2019). It has a temperate Andean climate averaging with 16.3 °C and an annual precipitation of 876 mm (WMO, 2025). The last site in this study area is the municipality of Tomebamba, located around 37 km north-east of the city of Cuenca. The site has a comparable climate to Cuenca with an elevation of approx. 2,380 m a.s.l. (World Bank, 2025).

HydroCrowd stations at sites in the Cajas National Park and Tomebamba were installed in June 2023 while stations in Cuenca were installed in August 2024 and January 2025. There are currently twelve weather and four water stations in use. Five weather stations and three water stations have been installed in the Cajas National Park site, one weather station and one water station in Tomebamba, and six weather stations in Cuenca. Due to theft and vandalism, six additional water stations and one weather station in Cuenca city were damaged and unavailable for this study.

2.1.2 Honduras

The Cacique Lempira Señor de las Montañas Biosphere Reserve (from here referred as Cacique Lempira Biosphere Reserve) which encompasses the Celaque National Park, is located in Western Honduras (HND) (Figure 3). HydroCrowd stations were installed in May 2023, May 2024 and August 2024, with a total of nine weather stations and five water stations.

The region is characterized by mountainous topography (highest point at Cerro Las Minas with 2,870 m a.s.l) and rocky thin lithosols, where most parts of the area is considered unsuitable for intensive agriculture (FAO, 1966; Southworth et al., 2004; Anderson and Devenish, 2009). The area above 1,800 m (including the National Park) has been protected since 1987, with agricultural and industrial activities prohibited (Pfeffer et al., 2001). Land use can be described as a combination of coniferous forests, coffee plantation, shrubland and a small share of annual crops outside the national park (Valdez et al., 2017). The region has a tropical savannah climate with an average precipitation of 1,600 mm/yr and average temperatures of 24 °C in the lower areas, and with up to 2,400 mm/yr precipitation at higher elevations (Aguilar, 2005; Valdez et al., 2017). The largest proportion of annual precipitation falls between May and October, while the rest of the year is dry (Aguilar, 2005).

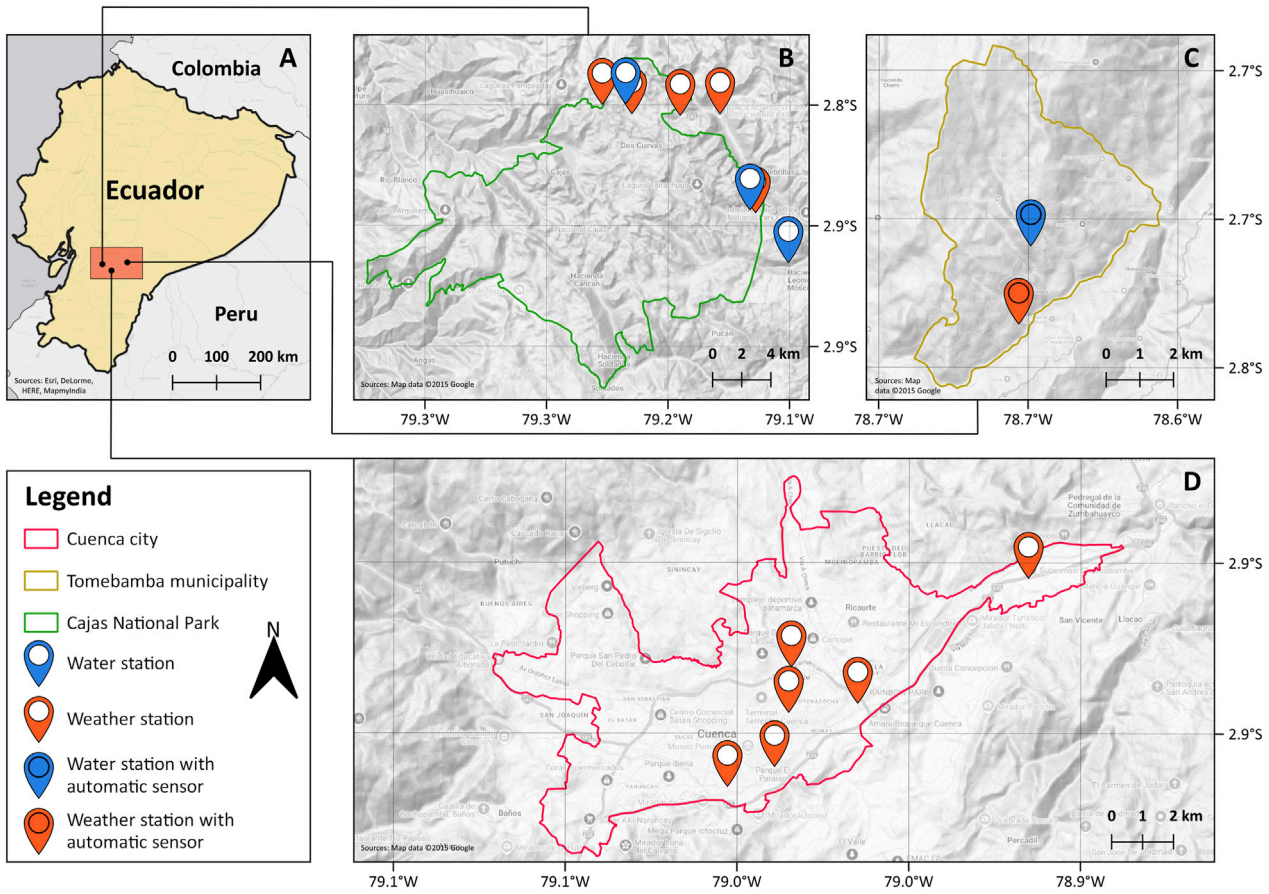


FIGURE 2
Study area in Southern Ecuador **(A)** with the three sites within and around the Cajas National Park **(B)**, within the municipality of Tomebamba **(C)** and within the city of Cuenca **(D)**.

2.1.3 Tanzania

The study area in Tanzania (TNZ) is located on the southern slopes of the Kilimanjaro National Park (Figure 4). The area has a sharp elevation gradient ranging from around 770 m a.s.l. in the lowlands up to 5,895 m a.s.l., with Kibo (the highest volcanic cone).

Climate, vegetation types and land use differ significantly with changing elevation (Hemp et al., 1998). Rainfall amounts to 900 mm at 800 m above sea level in the lowlands, peaking at around 2,700 mm at 2,200 m a.s.l. (Røhr and Killingtveit, 2003; Hemp, 2006) before dropping sharply to 750 mm at 3,750 m a.s.l. and continuing to decrease beyond this point (Appelhans et al., 2016). Precipitation follows a bi-modal annual pattern, with a first peak from March to May and a second one from November to December (Shagega et al., 2025). The area can be divided into multiple ecological zones which also differ greatly in land use and are described in more detail in Hemp et al. (1998). Andosols are the dominant soil type in this area (Zech, 2006).

HydroCrowd stations were installed in August 2023, with a total of ten weather and three water stations. Additionally, nine "weather@home" stations were installed on private property of interested locals as well as hotels and guest houses, which are reduced variant of weather stations consisting only of a metal holder with the rain gauge and a smaller panel with a description of the approach. An overview of all stations installed for the project can be found in the Supplementary Material.

2.2 Data collection

2.2.1 Station types

All weather stations are made up of a roofed wooden signpost with a printed PVC banner and are equipped with three sensors: an analog hygrometer, thermometer and a plastic rain gauge. Figure 5 shows an example of a weather station.

In order to engage participants, the panel incorporates general information regarding the project, the importance of hydrometeorological data for measurement, and the reason behind the selection of the station's location in the region. The submission of observations was facilitated by the development of a smartphone application, "HydroCrowd", for Android and iOS operating systems. This application was developed by SPOTTERON, a company based in Vienna, Austria, and was released in May 2023. It is available in English, Spanish and Swahili. The panel also gives instructions on how to use the app. Alternatively, the provided QR-Code can be used to access a web application for data submission (www.spotteron.com/hydrocrowd). Participants are asked to submit

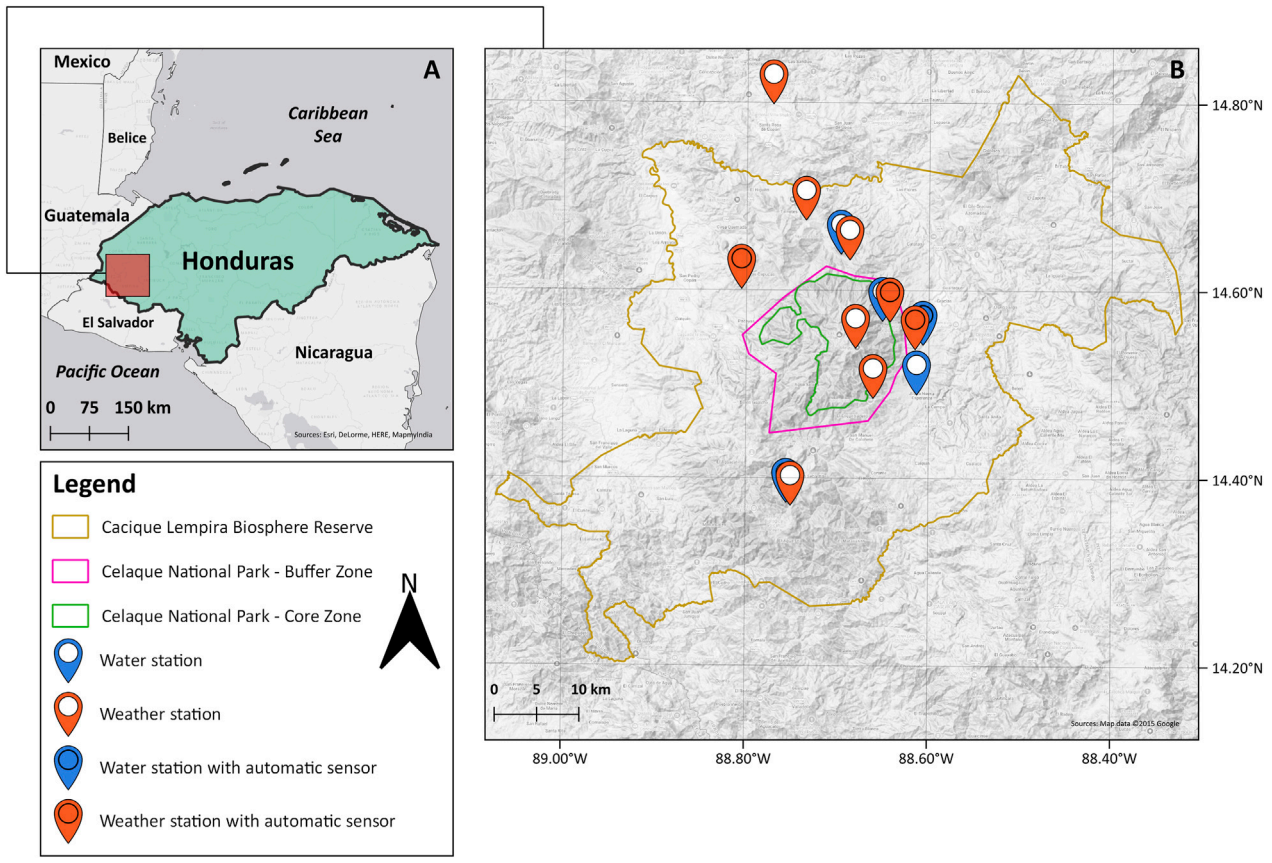


FIGURE 3
Study area in Honduras **(A, B)** in the Cacique Lempira Biosphere Reserve.

a photo in addition to the actual observations. The sensors were installed in such a manner that all three sensors are clearly visible in a single photograph.

For the water stations, similar signposts were used with customized information content (Figure 6). The water level gauges were installed in sight in the river (Figure 5B). Additionally, turbidity can be measured at the water stations using a jug for taking a water sample and a turbidity tube for measurements (Figure 6A; Table 1). However, the latter data were not analyzed, as no validation photos nor automatic sensor data were available.

When possible, water level gauges were installed on stable, immovable structures like bridges or big rocks. If no such option was available, the gauges were mounted on metal structures with spikes which were hammered into the riverbed and stabilized with tension cables to avoid movement.

2.2.2 Analog sensors

Various criteria were taken into account for the selection of analog sensors for the weather and water stations. Firstly, the sensors needed to be user-friendly and easy to read. To this end, they needed to have a simple, clear scale, whereby measurement accuracy should be affected as little as possible. An easy-to-read scale was also a prerequisite for another criterion: the ability to verify the observations with a photograph. The final important criterion was commercial availability and low cost of the sensors. The low cost was also intended to minimize the probability of theft and enable a cost-effective replacement if a sensor is lost. These criteria were used to select the analog sensors listed in Table 1, which are also described in more detail below.

For relative humidity and air temperature, analog hygrometers and thermometers were used (Figure 5). Both sensor types were tested by conducting parallel measurements (n = 100) using three hygrometers and three thermometers in Germany (see Supplementary Material). These were compared to automatic sensor measurements (Lascar Electronics, EL-USB-2+, Whiteparish, United Kingdom) using the root mean square error (RSME - Equation 1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

where n = number of observations, y_i = automatic sensor value and $\hat{y}_i$ = PM value.

The test confirmed the manufacturer's confidence intervals (RMSE 0.57 °C–0.86 °C for air temperature and RMSE 2.63%–4.66% for relative humidity).

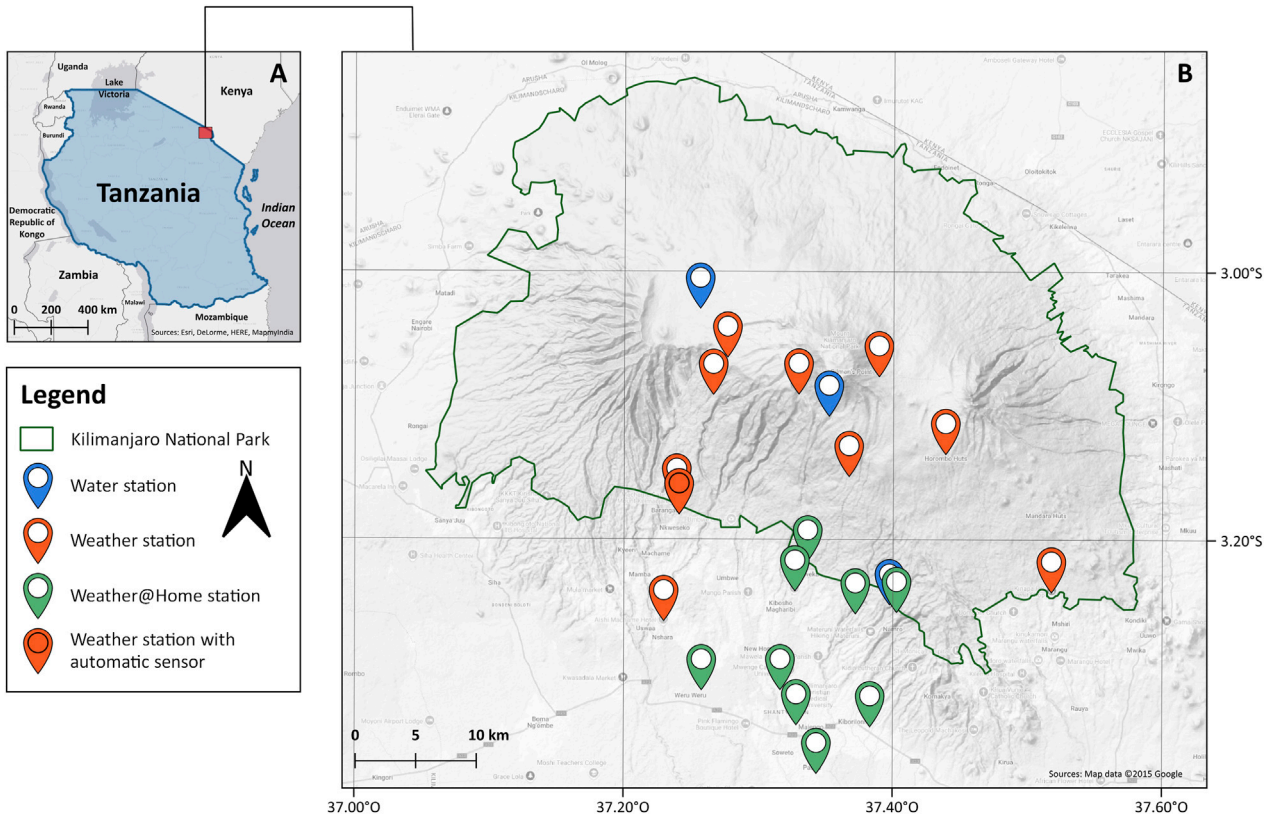


FIGURE 4
Study area in Tanzania **(A)** at the southern slopes of Mt. Kilimanjaro **(B)**.

Due to the design of the weather station, simple funnel-shaped rain gauges (35 mm capacity) with an easy-to-read millimeter scale were selected for the PM rainfall collection (see Figure 4). With a rotating holder on the station, they can be emptied by simply turning them upside down after the measurement. It was expected that the majority of the rainfall would be measured, however, its volume might render it inadequate for inclusion in the analysis of heavy rainfall events.

For water level, 1 m rigid foam water level gauges were installed in Honduras and Tanzania. Due to import regulations, metal staff gauges sourced locally and printed with the same measurement scale were used in Ecuador. Depending on the expected maximum water level, several staff gauges were installed. On top of each gauge, a red number indicated the maximum height for each staff gauge (e.g., "1" for 1 m).

For comparability, all analog sensors except the metal staff gauges were purchased in Germany, while all station materials were sourced locally. Further information and a detailed cost breakdown are available in Campos Zeballos et al. (2025). Since hydrometeorological measurements may be affected by various interferences, the wooden station panels and attached sensors were installed according to WMO guidelines, where possible. However, this could not always be ensured, consequently the location of the stations was sometimes a compromise between accessibility, participants safety, station security and ease of installation.

2.2.3 Automatic sensors

Automatic sensors were installed at selected stations to collect reference data to validate the participatory observations. Table 2 provides an overview of the stations at which sensors were installed, as well as the periods covered.

Overall, air temperature and relative humidity were automatically monitored at five locations: one in Ecuador and Tanzania, and three in Honduras. Rainfall was monitored at one location in each country, and water levels were monitored at one station in Ecuador and in Honduras.

Air temperature and relative humidity measured by automatic sensors at stations in Ecuador and Honduras were collected in 15-min (Tanzania: 1 h) intervals using stand-alone loggers (Lascar Electronics, EL-USB-2+, Whiteparish, United Kingdom; accuracy: ±0.3 °C and ±2.0%), which were mounted to the weather stations hidden under the roof. For rainfall, automatic tipping buckets (Metek, Rain gauge 7043.0100, Elmshorn, Germany; accuracy: 4% for 0–50 mm/h and 5% for ≥50 mm/h) were installed near the weather stations measuring as well in 15-min (Tanzania: 10 min) intervals. Water levels were measured at 15-min intervals by pressure transducers and corrected for air pressure. For this, a pressure transducer (Diver, Driesen and Kern, P-Log3020-PA-INT, Bad Bramstedt, Germany; accuracy: ±10 mm) was installed in a perforated pipe near the water level gauge. A corresponding barometer (Baro, Driesen and Kern, P-Log3020-baro, Bad Bramstedt, Germany; accuracy:



FIGURE 5
Weather station in Honduras, consisting of a wooden structure, a signpost with general information (left side) and instructions how to upload data (lower right side), and three analog sensors: a hygrometer for relative humidity, a thermometer for temperature and a rain gauge for rainfall (upper right side from left to right).

±0.6 hPa) was mounted nearby (e.g., on the water stations panel). All automatic sensors were installed according to WMO guidelines, where possible, taking local conditions into account. Water level was subsequently calculated according to hydrostatic pressure (Equation 2), assuming a constant water density:

$$h = \frac{(p_{abs} - p_{bar}) * 100}{\rho * g} \quad (2)$$

where h = water level in m, p_{abs} = absolute pressure in mbar, p_{bar} = barometric pressure in mbar, ρ = density of the water (997 kg m^{-3} at 25 °C), and g = acceleration due to gravity (9.81 m s^{-2}).

As the water level gauges and pressure transducers could not be installed directly next to each other at the same height, there is a constant offset of a few centimeters in the automatic measurements. To correct this, a HydroCrowd team member carried out a reference measurement at both stations. The difference between the analog and automatic water level of these reference measurements was then used to correct the offset in all subsequent automatic measurements at both stations.

Due to installations at different times, relocation of sensors, repeated theft and vandalism in Honduras and Ecuador, it was not possible to maintain similar measurement periods for all study areas.

2.3 Data validation

Data validation was conducted in two independent parts in accordance with the two research questions of this study for the period from May 2023 to May 2025 for observations with corresponding 1) photos and 2) automatic sensor data. Observations by HydroCrowd team members were excluded.

2.3.1 Validation of different participants using photos

Participants were given a unique user ID when registering for the smartphone application. This ID was used to divide them into two groups of users: frequent and non-frequent users, similar to the analysis of Campos Zeballos et al. (2025). The former are people who often submit readings, such as community members, farmers or park rangers, while the latter are only on site occasionally, such as tourists who only measure once or a few times, for instance during a hike. The groups were defined as follows: non-frequent participants submitted a maximum of six observations within the first 7 days after their first contribution. If they submit more or over a longer period of time, they are considered to be frequent participants. Participants who uploaded observations



FIGURE 6
Water station **(A)** with general information and instructions, a turbidity tube (white box), a jug for taking water samples connected with a chain to the station, and water level gauges **(B)** mounted on a rock in the river. A number on top of the gauge indicates the maximum height for each staff gauge reading.

TABLE 1 Station types with installed analog sensors and sensor specifications.

Type	Parameter	Range	Sensor type	Model	Cost
Weather station	Air temperature	−20 °C to 50 °C[a]	Bimetallic spiral spring	TFA Dostmann K1.100273	7 €
	Relative humidity	0%–100%[b]	Bimetallic spiral spring	TFA-Dostmann K1.100445	7 €
	Rainfall	0–35 mm	Plastic funnel	TFA-Dostmann 47.1013 and Relaxdays 10025387[c]	6 €
Water station	Water level	0–100 cm[d]	Rigid foam staff gauge Metal staff gauge	Nestle 18500000 Locally made	42 € 150 €
	Turbidity	5–1000 NTU	Plastic turbidity tube	Trace2o Turbidity tube	52 €

[a]Accuracy according to manufacturer's specifications ±1 °C.
[b]Accuracy according to manufacturer's specifications ±5%.
[c]the two models are identical in design and volume.
[d]per unit installed–some sites required more than one staff gauge to cover the full range of water levels.

without registration were always indicated as "anonymous", received the same ID and were considered as non-frequent participants.

To address the first research question, all analog observations were validated using the photos of the observations, if submitted alongside the observation. The submitted observations were

TABLE 2 Stations with automatic sensors and their measurement periods.

Parameter and station name	Country	Period monitored
Air temperature and relative humidity		
Nkweseko	TNZ	26.08.2023–15.02.2025
Tombamba	ECU	07.12.2023–19.06.2024
Don Tito	HND	08.05.2024–01.05.2025
Finca El Nogal	HND	17.05.2024–02.12.2024
Parque Celaque	HND	03.12.2024–01.05.2025
Rainfall		
Don Tito	HND	25.05.2023–01.05.2025
Nkweseko	TNZ	27.08.2023–01.05.2025
Tombamba	ECU	07.12.2023–18.12.2024
Water level		
Rio Arcilaca	HND	29.05.2023–01.05.2025[a]
Quebrada Santul	ECU	28.02.2024–18.06.2024

[a]No data was recorded from 19.12.2023 to 08.05.2024 due to incorrect reinstallation of the sensor.

compared with photos of the measuring devices submitted at the same time and the mean absolute error (MAE, Equation 3), the RMSE (Equation 1) and the coefficient of variation (CV, Equation 4) were calculated. As a normal distribution, tested with the Shapiro-Wilk test (Shapiro and Wilk, 1965), could not be confirmed for all parameters, the Spearman Rank correlation (r_{spear}, Equation 5) was used to determine the degree of correlation between analog and automatic sensor measurements. Additionally, a Wilcoxon signed-rank test (Wilcoxon, 1945) was performed to statistically compare frequent and non-frequent users' data (alpha level = 0.01).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

where n = number of observations, y_i = automatic sensor value, and $\hat{y}_i$ = PM value.

$$C_V = \frac{\sigma}{\mu} \tag{4}$$

where σ = standard deviation of the data, μ = arithmetic mean of the data.

$$r_{spear} = \frac{\mathbf{cov}[\mathbf{R}[X], \mathbf{R}[Y]]}{\sigma_{R[X]}\sigma_{R[Y]}} \tag{5}$$

where cov = covariance of the rank variables, σ_X, σ_Y = standard deviations of the rank variables.

2.3.2 Validation with automatic sensor data

To address the second research question, the PM observations were validated against the automatically measured reference data (Table 2). To compare the data, the following steps were carried out.

- To ensure comparability between the study regions all analog observations were assigned to the nearest full hour. For instance, a measurement taken at 10:47 a.m. was assigned to 11:00 a.m. The air temperature, relative humidity and water level observations were then compared to the corresponding automatic measurements.
- Automatic rainfall measurements were summed up for the period between two analog observations and compared with the second analog observation. Evaporation of water from the analog rain gauge was not considered.
- All rainfall totals compared where the automatically measured rainfall was higher than 35 mm were excluded from further analysis.
- Despite the roof, analog hygrometers and thermometers were not always completely shielded from sunlight. This may have caused observations to be distorted due to overheating of the bimetal spiral spring inside the sensors. Assuming generally correct observations by participants and only a slight deviation of the analog sensors compared to the automatic sensors, outliers were eliminated by calculating the interquartile range (IQR) of the difference between the analog and automatic sensor measurements. An observation is considered an outlier if the value is 1.5 times greater or 1.5 times less than the IQR (Equation 6). If a PM air temperature observation was filtered out as an outlier, the corresponding relative humidity value was removed too as the analog hygrometers are also bimetal based and seemed to be affected by intense exposure to sunlight as well.

$$(Q_1 - 1.5\,IQR) > x > (Q_3 + 1.5\,IQR) \tag{6}$$

where x = individual air temperature measurement, Q_1 = first quartile of the air temperature difference, Q_3 = third quartile of the air temperature difference and $IQR = Q_3 - Q_1$.

- As the barometer from the station Rio Arcilaca was temporarily moved to a different location, the air pressure values in the periods from 04.06.2023 to 12.06.2023 and from 28.09.2023 to 20.11.2023 were corrected for the difference in altitude.

For all stations with automatic sensor reference data, the analog observations were compared by calculating the range, the arithmetic mean, MAE, RMSE and CV. Similar to the photo validation, data was not normally distributed based on the Shapiro-Wilk test. Therefore, again r_{spear} was calculated for all stations to determine the correlation with the automatically measured data. To evaluate the influence of measurement frequency on the accuracy of rainfall observations, the effect of the time between individual analog observations on the difference in measured rainfall was also analyzed. The Wilcoxon signed-rank test was used to statistically compare analog and automatic data with an alpha level of 0.01. Due to the findings of this analysis the analog relative humidity observations were first validated following the procedure introduced above, then corrected using linear regression and validated again afterwards.

TABLE 3 Distribution by parameter and number of observations per country.

Country	Rainfall	Air temperature	Relative humidity	Water level
ECU	733	750	751	89
HND	568	551	552	133
TNZ	675 (1,322[a])	669	669	8
Total	1,976 (2,624[a])	1,970	1,972	230

[a]Including measurements carried out at weather@home stations.

3 Results

In the period from May 2023 to May 2025 a total of 2,982 PM observations were received. Table 3 provides an overview of the distribution of these by country and parameter.

The most individual measurements were collected in Tanzania (2,668 including weather@home measurements) followed by Ecuador (2,323) and Honduras (1,804). Excluding observations from weather@home stations, the number of rainfall, air temperature and relative humidity measurements were comparable for the three countries. The number of observations from water stations (water level measurements) differed substantially between the countries.

3.1 Frequent and non-frequent participants and photo validation

When dividing all participants into the two user groups, a total of 2,518 observations (84.4%) were submitted by frequent participants, while non-frequent participants submitted a total of 464 observations (15.6%). From the frequent participants' observations, 2,292 were from weather and weather@home stations and 226 from water stations. Non-frequent participants submitted 439 weather and weather@home station and 25 water station observations. Table 4 provides the validation results of the PM observations using the submitted photos, separated into frequent and non-frequent participants.

For all parameters, except water level, less than 10% of the observations were classified as incorrect and could be corrected using the submitted photos. Observations from frequent participants are characterized by a lower error rate across all parameters. The smallest error rate was observed for air temperature measured by frequent participants with 2.7% while water level measured by non-frequent participants showed the largest error rate with 23.5%. The correlation between submitted and corrected observations was very high with r_{spear} = 0.99 for all frequent participant's observations and r_{spear} ranging from 0.90–0.98 for non-frequent participants. The CVs revealed similar patterns of variation where the difference between $CV_{submitted}$ and $CV_{corrected}$ was higher for non-frequent participants. The Wilcoxon signed-rank test showed that there were no statistically significant differences in the distribution of the two user groups for any of the four parameters ($p\text{-value}_{air\ temperature}$ = 0.128, $p\text{-value}_{relative\ humidity}$ = 0.506, $p\text{-value}_{rainfall}$ = 0.143 and $p\text{-value}_{water\ level}$ = 0.738).

3.2 Validation using automatic sensor data

For the validation using automatic sensor data, the IQR analysis enabled the detection of potential outliers in the PM air temperature and relative humidity data. Between 8.2% and 20.0% of the measurements were identified as outliers and were excluded from further analysis (Table 5). An additional 4.7%–17.0% of all rainfall events were excluded where the automatically measured rainfall was higher than 35 mm. Table 6 gives an overview of the validation results for the four parameters at all stations equipped with automatic sensors.

A high correlation was revealed for all stations and parameters (0.72–0.96) except for rainfall at station Don Tito (0.42). For air temperature, the results were overall the best, with the lowest deviation (MAE and RMSE) and the highest correlation (r_{spear}). Similar results but with lower r_{spear} and slightly higher deviation were found for water level. Analog rainfall measurements were characterized by high deviation (MAE = 2.55–3.10) compared to the mean values (2.3–6.1) and low to good correlation (0.42–0.80). The coefficients of variation of PM and automatically measured data were comparable for water level data at Rio Arcilaca and all air temperature and rainfall data, but not for water levels at Quebrada Santul and all relative humidity data.

A systematic underestimation was determined for PM relative humidity, resulting in substantial deviations with MAE ranging from 16% to 31%. Nevertheless, an acceptable to high r_{spear} was found (0.76–0.91). This significant deviation was only detected during validation, as the test measurements carried out before deployment of the sensors (see Section 2.2.2) showed no major deviation from the automatic sensor measurements. Given the relatively high r_{spear}, we corrected the values using linear regression. As the deviations differed per station, a separate model was developed for each station. Considering the low total number of measurements and for keeping the correction comparable, each model was trained using six randomly selected pairs of values from each station, after which the remaining values were estimated and the comparison metrics recalculated (Table 7). For all stations the deviation was substantially reduced (MAE: 5.45%–9.50%) while r_{spear} remained at a similarly high value.

For all stations and parameters, a statistical test was carried out to compare analog and automatic measurements. The Wilcoxon signed-rank test revealed significant differences in distribution for air temperature at station Finca El Nogal ($p = 0.008$) and corrected relative humidity at Nkweseko ($p < 0.001$) and Finca El Nogal

TABLE 4 Validation results for the photo validation divided by "frequent" and "non-frequent" participants (n = number of specific measurements, MAE = mean absolute error, RMSE = root mean squared error, rspear = Spearman Rank correlation, CV = coefficient of variation for submitted and with photos corrected values and percentage = percentage share of the differing values from n).

Parameter	n	Differing values	Percentage	MAE	RMSE	r_{spear}	$CV_{submitted}$	$CV_{corrected}$
Frequent								
Rainfall	1,621	49	3.0%	0.17 mm	1.78 mm	0.99	1.70	1.71
Air temperature	1,608	44	2.7%	0.14 °C	1.04 °C	0.99	0.28	0.28
Relative humidity	1,609	100	6.2%	0.48%	3.25%	0.99	0.35	0.35
Water level	206	24	11.7%	0.01 m	0.02 m	0.99	0.65	0.65
Non-frequent								
Rainfall	333	15	4.5%	0.49 mm	2.53 mm	0.93	1.65	1.74
Air temperature	343	12	3.5%	0.29 °C	2.03 °C	0.97	0.34	0.32
Relative humidity	344	17	7.6%	0.85%	4.62%	0.98	0.43	0.41
Water level	17	4	23.5%	0.03 m	0.12 m	0.90	0.74	0.65

TABLE 5 Stations with original (=n) and filtered (excluding outliers) (=m) air temperature, relative humidity data and rainfall data.

Parameter	Station name	n	m	Excluded	Excluded share (%)
	Tomebamba	73	67	6	8.2
Air temperature	Don Tito	20	16	4	20.0
and	Finca El Nogal	59	54	5	8.5
Relative humidity	Parque Celaque	19	16	3	15.8
	Nkweseko	314	275	39	12.4
	Tomebamba	106	101	5	4.7
Rainfall	Don Tito	112	93	19	17.0
	Nkweseko	315	280	35	11.1

($p < 0.001$). For all other stations and parameters no significant differences were observed ($p > 0.01$).

The distribution of the data from the various stations is shown in Figure 7, comparing automatic and PM measurements. For air temperature, a slight overestimation of most values can be noted at station Finca El Nogal (Figure 7C), which corresponds with the relatively high MAE and RMSE (Table 6). As shown in Figures 7F–J, the values for corrected relative humidity demonstrate a wider variation yet also exhibit a linear trend. It is evident that the values of Finca El Nogal (7H) exhibit a marginally higher underestimation in comparison to the other values. A strong accumulation of measurements of 0 mm can be noted for rainfall (Figures 7K–M), and it is visible that the deviation in both directions, under- and overestimation, between PM and automatically measured rainfall increases with higher rainfall amounts. Looking at the plots for water level data, a monotonic trend and low deviation from the sensor values can be recognized for both stations. Considering the comparatively low number of measurements from station Quebrada Santul (Figure 7N), only a slight hint for a linear trend is visible. Participants' measurements at the Rio Arcilaca station also showed that lower water levels (<0.6 m) were slightly overestimated and higher levels (above 0.6 m) underestimated (Figure 7O).

To understand whether the length of the interval between subsequent measurements influences the deviation from 'true' rainfall, the difference between each PM rainfall measurement and the corresponding automatically measured rainfall was plotted against the number of days since the last PM

TABLE 6 Validation results for air temperature, relative humidity, rainfall and water level (n = number of measurements compared, pm = participatory monitoring, aut. = automatic sensor, std = standard deviation, CV = coefficient of variation, MAE = mean absolute error, RMSE = root mean squared error, r_{spear} = Spearman Rank correlation).

Parameter	Station	Country	n	$Range_{pm}$	$Range_{aut}$	$Mean_{pm}$	$Mean_{aut}$	Std_{pm}	Std_{aut}	CV_{pm}	CV_{aut}	MAE	RMSE	r_{spear}
	Tomebamba	ECU	67	14–30	13.5–28.5	20.7	20.0	4.7	4.6	0.22	0.23	0.95	1.27	0.94
	Don Tito	HND	16	24–33	20.5–33.0	28.1	26.9	3.2	3.4	0.11	0.12	1.44	1.83	0.96
Air	Finca El Nogal	HND	54	20–34	19.0–31.5	26.7	25.1	3.5	3.1	0.13	0.12	1.65	1.93	0.92
Temperature (°C)	Parque Celaque	HND	16	18–28	17.0–25.5	22.2	21.2	3.3	3.0	0.14	0.14	1.28	1.46	0.92
	Nkweseko	TNZ	275	11–33	11.5–30.0	17.8	17.8	3.8	3.4	0.21	0.19	0.74	0.95	0.96
	Tomebamba	ECU	67	18–87	36.5–94.5	51.7	68.7	20.8	16.7	0.40	0.24	16.96	18.75	0.91
	Don Tito	HND	16	25–52	45.5–93.0	39.0	66.4	8.9	14.9	0.22	0.22	27.44	28.57	0.87
Relative	Finca El Nogal	HND	54	19–79	46.5–98.0	45.8	72.9	13.6	13.0	0.29	0.18	27.04	27.72	0.76
Humidity (%)	Parque Celaque	HND	16	21–66	59.0–96.5	45.4	77.1	14.5	13.0	0.31	0.16	31.69	32.22	0.85
	Nkweseko	TNZ	275	18.5–82	34.0–100	58.2	88.4	10.3	11.7	0.18	0.13	30.21	30.93	0.88
	Tomebamba	ECU	101	0–35	0–30.6	4.3	5.4	6.5	7.5	1.49	1.37	2.55	6.50	0.72
Rainfall (mm)	Don Tito	HND	93	0–35	0–30.6	2.3	2.3	5.5	5.5	2.41	2.37	2.56	6.58	0.42
	Nkweseko	TNZ	280	0–35	0–34.8	6.4	6.1	8.6	8.1	1.34	1.33	3.10	7.03	0.80
Water level (m)	Quebrada Santul	ECU	7	0.12–0.32	0.18–0.28	0.20	0.21	0.08	0.04	0.39	0.19	0.04	0.04	0.81
	Rio Arcilaca	HND	48	0–0.90	0–0.98	0.46	0.46	0.17	0.21	0.39	0.46	0.08	0.10	0.87

10.3389/feart.2026.1721642

TABLE 7 Validation results for corrected relative humidity (n = number of measurements compared, pm = participatory monitoring, std = standard deviation, CV = coefficient of variation, MAE = mean absolute error, RMSE = root mean squared error, r_{spear} = Spearman Rank correlation).

Station	n	Coefficient	$Range_{pm}$	$Mean_{pm}$	Std_{pm}	CV_{pm}	MAE	RMSE	r_{spear}
Tomebamba	61	0.95[a]	45.3–95.7	71.5	16.7	0.23	5.60	7.05	0.89
Don Tito	10	0.71[a]	49.2–80.5	63.7	11.9	0.18	5.45	6.97	0.91
Finca El Nogal	48	0.90[a]	42.6–89.0	63.1	10.5	0.16	9.50	11.24	0.72
Parque Celaque	10	0.94	54.3–89.4	72.6	13.1	0.17	6.14	6.83	0.92
Nkweseko	269	0.84[a]	50.1–100	84.9	8.9	0.11	5.92	7.53	0.88

[a]slope is significant.

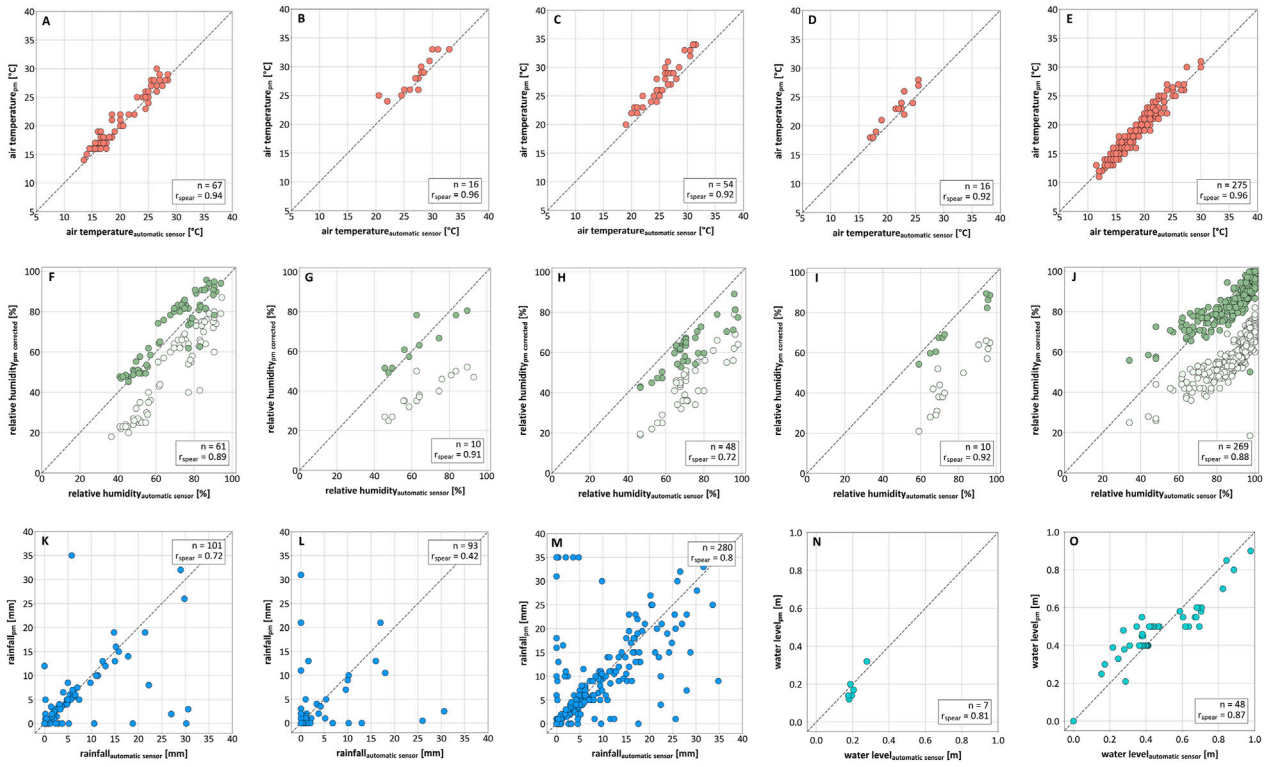


FIGURE 7
Distribution of PM versus automatic sensor data (n = number of measurements compared where for **(F–J)** only the corrected numbers are presented, r_{spear} = Spearman Rank correlation) for air temperature (Tomebamba = **(A)**, Don Tito = **(B)**, Finca El Nogal = **(C)**, Parque Celaque = **(D)** and Nkweseko = **(E)**), raw (light green) and corrected (dark green) relative humidity (Tomebamba = **(F)**, Don Tito = **(G)**, Finca El Nogal = **(H)**, Parque Celaque = **(I)** and "Nkweseko = **(J)**), rainfall (Tomebamba = **(K)**, Don Tito = **(L)** and Nkweseko = **(M)**) and water level (Quebrada Santul = **(N)** and Rio Arcilaca = **(O)**).

measurement (Figure 8). The total rainfall for both analog and automatic measurements was also calculated.

Substantial under- and overestimation of rainfall can already be noted at all stations for periods ranging from less than a day up to 5 days, suggesting that increasing the measurement interval does not necessarily substantially improve the accuracy of the PM measurements. The total rainfall amounts show an underestimation for Tomebamba (19.80%) and Don Tito (1.64%), and an overestimation for Nkweseko (5.40%).

4 Discussion

Different groups of participants were able to successfully measure hydrometeorological parameters with predominantly low errors using simple analog sensors. However, not all analog sensor measurements proved to be a good alternative for automatic sensors regarding measurement accuracy. This provides scope for critical discussion as to whether PM and the use of analog sensors are suitable for monitoring these parameters.

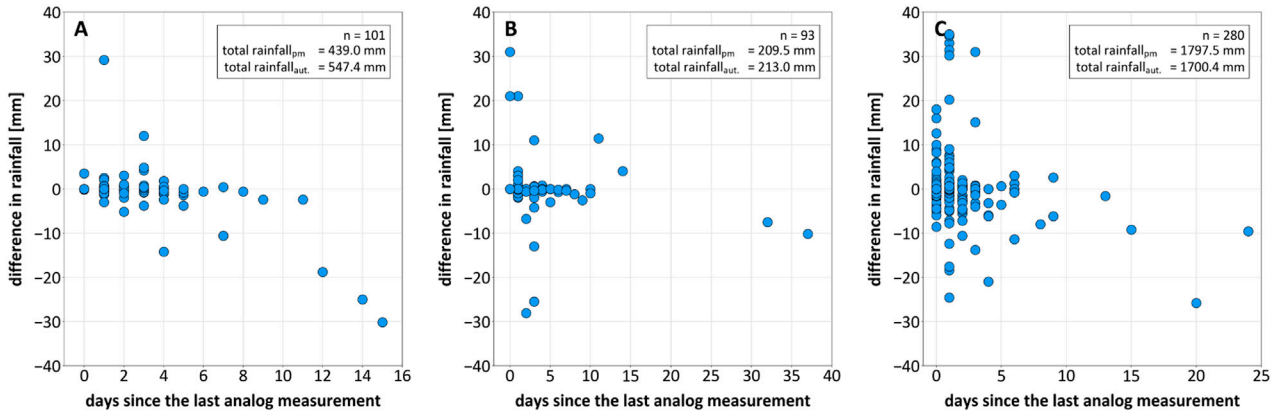


FIGURE 8
Difference (PM−automatic sensor) in rainfall between PM and automatic sensor measurements (with n = number of PM measurements) depending on the time between each analog measurement at Tomebamba from 07.12.2023 to 17.12.2024 **(A)**, at Don Tito from 11.07.2023 to 26.04.2025 **(B)** and at Nkweseko from 28.08.2023 to 03.02.2025 **(C)**.

4.1 Performance of target groups

The integration of photo-based validation of analog measurements was found to be a suitable method for cross-checking analog measurements and for comparing the quality of submissions from frequent and non-frequent participants. The photo feature of the smartphone application can also be employed for long-term monitoring, thereby allowing the verification of stations independent of physical visits. In this manner, it is possible to verify the status of the sensors, including whether they are still present, whether there has been possible damage or other impairments, which are factors that compromise the readability of the sensors. The use of this method of photo validation was previously applied by other research projects for analyzing hydrometeorological observations (Davids et al., 2019a; Thatoe Nwe Win et al., 2019; Eisma et al., 2023). Davids et al. (2019a), analyzed rainfall data collected via PM in Nepal with DIY rain gauges made of repurposed soda bottles in the context of the SmartPhones4Water monitoring network. Participants were asked to submit a photo of the bottles alongside their measurements, similar to HydroCrowd. From May to September 2018, 9% of all observations were classified as faulty and corrected using the values recorded by photos which is nearly three times more than for the rainfall observations analyzed in our study. Another example is a PM approach in Myanmar where photos were used to verify participants performance in water quality monitoring (Thatoe Nwe Win et al., 2019). Considering the greater uncertainty of the methods used, about half of the data was correctly assigned to the correct classes by participants revealing no systematic errors for the parameters compared.

The comparison between frequent and non-frequent participants showed clear differences in data collection frequency and data quality between the two groups. Frequent participants in our study not only collected significantly more data with a share of 84.4%, but also data of better quality. However, a Wilcoxon signed-rank test did not identify statistically significant differences in the distribution of the compared data. These results correspond to the observations of Campos Zeballos et al. (2025) for the period from May 2023 to July 2024, where contribution relied mainly on frequent users and higher errors could predominantly be linked to non-frequent users. Other studies revealed clear differences in different user groups within PM projects. For instance, Ali et al. (2019) assessed the accuracy of participants measuring agrochemical contaminants in river water in the United States. Participants were grouped into different groups depending on how often they conducted such measurements: inexperienced, experienced and experts. Experienced and expert participants achieved better overall accuracy in correctly measuring the contaminants, while inexperienced participants required additional training. They concluded, based on their results and prior research (Sauermann and Franzoni, 2015; Scott and Frost, 2017) that higher participant's experience level might not only lead to higher accuracy but also affect motivation of participants regarding further participation. Another study by Meschini et al. (2021) analyzed a PM program between 2007 and 2015, in which over 16,000 participants collected marine biodiversity data during dives in the Red Sea. Well known species could be identified better than rare species and participants' accuracy improved with experience gained.

However, the complexity of measuring a parameter can also be linked to the resulting accuracy. For instance, the errors of water level measurements in our study were higher, and participants described this parameter as more difficult to measure than air temperature, relative humidity or rainfall (Campos Zeballos et al., 2025). This might also be linked to the fact that the three weather station sensors could be read directly in front of the panel, while the stream gauges for water level are a little further away in the river and must be read from a certain distance. These results suggest that easier methods are more suitable for PM projects, although this might lead to a trade-off with data accuracy, which is also supported by previous PM research (Davids et al., 2019b; Ramírez et al., 2023). Ramírez et al. (2023) reviewed different water quality monitoring methods in various PM projects. They concluded that, while simpler, low-cost methods were more user-friendly and enabled wider participation, they produced lower-quality data. In contrast, more complex methods that required more training produced better, more accurate data. Different streamflow PM methods were evaluated by Davids et al. (2019b). While the

salt dilution method was recognized as the most accurate, it was perceived as the least favorable in terms of required training, cost and accuracy by the participants involved. Overall, a human factor (= participants measurement uncertainty) contributed more to the error for water level than for the other parameters.

4.2 Suitability and accuracy of analog sensors for hydrometeorological monitoring

As our results indicated, participants generally appeared to be able to read the analog sensors well. However, the comparison between analog and automatic sensor measurements revealed different accuracy issues for the different parameters. Here the question arises as to whether all analog sensors used in this study are an adequate choice for PM.

Several analog measurements of air temperature and relative humidity showed extraordinary deviations. These were not caused by wrong readings of the sensors and could therefore be considered possible outliers due to exposure to intense sunlight at certain times of day. The use of the IQR to identify outliers in air temperature and relative humidity datasets, as applied previously in other studies (Fredianto and Putri, 2023; Zafeirelli and Kavroudakis, 2024), proved to be a suitable approach to remove these erroneous values from the datasets. Based on the cleaned dataset, participants achieved the lowest measurement errors with analog air temperature measurements, and these also performed best overall in terms of deviation from and correlation with automatic sensors. Several other projects implemented a crowdsourced approach to measure air temperature (Meier et al., 2017; Weyhenmeyer et al., 2017; Rajagopalan et al., 2020; Beele et al., 2022; Leichtle et al., 2023; Barros et al., 2024; Peerlings et al., 2024; Sampson et al., 2025), but to the authors' knowledge, there are currently no PM studies that consider similar analog sensors like those used in HydroCrowd. Those that are most comparable used simple digital sensors (Meier et al., 2017; Rajagopalan et al., 2020; Beele et al., 2022; Loglisci et al., 2024; Sampson et al., 2025). However, the PM measurements across all these studies are of good to very good quality compared to regular weather stations, with better (±0.5 °C) or comparable accuracies (Rajagopalan et al., 2020; Loglisci et al., 2024) than the analog sensors used for HydroCrowd (±1 °C).

The comparison with PM relative humidity and automatic sensor measurements revealed a high correlation but also substantial deviation and therefore did not provide accurate data. A correction through linear regression substantially reduced the high deviation of up to 30% down to 5.45%–9.50%. Nevertheless, a statistical test revealed significant differences between the distributions of the compared data at two out of five stations, which indicates that the selected hygrometers do not have sufficient accuracy to replace automatic sensors at all locations investigated. As the preceding test of the hygrometers confirmed the manufacturer's confidence intervals and the reading errors by participants are quite low, the high error rate is open to speculation. External circumstances, such as vibration during transportation from Europe to the study regions or the high altitude of the stations, might possibly have caused the deviation. Similar to air temperature, there are no PM studies comparing analog sensors with automatic sensors for relative humidity, but some where participants used professional handheld sensors (Rajagopalan et al., 2020; Barros et al., 2024; Loglisci et al., 2024). Compared to the analog hygrometers used in HydroCrowd (accuracy = ±5%), the digital sensors used in these studies have comparable (Rajagopalan et al., 2020) or higher accuracies specified by the manufacturers with ±2% (Barros et al., 2024), and did not show general under- or overestimation for different locations like observed in our study.

Analog rainfall measurements were characterized by a comparable error rate as air temperature, which indicates that it is easy to measure. Similarly, previous research concluded that PM holds a large potential for rainfall collection (Buytaert et al., 2014; Elmore et al., 2014; Njue et al., 2019). Nevertheless, while correlation with automatically measured rainfall in the same period varied from low to high, the deviation was quite high for all stations. Substantial deviations were observed for both low and high precipitation amounts. Furthermore, there was a trend observed for all stations analyzed that an increasing number of days between the measurements leads to higher deviations. While results for Tomebamba and Don Tito also showed that only a low number of days can already lead to high deviation, results for Nkweseko showed the opposite where many high deviations were found for already only a few days. This indicates the analog sensors cannot match the measuring accuracy of an automatic sensor. A possible explanation for this could be evaporation, against which the rain gauges offer no protection. Davids et al. (2019a) collected rainfall data via PM in Nepal with DIY rain gauges made of repurposed soda bottles with a total capacity of 200 mm. The rainfall measured with these bottles was compared to standard 203 mm rain gauges, resulting in a low error of −2.9%. The lowest error was revealed for the version of the bottle rain gauge where the upper part of the bottle was used as a funnel and protection against evaporation, suggesting that this could have significant influence on the accuracy of the data. Therefore, the irregularity of the measurements is problematic, since it cannot be ensured that correct rainfall amounts will be measured after several days. Since substantial deviations could be observed for both low and high rainfall amounts, it was not possible to determine an ideal measurement frequency with a low error rate. Nevertheless, from a hydrometeorological perspective and from practical feasibility within a PM approach, a daily measurement frequency should be pursued. Despite the observed deviations, the total amount of rainfall at the three stations only differed between 1% and 20% from those recorded by the automatic stations. This is similar to results obtained by Shinbrot et al. (2020). They conducted a rainfall collection study across two watersheds in Veracruz, Mexico. Trained participants used 250 mm rain gauges (WeatherYourWay/CoCoRaHS, https://weatheryourway.com/) to collect rainfall over a period of 1.5 years in two catchments with monitoring points between altitude range between 1,309 and 2,581 m a.s.l. (Shinbrot et al., 2020) which is comparable to HydroCrowd. Despite a high measurement frequency, resulting in data for of 91% of the days in the study period, the study revealed a general underestimation of rainfall by participants (12%), especially in wet periods (16%). Another core issue is the limited capacity of the rain gauge, due to which the analysis was limited to rainfall less than or equal to 35 mm. This is a substantial weakness of the

analog sensor, which is further emphasized as up to 17% of the rainfall events for the individual stations were excluded due to exceeding 35 mm. This means that a substantial proportion of total rainfall cannot be measured, which leads to the follow-up question of how informative the analog measurements with relatively small rain gauges can be. Considering the high error rate the rainfall data measured with these rain gauges is not recommended for direct practical application. Subsequent enhancements, such as the installation of larger rain gauges and the ensuring of at least daily measurement frequencies, could prove advantageous in this context.

Although water level showed the highest error rate of all parameters, this did not dramatically affect the accuracy of the measurements. This may also be attributable to the fact that a significantly smaller number of water level measurements were available in comparison with the other parameters. The results for water level were not as good as for air temperature but still good with a low deviation from and high correlation with automatic sensor measurements. Other participatory projects focusing on water level monitoring showed similar validation results to the current study. In the CrowdWater project (van Meerveld et al., 2017; Strobl et al., 2019; Etter et al., 2020; Seibert et al., 2022), a smartphone application was used to submit water level measurements using virtual water level gauges. Participants submitted pictures where water level was expressed in up to 10 water level classes rather than actual measurements (Etter et al., 2020). Most of the measurements analyzed revealed good agreements between water level classes and water level measurements (Etter et al., 2020). In another research by Weeser et al. (2018), water level was measured at 13 stations across a river basin in western Kenya, using comparable water level gauges similar to the ones used in HydroCrowd. At one station a radar-based sensor was installed to validate measurements by participants. Despite an absolute deviation of the water level values between PM and radar-based sensor measurements caused by an offset, an even higher correlation (R = 0.98) was found (Weeser et al., 2019).

Overall, not all analog sensors proved to be as accurate as automatic sensors. Air temperature data could be measured in very good quality, and the use of analog thermometers can be considered a suitable alternative to automatic sensors. Water level could also be measured with good accuracy using analog water level gauges, but frequent users can be considered more valuable for accurate readings. On the other hand, relative humidity showed moderate results, which might be improved by choosing other analog sensors than the ones used in this study. Ultimately, the rain gauges used did not prove to be suitable for accurate collection of actual rainfall, which can be mainly attributed to the irregular measurement frequency and most likely to the limited capacity of the rain gauges. In terms of sources of error for each parameter, the thermometers and hygrometers used are predominantly affected by environmental influences, such as intense sunlight. Rainfall is mainly affected by the capacity of the rain gauges, which most likely lack protection against evaporation. For water levels, a higher contribution to the error can be attributed to the reading errors by participants.

5 Conclusion

The objective of this study was to validate analog measurements by participants collected within the PM project HydroCrowd. Over a period of 2 years (May 2023 – May 2025), 2,982 analog hydrometeorological observations, consisting of air temperature, relative humidity, rainfall and water level were recorded. Considering these results of this study, we conclude the following.

- The slightly more accurate measurements by frequent participants for most parameters and their far better participation suggest that integration of local communities into PM programs is the most promising way to collect high-quality data instead of relying on untrained, non-frequent participants, such as tourists. The slightly higher complexity of specific parameters could be tackled through even more targeted recruitment of regular participants which are more experienced and therefore achieve higher accuracy measuring different parameters.
- Air temperature and water level data can be collected by participants in a high quality using simple analog sensors. For relative humidity further investigation under similar conditions is recommended to ensure accuracy of analog sensors. As both the thermo- and hygrometers seem quite sensitive to overheating, even better shielding against intense sunlight should be considered for PM projects using such sensors. As the 35 mm rain gauges cannot be considered reliable enough for continuous daily rainfall monitoring in areas where intense rainfall is expected, for instance, bigger rain gauges, ideally with sufficient protection against potential evaporation, should be used in future PM projects.

The next steps should consider the potential further use of the collected hydrometeorological data. As, for instance, air temperature proved to be a considerable alternative for automatic measurements in terms of accuracy, future PM projects should focus on expanding the density of the PM station network to further increase the availability of this data. A practical application could be a combination with other data sources, such as remote sensing datasets to further improve the spatial resolution of data. Since the air temperature data are of high quality and can be considered precise ground-based measurements, they could be combined for downscaling coarser remote sensing data. Considering the high correlation with automatic data, the relative humidity data could be used for that as well, despite the poorer accuracy. The rainfall data on the other hand could be combined with remote sensing rainfall products, such as CHIRPS or IMERG (Funk et al., 2015; Huffman et al., 2020) to test whether gaps where no measurements were taken or where the gauges' capacity was exceeded could be filled. As point observations have a limited spatial representativeness, further work could also analyze how different remote sensing datasets would be influenced by differing spatial distribution of the PM stations. Another conceivable application could be the integration of the PM data into hydrological modeling. As PM water level data has already been used successfully for different hydrological model applications (Weeser et al., 2019; Mitze et al., 2025), a next step could be the integration of other PM parameters. It could be investigated how much automatically measured data can be replaced with PM data, for example, using the air temperature and relative humidity data.

As air temperature and water level monitoring worked out well, it should also be considered to scale the approach up to other remote regions of the world, while alternatives for relative

humidity and rainfall monitoring require further investigation. It is most likely possible to source the station panel material locally in other regions as well, thus making it easy to establish a basis for the measurement network. The smartphone-based data collection worked well, and the ability to verify measurements with photos is useful. A critical and probably the most restricting aspect is the limited internet access in many remote regions, which was also a considerable barrier for participation in some of the HydroCrowd study regions (Campos Zeballos et al., 2025). This is why other data transmission methods should be investigated for remote areas with limited internet access. For site selection it is highly recommendable to include local authorities and institutions, to find the best locations for successful monitoring campaigns. Overall, local water resource management could benefit from increased data availability from PM projects and therefore, similar PM programs should be implemented in other countries of the Global South to address the general data scarcity in these regions.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://doi.org/10.5281/zenodo.17712676.

Author contributions

FM: Validation, Conceptualization, Data curation, Writing – review and editing, Methodology, Writing – original draft, Investigation, Resources, Visualization, Software, Formal Analysis. SJ: Writing – review and editing, Supervision, Resources, Formal Analysis, Methodology, Project administration, Conceptualization, Funding acquisition. LB: Funding acquisition, Conceptualization, Writing – review and editing. JZ: Data curation, Formal Analysis, Conceptualization, Resources, Writing – review and editing, Investigation. FC: Writing – review and editing, Resources. FS: Writing – review and editing, Resources. BW: Project administration, Writing – review and editing, Funding acquisition, Methodology, Conceptualization, Resources, Supervision.

Funding

The author(s) declared that financial support was received for this work and/or its publication. LB and SJ acknowledge funding of the DFG project "Biodiversity and the supply of water-related NCPs" (BR 2238/35-1/-2 and JA 3059/4-2) as part of the DFG Research Unit 5064 "The role of nature for human wellbeing in the Kilimanjaro Social-Ecological System" (Kili-SES). FM, JZ, SJ, and BW would like to thank the Kurt Eberhard Bode Foundation for funding the junior research group "HydroCrowd" (grant number 0122/40195/2022).

Acknowledgements

We would like to thank Mancomunidad de Municipios del Parque Nacional Montaña de Celaque (Mapance) and Alliance of Bioversity International and CIAT in Honduras; Empresa Pública Municipal de Telecomunicaciones, Agua Potable, Saneamiento y Gestión Ambiental del cantón Cuenca (ETAPA) and Universidad de Cuenca in Ecuador; the Kilimanjaro National Park Authority (KINAPA) and the DFG Research Unit "The role of nature for human wellbeing in the Kilimanjaro Social-Ecological System (Kili-SES)" in Tanzania, for their support of the HydroCrowd project. Special thanks go to Jefferson Valencia Gómez, José Miguel del Cid and Jensen Mauricio Bautista-Perdomo, Jürgen Baumann, Nicolás Zúñiga, Pedro Alexander Sanchez, María Augusta Bermeo and all the others for their help in implementing the project. Finally, we would like to say thank you to all volunteers for their invaluable contribution, without their dedication and commitment, the success of this project would not have been attainable.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2026.1721642/full#supplementary-material

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