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REVIEW

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Personal weather stations in hydrology and meteorology: a review of applications, challenges and future directions

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ABSTRACT
In recent years, personal weather stations (PWSs), which are low-cost citizen-installed devices, have emerged as a promising supplementary data source. These stations provide real-time high-resolution meteorological data and are proliferating globally through various commercial and volunteer-based networks. This review examines the role of PWSs in hydrology and meteorology, highlighting their potential for enhancing urban studies, flood modelling, and even numerical weather prediction. In this article, we provide an overview of major PWS networks and platforms, discuss recent applications, and explore methods for quality control and bias correction. We also present current approaches to quality assurance, describe methods for integration with official networks and remote sensing products, and outline emerging research directions. Emphasis is placed on the need for standardized benchmarking datasets, collaborative frameworks between institutions and citizen scientists, and ethical data governance.

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1 Introduction

Rainfall sustains human society and ecosystems but also poses risks like loss of life, infrastructure damage, and crop destruction, which are projected to escalate due to factors like population growth, urbanization, land mismanagement, and global warming (Swain *et al.* 2020). Rapid urbanization, land use change, and increasing settlements in floodplains have substantially amplified the risk of pluvial flooding in metropolitan areas, exposing a growing share of the global population to inundation hazards (Rogger *et al.* 2017, Tellman *et al.* 2021). In addition, rainfall can vary dramatically over short distances and within minutes, making it difficult to capture using sparse or low-resolution monitoring systems (Wang *et al.* 2023). Reliable high-resolution analyses thus rely on raingauge data (Xu *et al.* 2013, Girons Lopez *et al.* 2015), which have been a traditional source of in situ rainfall records for centuries. Over time, the temporal resolution and precision of these instruments have progressively improved, enhancing their utility for capturing short-duration events (Morbidelli *et al.* 2021, 2025, Mazzoglio *et al.* 2024). However, retrieving long and reliable rainfall time series could be tricky, and the raingauge stations are not equally distributed across the globe, resulting in large ungauged areas (Kidd *et al.* 2017, Garcia-Marti *et al.* 2023, Mazzoglio *et al.* 2023, Moccia *et al.* 2025a). Moreover, in several nations, accessing climatic data has become challenging due to decentralization and the reluctance of some agencies to publish data readily (Mazzoglio *et al.* 2020). Therefore, improving the understanding of rainfall processes and the ability to model and predict extremes is crucial for both scientists and policymakers (Sillmann *et al.* 2017, Moccia *et al.* 2024).

In addition to rainfall, other meteorological variables such as air temperature, humidity, wind speed, and wind direction play a fundamental role in hydro-meteorological processes and risk assessment (Back and Bretherton 2005, Hochman *et al.* 2022, Raffaele *et al.* 2024, Taylor *et al.* 2024). Temperature and humidity are key drivers of evapotranspiration and heatwave dynamics, while wind characteristics influence the development and transport of weather systems, as well as coastal and urban vulnerability (Allen *et al.* 1998, Perkins and Alexander 2013). The combined variability of these parameters, particularly in complex terrain and densely built environments, poses significant challenges for the accurate monitoring and forecasting of hydro-meteorological phenomena at the local scale.

In this context, the concept of crowdsourcing is particularly relevant. Traditionally, crowdsourcing is defined as the process of "obtaining data or information by enlisting the services of a (potentially large) number of people" (Muller *et al.* 2015, p.1). However, recent technological developments have broadened this definition to include data collected from a wide range of public sensors connected through the Internet (Muller *et al.* 2015, McCabe *et al.* 2017). While fields such as astrophysics and ecology have long embraced crowdsourcing through citizen science projects, web platforms, and low-cost sensors, its application within hydrology and meteorology is

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still relatively new but increasingly promising (Wiggins and Crowston 2011, Fortson *et al.* 2012, Buytaert *et al.* 2014).

The latest advancement in weather measurements is indeed represented by personal weather stations (PWSs), i.e. low-cost sensors installed mainly for home automation by citizens, which could be exploited as a promising tool for data collection. These stations, valued for their cost-effectiveness, ease of use, and ability to provide real-time online data, are rapidly spreading worldwide. Most PWSs automatically upload their observations to data repositories, which offer web platforms and applications for public access (McCabe *et al.* 2017, Hahn *et al.* 2022). These platforms currently aggregate tens of thousands of PWSs globally, forming an ecosystem of crowdsourced weather observations that could complement other opportunistic sensors like commercial microwave links (CML; Olsson *et al.* 2025). PWSs operate on Internet of Things (IoT) principles, leveraging crowdsourced data to share local meteorological conditions contributed by citizens.

However, PWSs were originally designed not to enhance hydroclimatic monitoring networks but rather for smart home applications and for use by amateur meteorologists, farmers, and other private users interested in local weather observations. Therefore, the accuracy of recorded data requires a proper investigation to be able to take advantage of its high temporal and spatial resolution (de Vos *et al.* 2019). Furthermore, due to the absence of specific installation guidelines from manufacturers, users often make inadvertent installation errors when setting up these stations, which can significantly impact the reliability of recorded data (Li *et al.* 2023). This lack, combined with other factors such as improper installation, sensor malfunctions, and insufficient maintenance, could lead to data inaccuracies.

This paper aims to provide a comprehensive overview of the current state of research on the use of PWSs in hydrology and meteorology. More in detail, in the first part of the article, we describe the main PWS networks and data platforms (Section 2). In Section 3, the methodology used to perform the review is presented, together with some summary statistics of the publications considered. Key applications emerging from the review are presented in Section 4. Then, particular attention is given to challenges in using PWS data in hydrometeorology research, covering topics like quality control (QC) procedures, installation and maintenance, structural limitations and sub-optimal manufacturing, the need to benchmark datasets, spatial representativeness and network sustainability (Section 5). In Section 6, we summarize the main pros and cons and outline future directions for improving their scientific usability in both research and operational contexts.

2 Personal weather station networks

In recent years, the proliferation of PWSs has given rise to large-scale, decentralized networks that provide real-time meteorological data with high spatial and temporal resolution. These networks are typically composed of low-cost IoT user-installed devices that transmit observations to their cloud platform. Access to the collected data is handled with policies and costs that depend on the data provider: some platforms provide bulk downloads of weather observations free of charge via an application programming interface (API), though commercial platforms may involve associated costs.

One of the most prominent PWS platforms is Netatmo (https://www.netatmo.com), which offers a network of citizen-operated smart weather stations, tipping bucket raingauges and anemometers. These devices communicate wirelessly with an internal module and transmit observations (such as rainfall, temperature, pressure, humidity, and wind) to a cloud service at 5 min intervals. Real-time observations are available on an interactive global map, which allows users to visualize current weather conditions and explore local variability of weather variables at high spatial resolution. While Netatmo provides an API for data access, retrieving and managing these large, rapidly updating datasets is not straightforward, especially for non-technical users or researchers unfamiliar with API protocols. To address this issue, several researchers have developed tools and workflows to simplify the process. For example, Varentsov *et al.* (2020), in their study of the Moscow megacity, created a freely available Python-based tool that automates data retrieval from the Netatmo API every 30 min. The tool not only handles data requests but also cleans and formats the responses, maintains an updated catalogue of all active PWSs in the area, and stores the data in structured CSV files. This system supports both real-time visualization through a web-mapping application and long-term archiving for use in urban climate research.

Weather Underground (WU; https://www.wunderground.com/), one of the pioneering online weather services, operates one of the world's largest networks of PWSs, with contributions from over 250,000 active stations worldwide. The platform aggregates real-time, hyper-local meteorological data (including temperature, rainfall, humidity, pressure, wind speed, and wind direction), offering a dense observational network that complements official monitoring systems. Data is voluntarily shared by private individuals and organizations.

AerisWeather (now acquired by Vaisala Group and renamed Xweather) operates PWSweather (https://www.pwsweather.com/), a platform designed to offer PWS owners an intuitive dashboard for monitoring, managing, and archiving their data. In addition to local visualization tools, the data contributed by each user is made accessible through the AerisWeather API via the PWSweather Contributor Plan.

Meteonetwork (https://www.meteonetwork.it/), an Italian association founded in 2002 by atmospheric science enthusiasts, has developed over time one of the largest PWS networks in the region (Giazzi *et al.* 2022). In recent years, the organization has expanded its scope across Europe, providing real-time weather observations and daily maps that integrate data from both PWSs and official monitoring networks.

Several other commercial platforms also play a key role in the ecosystem of crowdsourced meteorological data. These include WeatherLink (https://www.weatherlink.com/), developed by Davis Instruments, and Ambient Weather (https://ambientweather.net/).

In addition to commercial and enthusiast-driven networks, volunteer-based initiatives offer structured frameworks for citizen participation in meteorological observation. The

Citizen Weather Observer Program (CWOP; http://www.wxqa.com/cwop_info.htm) is a volunteer-based initiative that enables PWS owners to share real-time meteorological data with the U.S. National Weather Service (NWS) and other organizations. CWOP's collaborative framework bridges the gap between amateur meteorologists and professional services, fostering a community-driven approach to atmospheric data collection. The programme exemplifies the significant impact of citizen science in enhancing meteorological research and public safety.

The Cooperative Observer Program (COOP; https://www.weather.gov/coop/), established by the U.S. National Weather Service, is a nationwide network of thousands of volunteers who provide daily weather observations across the United States and its territories. These volunteers record data such as daily maximum and minimum temperatures, 24 h precipitation totals (including snowfall), and notable weather events. Some stations also monitor stream or tidal levels. Observations are submitted electronically or via mail, with many stations situated in rural areas, as well as urban centres, national parks, and other diverse locations.

The Weather Observations Website (WOW; https://wow.metoffice.gov.uk/) is an open-access platform developed by the UK Met Office and the Department of Education to facilitate the sharing of real-time weather observations from a wide range of sources, regardless of where they came from (Fig. 1). These include both official meteorological stations and PWSs. One of the primary goals of WOW is to offer an engaging, real-time platform that encourages people to explore and understand the weather. Indeed, the platform also provides a range of learning materials and resources designed to support weather education and public engagement, created in collaboration with the Royal Meteorological Society (https://wow.metoffice.gov.uk/education).

The growing scientific and institutional interest in this topic is underscored not only by the rapid expansion of sensor networks operated by citizens and private stakeholders, but also by the emergence of structured networks of researchers and institutions dedicated to studying and advancing these approaches. In this context, the establishment of a dedicated European research network in 2021 reflects a broader recognition that addressing the challenges of opportunistic and crowdsourced precipitation sensing requires coordinated scientific effort. In particular, the EU COST Action CA2016 OpenSense (https://opensenseaction.eu/) was funded to promote open standards, FAIR (Findable, Accessible, Interoperable, Reusable) principles, and open-source tools for opportunistic precipitation sensing networks, including PWS data, aiming to enhance interoperability and reproducibility while fostering collaborative approaches within the scientific community.

3 Literature review

This review aims to provide an overview of the current state of research on the use of PWSs in hydrology and meteorology. The work was conducted by consulting all documents indexed in Scopus containing the keywords "personal weather station", "private weather station," "PWS," "Netatmo" or "Weather Underground." The search was then repeated using Google Scholar to capture additional sources, such as conference proceedings not indexed in Scopus. The review was further complemented with selected online sources identified through similar keyword searches, as well as with relevant publications and websites known to the authors.

To provide a structured overview of the current state of research on PWSs, the reviewed studies (49 in total) were

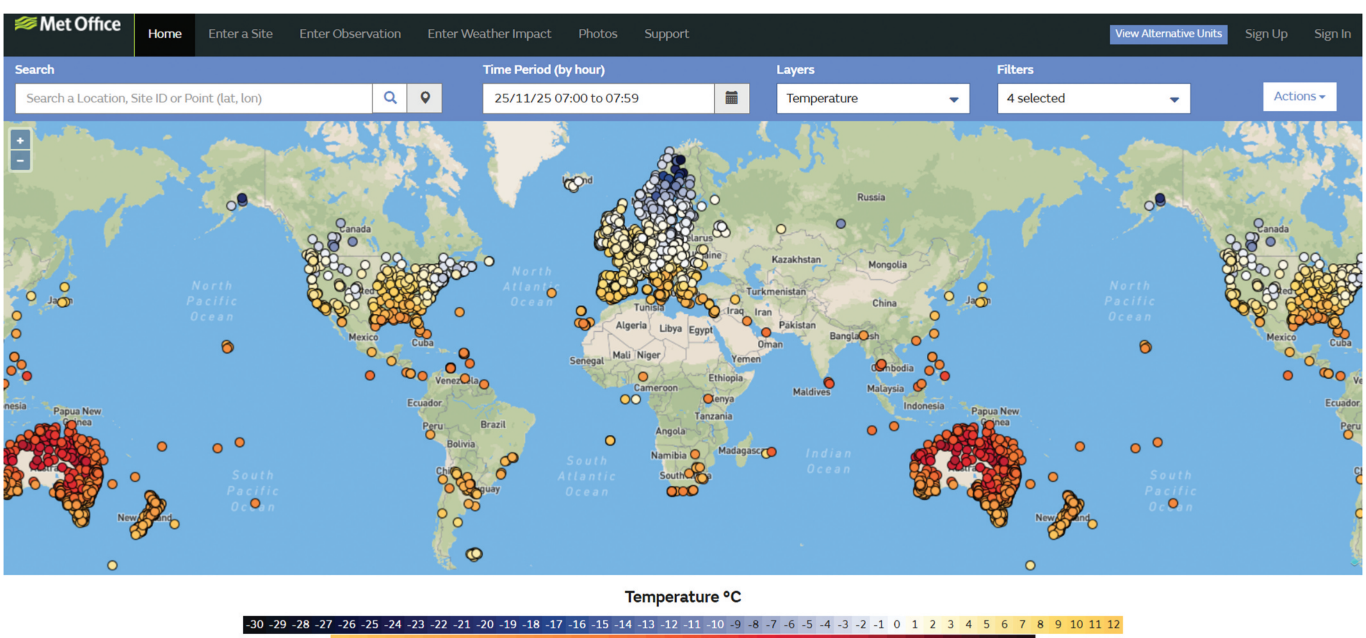

Figure 1. Screenshot of the Weather Observations Website (WOW; https://wow.metoffice.gov.uk/). Dots indicate the location of the available PWSs (colour refers to the hourly temperature measured on 25 November 2025 between 7.00 and 7.59am).

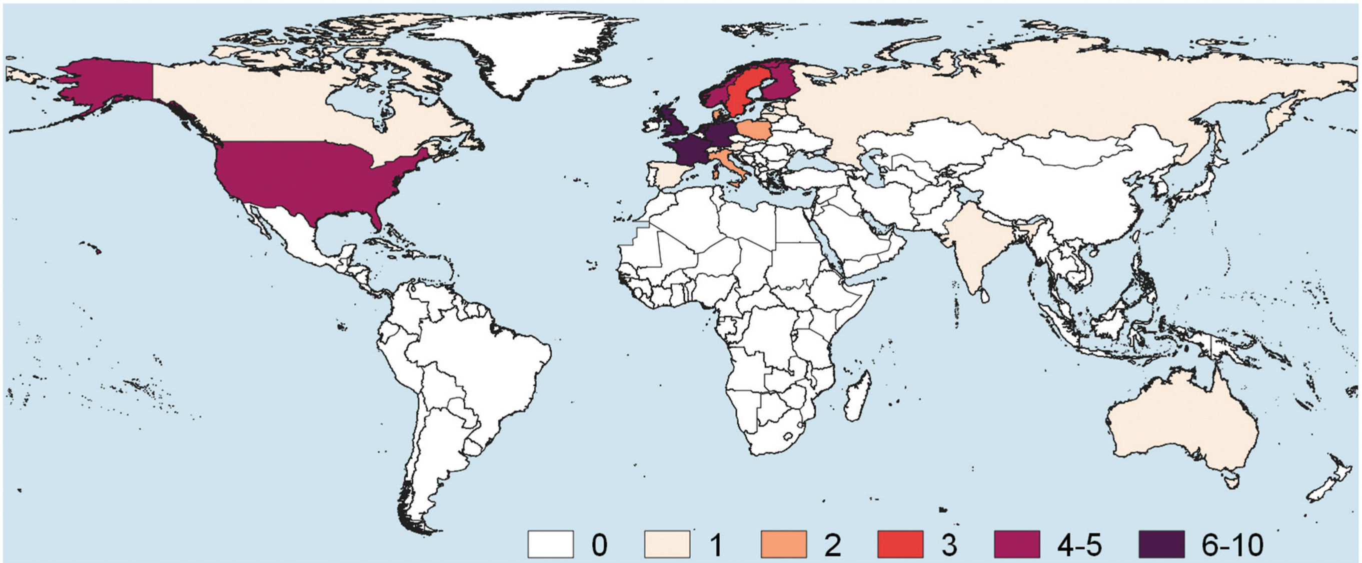

Figure 2. Number of studies performed in each country. Overeem *et al.* (2024) and Lopez Lorente *et al.* (2020) were not included in this map because their analyses were performed at broader spatial scales (across Europe in the former case and globally in the latter) and therefore cannot be attributed to a specific country.

classified according to five main dimensions: spatial distribution of the case studies (Fig. 2), publication year (Fig. 3), investigated variables (Table 1), type of PWS platform (Table 2), and application category (Table 3).

The temporal distribution of the literature (Fig. 3) shows that research on PWS data has increased markedly in recent years, with only sporadic publications before 2019 and a clear growth from 2020 onwards. This trend reflects the rapid expansion of citizen-operated weather station networks and the growing interest of the scientific community in exploiting these data sources. The focus of the scientific literature on PWS data has also evolved significantly over time. Early studies were primarily concerned with intercomparison exercises, aiming to evaluate the potential of PWS observations by comparing them with data from official stations or radar products, and to assess their overall suitability for hydro-meteorological applications. These initial investigations were often conducted over relatively limited spatial domains, such as single cities or small regional case studies, where controlled comparisons could be more easily performed. Subsequently, research shifted towards the development of QC procedures, recognizing that the heterogeneity and potential biases of PWS data required systematic filtering and correction before meaningful use. More recently, the field has entered a phase characterized by increasing emphasis on real-world applications. While the development and refinement of QC algorithms remain important, the primary focus has moved towards the operational use of PWS data in practical contexts. This shift reflects a growing confidence in the maturity of existing methodologies and a stronger interest in exploiting PWS data as a complementary observational resource.

Regarding the investigated variables (Table 1), temperature (29 studies) and precipitation (24 studies) dominate the literature. Other variables such as relative humidity, wind speed and direction, and pressure are less frequently analysed, while parameters like CO_2 concentration or solar radiation appear only in isolated studies.

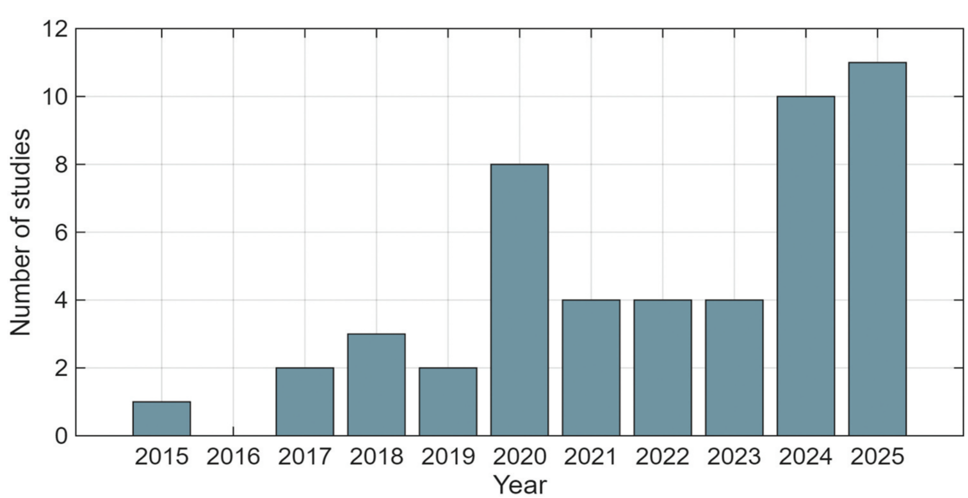

Figure 3. Number of studies published in each year.

Table 1. Investigated variables.

Investigated variable	Number of studies
Temperature	29
Precipitation	24
Relative humidity	11
Wind	8
Air pressure	5
CO_2	1
Global horizontal irradiance	1
Shortwave irradiance	1

Table 2. Type of PWS platforms.

PWS	Number of studies
Netatmo	36
Weather Underground	9
WOW	6
Other	4

Table 3. Main category of application of PWS data.

Application category	Number of studies
High-resolution urban studies	22
Data integration and spatial mapping over large areas	11
Hydro-meteorological real-time monitoring and forecasting	11
Integration in NWP models and RCM	5

From the perspective of data sources (Table 2), Netatmo clearly emerges as the most widely used platform (36 studies), largely due to its global availability, relatively dense station coverage, and accessible API. Other platforms, such as Weather Underground and the UK Met Office's WOW, appear less frequently in the reviewed studies. Finally, the classification by application (Table 3) highlights that most research focuses on high-resolution urban studies (22 studies), followed by hydro-meteorological real-time monitoring and forecasting (11 studies) and data integration and spatial mapping over large areas (10 studies). A smaller number of studies explore the assimilation or validation of PWS data within numerical weather prediction (NWP) models and regional climate models (RCMs). Overall, these statistics underline both the strong potential of PWS networks for urban and hydrological applications and the still limited exploration of their use in operational forecasting and climate modelling contexts.

A detailed summary of the studies included in this review is provided in tabular form in the Supplementary material, where key characteristics of each paper (reference, years, investigated variables, study focus, category of application, location of the study, PWS network, other datasets, QC procedure applied, results and limitations) are systematically reported. In contrast, Sections 4–6 present the narrative synthesis of the

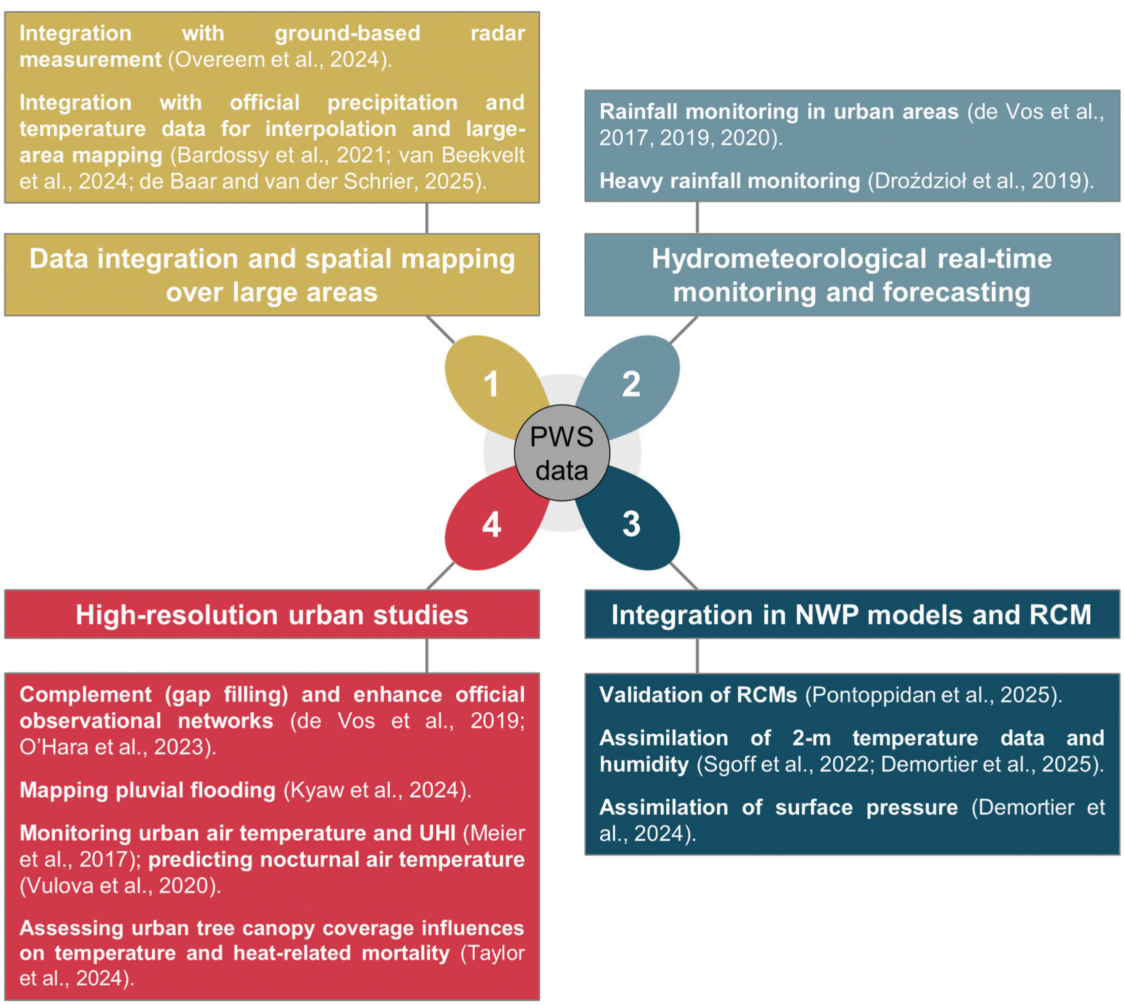

Figure 4. Main areas of application of PWS data.

literature, discussing the main methodological approaches for each area of application, challenges, and research directions emerging from the reviewed studies in a structured and thematic way rather than as a purely tabulated comparison.

4 Applications of PWS data in advancing hydro-meteorology research

PWS observations, when appropriately quality-controlled, can support a wide range of scientific and operational uses by increasing observational density and spatial coverage. Figure 4 provides a conceptual overview of the main hydro-meteorological applications as previously identified in Table 3. The applications are grouped into four major domains, as detailed in the following subsections. For each domain, some representative studies are cited to illustrate concrete use cases and demonstrated benefits.

4.1 Data integration and spatial mapping over large areas

One of the most compelling and transformative uses of data from PWSs is their application to the high-resolution mapping of meteorological variables across extensive spatial domains, usually covered by different hydro-meteorological agencies with different network densities and complex data policies.

One possible application of PWS data lies in its integration with ground-based radar precipitation measurements, which usually require an adjustment with in-situ observations to achieve acceptable accuracy (Nielsen *et al.* 2024, Overeem *et al.* 2024). Due to their significantly higher spatial density compared to official networks, PWSs offer valuable supplementary data (Olsson *et al.* 2025). In a recent study, Overeem *et al.* (2024) demonstrated the effectiveness of this approach by merging Netatmo PWS data with the pan-European OPERA radar product. After applying a default bias correction factor of 1.063 to the PWS accumulations, their results showed a substantial improvement in accuracy: the severe average underestimation of daily precipitation in the unadjusted radar data (~28%) was reduced to ~3% once merged with PWS observations.

Bárdossy *et al.* (2021), in turn, investigated the applicability of these data for the spatial interpolation of precipitation, using the state of Baden-Württemberg in Germany as a case study. Their results demonstrate that filtering PWS observations is necessary to reduce the interpolation error, with the greatest improvement achieved for short temporal aggregations.

In terms of temperature, van Beekvelt *et al.* (2024) introduced a multi-fidelity spatial regression framework to integrate heterogeneous datasets: official Royal Netherlands Meteorological Institute (KNMI) stations, road-network sensors and PWSs from the WOW platform. Applied during a severe ice warning event, the approach significantly improved high-resolution temperature mapping across the Netherlands, extending the effective sampling limit and capturing sub-mesoscale variability. Similarly, de Baar and van Der Schrier (2025) proposed a multi-fidelity regression Kriging to blend KNMI observations with WOW data and land-use covariates for gridded temperature products at the national scale, again in the Netherlands. Their analysis of 1704 hourly time steps in 2023 showed that including all PWS data without strict QC enhanced spatial detail and reduced RMSE (0.67°C compared to 0.88°C for official data only).

Mandement and Caumont (2020) assessed the PWS contribution to the observation and mapping of deep-convection features near the ground in four case studies over the west of France. After proper processing steps, the mean number of observations available increased by a factor of 134 in mean sea level pressure (MSLP), of 14 in relative humidity and of 11 in temperature. When using PWSs, leave-one-out cross-validation (LOOCV) root-mean-square errors (RMSEs) decreased for all parameters by 73 to 77% in MSLP, 12 to 23% in temperature and 17 to 21% in relative humidity. More importantly, fine-scale structures being partly, or not at all, visible in official weather observations only showed when adding PWSs in the analyses.

4.2 Hydro-meteorological real-time monitoring and forecasting

In addition to accuracy and spatial resolution, the timeliness and speed at which data become available are critical factors, particularly for applications such as nowcasting, early warning systems, and monitoring (De Luca *et al.* 2025). Indeed, most PWSs transmit data in near real-time via cloud-based platforms, supporting timely monitoring of rapidly changing weather conditions such as intense rainfall events.

In the literature, several research works were performed to assess the PWS data accuracy for monitoring purposes. As an example, Droździoł *et al.* (2019) investigated the possibility of using Weather Underground meteorological data to monitor heavy rainfall events in a Polish metropolis, while de Vos *et al.* (2017, 2019, 2020) used Netatmo data for urban rainfall monitoring in Amsterdam. Rivera *et al.* (2023) presented the design of a low-cost PWS that integrates sensors for multiple atmospheric variables, aimed at enhancing environmental monitoring and short-term forecasting capabilities. For forecasting purposes, the authors implemented an autoregressive integrated moving average (ARIMA) model trained on historical station records. This dual capability highlights the potential of low-cost PWSs not only for continuous monitoring but also for operational forecasting applications.

4.3 Integration in numerical weather prediction models and regional climate models

The assimilation of data from PWSs into numerical weather prediction models represents a promising but still emerging frontier in operational meteorology. NWP models require accurate, high-resolution initial conditions to simulate the evolution of the atmosphere. Traditionally, these inputs are derived from satellite observations, radar estimates, and official ground-based stations. However, the spatial coverage of official ground networks is often insufficient, particularly in urban areas, mountainous regions, or developing countries (Kidd *et al.* 2017). The dense distribution and increasing availability of PWSs can help fill these observational gaps and improve the accuracy of forecasts at local scales.

Pontoppidan *et al.* (2025) aimed to evaluate the potential of including PWSs in the validation of high-resolution regional climate models in Western Norway and Bergen. By using Netatmo rainfall data alongside 124 official meteorological stations and radar data, the authors tested the ability of PWSs to capture fine-scale variability during both frontal and convective events. After the application of a spatial QC procedure, their results showed that PWSs significantly enhanced spatial coverage, revealing heterogeneity missed by traditional datasets.

Coney *et al.* (2022) evaluated outdoor air temperature measurements from Netatmo PWSs by validating them against a calibrated laboratory chamber and, using a UK-wide Netatmo network, implemented three established QC procedures (Meier *et al.* 2017, Clark *et al.* 2018, Nipen *et al.* 2020) to quantify the sensor bias arising from environmental placement. The findings suggest that Netatmo temperature data hold promise for assimilation into numerical weather prediction systems in the United Kingdom. However, the authors stressed that further work is needed to establish a standardized and effective QC framework to reliably filter anomalous observations before operational integration.

For a similar purpose, Sgoff *et al.* (2022) assimilated Netatmo observations of 2 m temperature and humidity into a regional weather prediction model (Icosahedral Nonhydrostatic Model with 2 km resolution, ICON-D2). The authors showed that the assimilation of bias-corrected observations can reduce the forecast error considerably, while the assimilation of observations without bias correction leads to a strong bias with a negative impact on forecast performance.

Demortier *et al.* (2024) assessed the benefits of assimilating pre-processed PWS observations of surface pressure in the AROME-France model with both three-dimensional variational (3DVar) and three-dimensional ensemble variational (3DEnVar) data assimilation schemes and identified statistically significant improvements in mean sea level pressure forecasts of up to 9 h range with the 3DEnVar scheme. In a subsequent study, Demortier *et al.* (2025) extended this work by assessing the benefits of assimilating pre-processed PWS observations of temperature and relative humidity in the same modelling framework. When using two variables, Demortier *et al.* (2025) showed that a separate assimilation of each variable with the 3DEnVar data assimilation scheme significantly reduces the root-mean-square deviation between official observations and forecasts of the assimilated variable at a height of 2 m above ground level for up to 3 h of forecasts. Both studies (Demortier *et al.* 2024, 2025) demonstrated that the benefit of assimilating PWS observations can be highly dependent on the data assimilation schemes employed, with 3DEnVar providing better results in the selected application.

4.4 High-resolution urban studies

Urban areas are characterized by complex microclimates influenced by factors such as surface heterogeneity, building morphology, anthropogenic heat release, and reduced ventilation, all of which can produce strong spatial gradients in meteorological conditions even over short distances (Stewart and Oke 2012). Conventional ground-based instruments, such as raingauges, thermometers and anemometers, often lack the spatial and temporal resolution required to adequately capture the variability of hydro-meteorological variables in urban environments (Cristiano *et al.* 2017). Although advances in remote sensing technology and the emergence of high-resolution hydrological models have improved the ability to represent urban hydrological processes, accurately resolving near-surface meteorological variability in dense urban areas remains a major scientific challenge. In contrast, PWSs are widely distributed and often fill gaps in official monitoring networks, allowing improved spatial resolution of weather observations, which is particularly beneficial for urban hydrology, local forecasting, and early warning systems.

As an example, O'Hara *et al.* (2023) showed how crowdsourced rainfall data acquired from thousands of stations has the potential to fill the gaps within the official raingauge network in Britain. When properly quality-controlled, PWS data can thus complement and enhance official observational networks (de Vos *et al.* 2019, Bárdossy *et al.* 2021, O'Hara *et al.* 2023, El Hachem *et al.* 2024, Kyaw *et al.* 2024, Rombeek *et al.* 2025), contributing to improved interpolation and model calibration, allowing the high spatial-temporal variability of rainfall, especially in urban areas, to be captured (Hahn *et al.* 2022). Kyaw *et al.* (2024) explored the potential use of PWS data for mapping pluvial flooding in urban areas by employing both HEC-RAS 2D rain on grid and the UnTRIM hydrodynamic model, focusing on the city of Oslo. The authors highlighted that PWSs have excellent rain detection capabilities, although they are characterized by a 25% underestimation on average. Nevertheless, once bias-corrected, PWS rainfall data can yield more accurate inundation maps than those generated from official raingauges (using bias-corrected weather radar as benchmark), demonstrating their added value in small-scale urban hydrology and data scarce regions.

In addition, deploying and maintaining conventional, high-density sensor networks in cities is often prohibitively expensive and logistically challenging, if not impossible (de Vos *et al.* 2020). PWSs are significantly more affordable than professional-grade weather stations, making them accessible to individuals and communities, and enabling large-scale deployment at minimal cost. To investigate this matter, Lascano *et al.* (2024) conducted a 242-day (1 October 2022–31 May 2023) evaluation of a solar-powered PWS compared to a conventional automatic weather station (AWS) in cotton fields in Lubbock, Texas. They found that despite its reduced cost compared to a standard AWS, the PWS delivered rainfall measurements that closely matched those from the AWS for light to moderate events up to 25 mm. Similarly, Moccia *et al.* (2025b) compared 2020 rainfall data from a Netatmo PWS with those recorded by a conventional raingauge in Rome, located about 700 m apart. In their preliminary analysis, they reported a generally good agreement between the two datasets across multiple temporal scales (from 30 min to 24 h), with the Netatmo raw data performance improving with increasing aggregation level.

In the monsoon-driven city of Pune (India), Eingrüber *et al.* (2025) used 12 PWSs from the Netatmo network to capture microclimatic heterogeneity by monitoring air temperature, humidity, rainfall, wind and CO_2. Temperature and relative humidity sensors were quality-checked and periodically calibrated against high-accuracy reference instruments under laboratory conditions every 6 months. In addition, two professional meteorological stations of the Indian Meteorological Service (IMS) and the System of Air Quality and Weather Forecasting and Research of the Indian Institute of Tropical Meteorology (the SAFAR system of the IITM) were used as external references for QC. The PWS network successfully captured fine-scale microclimatic variability across contrasting urban settings (street canyons, courtyards, parks) and proved robust even under challenging monsoon conditions. Citizen engagement was integral: residents and schools hosted the stations, provided Wi-Fi and power, and accessed real-time data via the Netatmo app.

Crowdsourced and PWS data can also significantly advance our understanding of the urban heat island (UHI) effect and intra-urban heat patterns across cities (van der Meer *et al.* 2025). Meier *et al.* (2017) used a one-year dataset from up to 1500 PWSs in Berlin, Germany, to monitor urban air temperatures and investigate spatio-temporal patterns of the UHI. Hassani *et al.* (2024) compared three spatio-temporal mapping approaches (ordinary kriging, machine learning, and weather research and forecasting (WRF) modelling) for mapping daily urban air temperature in Warsaw at about 1 km resolution using Netatmo PWS data as input. In this work, predictions were compared against observations from five meteorological reference stations. Machine learning models, built and trained with open-access Earth observation data and PWS observations, showed strong performance and computational efficiency. Taylor *et al.* (2024) used Netatmo PWS data across the Greater London Authority to assess how urban tree canopy coverage influences temperature and heat-related mortality. Building on the potential of crowdsourced data and the high spatial resolution of these networks, Žuvela-Aloise *et al.* (2025) used quality-controlled PWS observations to verify city-scale thermal variability in Vienna, Austria, obtained by employing the PALM model. Chen *et al.* (2024) used PWS data for modelling air temperature with an urban climate model called TARGET (The Air-temperature Response to Green/blue-infrastructure Evaluation Tool; Broadbent *et al.* 2019) to assess the impacts of green and blue spaces and plan liveable cities. Romero Rodríguez *et al.* (2024) explored the potential of Netatmo data to improve urban temperature forecasts across five European cities (Madrid, London, Rome, Paris, and Berlin). Using hourly temperature data collected from 776 Netatmo stations, the authors implemented a QC procedure, produced spatial heat maps of urban temperatures, and built regression models with reference weather data as predictors. The validated models successfully forecasted hourly temperatures over a 168 h period, demonstrating that accurate PWS data combined with reliable reference forecasts can support cost-effective urban temperature prediction with applications for urban planning, public health, and climate adaptation. Vulova *et al.* (2020) presented a method for predicting summertime nocturnal air temperature one day in advance in Berlin using Landsat data, open-source geodata, and crowdsourced air temperature data. Marquès and Messier (2025) used quality-controlled PWS data from WU to develop a spatiotemporal Bayesian model capable of reconstructing hourly 2 m air temperatures at very high resolution, for improving heat exposure assessment in U.S. cities and detecting intra-urban variability linked to the UHI effect. Their results showed that the PWS-based model achieved an RMSE of 1.06°C and identified urban hotspots undetected by traditional gridded products. In four Finnish cities, Taylor *et al.* (2025) exploited a dense network of Netatmo PWSs (~1000) to characterize UHI intensity and heterogeneity. Their results demonstrate that, with robust cleaning through QC procedures, PWS can complement AWS networks and provide insights into UHIs, energy demand, and health exposures in cold-climate cities.

Despite the critical role of the urban energy balance in urban climate studies, direct measurements of urban surface fluxes remain limited due to the scarcity of professional flux observation networks (van der Meer *et al.* 2025). Thus, van der Meer *et al.* (2025) proposed a novel method to estimate urban fluxes of sensible heat, latent heat, and momentum using only PWS observations of temperature, humidity, and wind speed collected in the urban canopy, thus applicable also in cities lacking professional observations, but that do have about 40 (or more) Netatmo stations.

More recently, Netatmo smart weather stations were also used for indoor measurements. A relevant example is an application carried out in Belgium to investigate indoor environmental conditions in the classroom during heating and intermediate seasons (Carton *et al.* 2026).

5 Challenges in using PWS data in hydro-meteorology research

Despite their growing popularity and numerous advantages, PWSs also present several limitations and challenges that must be carefully considered to ensure their effective use in scientific and operational applications. These challenges primarily stem from the non-professional nature of PWS ownership, the lack of standardized installation practices, and the variable quality of sensors used. Indeed, one of the central issues is that, unlike stations managed by meteorological agencies, PWSs are typically installed and maintained by non-experts, often without adhering to official guidelines and international quality standards for their installation, maintenance, and data validation.

5.1 Installation and maintenance

One of the most influential factors affecting the reliability of PWS data is the quality of installation and (infrequent) maintenance, which can significantly impact the accuracy of rainfall measurements. de Vos *et al.* (2020) highlighted several critical challenges in the accuracy of PWS measurements strictly linked with these operations. For tipping-bucket gauges, mechanical obstructions (e.g. insects, twigs) and installation inaccuracies (such as an improper levelling of the device with the ground) can hinder the tipping mechanism, leading to systematic underestimation of rainfall. Shielded placements could exacerbate this issue. Conversely, overestimation may occur from PWS owners cleaning or handling the station, resulting in tipping-bucket tips, creating measurements of artificial rain.

5.2 Structural limitations and sub-optimal manufacturing leading to biases in extreme conditions

Independently of the installation and maintenance, uncorrected PWS data generally underestimate rainfall during intense events due to their inherent structural limitations and sub-optimal manufacturing. In addition, biases and errors in PWS rainfall measurements arise from both calibration issues and design flaws (Bell *et al.* 2015).

Lascano *et al.* (2024) noted that while the PWS considered in their case study closely matched the AWS for daily rainfall totals up to approximately 25 mm, its accuracy during heavier rainfall events remained uncertain, with discrepancies likely to increase beyond that threshold. Rombeek *et al.* (2025) found that the average of a cluster of PWSs severely underestimates rainfall (around 36% and 19% for the 1 and 24 h intervals, respectively, when no QC procedures are applied). Thus, according to Rombeek *et al.* (2025), on average, PWSs can reliably capture high rainfall intensities up to approximately 30 mm/h, and tend to significantly underestimate extreme rainfall events, particularly those with return periods of 10 to 50 years, which typically exceed 30 mm/h and are more frequent in spring and summer. Using three years of hourly precipitation data, Lussana *et al.* (2023) analysed the empirical distribution of crowdsourced Netatmo PWS measurements near official stations from national meteorological services, considered as reference observations. Results show that while reference values generally fall within the range of crowdsourced observations (between the 10th and the 90th percentiles), the spread increases with higher precipitation amounts, with official data often located in the right tail of the distribution. This indicates that the accuracy and precision of PWS data tend to decrease as rainfall intensity increases. Sensitivity analyses based on neighbourhood size (1, 3, and 5 km radii) revealed that spatial aggregation improves reliability, particularly for detecting precipitation occurrence.

In a European-scale data integration work on the integration of PWSs into a radar mosaic, Overeem *et al.* (2024) showed that PWS performance decreased under lower temperature conditions. A stratified analysis highlighted issues related to solid precipitation: for hourly precipitation, the average underestimation was approximately 7% when the mean daily air temperature was ≥ 5°C, while this underestimation increased markedly to around 27% when the mean daily air temperature was < 5°C. These results indicate that Netatmo PWSs are less effective in capturing solid precipitation, thereby limiting the accuracy of merged datasets in colder climates.

A systematic underestimation of wind speeds has also been highlighted by Droste *et al.* (2020) in an application over Amsterdam, leading the authors to develop a QC procedure. The limited sensitivity of the Netatmo PWS anemometer at near-zero wind speeds, however, reduces the effectiveness of the QC protocol during calm conditions. Droste *et al.* (2020) also pointed out that episodes with rain or high relative humidity degrade the PWS measurement quality.

5.3 QC procedures

QC procedures are essential to ensure the reliability and usability of data collected by PWSs: despite the significant potential of these new decentralized monitoring networks, their use faces several challenges, as highlighted in various literature studies. Thus, measurements performed by PWS include far more uncertainty than measurements provided by reference AWSs from national meteorological and hydrological services core networks (Hahn *et al.* 2022).

Different QC strategies have been developed in recent years, varying in their approach and level of complexity (El Hachem *et al.* 2024). Some methods focus on identifying and excluding entire stations as unreliable based on deviations or poor agreement with nearby observations (see e.g. Napoly *et al.* 2018, Fenner *et al.* 2021). Other approaches instead examine the time series at a finer scale, flagging only specific time intervals affected by errors, while preserving the remaining reliable observations (see e.g. de Vos *et al.* 2019).

Bell *et al.* (2015) emphasize that any application of PWS data must be supported by a comprehensive QC system capable of removing gross errors and correcting station-specific instrument biases while providing uncertainty estimates. A significant portion of the bias in PWS data can be parameterized, making it possible to learn and correct for it. However, since such biases are often specific to individual stations and may vary over time, they are best identified using the station's own data.

Muller *et al.* (2015) introduced and evaluated a wide range of crowdsourcing approaches for atmospheric data, highlighting the untapped potential of these non-traditional observations if supported by rigorous validation and QC procedures. The authors emphasize that to realize these benefits, one must conduct comprehensive assessments of data quality across different spatiotemporal scales, perform case-by-case analyses of precision and accuracy after QC, and account for geographical and application-specific contexts. They further argue that only through such targeted validation can crowdsourced data truly augment traditional networks, providing high-resolution, real-time information in regions where observations are sparse.

de Vos *et al.* (2017) investigated the quality of 63 PWSs installed in Amsterdam that measured rainfall over at least 4 months in a 17-month period by comparing them with one high-resolution electronic raingauge (with a time resolution of 12s) and with a meteorological radar. Although revealing a high coefficient of determination (0.94), which improved with longer time aggregation, PWSs recorded less rainfall than the other instruments. This underestimation, however, could be partially due to point versus areal observations (Sebastianelli *et al.* 2010).

In a follow-up work, de Vos *et al.* (2019) proposed a real-time QC algorithm for PWS measurements (PWSQC) that does not require auxiliary observations to perform the comparison, but only the PWS series itself (and a set of user-defined parameters). Instead of flagging entire stations, the

QC procedure identifies and flags specific time intervals affected by sampling and representativeness errors (like intrinsic tipping bucket errors where rain can be attributed to a later time stamp and gaps in the time series during connectivity problems), bias (due to wind-induced underestimation, faulty calibration or hindered tipping bucket mechanism) and by issues such as faulty zero observations (due to an obstructed tipping bucket mechanism), high influxes (caused by owners pouring liquids through the raingauge for cleaning, handling of the device with tilting movements, or presence of sprinklers for garden irrigation in the vicinity), and station outliers (due to incorrect station coordinates). A dynamic bias correction is also applied to improve data accuracy. More details on the filters are reported in Table 4. The QC method was initially developed using one year of PWS data from the Amsterdam metropolitan area, and subsequently tested on measurements from the same area in the following year, as well as on a one-month dataset covering all PWS observations across the Netherlands. With this approach, each PWS is compared to its spatial neighbours (within a user-defined radius) and, thus, is more applicable in highly monitored urban areas. PWSQC's strengths are that it can run without any official gauge or radar data, making it applicable in areas lacking reference measurements. Its filters catch common PWS errors (false zeros, spikes, uncorrelated sensors) and it even computes a bias correction if needed. A limitation is that it relies purely on inter-PWS comparisons, so any bias common to the whole network is not corrected unless auxiliary data are used. The code has been implemented in R and is available at https://github.com/LottedeVos/PWSQC. PWSQC cannot be parallelized per time subset due to the lead-up time (El Hachem *et al.* 2024). However, parallelization per subset of stations is feasible, provided that the entire PWS dataset remains in memory for each parallel run, ensuring that neighbouring stations are always available for comparison (El Hachem *et al.* 2024).

Later, Rombeek *et al.* (2025) applied part of the PWSQC developed by de Vos *et al.* (2019) on a sample of 1760 individual rainfall events in the Netherlands in the 2018–2023 period. They found that applying a mean field bias correction factor of 1.22 to the PWS data substantially reduced the systematic undercatch in the dataset. With this adjustment, the 1 h underestimation dropped to about 21%, and bias for totals of 3 h (or longer) was essentially eliminated. The highest correlations between PWS and reference data were observed in winter and autumn (0.83), along with the lowest coefficients of variation (0.15 and 0.18, respectively). Most PWSs reliably captured moderate rainfall intensities up to ~30 mm/h, making them suitable for high-resolution applications such as flood forecasting in small, fast-responding catchments. However, they significantly underestimated extreme rainfall events, particularly those with return periods over 10 to 50 years, by more than 50% on average, especially during spring and summer. This underestimation was linked to large areal reduction factors and the known limitations of tipping bucket gauges at high intensities, which may cause errors of up to 17% for 1 h events with a 50-year return period. To address this, dynamic calibration of tipping volumes is recommended. Additionally, they suggest that winter outliers were likely caused by solid precipitation and could potentially be filtered using integrated temperature sensors.

Napoly *et al.* (2018) proposed a multi-level statistically based QC framework (CrowdQC) to identify implausible temperature measurements without relying on external reference networks. The procedure includes four mandatory steps (M1–M4) and three optional levels (O1–O3):

(1) level M1: metadata validation. This step ensures that no two stations share identical geographic coordinates (latitude and longitude). If duplicates are found, all stations at that exact location are excluded from further analysis;
(2) level M2: (i) temperatures are normalized for elevation differences using a standard lapse rate of 0.0065 K m^{-1} and Shuttle Radar Topography Mission (SRTM) topography, and (ii) hourly outliers are detected using modified z-scores computed from the median and the Qn robust scale estimator. Asymmetric thresholds ($Z < -2.32$ and $Z > 1.64$) are used to detect positive biases associated with indoor placement or radiative heating, while still capturing unrealistically low values;
(3) level M3: the temporal reliability of each station is assessed by examining the proportion of values flagged in M2: if more than 20% of hourly observations within a month are rejected, the entire month for that station is discarded, ensuring the removal of sensors with persistent siting or exposure issues;
(4) level M4: evaluates the physical consistency of each station's diurnal cycle by computing the monthly Pearson correlation coefficient between the station time series and the spatial median of all PWSs. Months with correlation coefficients below 0.9 are

Table 4. Description of the filters used in de Vos *et al.* (2019).

Filter name	Approach
Faulty zero (FZ) filter	All stations within a range *d* around a given station are selected to compute the median rainfall of the surrounding area. The FZ flag is set to 1 if this median rainfall is larger than zero for at least *n* time intervals while the station itself reports zero rainfall.
High influx (HI) filter	Unrealistically high rainfall amounts are checked based on a comparison with the median rainfall computed by using the stations installed within a range *d* around a given station. A fixed low-intensity threshold is used. When the surrounding stations report moderate to heavy rainfall, the threshold becomes variable.
Bias correction and station outlier (SO) filter	First, a default bias correction factor (DBC) is determined to correct the general tendency towards rainfall underestimation. DBC can be determined a priori by comparing PWS measurements over a period with rainfall measurements of the location. If no reference is available, DBC could be set to 1 or to a literature value. Initially, the bias correction factor (BCF) for each PWS is equal to DBC. DBC = 1 is also applied. To determine whether a station yields nonsensical measurements for that location (station outlier), it is compared with time series of neighbouring stations within a range *d*. There needs to be at least n_{stat} stations with at least m_{match} intervals of nonzero rainfall overlapping with the evaluated station to compute the SO flag.

removed, effectively filtering indoor stations, stations with strong thermal inertia, or sensors affected by systematic shading or heating;

(5) level O1: linearly interpolates isolated single-hour gaps to maintain continuity;

(6) Level O2: removes days with less than 80% valid hourly data to ensure robust daily statistics;

(7) level O3: removes months with less than 80% valid days, producing a temporally consistent dataset suitable for climatological analyses.

Napoly *et al.* (2018) tested the CrowdQC by using Netatmo PWSs in Berlin (Germany) and Toulouse (France) over a one-year period (July 2016–June 2017). After the application of all the steps, approximately 58% of the original data remained, but with substantially improved physical consistency. The validation against reference networks (namely the Urban Climate Observation Network (UCON) and German weather service in Berlin, and Météo France in Toulouse), showed substantial improvement: stations failing correlation tests dropped from ~15–19% in the raw data to < 2% after the application of CrowdQC. The authors importantly proved that the method is transferable across cities; indeed, it performed similarly in Berlin and Toulouse despite differences in station density and urban morphology.

Later on, Fenner *et al.* (2021) introduced CrowdQC+ as an advanced version of CrowdQC, retaining the original structure proposed by Napoly *et al.* (2018) while adding functionalities aimed at improving daytime performance, operational flexibility, and user friendliness. CrowdQC+ augmented the four mandatory levels with a level M5 consisting of a spatial buddy check that applies median and Qn statistics within a configurable radius to better suppress residual radiative errors and to flag isolated stations. This level is designed to detect remaining faulty stations, typically those with sporadic, unrealistic peaks not identified in earlier steps. They also added an optional level O4 to mitigate slow thermal response, typical of PWS sensors. A comparative test on the performance of both QCs was then performed in Amsterdam and Toulouse, using Netatmo networks. CrowdQC+ consistently removed erroneous data, providing an improvement compared to CrowdQC.

Geostatistical and statistical approaches have also been employed to validate and integrate PWS data with official observations. Bárdossy *et al.* (2021) suggested a method that combines indicator correlation, rank statistics, and a geostatistical interpolation to integrate PWS rainfall data with the official network in a German federal state, emphasizing the need for validation and correction before hydrological applications. This methodology (named the PWS-pyQC algorithm) requires a reliable primary network collecting data at high temporal resolution, and was implemented in Python (El Hachem 2022) and then used in Graf *et al.* (2021). PWS-pyQC consists of three main steps (El Hachem *et al.* 2024):

(1) reliable PWSs are identified by using a space-time dependence structure derived from a reference monitoring network. The main assumption of this step is that the PWS values might be incorrect, but their ranks (i.e. their relative order) are correct;

(2) a correction of the bias in the magnitudes of the PWS values is performed using the PWS ranks and the corresponding neighbouring primary observations;

(3) an event-based filter is applied to identify erroneous PWS observations (like false zeros and false extremes) based on a leave-one-out cross-validation approach.

Chen *et al.* (2018) highlight that, unlike stations managed by experts, enforcing standardization across large-scale networks of PWSs is challenging. Traditional QC and assurance methods typically require extensive historical data from validated equipment, which are often unavailable for PWS networks. To address this, they propose the Reputation System for Crowdsourced Rainfall Networks (RSCRN), which computes and assigns trust scores to PWSs in real time by evaluating their rainfall measurements against those of neighbouring stations. The study demonstrates that RSCRN effectively identifies cooperative (accurate) and non-cooperative (inaccurate) behaviours of PWSs over time, with the system converging to a reliable trust score after receiving approximately 10 to 20 rainfall observations after installation. A similar approach was used by Chen *et al.* (2021) in Houston, Texas, USA, where dynamic trust scores were assigned to PWSs, improving rainfall estimates of analysed storm events.

The Titan automatic spatial QC framework (Båserud *et al.* 2020) has been operationally implemented to filter PWSs data before the integration into meteorological applications. Developed by the Norwegian Meteorological Institute (MET Norway), Titan applies spatially oriented tests, making it particularly suitable for dense and heterogeneous networks. The QC framework is available as the Python package titanlib and implements a sequential chain of tests to flag suspicious observations (Table 5).

Recent applications of the Titan QC framework demonstrate its effectiveness in integrating PWS data into meteorological workflows across Scandinavia and regions with complex terrain. Nipen *et al.* (2020) integrated Titan into MET Norway's operational production chain to perform real-time QC on Netatmo temperature observations across Norway, Sweden, Finland, and the Baltic countries, supporting short-range forecasts. The same spatial tests were also applied hourly, removing ~21% of observations. Their results indicated that the QC significantly improved forecast accuracy, particularly under winter inversion conditions. Båserud *et al.* (2020) applied Titan QC to both hourly temperature and precipitation Netatmo PWSs observations across Fennoscandia. On average, 21% of temperature observations were flagged, with SCT responsible for ~16%, isolation ~3.6%, and buddy checks ~1.5%. For precipitation, about 13% of hourly PWS data were removed, mainly through buddy event and isolation checks. After QC, gridded temperature analysis showed a 33% reduction in MAE (from 1.24°C to 0.84°C) and a 68% decrease in large errors (>3°C) compared to raw model output. Finally, Pontoppidan *et al.* (2025) conducted two complementary analyses to assess the added value of Netatmo precipitation data in complex terrain. The first focused on a 4 day frontal event (9–13 November 2022) over Western

Table 5. Description of Titan's sequential checks for temperature and precipitation from Båserud *et al.* (2020).

Step	Test name	Description	Main objective
1	DEM	Compare station elevation with digital elevation model	Detect mislocated stations/metadata errors
2	Cross-check	Precipitation validated against temperature fields	Remove implausible cold-season precipitation
3	Missing data/metadata	Exclude records with incomplete values or metadata	Identify gross measurement errors
4	Plausibility range	Range check against sensor specifications	Ensure dataset consistency
5	Climatological range	Range check against monthly climatological thresholds	Flag seasonal extreme (possible but atypical)
6	Buddy event	Validate binary event (e.g. rain/no rain) against neighbours	Ensure categorical coherence
7	Buddy check	Compare continuous variables with local neighbour averages (adjusted for elevation)	Detect statistical outliers
8	First-guess deterministic	Compare observations with gridded model/radar fields	Identify inconsistencies with background fields
9	First-guess ensemble	Compare observations with ensemble model outputs	Account for model uncertainty and spread
10	Spatial consistency test (SCT)	Optimal interpolation against local neighbours	Refine detection of representativeness errors
11	COOL test	Detect unrealistic "holes" in precipitation fields	Preserve spatial continuity
12	Isolation test	Flag stations with insufficient neighbours	Highlight low-redundancy observations

Norway; the second examined a short convective burst (26 August 2023) in Bergen. Both analyses combined observations from Netatmo PWSs and official MET Norway stations, applying the Titan QC framework to hourly precipitation data to ensure spatial consistency. Additional benchmark datasets included national radar for the convective case and high-resolution WRF simulations for both events. Results highlight clear differences between the two cases. For the 4-day frontal event, Titan flagged ~13% of PWS observations. After QC, PWS data improved spatial coverage, with PWS and MET achieving similar detection skills (POD ~ 0.93). Correlation with WRF was moderate (R^2 ~ 0.40), but increased at the daily aggregation R^2 ~ 0.84. Performance improved with altitude, as CSI rose from 0.62 to 0.83 and FAR dropped from 0.34 to 0.14. For the convective burst in Bergen, PWS captured localized extremes missed by MET stations (up to 44.2 mm/h versus 25.5 mm/h). Compared to radar, both networks achieved POD = 1.00, but PWS had higher FAR and lower CSI compared to MET. Against WRF, which underestimated intensity, PWS showed smaller bias and lower RMSE. Overall, Titan QC enabled robust integration of PWS data, improving spatial detail and maintaining skill comparable to official networks, particularly for complex terrain and high-altitude sites.

In Australia, Li *et al.* (2023) proposed a statistical method for an automated QC system to evaluate daily rainfall observations collected from PWSs in near real time, detecting 76.7% erroneous data and keeping the false alarm rate as low as 1.7%. The approach consists of: (i) a domain test designed to filter out erroneous observations by verifying that the recorded values fall within physically plausible limits; (ii) a test to check the agreement between daily rainfall observations from PWSs and official estimates; (iii) a test designed to compare PWS rainfall observations with radar estimates of daily rainfall accumulation.

Lopez Lorente *et al.* (2020) evaluated the accuracy of irradiance measurements from PWSs and proposed a calibration method to obtain the broadband irradiance for all sky conditions based on the temperature of the sensor, solar zenith angle and clear-sky index.

All the works emphasize that good QC is essential before using the data and highlight the need for careful interpretation. One might naturally ask which QC methods perform best when dealing with the often noisy and heterogeneous data from PWSs. While numerous approaches have been proposed in the literature, their effectiveness can vary substantially depending on the context, including data availability, station density, and environmental conditions. El Hachem *et al.* (2024) offer a technical comparison of three open-source QC algorithms: PWSQC (developed by de Vos *et al.* 2019), PWS-pyQS (developed by Bárdossy *et al.* 2021) and GSDR-QC (the QC algorithm developed to construct the "Global SubDaily Rainfall" dataset; Lewis *et al.* 2021). The results demonstrate that all three algorithms enhance the quality of PWS data when validated against radar-based rainfall products. However, each algorithm exhibits distinct strengths and limitations depending on the availability and characteristics of both PWS and official reference data. As such, no single approach can be universally recommended without careful consideration of the specific context. The authors emphasize the need for more objective, quantitative benchmarking of QC algorithms, which in turn requires the availability of open, representative test datasets encompassing diverse environmental conditions, station densities, and meteorological patterns. As a follow-up initiative, researchers within the OpenSense network developed pypwsqc (https://github.com/OpenSenseAction/pypwsqc; Chwala *et al.* 2026), a processing software package that consolidates and implement some QC algorithms previously available as separate package. More in detail, pypwsqc currently includes both PWSQC (de Vos *et al.* 2019) and PWS-pyQS (Bárdossy *et al.* 2021). Rather than simply copying the original codebases, the QC methods were refactored and reorganized into a modular and extensible set of functions. As a next step, the developers plan either to integrate the most effective filters from GSDR-QC directly into pypwsqc or to establish interoperability with the recent GSDR-QC implementation available in the RainfallQC package (https://github.com/NERC-CEH/RainfallQC).

5.4 Benchmarking datasets

Accurately quantifying a station's bias requires a reliable reference for the local weather conditions at the PWS location, against which the observations can be validated. This will help to separate true instrument- or installation-related biases from the natural spatial variability of rainfall patterns that the network is intended to capture.

Another critical barrier to the advancement and broader adoption of QC algorithms for crowdsourced rainfall data is the lack of standardized, openly accessible benchmarking datasets. Currently, most studies develop and test their own QC procedures on proprietary or geographically limited datasets, making it difficult to objectively compare the performance of different algorithms across diverse climatic, geographic, and network conditions. This fragmentation hinders reproducibility and makes it difficult to assess the robustness and transferability of algorithms under different environmental and operational conditions.

5.5 Spatial representativeness and network sustainability

It is important to note that the vast majority of published case studies focus on regions in Europe, with some contributions from North America and Australia. To date, very few peer-reviewed applications have explored the use of PWS data in low- and middle-income countries, where conventional observation networks are often limited or deteriorated. This gap represents a missed opportunity, as these regions could particularly benefit from the high-density and low-cost nature of PWS networks (Olsson *et al.* 2025). Future research should explore how to promote the deployment and integration of PWSs in these underrepresented areas, both to support local risk monitoring and to foster more globally inclusive climatological knowledge.

In addition to technical and observational limitations, the sustainability of the PWS networks, whose costs are covered by citizens, over time is of increasing interest in the scientific community. Chapman *et al.* (2023) raised concerns about the long-term durability of the crowdsourcing model. According to the authors, there is a possibility that we have already reached a saturation point (so-called "peak Netatmo") after which the availability of PWSs may naturally begin to decline. If this trend is confirmed, alternative data sources, such as connected vehicles or emerging IoT technologies, will need to be explored to maintain and enhance observational density for urban climate monitoring. In other words, although crowdsourcing remains a cost-effective solution, its transient nature poses challenges for long-term monitoring, raising questions about future viability and the need for new approaches (Chapman *et al.* 2023).

While the growing density of PWSs in urban areas enhances the potential for high-resolution monitoring, it also introduces important concerns regarding spatial representativeness. Chen *et al.* (2022) demonstrated that the adoption of PWSs has increased substantially in U.S. cities such as Houston, where station density rose from 0.06 to 0.24 PWS per km^2 between 2016 and 2019. While this growth reflects the potential of crowdsourced rainfall data to strengthen urban flood monitoring and resilience, the study also revealed spatial disparities in adoption. Specifically, PWS deployment is disproportionately concentrated in higher-income neighbourhoods and flood-prone areas. These patterns highlight the importance of accounting for social and spatial biases when using PWS data for hydrological modelling and flood risk management. A similar concern has also been raised by Sakthivel and Sengupta (2025), who investigated spatial biases in the placement of citizen and conventional weather stations and their impact on urban climate research, suggesting the added value of using PWS only in urban areas.

Thanks to a conceptual framework that enables a systematic review of the features and functioning of these expanding PWS networks, Gharesifard *et al.* (2017) highlighted that: (i) several important stakeholder groups, such as emergency services and local authorities, are still not actively involved in these networks; (ii) the financial sustainability of online amateur weather networks remains largely overlooked, despite the critical role that revenue streams play in ensuring their long-term viability; and (iii) while all networks examined in this study incorporate some form of bidirectional communication, these are primarily limited to feedback mechanisms aimed at educating contributors.

6 Conclusions and future directions

In recent years, personal weather stations have emerged as a promising resource for enhancing meteorological observations, especially in regions where official monitoring networks are sparse or limited in spatial resolution. Their increasing availability and affordability have enabled the creation of dense, decentralized observational networks that can provide high-frequency, hyperlocal data useful for a wide range of applications, from urban analyses and forecasting to model validation. The growing number of personal weather stations thus presents a significant opportunity to better capture the spatio-temporal variability of hydro-meteorological phenomena. This is especially crucial in regions with limited conventional meteorological observations, where PWSs have seen a considerable increase in the number of stations in recent years (El Hachem *et al.* 2024). The growing number of studies with promising results in fields like high-resolution mapping, urban application, and data integration in numerical weather prediction models, and the ongoing development of quality control procedures and software packages, increase the interest in PWS data and their usage for specific applications (Hahn *et al.* 2022).

However, as discussed in Section 5, several challenges remain, primarily related to data quality, station heterogeneity, and the non-standardized deployment of these citizen-operated sensors (see Fig. 5 for a summary of Sections 4 and 5).

As discussed earlier, further research is needed to:

(1) provide specific installation guidelines;
(2) standardize PWS data processing frameworks and improve the accuracy of rainfall measurements for scientific and operational applications. Future work should explore the role of advanced QC algorithms and automated error detection systems;
(3) establish best practices for PWS integration into official networks, also through collaborative efforts between meteorological agencies and citizen scientists;

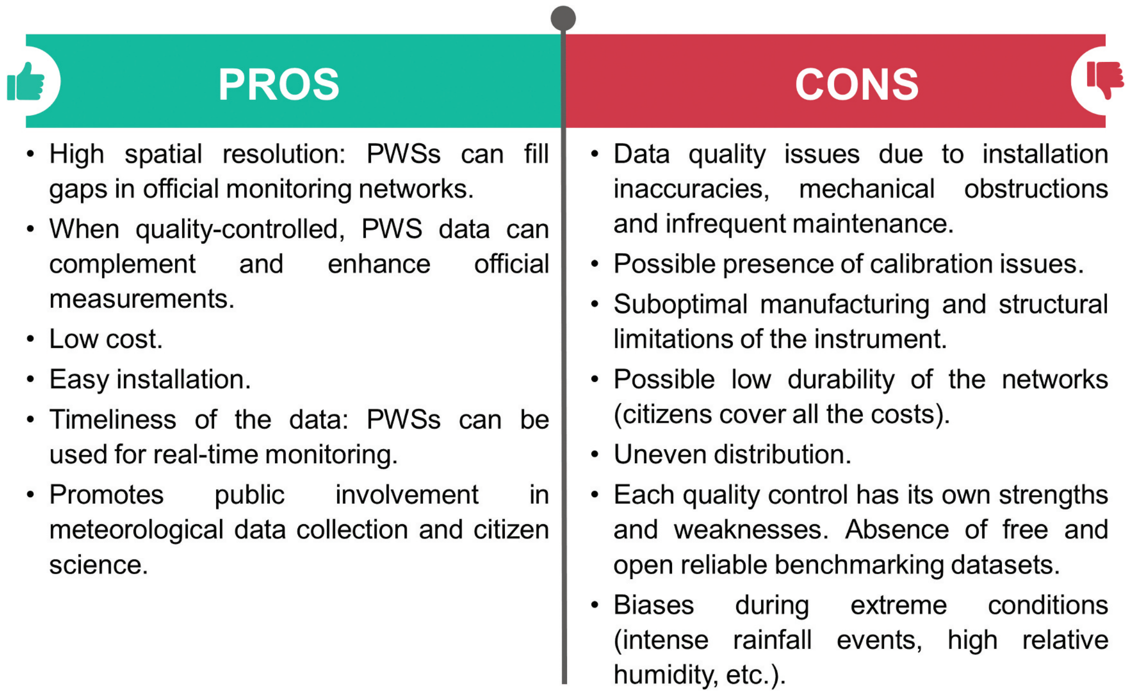

Figure 5. Pros and cons of PWSs and their data. The figure summarizes the main points covered in Sections 4 and 5.

(4) investigate the long-term stability and performance of PWS networks, particularly in light of climate change and increasing variability in rainfall patterns. For instance, understanding how PWSs perform under prolonged wet or dry periods, or in areas subject to snow, wind, or hail, will be crucial for assessing their reliability under a wide range of conditions;
(5) identify conditions and opportunities for promoting the deployment and integration of PWSs in underrepresented areas.

As highlighted before, the application of PWS data remains limited when it comes to capturing extreme precipitation events and solid precipitation (i.e. snow). In the case of intense rainfall, indeed, PWSs may suffer from mechanical limitations at high intensities. In addition, most private weather station raingauges are not heated, which significantly limits their ability to measure snowfall accurately. Solid precipitation may accumulate without being recorded, may melt irregularly, or may not be captured at all, leading to substantial underestimation and timing errors during winter events. To improve the reliability of PWS data for extremes and solid precipitation, targeted field campaigns during convective storms and snowfall events could be essential. These campaigns should involve the temporary co-location of PWS units with professional-grade meteorological instruments to develop a high-resolution dataset for benchmarking and calibration. By analysing how PWSs respond to varying intensities of rainfall and snow under controlled observational set-ups, researchers can identify systematic biases and derive correction factors specific to different event types. For intense summer convective events, campaigns could focus on capturing the peak intensities and short durations characteristic of flash floods. These observations would be particularly valuable for developing real-time bias correction schemes and improving PWS performance in applications such as urban flood forecasting or early warning systems. In addition, efforts should be made to quantify and communicate uncertainty in PWS-derived datasets, especially when these data are intended for use in critical applications such as monitoring or hydraulic modelling.

Beyond technical improvements, there is a need for greater institutional engagement and coordination. National meteorological and hydrological services, regional authorities, and research organizations should recognize the value of crowdsourced data and actively support their integration into official workflows. This includes not only technical collaboration but also the development of shared protocols for metadata collection, station registration, and user training.

Another important direction concerns data governance and ethical considerations. As PWS networks expand and increasingly interface with official systems, questions around data ownership, privacy, accessibility, and licensing become more relevant. Clear frameworks should be established to ensure that contributors maintain agency over their data while enabling broad and equitable access for scientific and societal use. Transparent policies and open-data platforms will be critical to maintaining trust and encouraging ongoing participation among citizen observers.

Moreover, the growing interest in crowdsourced weather data offers a valuable opportunity to involve the public in environmental monitoring, fostering a more participatory approach to climate resilience and disaster preparedness (Eingrüber *et al.* 2025). By enabling citizens to take part in data collection, PWS networks contribute to the advancement of citizen science and strengthen public awareness of climate and water-related challenges. These grassroots contributions have the potential not only to enhance the resolution of weather datasets but also to support community-based decision making and resilience planning. This need has already been highlighted by recent initiatives, such as the IAHS's Science for Solutions decade HELPING (Hydrology Engaging Local People IN one Global world), which emphasizes the increasing role of citizen-generated data in hydrology (Arheimer *et al*. 2024). This initiative advocates for co-created, local-to-global hydrological research, encouraging partnerships among scientists, stakeholders, and communities worldwide.

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Author contributions

CRediT: **Paola Mazzoglio:** Conceptualization, Investigation, Methodology, Project administration, Supervision, Visualization, Writing – original draft, Writing – review & editing; **Benedetta Moccia:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing; **Elaheh Ghaffaripour:** Investigation, Writing – original draft.

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