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End-user perspective of low-cost sensors for urban stormwater monitoring: a review

Qingchuan Zhu [a,*], Frédéric Cherqui [a,b] and Jean-Luc Bertrand-Krajewski [a]
[a] University of Lyon, INSA Lyon, DEEP, EA7429, Villeurbanne cedex F-69621, France
[b] University of Lyon, Université Claude Bernard Lyon-1, Villeurbanne cedex F-69622, France
*Corresponding author. E-mail: qingchuan.zhu@insa-lyon.fr

QZ, 0000-0003-1816-070X; FC, 0000-0001-8836; J-LB, 0000-0003-3204-8861

ABSTRACT

The large-scale deployment of low-cost monitoring systems has the potential to revolutionize the field of urban hydrology monitoring, bringing improved urban management, and a better living environment. Even though low-cost sensors emerged a few decades ago, versatile and cheap electronics like Arduino could give stormwater researchers a new opportunity to build their own monitoring systems to support their work. To find out sensors which are ready for low-cost stormwater monitoring systems, for the first time, we review the performance assessments of low-cost sensors for monitoring air humidity, wind speed, solar radiation, rainfall, water level, water flow, soil moisture, water pH, conductivity, turbidity, nitrogen, and phosphorus in a unified metrological framework considering numerous parameters. In general, as these low-cost sensors are not initially designed for scientific monitoring, there is extra work to make them suitable for *in situ* monitoring, to calibrate them, to validate their performance, and to connect them with open-source hardware for data transmission. We, therefore, call for international cooperation to develop uniform low-cost sensor production, interface, performance, calibration and system design, installation, and data validation guides which will greatly regulate and facilitate the sharing of experience and knowledge.

Key words: measurement, urban drainage, urban hydrology, water quality, water quantity, weather station

HIGHLIGHTS

- Low-cost sensors have the potential to revolutionize water monitoring.
- We provide an up-to-date scientific review of commercially available low-cost sensors.
- We introduce a unified metrological framework for various low-cost sensors.
- Suggestions and recommendations for sensor modules choice and uses are given.
- The development of low-cost monitoring systems requires elaborating common guidelines.

GRAPHICAL ABSTRACT

1. INTRODUCTION

Urban stormwater refers to water transferred in built environments from rainfall or snowmelt (Müller *et al.* 2020). In the past centuries, with the development of the economy and society, there were more and more built areas all over the world. In these built environments, biodiversity and ecosystems services related to stormwater are reduced due to impervious surfaces such as streets, parking lots, and rooftops (Berland *et al.* 2017), and as a result, many environmental issues have arisen (Prudencio & Null 2018). These environmental issues include but are not limited to (i) urban flooding due to reduced water infiltration that is also linked to climate change (Cousins 2017), such as floods in Zhengzhou City, China on July 20, 2021 (Wang *et al.* 2021) and (ii) water contamination due to stormwater runoff over polluted impervious surfaces (Gasperi *et al.* 2014; Becouze-Lareure *et al.* 2016; Liu *et al.* 2019; Müller *et al.* 2020).

Since the middle of the 19th century, modern storm drains, gutters, and underground systems which are also known as gray infrastructures are constructed in cities worldwide (Qiao *et al.* 2018; Fu *et al.* 2019). The last decades have also seen the emergence of green infrastructures including wet ponds, constructed stormwater wetlands, bioretention, infiltration facilities, permeable pavement, swales, green roofs, and rainwater harvesting systems, etc., also named nature-based solutions (NBSs), stormwater control measures (SCMs), best management practices (BMPs), with issues related to their design, operation, and long-term performance (Fletcher *et al.* 2015; Cherqui *et al.* 2019). Traditionally, stormwater quantity and quality in the infrastructures mentioned above are monitored by water technicians using accurate and expensive instrumentation (Salehi *et al.* 2020; Thebault *et al.* 2020; Nickel *et al.* 2021). Because of resource limitations, it is difficult in theory and impossible in practice to monitor stormwater in these infrastructures with high temporal and spatial resolution. The drawbacks of this condition are numerous and include (i) lag in urban flood warning and relief decision-making due to inaccurate rainfall estimates (Wang *et al.* 2021); (ii) lack of proactive response to water contamination due to the inadequacy of data (Pule *et al.* 2017); and (iii) lack of maintenance due to lack of monitoring and leading to failure of the stormwater infrastructures themselves (Thomas *et al.* 2016; Wong & Kerkez 2016; Al-Rubaei *et al.* 2017).

Facing the above-mentioned drawbacks of insufficient monitoring, thanks to the development of open-source hardware, wireless communication technology and sensors in the last few years, a promising paradigm for soil, air and water monitoring appeared and a large number of papers have emerged in this area (Montserrat *et al.* 2013; Gaddam *et al.* 2014; Rai *et al.* 2017; Morawska *et al.* 2018; Valente *et al.* 2020). In this paradigm, high-resolution spatiotemporal and relatively reliable data are collected by using a ubiquitous network of low-cost sensors. The potential benefits of applying such a paradigm for stormwater monitoring are (i) supplementing conventional stormwater monitoring; (ii) enhancing the capacity of urban flood warning; (iii) improving the ability of water contamination detection; (iv) accumulating a wealth of new knowledge on stormwater and stormwater infrastructure management and maintenance; (v) provide the means for real-time control of infrastructure; and (vi) making the most of the Big Data approach to discover new beneficial information. Therefore, this paradigm attracts urban hydrologists like the authors of this review to devote themselves to this attractive but unfamiliar area to build their own monitoring network to support research.

Indeed, as urban stormwater management rapidly evolves worldwide toward numerous decentralized source control facilities, widely disseminated across catchments and cities, there is a growing need for monitoring these facilities, to obtain spatially distributed information and data about their functioning. With traditional reliable and well-known but expensive sensors and monitoring systems, only a few of these facilities can be monitored. This is why it is worth evaluating the potential of massively using low-cost sensors to monitor these numerous decentralized stormwater facilities, with particular attention to their levels of reliability, accuracy, and uncertainty, along with adapted specifications. An example of the applicability of the crowd-sourcing approach to urban rainfall monitoring with low-cost sensors used by citizens has shown that it could, under some conditions, overperform for rainfall runoff modeling compared to a sparse traditional rain gauge network (Yang & Ng 2017).

This review is linked to the collaborative project Cheap'Eau, funded by the French Rhône-Méditerranée-Corse water agency (http://graie.org/othu/progr_cheapeau.htm, visited on 28 Feb. 2023.). Cheap'Eau aims to evaluate if and how low-cost sensors can be used by researchers and practitioners for stormwater monitoring. In addition to this review, various low-costs sensors are presently tested for monitoring stormwater facilities like green roofs, detention tanks, and trenches (Cherqui *et al.* 2020). Results and conclusions of the on-going Cheap'Eau project will be published separately.

Three technical parts can be distinguished in this emerging paradigm: open-source hardware, communication protocols and low-cost sensors. Open-source hardware and communication protocols are relatively reliable and there are a few commonly used solutions. These solutions have been in development for several years and are designed, developed, promoted, and guaranteed by professional companies such as, e.g., Arduino and Raspberry Pi. On the contrary, low-cost sensors are a more complex part. Most of them were originally designed for teaching purposes, small parts for other goods or for do-it-yourself (DIY) use by electronics enthusiasts. Their reliability is questioned (Kumar *et al.* 2015). As a trade-off of price, some of them do not have a clear manufacturing company and brand, and do not provide end-users with (detailed) datasheets. There is also no universally agreed definition of 'low-cost' sensors. In this context, there have been some high-quality reviews in scientific papers about low-cost sensors for monitoring air quality, with recommendations to end-users (Rai *et al.* 2017; Morawska *et al.* 2018). But the authors of this article could not find similar reviews in the field of low-cost sensors for stormwater monitoring. This undoubtedly may hinder the large-scale application of low-cost sensors in this field.

To fill this gap, we review scientific articles about using or assessing 12 types of commercially available low-cost sensors for monitoring stormwater and related meteorological variables. The method for literature selection is presented in the next section. Three categories of low-cost sensors are distinguished: (i) meteorological sensors for monitoring air humidity, wind speed, solar radiation, and rainfall; (ii) water quantity sensors for monitoring water level, water flow and soil moisture; and (iii) water quality sensors for monitoring pH, conductivity, turbidity, nitrogen, and phosphorus. In this review, a sensor is identified to be low-cost according to two possible criteria: (i) its price is at least 10 times lower than equivalent traditional sensors or (ii) it has been reported in the literature to be working with open-source hardware to build a low-cost monitoring unit.

The authors of this article speculate that the main readers of this review are stormwater researchers who are aiming to conduct stormwater monitoring projects with full control but a limited budget. On the one hand, one may to some extent assume they are low-cost sensor hobbyists: the information provided in this review is important to design and build their own systems. On the other hand, they are researchers who must ensure reliable and robust best practices in stormwater monitoring. Performance criteria like trueness, repeatability, and uncertainty, etc. are of key importance in their evaluation of low-cost sensors and in their possible use of such sensors for data acquisition to support research conclusions.

To the best knowledge of the authors, this review is the first one on a diversity of low-costs sensors that could potentially be used for stormwater monitoring, by gathering and summarizing information from various sources. Special attention is devoted to the metrological performance criteria of the sensors, for example, trueness, repeatability, reproducibility, and uncertainty to provide objective information to potential users and clarify the current level of knowledge of such technologies. It reveals that such information is frequently missing in the reviewed papers, which indicates that further work is necessary to reach the required level of maturity and reliability for efficient routine use of such sensors in urban hydrology. Low-cost sensors could potentially hold the promise to complete (and not replace) both the traditional (e.g., Bertrand-Krajewski *et al.* 2021; Sambito & Freni 2021) and emerging (e.g., Yaroshenko *et al.* 2020) monitoring systems in the urban drainage field.

2. METHODOLOGY

2.1. Paper selection

To make this review paper as comprehensive as possible, there are no specific price restrictions when using the term 'low-cost'. We reviewed scientific literature that contains low-cost or related expressions. Web of Science and Google Scholar (Martín-Martín *et al.* 2021) are used to search papers in which commercial off-the-shelf (COTS) low-cost sensors are used in sensing networks.

In the advanced search query builder tool of Web of Science, for example, query 'ALL = ((Low-cost OR cheap OR frugal) AND (sensor OR instrument) AND (off-the-shelf OR commercial) AND (sensor network OR sensing network) AND (water flow OR discharge OR flow rate))' is used to search the usage of COTS low-cost water flow sensors. The search timespan is from 2012-01-01 to 2022-12-31 (publication date). And then, all results are browsed. A paper which indicates the usage of specific COST sensors is selected to review.

In the advanced search tool of Google Scholar, similar queries are used. Google Scholar is also forced to return articles dated between 2012 and 2022. Papers are sorted by relevance based on full text matching and information on journal, author, and citation. The results in the first five pages are browsed to select papers to review due to the very high number of references (several tens of thousands) returned by Google Scholar.

When a specific sensor model is detected, Google Scholar is used to search papers that give the performance assessment of this specific type of sensor (e.g., search 'SHT20', 'HC-SR04', 'SEN0161'). Papers are sorted by relevance. The results in the first three pages are browsed to select papers to review.

Numbers of search results and final selected papers are given in Table 1.

202 papers have been reviewed by authors for this review. A general concern is that these low-cost sensors very quickly evolve thanks to the rapid development of technologies. There is a lag between the application of sensors in projects and

Table 1 | Number of Web of Science and Google Scholar search results, selected papers, and reviewed papers

	Web of Science		Google Scholar		
Search category	**Total number**	**Selected number**	**Total number**	**Selected number**	**Reviewed number**
Low-cost sensor	49,135	40	about 18,000	163	202
COTS low-cost sensor	4,148	40	about 45,100	163	202
Sensor network	776	40	about 17,100	163	202
Air humidity sensor	26	17	about 17,100	15	32
Anemometer	8	2	about 23,000	12	14
Pyranometer	7	3	about 25,600	13	16
Rainfall	5	1	about 10,900	16	17
Water level sensor	16	4	about 17,200	10	13
Water flow sensor	15	0	about 17,200	10	10
Soil moisture sensor	14	5	about 17,300	13	18
Water pH sensor	8	3	about 17,500	28	31
Water conductivity sensor	19	3	about 17,000	19	22
Turbidimeter	5	2	about 6,810	16	18
Water nitrogen and phosphorus sensor	11	0	about 16,100	11	11

the publication of papers. During the review, we found that most low-cost sensor models are sold, tested, and used for several years which proves they have a stable design and supply. This review also included some abstracts to enhance its timeliness.

2.2. Sensor performance evaluation

Even though the evaluation of sensors is dependent on application scenarios, contexts, and purposes, the authors of this review believe that the greatest challenge is to identify sensors which are not only low-cost, but which can generate useful data over an extended period. Like any sensors, the performance information of low-cost sensors is collected and classified by parameters as shown in Table 2.

Information from manufacturers and scientific literature of every type of sensor is connected as much as possible. Many low-cost sensor's datasheets use the term 'accuracy' to describe their sensor's performance, combining and/or likely confusing trueness and repeatability. In the tables of this review, we put manufacturers' accuracy metric into trueness criteria.

Table 2 | Major performance criteria for the performance assessment of low-cost sensors

Parameters	Description
Trueness	Output closeness with the reading of the reference measurement at the same place and same time.
Repeatability	Output closeness under a set of repeatable conditions of measurement (NF EN 17075 2018).
Reproducibility	Dispersion between measurements obtained using different sensors of the same model (Rai *et al.* 2017).
Resolution	Smallest change in a quantity being measured that causes a perceptible change in the corresponding indication (JCGM 2012).
Response time	Time interval between the instant when a continuous measuring device is subjected to an abrupt change in the measurand value and the instant when the readings cross the limits of (and remain inside) a band defined by the 90% and the 110% of the difference between the initial and final value of the abrupt change (NF EN 17075 2018).
Sensitivity to environment	Effect of environmental factors (temperature, relative humidity and so on) on sensor output (Rai *et al.* 2017).
Maintenance needs	Frequency and hours dedicated to the maintenance of sensors (including controls and cleaning).
Longevity	Time of operation before replacement (Kumar *et al.* 2015).

As in low-cost air quality field (e.g., Rai *et al.* 2017), due to the lack of a standard calibration protocol specific for low-cost sensors, studies have used dissimilar calibration methods, against a variety of reference instruments, which makes intercomparison between them infeasible. Nevertheless, these studies provide valuable information about the performance of low-cost sensors under a variety of operating conditions (Rai *et al.* 2017). Some authors used subjective judgment vocabulary such as 'good', 'acceptable', 'reasonable', 'satisfactory', 'not severe' to describe the performance of low-cost sensors. We use quotation marks to indicate that this is the judgment of the authors of the papers, and not our own opinion. Various performance metrics have been cited in this review and their definitions are given and harmonized in Table 3 in the order of their appearance. All notations are unified in this review, where n is the number of samples, p_i is the reading of low-cost sensors, P_i is the reading of reference sensors, $\bar{p}$ and $\bar{P}$ are the average values of p_i and P_i, $R(p_i)$ and $R(P_i)$ are the ranks of p_i and P_i. When computing dynamic residuals (DR), $\widehat{p_i}$ is the averaged linear model output of the given sensor (Araújo *et al.* 2020). When computing pooled relative standard deviation (SD) ($s_{r,p}$), k, n_k, m and s^k are the index of the current series, number of measurements in series k, the total number of series, and corresponding SD of the series, respectively (Adla *et al.* 2020).

Table 3 | Performance metrics used in references of this review

Symbol	**Metric**	**Equation**	**References**
r_s	Spearman's rank-order correlation	$1-\frac{1-6\sum_{i=1}^{n}(R(P_i)-R(p_i))^2}{n(n^2-1)}$	(Moreno-Rangel *et al.* 2018)
R^2	Coefficient of determination	$\frac{\left(n\sum_{i=1}^{n}p_iP_i\right)-\left(\sum_{i=1}^{n}p_i\right)\left(\sum_{i=1}^{n}P_i\right)}{\sqrt{n\sum_{i=1}^{n}(p_i)^2-\left(\sum_{i=1}^{n}(p_i)\right)^2}\sqrt{n\sum_{i=1}^{n}(P_i)^2-\left(\sum_{i=1}^{n}(P_i)\right)^2}}$	(Bitella *et al.* 2014; Angraini *et al.* 2016; Faisal *et al.* 2016; Akhter *et al.* 2018; Demetillo *et al.* 2019; Coloch Tahuico 2021)
DR	Dynamic residual	$\sqrt{\frac{\sum_{i=1}^{n}(\widehat{p_i}-P_i)^2}{P_n-P_1}}$	(Araújo *et al.* 2020)
MBE	Mean bias error	$\frac{1}{n}\sum_{i=1}^{n}(P_i-p_i)$	(Azouzoute *et al.* 2019; Domínguez-Brito *et al.* 2020)
RMSE	Root mean square error	$\sqrt{\frac{\sum_{i=1}^{n}(P_i-p_i)^2}{n}}$	(Bitella *et al.* 2014; Nagahage *et al.* 2019; Adla *et al.* 2020; Burgt 2020; Domínguez-Brito *et al.* 2020)
MAE	Mean ABSOLUTE ERROR	$\frac{1}{n}\sum_{i=1}^{n}(\lvert P_i-p_i\rvert)$	(Adla *et al.* 2020)
RAE	Relative absolute error	$\frac{\sum_{i=1}^{n}\lvert P_i-p_i\rvert}{\sum_{i=1}^{n}\lvert p_i-\bar{P}\rvert}$	(Adla *et al.* 2020)
NRMSE	Normalized root mean square error	$\frac{\mathrm{RMSE}}{\bar{P}}$	(Bitella *et al.* 2014; Azouzoute *et al.* 2019)
SD	Standard deviation	$\sqrt{\frac{n(\mathrm{RMSE}^2-\mathrm{MBE}^2)}{n-1}}$	(Azouzoute *et al.* 2019)
TS	t-statistic	$\sqrt{\frac{(n-1)\mathrm{MBE}^2}{\mathrm{RMSE}^2-\mathrm{MBE}^2}}$	(Azouzoute *et al.* 2019)
$s_{r,p}$	Pooled relative standard deviation	$\sqrt{\frac{\sum_{k=1}^{m}(n_k-1)s_k^2(1/\overline{P_k}^2)}{\sum_{k=1}^{m}(n_k-1)}}$	(Adla *et al.* 2020)

In addition, price ranges are estimated as indicated on commercial websites in October–November 2022. We found only a very limited number of papers reporting about sensitivity to the environment, maintenance needs and longevity of the tested sensors. Consequently, we provide this information only when it is available.

The review revealed that low-cost sensors are frequently poorly documented and described in the literature, with many of the criteria listed in Table 2 not provided, or, when provided, given without or with insufficient details or references to the protocols and methods used. To reflect this finding, we indicate 'NA' when information is missing. In the same way, the review also shows that the available literature on low-cost sensors is not always sufficiently detailed, according to metrology good practice requirements, which leads to some difficulties in interpretation. These difficulties are discussed further in Section 6.

3. LOW-COST METEOROLOGICAL SENSORS REVIEW

In this chapter, performance assessments of four low-cost meteorological sensors are reviewed: air humidity, wind speed, solar radiation and rainfall, which are typical components of weather monitoring stations.

The reason for measuring air humidity, wind speed and solar radiation is that a critical component of the water cycle in urban areas and green infrastructures is evapotranspiration, which can be estimated by the FAO Penman–Monteith equation using air humidity, radiation, and wind speed data (Ndulue & Ranjan 2021). In addition, the optimization of management and maintenance of some SCMs such as wet ponds, wetlands, swales, and green roofs also depend on these local weather data (Czemiel Berndtsson 2010).

Accurate rainfall measurements are essential for the effective management of stormwater. Historical rainfall records are used extensively in the design of water infrastructure, while at finer scales, real-time rainfall measurements are a key component of flood forecasting systems. But current methods for measuring precipitation often do not provide the spatial resolution or measurement quality required for real-time applications (Bartos *et al.* 2019) despite the progress of rainfall radar measurement with high spatial resolution (Vos *et al.* 2018). Large-scale ubiquitous low-cost rain gauge sensor networks hold promise to fill this gap.

3.1. Air humidity sensors

There are three basic types of air humidity sensors: capacitive, resistive, and thermal. Lorek (2014) tests the capacitive sensor Sensirion SHT75 in low vacuum (10–1,000 hpa) and temperature (−70–25 °C) ranges and reports that it works 'reliably and with reproducibly measured values'.

Most low-cost humidity sensors mentioned in the scientific literature are DHT11 (Adepoju *et al.* 2020; Hernández *et al.* 2020; Hussein *et al.* 2020; Leonowicz *et al.* n.d.; Morales-Morales *et al.* 2020), DHT22 (also named AM2302) (Math & Dharwadkar 2017; Azma Zakaria *et al.* 2018; Morón *et al.* 2018; Arzoumanian *et al.* 2019; Bankar & Sagat 2020; Institute of Electrical & Electronics Engineers & Università di Napoli n.d.; Pereira *et al.* 2020; Sulzer *et al.* 2022), BME280 (Lee *et al.* 2020; Tagle *et al.* 2020; Cowell *et al.* 2022; Radogna *et al.* 2022), 808H5V5 (SM *et al.* 2019), SHT20 (Moreno-Rangel *et al.* 2018; Nouman *et al.* 2019), HTU21D (Farhat *et al.* 2017), and HIH4000 (Bastos *et al.* 2020).

According to manufacturer's manuals, DHT11 cannot read the full range of relative humidity (only 20–90% RH), and 808H5V5 and HIH4000 cannot provide satisfactory performance (trueness of 808H5V5 at 25 °C, over the range 30–80% RH is 4% RH, trueness of HIH4000 at 25 °C, over the range 0–59% RH is 5% RH and increases to ±8% RH over the sub-range 60–100% RH). HTU21D is observed presenting significantly biased data (Araújo *et al.* 2020). We thus do not discuss them further. The sensors we consider the most promising ones (low cost, full humidity range, best accuracy) are presented in Table 4 including their main technical specifications. About the performance assessments of SHT20, DHT22, and BME280, Table 5 gives a summary based on manufacturers' data and tests in scientific studies.

Moreno-Rangel *et al.* (2018) report that for SHT20 deviations are from −0.78 to 1.08% RH and the average deviation is −0.01% RH, Spearman's rank-order correlation (r_s) are from 0.935 to 0.948, p-value < 0.001. About its reproducibility, deviations are from −1.86 to 0.75% RH and the average deviation is 0.52% RH, r_s are from 0.985 to 0.991, p-value < 0.001. They conclude that SHT20 inside air quality monitoring has 'very low variability' in trueness and 'very strong uniformity' in reproducibility. According to the datasheet, trueness is 3% RH, repeatability is ±0.1% RH, the resolution is 0.04% RH and response time is 8 s.

About DHT22 (also named AM2302), Smith (2018, 2017) report that its trueness is expected to be around 5%, repeatability in a range 0.5–1% RH and reproducibility is around 5% RH, response time is about 30 s (30-s delay in response

Table 4 | Specifications of low-cost air humidity sensor modules

Model	SHT20	DHT22/AM2302	BME280
Type	Capacitive	Capacitive	Resistive
Size (mm)	73 × 17	14 × 18 × 5.5	15 × 12
Weight (g)	44	~1	~1
Operating range	0–100% RH, −10 to 125 °C	0–100% RH, −40 to 80 °C	0–100% RH, −40 to 85 °C
Power supply	3.36–5 V DC	3.3–6 V DC	3.3 or 5 V DC
Communication	I^2C protocol	digital signal via single bus	I^2C or SPI protocol
Performance tested in the scientific literature	Yes	Yes	Yes

Table 5 | A summary of performance characteristics of low-cost humidity sensors

	SHT20	DHT22/AM2302	BME280
Trueness	3% RH* Mean deviation = 0.01% RH, r_s = 0.935–0.948, $p < 0.001$[a]	2% RH Error ~ 5% RH[b] Mean error < 5% RH, $R^2 = 0.992$, DR = 3.5% RH[c]	3% RH[b] Mean error < 4% RH, $R^2 = 0.995$, DR = 2.3% RH[c]
Repeatability	±0.1% RH	±1% RH 0.5–1% RH[b] Average standard deviation < 0.7% RH[c]	Average standard deviation < 0.6% RH[c]
Reproducibility	Mean deviation = 0.52% RH, r_s = 0.985–0.991, $p < 0.001$[a]	~5% RH[b]	R^2 = 0.92, 0.76, 0.90[d]
Resolution	0.04% RH	0.1% RH	0.008% RH
Response time	8 s	2 s ~30 s[b]	1 s
Sensitivity to environment	NA	Dependent on temperature[b]	'Least' dependent on temperature[b]
Maintenance needs	NA	NA	NA
Longevity	NA	~1 year[b]	NA

*According to manufacturers (*Italic type*).

[a] Moreno-Rangel *et al.* (2018) test five SHT20 used in Fooboot FBT0002100 air quality monitor compared to a validated instrument from GrayWolf and show 2 days of data.

[b] Smith (2018, 2017) tests six DHT22 and nine BME280 with reference to saturated solutions and distilled water.

[c] Araújo *et al.* (2020) test three AM2302 and three BME280 inside a controlled climatic chamber (Aralab© Fitoclima®) with reference to Lascar Electronics EL-USB-2.

[d] Tagle *et al.* (2020) compare the output of three BME280 with three regulatory air quality monitoring stations (HMP 35A, Vaisala) in three sites.

For each parameter, the source of the information is given in the superscript and when available, criteria are given (associated formulae can be found in Table 2). NA stands for not available.

compared to other humidity sensors). The authors of this review think this delay may be due to a mistake in the Arduino library. Smith also reports that the sensor output shows a dependence of up to 8% RH over the temperature range 10–40 °C. We cannot understand this statement because relative humidity itself is a quantity related to air temperature. About longevity, in this test, two sensors failed after about 1 year and five failed after 3 years, with output which may suddenly increase or even saturate. Araújo *et al.* (2020) report that AM2302 showed mean error −4.4 to −4.2% RH at 30% RH, −4.2 to −2.5% RH at 50% RH and 0.0–1.5 at 80% RH when the temperature is 10, 24, and 40 °C, respectively, and SD of mean errors is 2.7% RH. When using a linear model to fit AM2302 output p and reference output P, they get $p = 1.118P - 9.626$ with $R^2 = 0.992$ and dynamic residual is 3.5% RH. They concluded that AM2302 is 'overestimating the relative humidity variations'. In all above situations, the average SD of repeatability is less than 0.70% RH. The sensor datasheet claims that trueness is 2% RH, repeatability is ±1% RH, the resolution is 0.1% RH and response time is 2 s.

About BME280, Smith (2018) reports that it performed within specifications. Its output values had a dependence of less than 3% RH over the range 10–40 °C. Araújo *et al.* (2020) report that BME280 showed mean error −1.4 to −3.9% RH at 30% RH, −3.0 to −1.2% RH at 50% RH, and 0.7–2.2 at 80% RH when the temperature is 10, 24 and 40 °C, respectively, and SD of mean error is 2.1% RH. When using a linear model to fit BME280 output p and reference output P, they get $p = 1.084P - 6.333$ with $R^2 = 0.995$ and dynamic residual is 2.3% RH. In all above situations, the average standard deviation of repeatability is less than 0.60% RH. In the comparison work of Tagle *et al.* (2020), some of their BME280 modules show output saturation (at 30% RH) and underestimate 100% RH, this indicates its poor reproducibility. The sensor datasheet claims that trueness is 3% RH, the resolution is 0.0008% RH and response time is 1 s.

The World Meteorological Organization (WMO) recommends the following accuracy performances: 1% at high values of relative humidity (80% or more) and 5% at moderate values of relative humidity (Araújo *et al.* 2020). According to available literature, trueness, repeatability, and resolution of SHT20, DHT22, and BME280 modules are close to this recommendation. Their resolution and response time can meet every minute of monitoring. We do not think they have maintenance needs, because it is more convenient to replace them when using separate modules. The main problems of these low-cost air humidity sensors are their reproducibility (high variability from sensor to sensor) and longevity (output saturation or underestimation). Facing these problems, we recommend end-users to purchase them from reliable sources, take care of data quality and replace them every year. The sensor housing is another key concern. We note that these low-cost sensors are provided with naked circuit boards, plastic housings or waterproof probes. What housing is more suitable for field use and the effect of the housing on sensor performance are issues that need to be investigated.

3.2. Wind speed sensors

Many types of anemometers exist. When examining the low-cost anemometers cited in the literature, we found that three-cup anemometers are used in many applications due to their simplicity and low-cost features. The modules mentioned in the papers are SKU: SEN-08942 (Khattab *et al.* 2016; Prabhakaran & Ravindran 2019; Sarkar *et al.* 2020), SKU: SEN-15901 (Flores 2020; Kaewwongsri & Silanon 2020; Fortes *et al.* 2021), WS-2080 (Tai *et al.* 2017; Domínguez-Brito *et al.* 2020), and SKU: SEN0170 (Nouman *et al.* 2019; Semenov *et al.* 2019; Hussein *et al.* 2020).

Based on the information available on the internet, SEN-08942, SEN-15901 and WS-2080 are weather station kits. SEN-15901 is the new version of SEN-08942 and has the same appearance as WS-2080. It seems that the difference between SEN-15901 and WS-2080 is that SEN-15091 has only mechanical parts and does not contain electronic parts such as a controller and monitor. The separate anemometer module used in SEN-15901 is called WH-SP-WS01. SEN0170 is a separate anemometer module. Specifications of WS-2080, WH-SP-01 and SEN0170 are presented in Table 6. Table 7 gives a summary of the performance of the low-cost anemometer modules by manufacturer and tested by scientific studies.

About the anemometer part of WS-2080 or named WH-SP-WS01, regarding its trueness, in the test of Domínguez-Brito *et al.* (2020), data were collected at 1 Hz, and they applied a centered median filter with 30 s threshold to cancel noises in the wind speed data. They report that between low-cost sensor and reference, the regression analysis coefficient is 0.951, but they do not give the function, mean bias error (MBE) is −0.167 m/s and mean square error is 0.468 m/s. They consider

Table 6 | Specifications of low-cost anemometer modules

Model	**WS-2080**	**WH-SP-WS01**	**SEN0170**
Type	Weather station kit	Three cups anemometer	Three cups anemometer
Material	Plastic	Plastic	Aluminum alloy
Size (cm)	76 × 48	~7 × 10 × 10	13 × 20 × 20
Weight (kg)	2.5	0.3	NA
Measurement range (m/s)	0–50	NA	0.8–30
Power supply	Batteries	No need	9–24 V DC
Output signal	Wireless communication	Close of reed switch	0–5 V
Price range (€)	~150	~20	~50
Performance tested in the scientific literature	Yes	No	Yes

Table 7 | A summary of performance characteristics of low-cost anemometer modules

Model	WS-2080	WH-SP-WS01	SEN0170
Trueness	0.98 m/s or 10%[a] $R^2 = 0.951$, MBE $= -0.167$ m/s, RMSE $= 0.468$ m/s[d]	NA	*3%* $R^2 = 0.3162$[f]
Repeatability	NA	NA	NA
Reproducibility	NA	NA	NA
Resolution	0.04 m/s	0.33[b] or 0.67[c]	0.1 m/s
Response time	NA	NA	NA
Sensitivity to environment	NA	NA	Working humidity: 35–85% RH (no condensation)
Maintenance needs	Clean the connectors once every 1–2 year	NA	NA
Longevity	>1 year[e]	NA	NA

[a] The original remark in user manual is 'whichever is greater'.

[b] The original text in the datasheet is 'wind speed 0.33 m/s causes the switch to close once' in Chinese.

[c] The original text in the datasheet is 'a wind speed of 2.4 km/h causes the switch to close once per second' in English.

[d] Domínguez-Brito *et al.* (2020) undertake an experimental comparison in real conditions with scientific-grade Thies Clima anemometer model 4.3159.00.140 for 90 min.

[e] Tai *et al.* (2017) use WS-2080 at northern Lake Tahoe.

[f] Nouman *et al.* (2019) test performance of SEN0170 compared to a TESTO Air Flow Probe 06280143 whose accuracy is ±0.03 m/s.

these results 'to be a good fit' because that 'sensors not being mechanically identical and not being situated at exactly the same position'. Regarding its longevity, Tai *et al.* (2017) use it in the field for 1 year and do not mention any running problems. According to the user manual of WS-2080, the maintenance need is cleaning the connectors once every 1–2 years. Unfortunately, user manual of WS-2080 and data sheet of WH-SP-WS01 give three resolutions to convert raw signal (close of reed switch) to wind speeds (0.04, 0.33, and 0.67 m/s) and Domínguez-Brito *et al.* (2020) do not report the value that they use.

About SEN0170, it showed poor trueness ($R^2 = 0.3162$) as it is not sensitive to wind speed below 0.8 m/s (Nouman *et al.* 2019). According to the datasheet, accuracy is 3%, resolution is 0.1 m/s, and it is recommended to work in air humidity range 35–85% RH (no condensation). We do not find assessments of other criteria.

In general, it seems that the only low-cost anemometer choice is WH-SP-WS01. The maintenance need is that the connectors should be cleaned every 1 or 2 years and users can avoid this if they do not use the original connectors. The main problems of WH-SP-WS01 are (i) unknown repeatability and reproducibility which is especially critical when using many of them to model a wind field and (ii) unknown true resolution to convert the close signal of internal reed switch into wind speed: this problem can be solved when comparing it with a reference.

3.3. Solar radiation sensors

Broadband solar radiation or global irradiance is an electromagnetic spectrum in the wavelength range of 300–3,000 nm (WMO) or 350–1,500 nm (ISO) (Azouzoute *et al.* 2019). Pyranometers are designed to measure this physical quantity. They are standardized according to the ISO 9060 (International Organization for Standardization 2018) standard, which is also adopted by the WMO. This standard discriminates three classes: the best is called Class A (old name: secondary standard), the second-best Class B (old name: first class), and the last one Class C (old name: second class).

There are three kinds of pyranometers: thermopile pyranometers, silicon photodiode pyranometers and photovoltaics (PV) reference cells (Karki *et al.* 2021). Thermopile pyranometers measure irradiance with a spectral response from 280 to 2,800 nm. They usually cost thousands of euros, are often considered as Class A standards and are used as reference devices to test other types of pyranometers. Silicon photodiode pyranometers usually cost hundreds of euros. They are a low-cost and lower-maintenance option compared to thermopile pyranometers but can only measure irradiance with a spectral response from 300 to 1,100 nm (López Lorente *et al.* 2020). Recently, an emphasis focused on the use of separate photodiodes which cost tens of euros to measure solar radiation (Espinosa-Gavira *et al.* 2018; Tohsing *et al.* 2019; Salgado *et al.* 2020). As for photovoltaic reference cells, we found that their prices were hundreds of euros in 2010 and decreased due to the price decrease of photovoltaic modules.

The authors of this review believe that there are hundreds of commercially available pyranometers on the shelf. There are no need and necessity to list them all out. We present four widely used and representative sensors: Apogee CS300 (Schenk *et al.* 2015; Patrignani *et al.* 2020), ISET (Azouzoute *et al.* 2019), Si1145 (Burgt 2020; Theisen *et al.* 2020), and ML8511 (Burgt 2020). Their specifications are given in Table 8. Table 9 gives a summary of the performance of the low-cost pyranometers given by the manufacturer and tested by scientific studies.

Table 8 | Specifications of low-cost pyranometers

Model	**CS300**	**ISET**	**Si1145**	**ML8511**
Type	Photodiode	Photovoltaics	Light sensor	UV sensor
Size (mm)	24 × 24 × 25	NA	20 × 18 × 2[a]	30 × 22[b]
Weight (g)	65	NA	1.4[a]	NA
Light spectrum waveband (nm)	360–1,120	NA	400–1,000[c]	280–560[d]
Measurement range	0–2,000 W/m^2	NA	1–128 kilolux	NA
Output	Voltage signal	Voltage signal	Counts through I^2C	1–2.8 V DC
Power requirements	Non-self-powered	NA	3–5 V DC	3.3–5 V DC
Price range (€)	~300	~400	~10	~10
Performance tested in the scientific literature	Yes	Yes	Yes	Yes

[a] Specifications of module from Adafruit.

[b] Specifications of module from DFRobot.

[c] Infrared sensor spectrum: wavelength: 550–1,000 nm (centered on 800 nm), visible light sensor spectrum: wavelength: 400–800 nm (centered on 530 nm).

[d] Sensitivity wavelength: UV-A (320–400 nm), UV-B (280–320 nm).

Table 9 | A summary of performance characteristics of low-cost pyranometers

Model	**CS300**	**ISET**	**Si1145**	**ML8511**
Trueness	±5%[a] Mean deviation = −10.4–9.1 W/m^2, standard deviation = 41.4–47.1 W/m^2 [c]	<± 5%[b] MBE = −19.57 W/m^2 (June), MBE = −2.398 W/m^2 (December)[d]	RMSE = 34.14–81.64 W/m^2, R^2 = 0.96–0.99[e] RMSE = 46.37 W/m^2 [f]	RMSE = 46.37 W/m^2 [f]
Repeatability	Manufacture calibration	Manufacture calibration	NA	NA
Reproducibility	Manufacture calibration 'Show good agreement when not shaded'[c]	Manufacture calibration	NA	NA
Resolution	0.2 mV per W/m^2	0.1 mV per W/m^2	100 microlux	NA
Response time	<1 ms	<10 s[d]	<2 s[f]	<2 s[f]
Sensitivity to environment	NA	'PV cells are highly affected by the high-temperature values.'[d]	NA	NA
Maintenance needs	Check and clean once very month	NA	NA	NA
Longevity	>1 year[c]	NA	>8 months[e]	NA

[a] For daily total radiation.

[b] The relative measurement uncertainty is <± 4% (crystalline material) and <± 5% (amorphous material). The measurement uncertainty refers to a confidence level of 1-alpha = 95%.

[c] Schenk *et al.* (2015) compare three CS300 with a Kipp & Zonen CMP11 thermopile pyranometer that is installed 250 m away and then use CS300 in field.

[d] Azouzoute *et al.* (2019) compare ISET sensor 02581 with a Hukseflux thermal sensor SR11 classified as a Class B specification sensor at same site and give the results in June and December, respectively.

[e] Theisen *et al.* (2020) compare output counts of Si1145 with LI-COR pyranometer that has an accuracy of ±5% from August 2018 to March 2019.

[f] Burgt (2020) calibrate and validate output of ML8511 and Si1145 compared with pyranometer Davis Instruments Vantage Pro 2.

About CS300, regarding its trueness, Schenk *et al.* (2015) reported that, compared to the reference, the mean deviations of three CS300 are 6.2, 9.1, and $-10.4\ \mathrm{W/m^2}$, respectively, and standard deviations are 43.2, 41.4, and $47.1\ \mathrm{W/m^2}$, respectively. They conclude that CS300 is 'the most economical solution' compared to the two semiconductor pyranometers they tested. After this test, Schenk *et al.* (2015) use 20 CS300 in the field for more than 1 year and report that CS300 show 'good agreement between the sensors' when they are not shaded but do not give any metric details. The manufacturer of CS300 indicates that it is calibrated against a Kipp & Zonen CM21 thermopile pyranometer and has an absolute accuracy of $\pm 5\%$ for daily total radiation, its resolution is 0.2 mV per $\mathrm{W/m^2}$, its response time is less than 1 ms and it needs to be checked and cleaned every month.

About the ISET sensor, Azouzoute *et al.* (2019) read its output every 10 s and compare it to the reference in time resolution 1 min. Regarding trueness, they report that in June, MBE is $-19.57\ \mathrm{W/m^2}$, root mean square error (RMSE) is $45.946\ \mathrm{W/m^2}$, normalized root mean square error (NRMSE) is 11.292%, t-statistic (TS) is 82.381, SD is 41.569 and coefficient of determination (R^2) is 0.993. In December, MBE is $-2.398\ \mathrm{W/m^2}$, RMSE is $13.027\ \mathrm{W/m^2}$, NRMSE is 3.913%, TS is 30.975, SD is 12.804, and R^2 is 0.999. They conclude that 'the reference cells underestimate the plane of array irradiance values. This underestimation is much higher in the summer than in the winter, which is completely understandable, since the PV cells are highly affected by the high-temperature values', even though the ISET sensor has an integrated Pt100 temperature sensor to compensate for its output. According to the manufacturer, it is professionally calibrated and came with a certificate. It has a relative measurement uncertainty of $< \pm\ 5\%$, and a resolution of 0.1 mV per $\mathrm{W/m^2}$.

About light sensors Si1145 and ML8511, they are not initially designed to be a pyranometer. Theisen *et al.* (2020) find there is a linear correlation between the downwelling global solar radiation measured by the LI-COR pyranometer P and the output counts p of Si1145: $P = 0.70p + 170.66$. But Si1145 has three outputs: infrared light counts, visible light counts, and UV index, and Theisen *et al.* (2020) do not describe which Si1145 output they use. Using this calibration function, they report that from August 2018 to March 2019, every month RMSE is from 34.14 to $81.64\ \mathrm{W/m^2}$ and the correlation coefficient is from 0.96 to 0.99. Burgt (2020) connects ML8511, Si1145 and reference pyranometer to a Wemos D1 Mini microcontroller and uses an analog-to-digital converter ADS1115 to read the output of ML8511 and reference pyranometer. All his measurements are taken every 2 s. He reports that the calibration function is $P = -224.739\ p_{Si\ UV} + 1.410168 p_{Si\ VIS} + 0.036012 p_{Si\ IR} + 3.626188 p_{ML} - 397.597$ where P is the output of the reference pyranometer in $\mathrm{W/m^2}$. The authors of this review guess that $p_{Si\ UV}$ is the UV index output of Si1145, $p_{Si\ VIS}$ is the visible light counts output of Si1145, $p_{Si\ IR}$ is the infrared light counts output of Si1145 and P_{ML} is the output voltage of ML8511 but we do not know their units. About this calibration function, the adjusted R^2 is 0.995, the SD is 23.93, the significance F is 0 and all p-values are below 0.05. In the 2 h validation test on a sunny afternoon, RMSE is $46.37\ \mathrm{W/m^2}$, but there is a negative 'offset of about $50\ \mathrm{W/m^2}$, when the solar irradiance is at a value of about $200–400\ \mathrm{W/m^2}$.' (Burgt 2020). The datasheet of Si1145 indicates that its resolution is 100 microlux.

When designing a solar radiation sensing network, there are two main choices. One choice is to use commercial pyranometers such as CS300 and ISET: they are calibrated by manufacturers and provide reliable trueness, repeatability, reproducibility, resolution, response time and longevity (Schenk *et al.* 2015; Azouzoute *et al.* 2019). Another choice is to use cheaper light sensors such as Si1145 and ML8511. In that case, users need to calibrate and house them (Burgt 2020; Theisen *et al.* 2020). If funds allow, it is highly recommended to use a Class A thermopile pyranometer as a reference. WMO standard specifies a resolution of $5\ \mathrm{W/m^2}$ and uncertainty of 8% hourly totals (5% daily totals for Class B pyranometers). According to the authors of this review experience, the output of CS300, ISET, and ML8511 is a voltage signal and the analog-to-digital conversion module of Arduino is not accurate enough, it is thus necessary to use an additional analog-to-digital converter such as an ADS1115. All pyranometers are recommended to be checked and cleaned every month.

3.4. Rainfall sensors

In stormwater management, accurate and timely rainfall monitoring is a prerequisite. Rain gauges are the key standard equipment for monitoring rainfall. A variety of rain gauges exist. To compare rain gauges based on different measuring principles, the WMO organized field intercomparison from October 2007 to April 2009 in Vigna di Valle, Rome (Italy) involving 30 different types of rain gauges. Results indicate that synchronized tipping-bucket rain gauges (TBRG), using internal correction algorithms, and weighing gauges (WG) with improved dynamic stability and short step response are the most accurate gauges for 1-min rainfall intensity measurements, providing the lowest measurement uncertainty with respect to the assumed working reference (Lanza & Vuerich 2009). But this report does not mention any gauge model or any manufacturer.

We identified four low-cost rainfall sensors mentioned in the scientific literature: droplet detector YL-83 (Rivas-Sánchez *et al.* 2019; Islam *et al.* 2021), tipping-bucket rain gauge WH-SP-RG (Abeledo *et al.* 2016; Chan *et al.* 2021), optical rainfall detector RG-11 (Bartos *et al.* 2018) with no guaranteed accuracy to measure rainfall intensity, and Pluvimate drop-counting rain gauge (Michelon *et al.* 2020). According to information available on the internet, WH-SP-RG is part of the weather station kit SEN-15901 or WS-2080. RG-11's manufacturer also provides a new version named RG-15 with guaranteed accuracy. Their specifications are given in Table 10.

According to the datasheet from VASALA, YL-83 capacitive sensor has a housing which makes it waterproof. But only its bare circuit boards can be retrieved and purchased online. Although some applications have been reported (Rivas-Sánchez *et al.* 2019; Islam *et al.* 2021; Wisudawan 2021), papers do not mention any evaluation. Rivas-Sánchez *et al.* (2019) calibrate YL-83 with the value (ON/OFF) to detect if there is rainfall or not and they show the output voltage change of YL-83 during a rainfall event. But they do not describe the method of calibration and the correspondence of the output of YL-83 to the rainfall intensity. Dias (2019) reports that YL-83 is oxidated after the first occurrence of rain.

Probably because RG-15 appeared more recently on the market, there is no scientific literature reporting the application of RG-15. RG-15 and RG-11 appear very similar and there are some scientific papers about RG-11.

Table 11 gives a summary of the performance of the low-cost rain gauges given by the manufacturer and tested by scientific studies.

WH-SP-RG appears as part of weather station kits WS-2080. Coloch Tahuico (2021) increases its collector area from 55 to 314 cm^2 (calculated from the design drawing, he describes it in the text as 1,000 cm^2, which may be a mistake). And then he pours 1.6–1,000 mL water and the sensor output 1–434 tips. he concludes that sensor resolution is 2.5 ± 0.08 mL/tip ($R^2 = 0.98$). The authors of this review do not think this a correct dynamic calibration method because pouring much water into the tipping-bucket rain gauge means always simulating an unrealistic heavy rainfall and it seems that a curve function is much more suitable in his calibration chart. Coloch Tahuico (2021) does not mention any in field test results. Tai *et al.* (2017) use WS-2080 at northern Lake Tahoe for 1 year and did not mention any running problems. According to the user manual of WS-2080, WH-SP-RG has an accuracy of 10% and a resolution of 0.254 mm, but according to the datasheet of WH-SP-RG, its resolution is 0.2794 or 0.3 mm/tip in different languages.

About RG-15, its appearance is very similar to RG-11. Steele *et al.* (2014) report that the average absolute percent deviation of RG-11 from a manual rain gauge is 86.9% and linear regression produces an R^2 of 0.75. They find that RG-11 tended to overestimate large rainfall events and underestimate smaller rainfall events. Moore *et al.* (2020) used RG-11 for 1 year in the field to detect rainfall events without error which is a reference to the longevity of RG-15. The manufacturer indicates that its accuracy is $\pm 10\%$ but field accuracy will vary. It has a resolution of 0.2 or 0.02 mm depending on the selected option, and its maintenance need is only replacing the lens after 7–10 years.

About the Pluvimate sensor, Benoit *et al.* (2018) report that after bias correction for rainfall intensities 5–20 mm/h, the measurement uncertainties of seven Pluvimates sensors are less than 5% and one was slightly exceeding this value. For its

Table 10 | Specifications of low-cost rain sensors

Model	**YL-83**	**WH-SP-RG**	**RG-15**	**Pluvimate**
Type	Droplet detection[a]	Tipping-bucket	Optical monitoring	Drop-counting
Size (mm)	90 × 46 × 157	110 × 55 × 95	120 × 70 × 55	NA
Weight (g)	500	160	155	NA
Range (mm)	NA	0–155[b]	NA	NA
Supply voltage	12 V DC ±10%	NA	5–15 V or 3.3 V[c]	3.6 V battery
Supply current	≤260 mA	NA	≤4 mA	NA
Output	1–3 V	tips	RS232 at 3.3 V	NA
Price range (€)	~3	~20	~80	~600
Performance tested in scientific literature	No	Yes	No	Yes

[a] Minimum wet area 0.05 cm^2 and sensing area is 7.2 cm^2.

[b] According to user manual of WS-2080 page 35.

[c] 5–15 V DC on J1 (reverse polarity protected to 50 V), or 3.3 V DC through pin 8 on J2.

Table 11 | A summary of performance characteristics of low-cost rain gauges

Model	WH-SP-RG	RG-15/ RG-11	Pluvimate
Trueness	10%[a]	10%[b] Average absolute percent deviation = 86.9%, $R^2 = 0.75$[h]	<15% (before calibration, 0–150 mm/h)[k] ~5% (after calibration, 5–20 mm/h)[j]
Repeatability	NA	NA	NA
Reproducibility	NA	NA	Mean bias 13.9%[j]
Resolution	0.254[a] or 0.2794[c] or 0.3 mm/tip[d] 2.5 ± 0.08 mL/tip, $R^2 = 0.98$[f]	0.2 or 0.02 mm[e]	0.010 mm
Response time	NA	NA	NA
Sensitivity to environment	NA	NA	NA
Maintenance needs	NA	After 7–10 years the lens will need to be replaced.	Check the filter and the drain holes from time to time
Longevity	>1 year[g]	>1 year[i]	>3 months[k]

[a] According to user manual of WS-2080 page 35.
[b] On the website of RG-15, manufacturer writes 'Field accuracy will vary'.
[c] In datasheet of SEN-15901: the original text is 'Each 0.2794 mm of rain causes one momentary contact' in English.
[d] In datasheet of SEN-15901: the original text is 'Each 0.3 mm of rain causes one momentary contact closure' in English.
[e] In the website of RG-15, 'Depending on option selected' written by manufacturer.
[f] Coloch Tahuico (2021) checks the resolution of WH-SP-RG by pouring a known volume of water inside it and then counting the tips.
[g] Tai *et al.* (2017) use WS-2080 at northern Lake Tahoe.
[h] Steele *et al.* (2014) compare RG-11 with manual rain gauge (typically are cylindrical and totalize the rainfall accumulated between visits to the field site).
[i] Moore *et al.* (2020) use RG-11 in Zadko Obervatory.
[j] Benoit *et al.* (2018) evaluate the performance of eight Pluvimates.
[k] Michelon *et al.* (2020) claim that Pluvimate is a low-cost sensor, and they use 12 Pluvimates in the Swiss Alps for 3 months.

reproducibility, they pass a known amount of water through the funnel and compare the recorded water depth to the known input (i.e., static calibration). The measured bias of eight sensors ranges from 2.8 to 23% with a mean bias of 13.9%. Michelon *et al.* (2020) do a dynamic calibration of a Pluvimate and report that the calibration curve is $p = -0.00059P^2 + 0.92P + 0.89$, $R^2 = 0.998$, where P is the generated rainfall intensity and p is the measured rainfall intensity in mm/h, which means that the measuring uncertainty is below 5% for 0 to 20 mm/h generated rainfall intensity and reach −10% of error at 60 mm/h and −15% at 150 mm/h. They used it in the field for 3 months. The manufacturer indicates a resolution of 0.010 mm and maintenance needs include checking its filter and drain hole.

In general, rain gauges WH-SP-RG and RG-15 deserve further tests. The drawbacks of WH-SP-RG are (i) a small collection area (only 55 cm^2), and (ii) in case of heavy rainfall events, water tends to splash because it has no visible cone or funnel (Coloch Tahuico 2021). So WH-SP-RG needs to be adapted or transformed to be used in the field. The resolution of WH-SP-RG needs more investigation. It needs to check and clean every month to avoid drain hole blockage. For the optical rain gauge RG-15, the point is to test whether it can really deliver the performance claimed by the manufacturer. We think that it is better to check and clean the surface of RG-15 every month like pyranometers.

4. LOW-COST WATER QUANTITY SENSORS REVIEW

In this chapter, three water quantity parameters are selected for review: water level, flow, and soil moisture.

4.1. Water level sensors

Water level is one of the most important parameters when monitoring stormwater. The correct and timely monitoring of this quantity is also related to the ability to achieve good urban stormwater management. There are many types of water level measurement devices such as float systems, pressure-measuring devices, capacitive devices, ultrasonic devices, radar devices, and radiation devices (Morris & Langari 2016). When narrowing the range to low-cost sensors. according to available comparisons and wireless system design, two types of water level sensors are commonly used: non-contact ultrasonic sensors and contact pressure sensors.

There are many kinds of ultrasonic and pressure sensors reported in the literature. We only focus on representative and validated sensors. Five sensors are selected: HC-SR04 (Intharasombat & Khoenkaw 2015; Shrenika *et al.* 2017; Sumitra *et al.* 2017; Nasution *et al.* 2018), JSN-SR04T (Andang *et al.* 2019; Cherqui *et al.* 2020; Dswilan *et al.* 2021), MS5803-01BA (Cherqui *et al.* 2020; Kombo *et al.* 2021; Shi *et al.* 2021), Kingspan Watchman Anywhere Pro (Zhang *et al.* 2019), and TL231 (or named TL-231, TL136, ASL-MP-2F) which has not been investigated in scientific papers. Their user manuals specifications are listed in Table 12. In addition, we noted that JSN-SR04T has different versions. In some papers, it may be the original version while the version indicated in Table 12 is version 2.0 with higher specifications. Kingspan Watchman Anywhere Pro is a complete off-the-shelf solution with an ultrasonic transducer, control board, communication module, battery and housing. Table 13 gives a summary of the performance of the low-cost water level sensors given by the manufacturer and tested by scientific studies.

About HC-SR04, Sumitra *et al.* (2017) report that its mean error is 0.97% but they only record data in centimeters and do not describe the calculation details of water level from echo time. Nasution *et al.* (2018) do a laboratory test and report that the average accuracy is 96.6% (they define accuracy as measurement value/reference value) but in their test, the measurement value is always lower than the true value, we think there may be a systematic error that is not corrected, and they also do not describe the calculation details.

About JSN-SR04T, Andang *et al.* (2019) use $D = 170T$ where D is the distance in meter and T is the echo time in seconds and they assume that sound speed is always 340 m/s. They report that the errors between JSN-SR04T and reference are always less than 5 cm in a range 0–200 cm and that the error rate is 0.74%. Cherqui *et al.* (2020) report that its distance measure range is 0.225 to1.9 m, and expected accuracy can be less than 10 mm when adjusting the speed of sound for the correct temperature and humidity (error can increase up to 130 mm with a 40 °C difference and increase to 23 mm with a 100% relative humidity difference), its repeatability is 7 mm and it should be installed far from obstacles because it has a wide beam (70 degrees). During the laboratory experiment, JSN-SR04T recorded a total of more than 300,000 values without fault or drift. The maximum measurement time is 250 ms (includes the measurement itself, processing of the measure by the microcontroller and transfer to the computer to be stored via serial). They believe that the ultrasonic sensor needs very little maintenance because it is not in contact with water so that it will be not fouled by sediment, debris or algal growth. According to the datasheet of JSN-SR04T, its resolution is 1 mm.

About Kingspan Watchman Anywhere Pro, Zhang *et al.* (2019) report that during their four units in field comparison in a water level in the range 0–1.2 m, Spearman's rank correlations between Kingspan sensor and reference outputs are 0.9907, 0.9893, 0.9736, 0.9786, respectively, and mean absolute errors are 0.92, 0.76, 1.12, 0.74 mm, respectively. They conclude that

Table 12 | Specifications of low-cost water level sensors

Model	HC-SR04	JSN-SR04T	Kingspan…Pro	MS5803-01BA	TL231
Principle	Ultrasonic	Ultrasonic	Ultrasonic	Pressure	Pressure
Type	Module	Waterproof module	Waterproof kit	Module	Waterproof module
Installation	Above water	Above water	Above water	Under water	Under water
Size (mm)	45 × 20 × 15	42 × 29 × 12	NA	NA	100 × 280
Weight (g)	~5	~20	NA	~3	577
Range (cm)	2–400	20–600	12–400[a]	0–1,200	0–500
Power supply	5 V DC	3–5.5 V DC	Fitted batteries[b]	1.8–3.6 V DC	24 V DC
Working frequency	40 kHz	40 kHz	NA	NA	NA
Output	Digital (voltage)	Digital (voltage)	NA	I^2C or SPI	4–20 mA
Price range (€)	<5	<10	<200	<30	~50
Performance tested in scientific literature	Yes	Yes	Yes	Yes	No[c]

[a] Based on a measurement to a flat liquid target of size 30 cm^2.

[b] Four of Type C LR14 Alkaline 1.5 V.

[c] Trueness of TL231 given by manufacturer is 0.2 but unit is not specified.

Table 13 | A summary of performance characteristics of low-cost water level sensors

Model	HC-SR04	JSN-SR04T	Kingspan…Pro	MS5803-01BA
Trueness	Mean error = 0.97%, RMSE = 0.36 cm[a] Average accuracy = 96.6%[b]	10 mm Error < 5 mm, error rate = 0.74%[c] Expected accuracy <10 mm[d]	20 mm $r_s > 0.97$, MAE < 1.12 mm[e]	2.5 mbar (to 25 mm) ±5 mm[d] Errors from −36.7 to 33.8 mm[f]
Repeatability	NA	7 mm[d]	NA	3 mm[d]
Reproducibility	NA	NA	NA	0.72 mbar (~7.2 mm)[d]
Resolution	NA	1 mm	10 mm	0.012–0.065 mbar (About 0.12–0.65 mm)
Response time	NA	<250 ms[d]	<15 mins	<150 ms[d]
Sensitivity to environment	NA	Mandatory to correct according to air temperature, there should be no obstacles surrounding the sensor[d]	Spider nests interference and vandalized by somebody, rainfall events make output noisy[e]	Not impacted by sediment loads, some moisture uptakes in the sensor white gel that can lead to sensor drift.[f]
Maintenance needs	NA	Very little[d]	No[e]	Calibrated every 2 weeks[f]
Longevity	NA	>300,000 measures[d]	>2 years[e]	>1 year[f]

[a] Sumitra *et al.* (2017) test HC-SR04 comparing to manual measurement in a distance to water surface less than 0.2 m.

[b] Nasution *et al.* (2018) test HC-SR04 comparing to manual measurement in a distance to water surface in the range 0.8–1.3 m.

[c] Andang *et al.* (2019) test JSN-SR04T by measuring the water level of a river compared with the manual distance measurement results.

[d] Cherqui *et al.* (2020) test the performance of JSN-SR04T and MS5803-01BA in laboratory in a water level range 0–2 m using an automatic system they developed with a reference sensor OTT PLS pressure transducer that has an accuracy ≤± 2 mm.

[e] Zhang *et al.* (2019) compare the output of four Kingspan Watchman Anywhere Pro with nearby hydrometric station for one month and use nine along the River Dodder.

[f] Shi *et al.* (2021) test MS5803-01BA in laboratory for 2 months and in field (pipe) for 1 year comparing with a Hach probe.

'the low-cost remote sensor measurements are very close to the reference Dublin City Council (DCC) stations.' But the authors of this review found that in their comparison chart of the unit which has a mean absolute error 0.74 mm, at many reference water levels, the Kingspan sensor's output has a deviation of around 50 mm. Zhang *et al.* (2019) also report that throughout the duration the deployment in the field for more than 2 years with sample rates of 15 min, there is no field maintenance need, but one sensor is influenced by spider nests and two sensors are destroyed by somebody.

About the liquid pressure sensor MS5803-01BA, Cherqui *et al.* (2020) report that it includes temperature compensation, but that there is a need to use a second sensor to measure atmospheric pressure to calculate the relative pressure. They report that for two MS5803-01BA sensors (one under water and one above water), trueness is ±5 mm and repeatability is 3 mm when measuring water levels ranging from 0 to 1.9 m. During their test, like JSN-SR04T, MS5803-01BA can also output more than 300,000 measurements without fault or drift and the maximum measurement time is 150 ms. Shi *et al.* (2021) also use two MS5803-01BA to measure water level. They report that MS5803-01BA drifts clearly in water and they think this is because of water uptakes in the layer of white gel protection in the sensor. Facing this drawback, Shi *et al.* (2021) report that during manual recalibration, for three test sensors, absolute errors can decrease from −20.6 to 34.4 mm to −8.4 to 2.3 mm in the laboratory. In their field test, they install the reference sensor 76 mm higher than the low-cost sensor because that reference sensor is impacted by sediment loads and the low-cost sensor is not, but do not explain why. With automated recalibration every 14 days, absolute errors decrease from −18.1 to 110.8 mm to −36.7 to 33.8 mm. They find that even without calibration, MS5803-01BA can still 'adequately detect the water level trend' (almost the same results as the reference with $R^2 \sim 1$). They also report that two MS5803-01BA have 0.72 mbar difference in air which is an indicator of reproducibility. According to the datasheet, trueness is about 25 mm and resolution is about 0.12–0.65 mm.

Complete solutions like Kingspan Watchman Anywhere Pro with reasonable price allows for rapid deployment. In this way, end-users can focus on data collection and processing. For ubiquitous sensor networks, non-contact ultrasonic sensors HC-SR04 and JSN-SR04T installed above water have almost no maintenance needs except spider nest interference and man-made damage. But sensor outputs will be noisy in case of events. It is important to correct sound velocity by air temperature (correction for humidity is not really necessary). HC-SR04 is not waterproof, which means additional development work is required. JSN-SR04 is waterproof but its maximum accurate measurement range is only 2 m. Contact pressure sensors installed under water can avoid human damage and situations where the water level cannot be monitored from above (e.g., presence of vegetation). However, Shi *et al.* (2021) report that MS5803-01BA experiences a drift issue in water due to water absorption of the sensor's white protective layer so that MS5803-01BA needs to be re-calibrated at least every 2 weeks to achieve 'accuracy' ±10 mm. TL231 is a sensor worth testing. Although slightly expensive, it provides waterproof metal housing and possible manufacturer calibration.

4.2. Water flow sensors

Water flow monitoring is crucial for hydrological monitoring. In this review, water flow (discharge) sensors are sensors that can measure the velocity of water in a river, a stream, or a sewer. Low-cost flow sensors currently off-the-shelf are relatively scarce.

The most frequent type of sensors are Doppler velocity radars. We identified two representative works. Alimenti *et al.* (2020) propose a prototype of a low-cost continuous wave (CW) Doppler radar sensor, able to monitor the surface flow velocity of rivers. Their field results show a residual velocity SD of 0.07 m/s compared to a commercial handheld radar sensor Decatur SVR. There are some 24 GHz radar modules off-the-shelf such as CDM324 (or named IPM165), SEN0306 (SKU, from DFRobot), and 10 GHz module HB100. We cannot find papers describing in detail the usage of these sensors for water flow monitoring. Fulton *et al.* (2020) use a Doppler velocity radar QCam to measure surface velocities and river discharge. Compared to conventional stream gauging methods, percent differences were 0.3, 2.5, −10.4, 7.3, and −18.8% in five flights. They thought QCam was relatively inexpensive (compared to traditional radar sensors) but still cost about 6,000 €. In addition, some papers reported the use of the low-cost flow sensor YF-S201 (or other similar models such as G1/2), initially designed for pipelines, to measure flow rate in open channels or natural watercourses (Jegadeesan & Dhamodaran 2018; Koshoeva *et al.* 2021; Yuniarti *et al.* 2021). However, these papers are poorly informative for our review. The specifications of YF-S201 are given in Table 14.

In general, water flow monitoring does not have low-cost solutions. Image-based methods (e.g., Sanyal *et al.* 2014; Patalano *et al.* 2017; Giordan *et al.* 2018; Koutalakis *et al.* 2019; Zhu & Lipeme Kouyi 2019) may be low-cost in the future thanks to

Table 14 | Specifications of YF-S201 low-cost discharge sensor

Parameter	Description
Principle	Hall effect
Size (mm)	63 × 36 × 35
Weight (g)	43
Range	1–30 L/min
Resolution	NA
Power supply	4.5 to18 V DC
Output	5 V TTL[a]
Longevity	300,000 cycles
Price range (€)	<5
Trueness	±10%
Repeatability	NA
Reproducibility	NA
Resolution	0.13 L/min
Response time	NA
Sensitivity to environment	Working environment: −25 to +80 °C, 35–80% RH, water pressure < 2.0 MPa
Maintenance needs	NA
Longevity	>300,000 cycles

[a] Flow rate pulse characteristic: frequency (Hz) = 7.5 × flow rate (L/min). Output duty cycle: 50 ± 10%. Output rise time: 0.04 μs. Output fall time: 0.18 μs. 450 pulses per litre.

advances in electronics and artificial intelligence technology. It seems unrealistic to send all the images to a centralized service for processing: images need to be processed locally. Flow rate information can then be sent to a server by means of a low-power wide-area network (LPWAN) and checked photographs can be sent only in case of high flow rates. There are some sensors off-the-shelf based on Doppler velocity radar, but they are still too expensive to be used on a large scale (Fulton *et al.* 2020). Given this situation, it may be feasible to develop a water flow velocity measurement system using commercially available Doppler radar modules such as CDM324 and SKU: SEN0306 which cost about 50€. But we cannot estimate the workload required to have a fully operational equipment. An alternative option is using a pipeline water flow sensor like YF-S201 to develop an immersed water flow monitoring system. However, we do not find high-quality literature about this solution.

Another interesting work is focusing on the presence or absence of water flow. Moody & Martin (2015) use resistor type instruments to develop overland flow detectors (OFDs). Hinrich Kaplan *et al.* (2019) use time-lapse imagery, electric conductivity (EC), and stage measurements to check the presence of streamflow. Chamber *et al.* (2020) use EC sensors (soil moisture sensors in fact) to develop their autonomous OFD.

Assendelft & Ilja van Meerveld (2019) chose electrical resistance (ER) sensors, temperature sensors, float switch sensors, and flow sensors like YF-S201 to monitor temporary streams. They define the percentage of correct state data (the percentage of the state data derived from the sensor data that corresponded to the state data derived from time-lapse photographs) and the percentage of correctly timed state changes (the percentage of the state changes derived from the sensor data that corresponded in timing with the state changes derived from time-lapse photographs) to assess the performance of sensors. They conclude that ER sensors (99.9% correct state data and 90.9% correctly timed state changes) and flow sensors (99.9% correct state data and 90.5% correctly timed state changes) perform best.

EC and ER sensors are presented in the next section dedicated to soil moisture sensors.

4.3. Soil moisture sensors

As mentioned just above, soil moisture sensors can work as OFD. Of course, the objectives of soil moisture monitoring are more numerous: large-scale soil moisture sensing networks can provide information about rainfall, runoff, water cycle and ecosystems (Robinson *et al.* 2008). Due to the important use of soil moisture sensors in agriculture, there is a large number of off-the-shelf sensors now and some are very cheap. In the field of science, the most frequent expression of soil moisture is volumetric water content (VWC) whose definition is volumetric soil content $(\%) = [\text{volume of water } (\text{cm}^3)/\text{volume of soil } (\text{cm}^3)] \times 100$.

There are several methods to measure VWC, e.g., gravimetry, time domain reflectometry (TDR), and time domain transmission (TDT). Two methods are usually low-cost (less than €100 approximately): ER and capacitance methods (Adla *et al.* 2020).

Resistive soil moisture sensors, which are extremely cheap, have been reported as inaccurate. Saleh *et al.* (2016) report that resistive soil moisture sensor EC-5 show an average percent error rate above 10% and is corroded after 1 month of use, which is a serious problem for continuous monitoring. Adla *et al.* (2020) tested resistive soil moisture sensors YL69 and YL100 with reference to a secondary standard sensor Delta-T ThetaProbe ML3 and concluded YL69 and YL100 are also not accurate (MAE, RMSE, and RAE of YL69 were 4.13, 5.54, and 0.41; MAE, RMSE, and RAE of YL100 were 3.51, 5.21, and 0.37, respectively) and they cannot work as standalone sensors.

As for capacitive soil moisture sensors, Adla *et al.* (2020) recommended SM100. There are also SKU: SEN0193 (DFRobot, Shanghai, China) (Akhter *et al.* 2018; Nagahage *et al.* 2019; Placidi *et al.* 2020, 2021; López *et al.* 2022) and 10HS (Mittelbach *et al.* 2011; Panjabi *et al.* 2018), and a low-cost TDR sensor VH400 (Bitella *et al.* 2014; Tebbs *et al.* 2019) which are reported. It is also worth mentioning the Chameleon sensor was developed and commercialized by the Commonwealth Scientific and Industrial Research Organization (CSIRO) for agriculture in low-income countries (Mdemu *et al.* 2020). Specifications of all the above sensors are given in Table 15.

According to the manufacturer, the Chameleon sensor measures how hard the roots of plants must suck (the tension required) to extract moisture. So that it does not need to be calibrated for different soil types. The sensor can provide a quantitative measure (based on resistance measurement) but for irrigation applications in agricultural production, a qualitative measurement is proposed (it can only report if the soil is wet, moist, or dry). Mdemu *et al.* (2020) reported large increases in yields of green maize by using tools like Chameleon sensors and implementing other changes, but they did not assess the performance of the Chameleon sensor.

Table 16 gives a summary of the performance of the low-cost soil moisture sensor SEN0189, SM100, 10HS, and VH400 modules given by the manufacturer and tested by scientific studies.

Table 15 | Specifications of low-cost soil moisture sensors

Model	SEN0193	SM100	10HS	VH400	Chameleon
Principle	Capacitive	Capacitive	Capacitive	TDR	Resistivity
Size (mm)	98 × 23	60 × 20 × 3	160 × 33 × 8	93.8 × 7	NA
Weight (g)	15	NA	NA	NA	NA
Range	NA	0 VWC to saturation	0–57% or 69%[b] VWC	NA	0 to >50 kPa[e]
Operating voltage (V DC)	3.3–5.5	3–5	3–15	3.5–20	NA
Interface	PH2.0-3P	2.5 mm stereo pin	NA	NA	NA
Output	0–3 V DC	Analog voltage[a]	0.3–1.25 V[c]	0–3 V[d]	Colors[e]
Price range (€)	<10	<100	<200	<60	~50
Performance tested in scientific literature	Yes	Yes	Yes	Yes	No

[a] Proportional to excitation voltage (0.5–1.5 V for a 3 V excitation).

[b] Mineral soil calibration: 0–57% VWC, Soilless media calibration: 0–69% VWC.

[c] Independent of excitation voltage.

[d] Related to moisture content.

[e] Measuring soil water suction: Blue 0–20 kPa (wet), Green 20–50 kPa (moist) and Red > 50 kPa (dry).

Table 16 | A summary of performance characteristics of low-cost soil moisture modules

Model	SEN0193	SM100	10HS	VH400
Trueness	RMSE = 5% VWC[f] Max error = 6.2%, 4.3%, $R^2 = 0.76, 0.73$[g]	*3% VWC*[a] average $r_s = 0.94$, MAE = 1.67%, RMSE = 2.36%, RAE = 0.21[h] RMSE = 0.91%, 1.03%[i]	*3% VWC*[b] $R^2 = 0.93$[j]	*2% VWC*[c] $R^2 = 0.89$, RMSE = 2.61, NRMSE = 0.09[k] $R^2 > 0.90$[l]
Repeatability	NA	average $s_{r,p} = 0.41\%$	NA	NA
Reproducibility	'Significant sensor-to-sensor variability'[f]	NA	NA	NA
Resolution (VWC)	NA	0.1%	*0.08%*[d]	NA
Response time	NA	NA	10 ms	400 ms[e]
Sensitivity to environment	'Not sensitive to high mineral content soil'[f] 'Affected by bulk density, not affected by temperature and depth'[g]	'Predicted and corrected positive temperature effect, not sensitive to changes in salinity'[h]	NA	'Sensitive to temperature changes in wet conditions (in water) and small changes in water content'[k] 'The response of VH400 was significantly affected by soil texture'[l]
Maintenance needs	NA	NA	NA	NA
Longevity	>6 months[g]	NA	>2 years[j]	NA

[a] EC < 8 mS/cm.

[b] With standard calibration equation, typical in mineral soils that have solution electrical conductivity <10 dS/m.

[c] Unit not specified.

[d] In mineral soils from 0 to 50% VWC.

[e] Power on to output stable.

[f] Nagahage *et al.* (2019) calibrate SKU: SEN0193 compared with gravimetric VWC.

[g] Akhter *et al.* (2018) test SKU: SEN0193 in two difference sites.

[h] Adla *et al.* (2020) test five SM100 with reference to gravimetric weight and ThetaProbe soil moisture sensor in fluid and four kinds of repacked soils.

[i] Salman *et al.* (2021) compare soil moisture measurements by the gravimetric method and SM100 readings in two sites.

[j] Panjabi *et al.* (2018) do a soil-specific calibration for 10HS in laboratory.

[k] Bitella *et al.* (2014) test VH400, in laboratory in three kinds of non-saline soils.

[l] Payero *et al.* (2017) test VH400 in four soil texture types (loamy sand, sandy clay, sandy clay loam and sandy loam) with the reference of gravimetric VWC and output of VH400 was measured by FLUKE 117 electrician multimeter.

Nagahage *et al.* (2019) report four SEN0189 sensors to have a significant sensor-to-sensor variability according to the analysis of variance (ANOVA). It is not sensitive to high mineral content soil. They suggest this is because SEN0189 sensors 'operate in low frequencies and are thereby more sensitive to effects of soil textural variances and salinity'. The calibration function of SEN0193 for organic-rich soil is $P = 13.248 - 2.576 \times 10^{-3}p + 1.726 \times 10^{-7}p^2 - 3.839 \times 10^{-12}p^3$ where P is gravimetric soil water content and p is mean raw analog-to-digital counts output of two SEN0193 with $R^2 = 0.98$. After calibration, at a gravimetric water content of 60–80%, the RMSE of SEN0189 is 5% VWC. Akhter *et al.* (2018) reported that after site-specific calibration (linear calibration function, $R^2 > 0.98$), in 6 months, the max errors are 6.2 and 4.3% and correlation coefficient are 0.76 and 0.73 between reference value (oven-dry method) and reading of SEN0189 for two sites, respectively. They also use a one-way ANOVA test (Tukey's multiple range test) to check sensitivity to the environment and report that soil temperature and measuring depth had no significant effect on the SEN0193 output. But the output of SEN0189 increases with an increase of the bulk density (if the bulk density is either higher than 1.3 g/cm^3 or lower than 0.9 g/cm^3), resulting in statistically significant differences (p-value < 0.05).

About SM100, Adla *et al.* (2020) report that using the manufacturer calibration equation, the average Spearman's rank correlation coefficient (r_s) between sensor readings and the actual VWC is 0.94. The average comparison of the precision performance of SM100 is 0.41%. Using a piecewise linear equations calibration function ($R^2 = 0.94$), MAE = 1.67%, RMSE = 2.36%, RAE = 0.21. It follows an expected positive temperature effect (at the actual VWC values of 7.63 and 18.38%, respectively, an increase of 30 °C resulted in an increase of estimated VWC by 7 and 2.99%) and is not sensitive to changes in salinity ($R^2 = 0.85$). Salman *et al.* (2021) report that after site-specific calibration at one site, the RMSE values for SM100 changed from 2.68% before calibration to 0.91%. At another site, the RMSE values changed from 3.09 to 1.03%. According to datasheet, resolution is 0.1% VWC.

Panjabi *et al.* (2018) report that their calibration function of 10HS is $P = 0.001p^2 - 0.2063p + 12.226$ with R^2 of 0.9299, where P is the soil moisture content in % by volume, p is the 10HS reading in mV. They use it in the field for about 2 years, but do not discuss data validation. According to datasheet, resolution is 0.08% VWC and the response time is 400 ms.

About VH400, Bitella *et al.* (2014) report that for all soil texture types, three parameters logistic model fits data (VH400 output and VWC getting from gravimetric water content) 'very well' ($R^2 = 0.89$), training RMSE = 2.63, validation RMSE = 2.61, and NRMSE = 0.09 in cross-validation (leave-one-out method). They also test its sensitivity to the environment, report that its output increases by 70 mV between 3 and 50 °C and that it is sensitive to small changes in water content but without details. Payero *et al.* (2017) report that VH400 responds linearly to changes in VWC for four soil types ($R^2 > 0.90$). An analysis of co-variance (ANCOVA) shows that soil texture has a highly significant effect ($p < 0.001$) on the output of VH400.

In general, resistive type soil moisture sensors are reported as inaccurate and easy to be corroded by water. Capacitive sensor SKU: SEN0193 is very cheap but shows significant sensor-to-sensor variability. There is also a soil moisture development board named HiGrow including SKU: SEN0193, microcontroller, and DHT11 on the same board, which is reported of very poor quality (Flashgamer 2019). Low-cost capacitive sensor SM100, 10HS and TDR sensor VH400 are worth trying. It is absolutely required to conduct a site-specific calibration before deploying these sensors because soil moisture sensors are impacted by many environment quantities such as soil texture, bulk density, temperature and salinity. Another worth trying sensor is Chameleon which claims no need to be calibrated thanks to its measurement principle.

5. LOW-COST WATER QUALITY SENSORS REVIEW

As all sensors cannot be reviewed here, five water quality parameters are selected for review: pH, conductivity, turbidity, nitrogen, and phosphorus. Among the numerous water quality parameters, we chose these five ones considering the technology development and the needs related to stormwater monitoring. We note that producers and sellers of water quality sensors usually categorize their products into two types: laboratorial usage and industrial usage. We cannot find any unambiguous definition of this categorization. Usually, laboratory usage requires sensors with high quality and accuracy, operated under strictly controlled conditions. Industrial usage requires monitoring in a more demanding environment (temperature, pressure, electromagnetic compatibility, resistance to shocks, and lightning shield) and robust sensors which deliver data continuously over weeks, months and years with online transmission to a control room. Industrial usage is closer to what is expected in the field of *in situ* stormwater monitoring. In addition, we find low-cost water turbidity sensors which are originally used in household appliances such as washing machines and dishwashers. Therefore, in this chapter, we propose three categories: laboratory, industry and household appliances.

5.1. pH sensors

There is an extensive literature (e.g., Zhou *et al.* 2017; Qin *et al.* 2018; Alam *et al.* 2020) describing the development of low-cost pH meters based on optical fiber, metal oxides, and micro-electro-mechanical system (MEMS) techniques. Their works are, however, only in the laboratory development stage and not related to low-cost commercial products yet available on the market.

Commonly used pH sensors in low-cost water quality monitoring systems are SKU:SEN0161 and SKU:SEN0169 from DFRobot (Harun *et al.* 2018; Saha *et al.* 2018; Nasution *et al.* 2020; Ilyas *et al.* 2021; Kelechi *et al.* 2021), pH sensor from Atlas Scientific (Faustine *et al.* 2014; Faustine & Mvuma 2014; Zakaria & Michael 2017; Bartos *et al.* 2018; Demetillo *et al.* 2019; Shamsi *et al.* 2020), pH sensor from Phidgets (Rao *et al.* 2013; Nazer *et al.* 2018), and pH sensor from SensoreX (Lambrou *et al.* 2014; Al Haji & Al Odwani 2015; Sun *et al.* 2016).

Some papers only state the brand but no model. Common models in reviewed papers are ENV-40-pH from Atlas Scientific (Faustine *et al.* 2014; Faustine & Mvuma 2014; Zakaria & Michael 2017). Alumno *et al.* (2021); Baéz Rodríguez & Rodríguez Jarquin (2019) use PC2121-5M from Phidgets. Specifications of the above models are given in Table 17. Table 18 gives a summary of the performance of the low-cost water PH sensor modules given by the manufacturer and tested by scientific studies.

Nasution *et al.* (2020) use the function $P = (7\text{-output})/59.16$ where P is the pH value and *output* is the SEN0161 output in mV. This formula has been first established by Shahrulakram & Johari (2016). In Nasution *et al.* (2020)'s field test, the deviation between SEN0161 output and a handheld pH meter is 0.02–0.26 pH at around 8.0 pH. But they do not provide calibration details. Yuzhakov *et al.* (2021) report that its calibration function is $P = a + bp$, where P is the measured pH and p is the measured voltage in mV, with $a = -7.17652 \pm 0.13704$ and $b = 7.89417 \pm 0.07516$. But using this calibration function, for a change of 1 pH unit, only a voltage of approximately 0.12–0.13 mV would be necessary. SEN0161, therefore, seems highly susceptible to electrical interferences. A possible explanation could be that Yuzhakov *et al.* (2021) in fact use volt to record SEN01610 output. In addition, the number of digits in a and b is too high for measuring pH with an accuracy of ± 0.1 pH according to the supplier. After calibration, its reading was 'similar' to the stationary pH meter OHAUS Starter 3100 which had a ± 0.01 pH measurement error. Mahardika *et al.* (2021) use ADS1115 to measure its output voltage and report that its calibration function is $P = 13.57p - 17.53$ where P is the measured pH and p is the measured voltage in mV. After calibration, the error is from 0.02 to 0.12 and the average error is 0.068. Akhir (2021) reports that using the manufacturer calibration function, in 3 h immersing test, the error rate increases from 1.11 to 5.45%. In the 5-day *in situ* test, the outputs pH of SEN0161 are from 7.15 to 11.27. Akhir (2021) indicates that 'SEN0161 can only be effectively performed in the range of pH 6–8 so that the sensor is not in optimal working condition' but does not give any further explanation and test results. According to the datasheet, response time is less than 2 min and longevity is more than 6 months but depends on the frequency of use.

Table 17 | Specifications of low-cost water pH sensors

Model	**SEN0161**	**SEN0169**	**ENV-40-pH**	**PC2121-5M**
Range of use	Laboratory	Industry	Laboratory	Industry
Size (mm)	NA	NA	150.6 × 12	160 × 29.3
Weight (g)	NA	NA	25	NA
Detection range (pH)	0–14	0–14	1–14[c]	0–14
Power supply (V DC)	3.3–5.5[b]	3.3–5.5[b]	3.3–5[c]	4.5–5.3[e]
Output	Analog voltage[d]	Analog voltage[d]	UART and I^2C[c]	NA
Probe connector	BNC	BNC	Male SMA/BNC	BNC
Price range (€)[a]	~30	~60	~130	~130
Performance tested in scientific literature	Yes	Yes	Yes	Yes

[a] Including interface circuit board.
[b] With meter pro kit V2 interface adapter.
[c] With EZO™ pH circuit.
[d] 0–3 V on meter pro kit V2.
[e] With pH/ORP adapter.

Table 18 | A summary of performance characteristics of low-cost water pH modules

Model	SEN0161	SEN0169	ENV-40-pH	PC2121-5M
Trueness	±0.1 pH[a] Deviation = 0.02–0.26 pH[f] ~0.1 pH[g] Error = 0.02–0.12 pH[l]	±0.1 pH[a] Absolute error ≤ 0.1 pH[i] Average deviation = 0.0766 pH, max. deviation = 0.16 pH[j]	±0.002 pH[b] Max. deviation = 0.60 pH, $R^2 = 0.9731$[k]	±0.09 pH[c] Errors = −0.5, −1.86 pH[m]
Repeatability	NA	NA	NA	NA
Reproducibility	NA	NA	NA	NA
Resolution	NA	NA	0.001[b]	0.018[c]
Response time	<2 min	≤ 1 min	95% in 1 s	<10 s
Sensitivity to environment	'May not be effective to be continuously immersed'[h]	NA	NA	NA
Maintenance needs	NA	NA	~1 year before recalibration	Recommend to store in a storage solution
Longevity	>6 months[d]	> 6 months[e]	>~ 30 month	NA

[a] At 25 °C, with meter pro kit V2 interface adapter.

[b] With EZO™ pH circuit.

[c] With pH/ORP adapter.

[d] Depending on the frequency of use.

[e] 7 × 24 h, depending on the water quality.

[f] Nasution *et al.* (2020) compare the reading of SKU: SEN0161 in a fishpond with handheld pH meter.

[g] Yuzhakov *et al.* (2021) do a three-point calibration and compare SEN0161 with OHAUS Starter 3100 stationary pH meter.

[h] Akhir (2021) calibrated SEN0161 and tested it in shrimp pond for 5 days.

[i] Moyón Rivera & Ordóñez Berrones (2019) compare SEN0169 to pH metro consort C562.

[j] Saputra *et al.* (2017) compare SEN0169 to pH meter PH-009(I) in three types of pH buffer solution.

[k] Demetillo *et al.* (2019) compared ENV-40-pH readings with a commercial multi-parameter water checker Horiba® probe.

[l] Mahardika *et al.* (2021) calibrate SEN0161 comparing to a pH meter.

[m] Baéz Rodríguez & Rodríguez Jarquin (2019) test PC2121-5M in buffer solutions.

About SEN0169, Moyón Rivera & Ordóñez Berrones (2019) report that its absolute error is ±0.1 pH, but they do not give the calibration equation. Saputra *et al.* (2017) report that compared to a reference, the average deviation is 0.0766 pH. The maximum deviation is 0.16 pH, but their reference sensor has less valid numbers than SEN0169 and they also do not give a calibration equation of SEN0169. The authors of this review think the researchers mentioned above use the manufacturer's Arduino code and calibration equation. According to the datasheet, response time is less than 1 min, and longevity is more than 6 months with 7 × 24 h use but depends on the water quality.

Demetillo *et al.* (2019) report that their Atlas Scientific pH sensor ENV-40-pH output p shows 'good' results compared to the reference sensor output P: $P = 0.1662p + 6.4617$ with $R^2 = 0.9731$. In their test, the maximum difference is 0.60 pH at around 8 pH. They deploy their WSN system in two creeks for 2 weeks and do not mention any operation problems. The datasheet of ENV-40-pH indicates that resolution is 0.001, response time is 1 s and calibration should be done every year.

About the PC2121-5M, Baéz Rodríguez & Rodríguez Jarquin (2019) use analog-to-digital converter (ADC) of Arduino to read its output and DS18B20 to account for temperature compensation. When using buffer solutions of, respectively, pH 8.86 and pH 9.7, the value measured were pH 7.00 and 9.2. They think these errors are due to improper calibration but do not give any further results. According to the datasheet, trueness is ±0.09 pH, resolution is 0.018 and response time is less than 10 s. This sensor has many usage cautions, and it is recommended to store it in a storage solution.

There are already some low-cost off-the-shelf pH probes and interface circuits with Arduino and other open-source hardware. According to the available literature, after calibration, at least all these sensors can indicate the acidity or alkalinity of the tested liquid. But most reviewed papers do not report the influence of temperature on pH measurement. Further research could focus on the following points: (i) the true performance of ready-to-use pH sensors with open-source hardware. For example, trueness is reported very differently for different sensors, e.g., 0.1 pH for SEN0161 and 0.002 pH for ENV-40-pH, which is meaningless for sensors based on the same measuring principle; (ii) can these sensors be suitable for submersion measurements in stormwater for months? (iii) can these sensors perform at the expected performance with as little maintenance as possible? It is worth mentioning that there are some on-going projects on the subject such as the Setier project (Prost-Boucle *et al.* 2022).

5.2. Conductivity sensors

Measuring the EC of water can indirectly provide information on the water quality condition or identify a specific water source (rainwater or groundwater for example) in relation to the increase or decrease of conductivity. In addition, total dissolved solids (TDS) concentration has an approximately proportional relationship with water conductivity (Rusydi 2018).

Commonly used low-cost conductivity sensors are SKU: DFR0300 from DFRobot (Nazer *et al.* 2018; Saha *et al.* 2018; Alimorong *et al.* 2020), and conductivity sensor from Atlas Scientific (Faustine *et al.* 2014; Lockridge *et al.* 2016; Siyang & Kerdcharoen 2016; Bartos *et al.* 2018; Shamsi *et al.* 2020; Othaman *et al.* 2021). A commonly used TDS sensor is SKU: SEN0244 (Ula 2020; Mahardika *et al.* 2021).

There are many segmented models of conductivity sensors from Atlas Scientific. The model commonly used in fresh water is ENV-40-EC-K0.1. We also found industry level water conductivity probes E201WM and 208DH. Specifications of the above models are given in Table 19. Table 20 gives a summary of the performance of the low-cost water conductivity sensor modules given by manufacturers and tested by scientific studies.

About DFR0300, Saputra *et al.* (2017) report that in 27 min of measurement and around 650 ppm, comparing to the reference, deviation is from 0 to 6 ppm and average deviation is 2.1 ppm, but they do not give calibration details. Rozaq *et al.* (2020) report that the calibration equation of DFR0300 is $P = 0.003p - 0.4175$ with $R^2 = 0.9587$ where P is the salinity value and p is ADC counters of Arduino Due. Using this calibration equation, the error rates are from 5.7 to 17.6% and average error rate of DFR0300 was 9.5%. But they do not divide the calibration and validation dataset and their reference values are integer and DFR0300 outputs are with two decimal places. According to the datasheet, longevity is more than 6 months but depends on the frequency of use.

Othaman *et al.* (2021) report that for ENV-40-EC all the percentage differences between measured EC and manufacturers' suggested values are less than 0.02% and EC values are directly proportional to temperature ($R^2 \sim 1$). Lockridge *et al.* (2016) report that compared to the reference, RMSE is 1.35 parts per thousand, approximately 10% of the observed salinity range and outputs of ENV-40-EC-K1.0 and reference are 'highly correlated' ($R^2 = 0.96$). They think this deviation is a slight offset/bias that is likely of a physical nature such as the distance between them (0.5 m). They also report that instrument biofouling is a significant issue during the summer in the field test, and commonly results in sensor drift after 3–4 weeks of deployment. The manufacturer claims that trueness is ±2%, response time is 1 s and longevity is 10 years.

About SEN0244, Mahardika *et al.* (2021) use ADS1115 to read its output voltage and report that its calibration function is $P = 352.7p - 42.76$ where P is the output of the TDS meter and p is the output of SEN0244 in mV. After calibration, its error

Table 19 | Specifications of low-cost conductivity sensors

Model	DFR0300	ENV-40-EC-K0.1	E201WM EC	208DH	SEN0244
Type	EC	EC	EC	EC	TDS
Range of use	Laboratory	Laboratory	Industry	Industry	Laboratory
Range	0–20,000 μS/cm[b]	0.07–50,000 μS/cm	0–19,990 μS/cm[e]	0–199,900 μS/cm[e]	0–1,000 ppm[f]
Size (mm)	NA	145.5 × 12	85 (length)	165 × 26 × 26	NA
Weight (g)	NA	25	41	41	NA
Power supply (V DC)	3.0–5.0[c]	3.3–5.5[d]	3.0–5.0[c]	3.0–5.0[c]	3.3–5.5[f]
Probe connector	BNC	Male SMA/BNC	BNC	BNC	XH2.54-2P
Output	0–3.4 V[c]	UART and I^2C[d]	0–3.4 V[c]	0–3.4 V[c]	0–2.3 V[f]
Price range (€)[a]	~70	~200	~70	~70	~10
Performance tested in scientific literature	Yes	Yes	No	No	Yes

[a] Including interface circuit board.

[b] Recommended detection range: 1,000–15,000 μS/cm.

[c] With DFRobot Signal Conversion Board (Transmitter) V2.

[d] With EZO™ Conductivity Circuit.

[e] Another type has a range 0–1,999 μS/cm and a resolution 1 μS.

[f] With DFRobot Signal Transmitter Board, at 25 °C.

Table 20 | A summary of performance characteristics of low-cost water conductivity sensor modules

Model	DFR0300	ENV-40-EC	E201WM EC	208DH	SEN0244
Trueness	±5%[a] Average deviation = 2.1 ppm, max deviation = 6 ppm[f] Error rate = 9.5%[g]	±2%[b] <0.02%[h] Error ~10%, RMSE = 1.35 ppt, $R^2 = 0.96$[i]	±1.5% + 2 digits	±1.5% + 2 digits	±10%[c] Average error = 4.896 ppm[j] Average error rate = 3.59%[k]
Repeatability	NA	NA	NA	NA	NA
Reproducibility	NA	NA	NA	NA	NA
Resolution	NA	NA	100 or 1 μS[d]	100 or 1 μS[d]	NA
Response time	NA	90% in 1 s	NA	NA	NA
Sensitivity to environment	NA	'Proportional to the temperature'[h] 'Instrument biofouling making sensor drift'[i]	NA	NA	NA
Maintenance needs	NA	Clean every month in summer[i]	NA	NA	NA
Longevity	>6 months[e]	~10 years	NA	NA	NA

[a] With DFRobot Signal Conversion Board (Transmitter) V2.
[b] With EZO™ Conductivity Circuit.
[c] With DFRobot Signal Transmitter Board, at 25 °C.
[d] Depend on range (range 0–19,990 μS/cm has a resolution of 100 μS, range 0–1,999 μS/cm has a resolution of 1 μS).
[e] Depending on the frequency of use.
[f] Saputra *et al.* (2017) compare the reading of DFR0300 with the measurement result of a TDS meter.
[g] Rozaq *et al.* (2020) calibrate DFR0300.
[h] Othaman *et al.* (2021) calibrate ENV-40-EC-K10 using 12,880 and 150,000 μS/cm standard buffer solutions in temperature range 5–50 °C in laboratory.
[i] Lockridge *et al.* (2016) compare ENV-40-EC-K1.0 with YSL6600 for 55 h at Dauphin Island Sea Laboratory.
[j] Mahardika *et al.* (2021) calibrate SEN0244 comparing to a TDS meter.
[k] Ula (2020) compare SEN0244 with TDS meter.

is from 0.18 to 12.9 ppm in a range from 400 to 700 ppm and the average error is 4.896 ppm. But they do not divide calibration and validation datasets. Ula (2020) reports that at about 820 ppm, the error rate of SEN0244 is from 2.54 to 0.24% and the average error is 1.89%; at about 400 ppm, the error rate is from 5.12 to 8.29% and the average error is 6.00%; and at about 170 ppm, error rate is from 0.47 to 7.39% and average error is 2.90%. But he does not provide the calibration details. The average error rate of the three experimental samples is 3.59%.

There are two other interesting works we identified: Geetha & Gouthami (2016) used resistive soil moisture YL-69 to measure water conductivity, but it is doubtful how long this resistance sensor can work continuously in water as aforementioned YL-83 and EC-5 are easily oxidated (Saleh *et al.* 2016; Dias 2019). Shi *et al.* (2021) built a DIY water conductivity sensor using two small stainless-steel rods with a simple voltage divider circuit (a resistor of 100 Ω and water as another resistor) and calibrate it comparing to a HANNA meter (linear calibration function in 0–10 mS/cm with $R^2 = 0.9871$). At four sites tested, they claim that their DIY EC sensors have 'highly linear correlation' with a HANNA meter even though relative uncertainties are from 17.42 to 31.12%. And they do not give temperature compensation details in test results and the longevity of their DIY EC sensor.

In general, *in situ* water conductivity measurement appears promising. There are some low-cost sensors off-the-shelf and even DIY sensors can give useful water quality information. It is mandatory to compensate EC readings with water temperature and DS18B20 is a commonly used waterproof temperature sensor. Like water pH sensors, the long-term performance of immersed EC sensor is also unstable because of, e.g., biofouling, so a self-clean or self-maintenance system is necessary.

5.3. Turbidity sensors

Turbidity is an optical determination of water clarity and total suspended solids (TSS) is a total quantity measurement of solid material per volume of water. These two parameters are related but not in a simple linear relationship. Turbidity is usually reported in nephelometric turbidity units (NTU).

Table 21 | Specifications of low-cost water turbidity sensors

Model	**SEN0189**	**TSD-10**	**TSW-10**	**TS-300B**
Principle	Optical principle			
Range of use	Household appliances			
Size (mm)	44 × 30 × 34	30 × 30 × 34	30 × 30 × 34	38.6 × 22.1
Weight (g)	30	NA	NA	NA
Range (NTU)	0–4,000	0–4,000	0–2,000	0–1,000 ± 30
Operating voltage (V DC)	5	5	5	5
Voltage differential (V)	NA	3.0 ± 20%	1.3 ± 20%	NA
Output	Two models[a]	Analog voltage	Analog voltage	Two models[a]
Price range (€)	~10	~10	~10	~10
Performance tested in scientific literature	Yes	Yes	Yes	No

[a] With adapter, analog output: 0–4.5 V, digital output: high/low level signal (can adjust the threshold value by adjusting the potentiometer) with an adapter board.

We found four low-cost optical turbidity sensors in scientific papers. They are SKU: SEN0189 from DFRobot (Ammari *et al.* 2019; Hakim *et al.* 2019; Hendri *et al.* 2019; Iskandar *et al.* 2019; Mwemezi 2020; Gusri & Harmadi 2021; Kelechi *et al.* 2021), TSD-10 and TSW-10 from Amphenol (Faisal *et al.* 2016; Camargo 2017; Nguyen & Rittmann 2018; Valenzuela *et al.* 2018), and TS-300B (Yuan *et al.* 2018; Angdresey *et al.* 2021). Specifications of the above models are given in Table 21. Table 22 gives a summary of the performance of the low-cost turbidimeter modules given by manufacturers and tested by scientific studies.

About SEN0189, Hakim *et al.* (2019) report that at 25 °C, the calibration function in the range 0–1,000 NTU is $P = 4999.25 - 1250p$ where P is the turbidity of water in NTU and p is the output voltage of SEN0189 in V, with $R^2 = 0.9762$ but they do not validate the relation between water NTU and the weight of sediment in the water. Gusri & Harmadi

Table 22 | A summary of performance characteristics of low-cost turbidimeter modules

Model	**SEN0189**	**TSD-10**	**TSW-10**
Trueness	$R^2 = 0.9762$[b] Average error rate = 7.7%[c]	$R^2 = 0.99$, average error rate = 6.51% $R^2 = 0.997$, average error rate = 9.35%	$R^2 = 0.9961$, average relative error = 3.86%[g]
Repeatability	NA	NA	NA
Reproducibility	Output 4.1 ± 0.3 V when NTU < 0.5 'Everyone needed to be individually calibrated'[d]	NA	NA
Resolution	NA	3.91 NTU/ADC count[e]	NA
Response time	<500 ms	NA	NA
Sensitivity to environment	'The effect of temperature was not significant, influenced by ambient IR'[d] <10%[a]	Not sensitive in low NTU[e,f] Influence by high intensity of light[f]	NA
Maintenance needs	Need clean regularly because of fouling[d]	NA	NA
Longevity	~7 months[d]	NA	NA

[a] In low temperature, thermal shock, damp heat, vibration tests, its output deviation is less than 10%.

[b] Hakim *et al.* (2019) calibrate SEN0189 referencing to water NTU calculated from weight of sediments in portable water.

[c] Gusri & Harmadi (2021) compare SEN0189 with Lutron TU-2016 meter.

[d] Trevathan *et al.* (2020) modify SEN0189 and only retain its original LED and IR phototransistor. They calibrate the modified sensor with Hach turbidimeter (relative error < 0.5%) using Formazin calibration samples. And then they deploy the sensors in various water bodies for several months.

[e] Faisal *et al.* (2016) calibrate and compare TSD-10 with a Hach 2100N.

[f] Angraini *et al.* (2016) compare TSD-10 with a turbidimeter and test it in a river.

[g] Valenzuela *et al.* (2018) calibrate TSW-10 with a reference T-100.

(2021) report that at 1 NTU, the error rate of SEN0189 is 31.37%; at 55 NTU, the error rate is 6.28%, and other error rates are less than 3.5% from 75 to 228 NTU. The average error rate is 7.7% but they do not give details about their calibration function. Trevathan *et al.* (2020) report that the performance of the original LED and IR phototransistor of SEN0189 is different so that it should be calibrated one by one. About their modified sensor, they believe that it is 'accurate for all turbidity levels', the actual changes due to temperature are 'not that significant' but do not give any details data such as calibration function and RMSE. In their 7 months in field test, they find that their sensor is influenced by ambient IR and in some water bodies, the sensor needs to be cleaned regularly because of fouling. According to the datasheet, output deviation is less than 10% in low temperature, thermal shock, damp heat, and vibration tests, and response time is less than 500 ms.

Faisal *et al.* (2016) report that at the range 0–700 NTU, the TSD-10 calibration curve is $P = 2277 - 500p$ where P is the turbidity of water in NTU and p is the output voltage of TSD-10 in V, with $R^2 = 0.99$. After calibration, its average measurement error is 6.51% but the measurement error is 24.63% when measuring at 37.8 NTU. They think this low sensitivity to low NTU is due to the fact that the range 0–4,000 NTU is mapped to over 0–1,023 digital counts and the IR phototransistor of TSD-10 is not sensitive enough. Angraini *et al.* (2016) calibrated TSD-10 in the range 169–771 NTU. The calibration equation was $P = 2298.89 - 0.619p$ where P is the turbidity of water in NTU and p is the output voltage in mV, with $R^2 = 0.997$. After calibration, the average relative error is 9.35%, and the error is large at low NTU (24.77% at 169 NTU). But they also do not separate calibration and validation datasets. In their field test, they find that at a point, sensor output NTU is abnormally lower than others and think this is because the light intensity at this point is higher than others.

About TSW-10, Valenzuela *et al.* (2018) report that in the range 0–180 NTU, the calibration equation is $P = 139.73p^3 - 1161.1p^2 + 2411.8p$, where P is the turbidity of water in NTU and p is the output voltage in V, with $R^2 = 0.9961$. After calibration, all the relative errors in 50 samples are in a range from 2.0 to 5.0% and the average relative error is 3.86%. Camargo (2017) reported the calibration equation in datasheet is $P = 261.05p^2 - 2607.5p + 6367$ where P is the turbidity of water in NTU and p is the output voltage in V.

Four sensors are originally used in washing machines (and thus already widely used): SKU: SEN0189, TSD-10, TSW-10 and TS-300B. Because their principles are the same, and appearances are very similar, we can discuss them together. Dedicated case-by-case calibration functions (linear to cubic depending on the NTU range of interest) are absolutely necessary. The reproducibility appears rather poor, may be due to the difference in performance of the LED and IR phototransistors inside them. Their resolution depends on the ADC that is used to read their voltage output so that an additional analog-to-digital converter such as ADS1115 is necessary. Their response time is sufficient for every second of monitoring. They are sensitive to ambient infrared light interference and temperature compensation is not mandatory. They should be cleaned regularly because of fouling. Their longevity depends on the remodeling work because they are not designed for field operation.

5.4. Nitrogen and phosphorus sensors

We identified three commercially available technologies to monitor nutrients in water: optical (UV) sensors (>15,000 €), wet-chemical sensors (>10,000 €), and ion-selective electrodes (ISE) (<1,000 €). It seems that only ISE could be a choice for ubiquitous low-cost sensor networks. ISE advantages are easy to use, fast response, no influence of color or turbidity, and availability for both ammonium and nitrate. Disadvantages are low resolution, accuracy and precision, ionic interferences, high instrument drift, and limited shelf life (Pellerin *et al.* 2016).

Kotamäki *et al.* (2009) used a s::can spectrometer probe. Wollheim *et al.* (2017) used a submersible ultraviolet nitrate analyzer from SUNA. Jones *et al.* (2020) used Hach Nitratax SC Plus to measure nitrate in water continuously. All sensors are optical (UV) sensors which are not low-cost. Wade *et al.* (2012) used Systea Micromac C to determine the total reactive phosphorus (TRP), nitrite and ammonium. Yu *et al.* (2021) used a Sigmatax sampler combined with a Phosphax Sigma auto analyzer to measure total phosphorus (TP) and Amtax combined with a Filtrax automatic sampler to measure ammonium. The devices mentioned above are large cabinets and thus are also not low-cost. It is expensive to use a colorimetric method to measure phosphates in water and low-cost microfluidic and electrochemical methods to determine phosphorus in water are still in their laboratory development phase.

Therefore, in terms of nutrient monitoring in water, the only current comparatively low-cost option is ISE probes to monitor nitrate or ammonia. Some ISE sensors are used: nitrate and ammonia ISE from Vernier (Rossi *et al.* 2015; Abu-Baker *et al.* 2016), Cooking Hacks (Ramadhan 2020), HYDRA (Menon *et al.* 2017), and Thermo Scientific (El-deen *et al.* 2018).

Specifications of the above models are given in Table 23. Table 24 gives a summary of the performance of the low-cost nitrogen sensors given by manufacturers and scientific literatures.

About the Vernier nitrate and ammonium ISE probes, Abu-Baker *et al.* (2016) report that outputs are within the range of the Environmental Protection Agency (EPA) results, but do not give details of comparison. According to the datasheet, repeatability is ±10% of reading, but depends on calibration. About sensitivity to the environment, the nitrate ion probe works in the pH range 2–11, the ammonium ion probe works in pH range 4–7.5, both work in the temperature range

Table 23 | Specifications of some water nitrogen ISE probes

Brand	Vernier	Vernier	Cooking Hacks	HYDRA	Thermo Scientific
Detection	Nitrate ion	Ammonium ion	Nitrate ion	Nitrate or ammonium ion	Ammonia ion
Range of use	Laboratory	Laboratory	Laboratory	Industry	Laboratory
Size (mm)	155 × 12	155 × 12	NA	148 × 23.8	150 × 12
Range (mg/L)	1–14,000	1–18,000	0.6–31,000[a]	0.1–14,000	0.01–17,000
Electrode slope (mV/decade at 25 °C)	+56 ± 4	+56 ± 4	NA	NA	NA
Price range (€)	~300	~300	NA	~500	~600
Performance tested in the scientific literature	No	No	No	No	No

[a] Linear range.

Table 24 | A summary of performance characteristics of the above water nitrogen ISE probes

Model	Vernier	Vernier	Cooking Hacks	HYDRA	Thermo
Detection of	Nitrate ion	Ammonium ion	Nitrate ion	Nitrate or Ammonium ion	Ammonia ion
Trueness	'Within the range of the government agency results'[e]	'Showed good agreement with laboratory results'[f]	±3%[a]	'Similar mentioned in user guide'[g]	
Repeatability	±10%[b]	±10%[b]	NA	NA	NA
Reproducibility	NA	NA	NA	NA	±2%
Resolution	NA	NA	NA	NA	NA
Response time	NA	NA	NA	T_{90} 1 minute	NA
pH range	2–11[c]	4–7.5[c]	2–11	NA	>11
Temperature range (°C)	0–40[d]	0–40[d]	5–50	0–50	0–50
Flow rate (m/s)	NA	NA	NA	0.1–3.0	NA
Interfering ions	CIO_4^-, I^-, ClO_3^-, CN^-, BF_4^-	K^+	Br^{-1}, Br^2, NO_2^{-1}, NO_2^7, OH^{-1}, OH^8, AcO^{-2}, AcO^2	NA	NA
Immersion	2.8 cm	2.8 cm	NA	NA	NA
Maintenance needs	NA	NA	NA	NA	NA
Longevity	NA	NA	>10 days[f]	4–6 months	NA

[a] Of reading, dependent on calibration.

[b] Of full scale (calibrated 1–100 mg/L).

[c] No pH compensation.

[d] No temperature compensation.

[e] Abu-Baker *et al.* (2016) use Vernier nitrate and ammonium ISE probes to test water samples from the Muskingum River.

[f] Ramadhan (2020) connect Cooking Hacks ISE probe with ESP8266 and test it in laboratory and then use in five water station 24 h a day for 10 days.

[g] El-deen *et al.* (2018) design interface circuits to use Thermo Scientific ammonia ISE probe with an Arduino Nano, calibrated the probe by Orion/mV benchtop meter and test his system on a fish tank.

0–40 °C and do not have pH and temperature compensation. The datasheet does not indicate a working flow rate and we think they can only work in stable water, and both interfere with some other ions.

About the Cooking Hacks nitrate ISE probe, Ramadhan (2020) report that its readings are in the range 10.5–11.7 mg/L in laboratory test and this results 'show good agreement with laboratory results' but did not give any comparison details. The system is equipped with a sensor that was 'functioning correctly' over 10-day *in situ* tests. According to the datasheet, it works in a pH range of 2–11 and a temperature range of 5–50 °C and interferes with many other ions. The manufacturer does not mention the water condition when using it.

About the HYDRA nitrate or ammonium ISE probe, Menon *et al.* (2017) do not mention any performance assessment. The manufacturer claims that trueness is ±3%, response time is 1 min, working temperature is 0–50 °C, that it can measure flow velocity from 0.1 to 3.0 m/s, and that its longevity is 4–6 months.

About the Thermo ammonia ISE probe, El-deen *et al.* (2018) claim that the performance of their own interface circuits is 'similar' to Orion/mV benchtop meter. They use three segments of linear functions to represent the relation between the electrode output potential in mV and the logarithm of the NH_3 concentration, and claim that this curve is 'similar to direct calibration curve mentioned in Thermo Scientific user guide' but do not give comparison details. In their fish tank test, the ammonia probe is output 0 and they think this is due to the fact that there is no ammonia in the fish tank. The manufacturer indicates that reproducibility is ±2%, samples and standards must be adjusted to above pH 11, and the temperature range is 0–50 °C.

In conclusion, there are some low-cost ISE probes to determine nitrate and/or ammonia concentrations, but no true low-cost option exists now to measure phosphorus in the water. ISE probes are designed for specialized equipment, and there is, therefore, need for extra work to combine them with open-source hardware such as Arduino and Raspberry Pi. This undoubtedly requires a certain amount of specialized hardware knowledge. It is possible that some commercial pH probe adapter boards as discussed in low-cost pH sensor part can also work with nitrate ISE probe.

6. DISCUSSION

In this review on low-cost sensors ready for ubiquitous stormwater sensing networks, we included off-the-shelf low-cost sensors referred to by open-source communities and scientific literature as systematically as possible. Various low-cost sensors, using different devices and methods in different environments, have been tested. There is to date no existing literature review dedicated to low-cost stormwater monitoring with a unified metrological framework considering numerous parameters and providing feedback from commercially available sensors. Performances of off-the-shelf low-cost sensors are summarized in six indicators: (i) trueness, (ii) repeatability, (iii) reproducibility, (iv) resolution, (v) response time, and (vi) sensitivity to the environment, maintenance needs and longevity.

Of course, when building a node of a sensing network, according to the experience of the authors of this review, there are many other aspects that must be considered. For example, the built-in real-time clock of some Arduino is easy to drift over time. Most open-source hardware does not have shielding, which means that they are easy to be disturbed by external interferences. Power efficiency is also essential for outdoor autonomous systems. However, the global performance of the sensing node is largely governed by the sensor it uses.

The present review is nevertheless positive in the sense that several low-cost sensors and solutions already exist. Low-cost sensors have been identified to measure continuously and *in situ* several quantities of interest for urban hydrology (research) and stormwater management (operation), including meteorology and water quantity. There are many low-cost sensors for monitoring air humidity, wind speed, solar radiation, rainfall, water level and soil moisture. But many of their performances and their uncertainty still need to be better quantified by means of further tests and evaluations. Water flow monitoring needs more creative sensor modules and system design, but they are not far away from giving relatively reliable results.

Compared to meteorological and water quantity, water quality monitoring by means of low-cost devices is more knowledge intensive, and users clearly need specific skills, with adaptation to the water matrix of interest (stormwater in this paper, but could be drinking water, and river water). Reviewed papers do not sufficiently report repeatable examples with references to metrology literature and methods. For example, a comparison between sensors, even a traditional more expensive one used as a reference, is not equivalent to a true calibration.

To a higher degree compared with traditional sensors, the quality of data generated by low-cost sensors not only depends on the sensors themselves, but also on the user and his/her knowledge, skills and metrological practice.

This is why users of low-cost sensors and monitoring systems shall not only have skills in electronics and informatics. They must be trained in metrology, including measuring principles, indispensable periodic calibration and verification of both sensors and measuring chains and systems, and uncertainty assessment.

Regarding the trueness of low-cost sensors, it seems that every metric in Table 3 can be used to describe this parameter. There are several discussions about its assessment: (i) many papers do not consider the trueness of reference sensors when they test low-cost sensors and give their results. (ii) Many papers do not distinguish calibration and validation datasets when they test low-cost sensors. (iii) Very different to traditional sensors, the output of low-cost sensor is frequently very primitive. Many low-cost sensors identified in this review deliver output voltage signals such as pyranometers, soil moisture and water quality sensors. It is better to use high performance ADC such ADS1115 to read their output. Using the build-in ADC of Arduino will introduce a higher system error (e.g., Arduino nano has a build-in 10-bit ADC while ADS1115 is a 15-bit ADC, which means that ADS1115 provides a resolution 32 times better (iv) As the output of low-cost sensor is very primitive, there is almost no manufacturer calibration to adapt the output, which gives users more freedom but also involves more preparatory work in using the sensors. The trueness of low-cost sensors really depends on building a good calibration equation by users. For example, the output of the ultrasonic water level sensor is the echo time. Users can improve the trueness by compensating for the change in wind speed by temperature and humidity. (v) Some users use unsuitable methods to calibrate low-cost sensors: for example, pouring too much water into a rain gauge means simulating an unrealistic heavy rainfall event.

Regarding the repeatability and reproducibility of low-cost sensors, some papers use pooled relative SD and ANOVA to check them. But many papers ignore these two important criteria. Almost no paper checks the reproducibility of low-cost sensors intentionally. In fact, this should be the manufacturer's duty to ensure each sensor is calibrated in the factory. But low-cost sensors often involve no guarantee of repeatability and reproducibility, and this is the buyer's duty to verify it. For example, the Pluvimate rain gauge has a mean bias of 13.9% in the reproducibility test even though we are skeptical of the test method. Specific tests of every low-cost sensor are mandatory before usage (as it should also be the case for any sensor), but this introduces another problem: when we plan to use tens to hundreds of low-cost sensors, testing all of them one by one is too costly and develop automated testing systems may facilitate this task but remains expensive.

In many cases, users cannot test the resolution of low-cost sensors because they do not have the required equipment. There is a risk of uninformed use of low-cost sensors if users only rely on information provided by manufacturers. Indeed, some datasheets of low-cost sensors are of poor quality (insurance quality and reliability are costly). For example, the datasheet of weather station kit SEN-15901 gives different resolution values in different languages as discussed in the wind speed and rainfall sensors subsections. There is another issue as many low-cost sensors only deliver voltage: using an ADC with more bits can increase resolution in theory but requires a case-by-case adaptation. However, more importantly, the original analytical performance of some of the low-cost sensors is low constrained by its principle such as low-cost turbidimeter. In addition, some low-cost sensors have a higher resolution than the reference sensors used to test them. For example, the optical rain gauge RG-15 has a resolution of 0.02 mm.

Regarding the response time, it appears that reviewed low-cost sensors can afford measuring every minute. In some cases, it may be better to read the output signal every several seconds and then compare to reference for calibration, or to calculate mean or median to improve repeatability.

Very rare information is given about the sensitivity to the environment, maintenance needs and longevity of low-cost sensors. Some papers use an ANOVA to check sensitivity to the environment. Indeed, most low-cost sensors need retrofit to make them suitable for *in situ* application: enclosure, coating, etc. So, this is not only related to low-cost sensor itself. For example, air humidity and water level sensors with waterproof housing should have longer longevity. We speculate that all the low-cost water quality sensors discussed in this review will be fouled when immersing in stormwater and/or wastewater for months, which will (i) require frequent cleaning and (ii) reduce longevity. It would be valuable to develop a plumbing system that can automatically sample water and clean water quality sensors.

7. FUTURE OUTLOOK

In one word, users of low-cost sensors should accept a trade-off between price and quality. The time needed to use operationally a low-cost sensor can be significant and lead to significant human resources costs: time to acquire the expertise, and time for prototyping, testing, calibrating, adapting, and assembling the commercial products into a ready-to-use monitoring equipment. There is another important task to be accounted for: connecting traditional sensors to open-source hardware such as Arduino.

Facing this situation, we believe the lack of top-level planning really hinders the large-scale application of low-cost sensors in urban hydrology. Most of the low-cost sensors come from hobbies of open-source geek communities, school teaching needs and other initially non-scientific monitoring areas. This market grows and evolves very rapidly, with decreasing prices. It attracts the attention of the urban hydrology scientific community and an increasing number of stormwater management operators who would like to use them to obtain spatially distributed data and information allowing developing knowledge, modeling, operation performance, maintenance planning, and providing support for decision-making. But it is clear this was not the original intent of the developers of low-cost sensors. It would therefore be highly beneficial to organize the urban hydrology and stormwater management community like international institutions such as WMO. Uniformed international guidelines for the sensor production, interface, performance, calibration and system design, installation and data validation of low-cost sensors become necessary. This will greatly regulate and facilitate the sharing of experience and knowledge. Low-cost sensors are challenging the way we monitor urban water systems: they bring new 'problems' (related to any DIY component) but also open new perspectives (full control, large deployment and high spatial resolution of monitoring networks, low-energy consumption, communication capabilities, fast evolving technologies, and very high diversity of sensors).

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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