



How Smart Sensors Are Changing the Way We Monitor the Air We Breathe

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Ambient air quality monitoring is undergoing a major transformation from sparse, expensive regulatory stations toward distributed networks incorporating low-cost sensors, mobile and wearable devices, Internet of Things (IoT) connectivity, satellite observations, and artificial intelligence (AI). This article examines these emerging approaches and their potential to improve the spatial and temporal resolution of air pollution monitoring. Low-cost sensors enable community-based, mobile, personal, and monitoring in data-scarce regions, while IoT systems facilitate real-time data transmission. However, sensor performance can vary with temperature, humidity, aerosol characteristics, and sensor type, highlighting the importance of calibration, validation, and standardized evaluation. Mobile and wearable monitoring can capture localized pollution hotspots and personal exposure that may remain undetected by conventional fixed stations. AI and machine learning further enhance monitoring through data imputation, sensor calibration, anomaly detection, Air Quality Index estimation, and short-term pollution forecasting. Nevertheless, increased data availability does not automatically ensure better information or decision-making. Effective monitoring requires integration of reference-grade instruments with distributed sensors, mobile platforms, IoT, AI-based analytics, satellite observations, and community participation. Such integrated systems can provide more comprehensive and actionable air-quality information, particularly in low- and middle-income regions where conventional monitoring infrastructure remains limited.

Keywords: Ambient air quality monitoring; Low-cost sensors; IoT; Artificial intelligence; Machine learning; Mobile monitoring; Personal exposure; Air pollution; Sensor calibration; Satellite monitoring.

Air pollution monitoring used to mean a handful of expensive stations scattered across a city. Today, low-cost sensors, mobile devices, and AI are creating far more detailed pictures of the air we breathe revealing hidden pollution hotspots, but also raising new questions about accuracy, trust, and what to do with all this new data.

“We Cannot Manage What We Cannot See”

You can't fix a problem you can't measure. That simple idea sits at the heart of air quality monitoring and it's also why the field is in the middle of a quiet revolution. For decades, measuring air pollution meant relying on a small number of regulatory monitoring stations: precise, government-run instruments capable of producing highly accurate, legally traceable data. The trouble is, these stations are expensive to install and operate, so they tend to be few and far between (Zimmerman, 2026; Wei et al., 2018). A city might have just a handful of them, which means most neighbourhoods and most people are never directly monitored at all.

That's beginning to change. Ambient air quality monitoring has shifted from sparse, expensive regulatory stations toward distributed networks of low-cost sensors, IoT (Internet of Things) connectivity, and mobile platforms that dramatically improve spatial and temporal resolution in plain terms, monitoring that covers more places and updates more often (Zimmerman, 2026; Wang et al., 2023; Shahid et al., 2025). This shift enables real-time, neighbourhood-level, and even personal exposure assessments that traditional networks simply cannot capture though it also introduces new challenges around sensor accuracy, calibration, and interpreting all that extra data (Zimmerman, 2026; García et al., 2025).

What's changed

To understand what's changed, it helps to compare the old and new approaches side by side. Traditional regulatory stations offer highly accurate, traceable measurements that underpin official compliance standards. But because they're costly to build and run, they're sparsely distributed and report at relatively low temporal resolution — meaning readings update infrequently (Zimmerman, 2026; Wei et al., 2018). These stations are also typically located away from emission sources, so they may miss local pollution spikes or neighbourhood-level variability altogether (Wei et al., 2018; Kubis et al., 2026). In the United States, for instance, regulatory networks are designed to capture regional air quality trends — but in doing so, they can systematically underestimate the exposure faced by vulnerable communities living closer to pollution sources (Kubis et al., 2026). Distributed, low-cost monitoring takes a different approach. Thanks to the miniaturization and falling cost of sensor technology, monitoring has expanded well beyond centralized government systems into mobile, wearable, and community-deployed networks (Wang et al., 2023; Zimmerman, 2026). Low-cost sensor usage has increased sharply in recent years, and these dense networks can provide far higher-resolution spatial and temporal data than a handful of fixed stations ever could (Wang et al., 2023; Liu et al., 2020). It's worth being clear about what this shift does and doesn't mean. Low-cost sensors complement, rather than automatically replace, reference-grade monitoring stations they extend the picture in space and time, but the gold-standard instruments remain essential for calibration and regulatory accuracy. China offers an instructive long-term example: its monitoring infrastructure has changed dramatically over four decades in what it measures, how it samples, how widely it monitors, and how it evaluates results a transformation that has contributed to declining trends in total suspended particulates, PM10, and sulfur dioxide (Zhang et al., 2020).

Low-Cost Sensors Matter

Cheaper, smaller sensors have done more than just add extra data points they've opened up entirely new *kinds* of monitoring that weren't practical before:

- **Community monitoring**, where residents themselves host sensors in their neighbourhoods
- **Mobile monitoring**, where sensors ride along on vehicles or drones
- **Wearable monitoring**, tracking the air around an individual person as they move through their day
- **Personal exposure monitoring**, capturing what someone actually breathes, not just what's in the air near a fixed station
- **Monitoring in data-scarce regions**, where regulatory networks barely exist at all

Can We Trust Cheap Sensors?

This is arguably the most important question in the whole conversation and the honest answer is: it depends, and it requires care. Low cost does not automatically mean poor performance. But it does mean that sensor data require more careful interpretation than data from a reference-grade instrument. A landmark evaluation of twelve low-cost PM2.5 sensor models found that six of them achieved an R^2 of 0.70 or higher against reference instruments meaning their readings tracked reasonably closely with the "true" pollution levels measured by professional-grade equipment with mean absolute errors ranging from 4.4 to 7.0 micrograms per cubic metre (Feenstra et al., 2019). Put simply: half of the sensors tested performed quite well, while the

rest showed more room for error and even the better performers weren't perfectly precise. Environmental conditions complicate the picture further. In that same study, relative humidity increased bias error in several sensor models (Feenstra et al., 2019) a soggy day, in other words, can throw off a cheap sensor's readings more than a dry one. Separately, a long-term evaluation of a network called KOALA found high inter-sensor correlations (above 0.91) for PM_{2.5} and carbon monoxide, suggesting the sensors were at least consistent with each other but two of the monitors failed outright at low temperatures in Beijing (Liu et al., 2020). When compared against reference instruments, correlations in that study ranged more widely from moderate to good, spanning 0.44 to 0.91 for PM_{2.5}, and 0.37 to 0.90 for carbon monoxide with performance varying by location and by the type of aerosol in the air (Liu et al., 2020). Sensors, it turns out, are also less responsive to marine aerosols and fresh vehicle emissions than to mixed urban background and industrial pollution (Liu et al., 2020). Electrochemical sensors a common low-cost sensor type show a similar pattern: comprehensive correction models substantially improved their performance compared to uncorrected raw readings, but temperature and humidity strongly affect sensor outputs in the first place (Wei et al., 2018). Even at the community scale, the picture is mixed but instructive. In one long-term deployment, outdoor PurpleAir sensors (a popular consumer air-quality monitor) showed correlations above 0.98 with each other — impressively consistent — but data completeness was only 54%, meaning nearly half the expected readings were missing. Indoor sensors in the same study performed more reliably, with 73% data completeness (Connolly et al., 2021). That gap is a useful reminder: a sensor's *precision* when it works and its *reliability* over time are two different things, and both matters. Stepping back, the broader evidence base confirms this nuance: low-cost sensors frequently show limitations in accuracy, precision, and long-term stability, with performance adversely affected by temperature, humidity, and pressure — and the field still lacks standardized evaluation procedures, which makes it hard to compare sensor performance across different studies (García et al., 2025).

About Calibration

Calibration means comparing a low-cost sensor's readings against a trusted reference instrument and developing a correction model to account for the gap. As the electrochemical-sensor research showed, comprehensive correction models meaningfully improved performance over uncorrected raw data (Wei et al., 2018). But calibration isn't a one-time fix: because temperature, humidity, and even the type of aerosol in the air all affect sensor behaviour, a sensor calibrated in one location or season may perform differently elsewhere (Wei et al., 2018; Liu et al., 2020). This is why standardized evaluation and local calibration testing and correcting a sensor's performance under the specific conditions where it will actually be deployed matter so much for producing air-quality data that can genuinely be trusted (García et al., 2025).

When the Monitoring System Becomes Mobile

Fixed sensors, however numerous, are still stuck in one place. Mobile monitoring solves a different problem: capturing how pollution changes as you move through a city. Mobile monitoring significantly enhances spatial and temporal resolution by deploying sensors on vehicles, pedestrians, and even unmanned aerial vehicles (drones), complementing traditional stationary sampling and satellite observation (Wang et al., 2023). One particularly resourceful example comes from routine municipal fleets: mounting optical particle counters on trash trucks enables continuous detection of fine-scale pollutant variation and identification of pollution hotspots, all at a lower cost than building fixed stations (deSouza et al., 2020) turning a city's existing garbage-collection routes into an ad hoc pollution-mapping network. Purpose-built devices are pushing this further still. The SMILE project developed a portable, multi-sensor device measuring nitrogen dioxide, ozone, carbon monoxide, and three particulate-matter size classes, and validated it against four government reference stations in Marseille, France, with strong correlation results (Pellegrino et al., 2025) evidence that carefully

engineered mobile devices can approach the reliability of fixed reference monitors under real-world conditions.

Community Science: Putting Monitors in People's Neighbourhoods

Perhaps the most striking evidence for why distributed monitoring matters comes from studies that placed sensors directly in the communities most affected by pollution and compared what they found to official government data. In Lower Price Hill, a Cincinnati neighbourhood, calibrated PurpleAir monitors found significantly increased PM_{2.5} levels at four of twelve sites, and elevated Air Quality Index readings at eleven of twelve sites, compared to nearby EPA regulatory monitors (Kubis et al., 2026). Personal wearable monitoring in the same study went even further: it detected two of three participants exceeding the EPA's 24-hour PM_{2.5} standard on every single study day exposure that was effectively invisible to the outdoor stationary monitoring network (Kubis et al., 2026). This distinction between "air quality where you live" and "air quality you personally experience" is exactly the gap that personal and wearable monitoring is designed to close, and it underscores why a single neighbourhood-level reading may not reflect what any one resident actually breathes. The same principle applies where formal monitoring infrastructure barely exists at all. In Uganda, low-cost sensors quantified PM_{2.5} levels exceeding health guidelines by four to six times across most study locations, demonstrating that low-cost approaches can be genuinely practicable for monitoring in data-scarce regions (Okure et al., 2022) regions where, without this technology, air pollution might otherwise go entirely unmeasured.

Sensors to the Internet of Things

None of this distributed monitoring would be useful without a way to get the data off the sensor and into someone's hands. That's where the Internet of Things, or IoT, comes in. In simple terms, IoT-based systems are networks of connected devices that can collect data, transmit it wirelessly, store it, and make it available in something close to real time. IoT-based air-quality systems enable exactly this kind of real-time data collection and transmission, using wireless technologies such as WiFi, ZigBee, and LoRa different flavours of wireless communication suited to different ranges and power needs with devices deployable across urban, industrial, and indoor settings alike (García et al., 2022). The reliability of that wireless transmission matters too: one study found that adaptive algorithms software that adjusts on the fly reduced cellular-network packet loss (data that fails to transmit successfully) by 9.8 to 11.6% under medium or poor signal conditions, meaningfully improving how dependably sensor data actually reaches its destination (Purbakawaca et al., 2022).

Where Artificial Intelligence Enters

With sensor networks now producing far more data than a handful of regulatory stations ever did, artificial intelligence and machine learning have become useful tools for making sense of it all. A systematic review classified these AI applications into five main areas (García et al., 2025):

1. **Data imputation:** filling in gaps when sensors miss readings or drop offline
2. **Sensor calibration:** helping correct raw sensor data using patterns learned from reference instruments
3. **Anomaly detection:** flagging readings that look unusual or unreliable
4. **AQI estimation:** translating raw pollutant readings into a standardized Air Quality Index
5. **Short-term forecasting:** predicting pollution levels a few hours or a day ahead

In industrial settings specifically, machine-learning models such as Gaussian Process Regression have achieved the highest accuracy for predicting when safety thresholds might be exceeded (García et al., 2022) useful for early warnings in workplaces with elevated pollution risks. It's important to be clear about what AI is *not* doing here. Nothing in the evidence suggests that AI replaces the need for monitoring experts, careful calibration, or regulatory oversight it's a tool for extracting more value from sensor data, not a substitute for the underlying measurement infrastructure and expertise.

Promise of Personal Air-Quality Monitoring

There's a meaningful difference between "air quality where you live" and "air quality you personally experience" and increasingly, monitoring technology is built to capture the second, not just the first. Stationary outdoor monitoring, however dense, describes conditions at fixed points in space. It cannot fully capture what happens when someone walks along a busy road, spends time near an idling engine, or moves between indoor and outdoor environments throughout the day. That's precisely the gap the Cincinnati wearable-monitoring findings illustrate: participants who exceeded health-based PM_{2.5} thresholds on every study day were experiencing exposure that no outdoor stationary sensor recorded (Kubis et al., 2026). Personal and wearable monitoring won't replace neighbourhood-level or city-level data but it adds a layer of information that only travels with the person wearing it.

Bigger Network Does Not Automatically Mean Better Information

It would be easy to assume that more sensors, more data points, and more real-time updates simply add up to a clearer picture. The evidence suggests otherwise. The technical capacity to collect air-quality data has outpaced the conceptual, institutional, and analytical frameworks needed to interpret that data and translate it into action — leaving many monitoring systems misaligned with the decisions they're actually meant to support (Zimmerman, 2026). This tension shows up acutely during fast-moving events: the demand for near-real-time information often conflicts directly with the time genuinely required for calibration, validation, and characterizing uncertainty, especially during rapidly changing episodes such as wildfire smoke (Zimmerman, 2026). Perhaps most importantly, increased data availability does not necessarily translate into increased interpretability or decision relevance (Zimmerman, 2026) — a reminder echoed by the broader literature on standardized evaluation gaps (García et al., 2025). The lesson is simple to state but easy to overlook: more data are useful only when they can be interpreted and translated into meaningful decisions. A flood of unvalidated readings is not automatically progress.

The Double Challenge in Low- and Middle-Income Regions

Nowhere is the need for smarter monitoring more urgent than in regions facing what researchers describe as a double burden: severe air pollution combined with genuinely inadequate monitoring infrastructure, leaving ground data too sparse for effective mitigation efforts (Wang et al., 2023; Okure et al., 2022). One practical path forward combines several of the technologies already discussed. Coupling low-cost wireless sensor stations with a limited number of conventional reference monitors can create networks that are both cost-effective and reasonably robust, while satellite-based remote sensing, calibrated against ground measurements, can capture transboundary pollution at a regional scale (Gulia et al., 2020). The Uganda findings described earlier are a working example of exactly this kind of practical, resource-conscious approach in action (Okure et al., 2022).

What Does the Future of Air Monitoring Look Like?

No single technology discussed here is likely to solve air-quality monitoring on its own. The clearest theme across the evidence is integration: distributed sensor networks, mobile and wearable monitoring, IoT connectivity, AI/ML analysis, satellite data, and reference-grade instruments all playing complementary roles, alongside automated calibration, real-time forecasting, community participation, and high-resolution spatial mapping.

The Future Air-Quality Monitoring Network

It helps to picture this as a connected pipeline, rather than a single device or dataset:

Reference monitors provide the accuracy baseline → **Low-cost sensors** extend spatial and temporal coverage → **Mobile and wearable monitoring** captures how exposure varies as people and vehicles move → **IoT data transmission** gets that information off the device and into a usable system → **AI/machine learning** cleans, calibrates, and forecasts based on the incoming data → **Real-time air-quality information** becomes available to the public and officials → **Decision-making** translates that information into action → **Public health and**

environmental outcomes are the ultimate goal the whole system serves. Each link in this chain depends on the one before it. A brilliant AI forecasting model is only as good as the calibrated sensor data feeding it; a wide sensor network is only as useful as the decisions it eventually informs.

Key Takeaways

- Monitoring is the foundation of air-quality management — you cannot manage pollution you cannot measure.
- Traditional regulatory stations remain the accuracy benchmark, but their high cost keeps them sparse and slow-updating (Zimmerman, 2026; Wei et al., 2018).
- Low-cost sensors dramatically expand spatial and temporal coverage, but their performance varies with temperature, humidity, aerosol type, and sensor model (Feenstra et al., 2019; Liu et al., 2020; Wei et al., 2018).
- Calibration against reference instruments is essential — low-cost sensor data are useful only when properly corrected and interpreted (Wei et al., 2018; García et al., 2025).
- Mobile monitoring (on vehicles, drones, and portable devices) can reveal fine-scale pollution hotspots that fixed stations miss (deSouza et al., 2020; Pellegrino et al., 2025).
- Community and personal monitoring have exposed pollution disparities and personal exposures invisible to regulatory networks alone (Kubis et al., 2026; Okure et al., 2022).
- IoT and AI extend what monitoring data can do — enabling real-time transmission, calibration support, anomaly detection, and short-term forecasting — but they support, rather than replace, monitoring expertise (García et al., 2022; García et al., 2025; Purbakawaca et al., 2022).
- More data does not automatically mean better decisions; interpretability and institutional capacity must grow alongside sensor networks (Zimmerman, 2026).

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