Environmental monitoring

Improvement of low-cost sensor accuracy in challenging environmental conditions to obtain near-reference data

4th December 2025

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Chief Scientific Officer

Low cost gas sensors – Issues and Challenge

1. **Environmental conditions effects:** Low-cost sensors have a non-linear response to *temperature, humidity and pressure*.

2. **Cross-sensitivities** in gas sensors from other common atmospheric compounds.

3. **Baseline and Sensitivity drift:** Low-cost gas sensors suffer from non-linear baseline and sensitivity drift over time. They will require regular calibration to adjust these parameters.

Lewis, A., Peltier, W. R., & von Schneidemesser, E. (2018). Low-cost sensors for the measurement of atmospheric composition: overview of topic and future applications.

Calibration methods

DETERMINISTIC MODELS

Establishing a deterministic relationship between → the reference values and raw sensor responses

- **Linear Regressions**
- **Multilinear Regressions**

Others:
Exponential, logarithmic, and quadratic models, the Kohler theory of particle growing factor used for PM LCSs

STOCHASTIC MODELS

Rely on supervised machine learning techniques

- **Artificial Neural Networks**
- **Random Forest**
- **Combined ML models**
- **New models based on AI**

Independent Sensor Measurement

Diez, S., Bannan, T.J., Chacón-Mateos, M. et al. A framework for advancing independent air quality sensor measurements via transparent data generating process classification. npj Clim Atmos Sci 8, 285 (2025).
https://doi.org/10.1038/s41612-025-01161-2

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Perspective
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A framework for advancing independent air quality sensor measurements via transparent data generating process classification

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We propose operational definitions and a classification framework for air quality sensor-derived data, thereby aiding users in interpreting and selecting suitable data products for their applications. We focus on differentiating independent sensor measurements (ISM) from other data products, emphasizing transparency and traceability. Recommendations are provided for manufacturers, academia, and standardization bodies to adopt these definitions, fostering data product differentiation and incentivizing the development of more robust, reliable sensor hardware.

Lower-cost sensing technologies are reshaping and expanding the landscape of Earth Observations[1], opening unprecedented opportunities for atmospheric composition measurements[2]. These innovations are relatively more affordable than reference-grade instrumentation, and therefore hold significant importance not only for Low- and Middle-Income Countries where they can enhance often limited air quality (AQ) data capabilities[3], but also in underserved regions within wealthier countries that are similarly deprived of adequate AQ infrastructure[4,5]. We use the more general term "regions" (or areas) to acknowledge that disparities in wealth concentration occur not only between countries, but also within national borders across the globe[6]. Globally, the pervasive shortage of traditional AQ monitoring amplifies the urgency for reliable data to support public health initiatives and policy making[7–10].

While sensor systems hold the promise of bridging data gaps related to air pollution sources, pollution distribution and population exposure[11]—potentially democratizing information and empowering public action[12]—gaps remain between their potential and the real-world performance: sensor-derived data vary significantly in quality, robustness, and traceability. Unless specified otherwise, we use the term "sensor" to refer to sensor systems (also commonly referred to as "sensor pods", "sensor devices", "sensor platforms")[13,14]. Part of these challenges can be attributed to the limitations of detection hardware[15] (e.g., drift, selectivity, cross-interferences, etc.). However, the process by which data outputs are constructed plays a critical but less tangible role. Concerns arise from the increasingly unclear and often untraceable methods employed to manipulate raw sensor signals to derive atmospheric concentrations[16,17], leading end-users to be unaware of the assumptions, hypotheses, and limitations of the data products they rely on.

This issue is exacerbated by the growing reliance on advanced data-intensive methods, including Machine Learning (ML), Big Data (BD), and Artificial Intelligence (AI), which, while enhancing processing efficiency, can also obscure the processing steps[18]. Additionally, commercial constraints often prevent the sharing of proprietary techniques, further clouding the transparency of how data outputs are derived. While the use of data-centric techniques may enhance performance metrics for a specific

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- **Independent Sensor Measurements (ISM)**: the output is primarily determined by **internal signals of the sensor system** (especially the primary sensor) plus **only justified corrections** for known artefacts. External dependency (other data sources, local specific calibration, etc.) is minimized.

- **Non-Independent Sensor Measurement:** rely on site-specific calibration, external data, or advanced corrections that reduce transparency

→ as **Machine Learning/AI models**

Machine Learning/AI algorithms work more like **predictive models** than direct measurement tools.

Instead of measuring the pollutant concentration, they analyse historical patterns to anticipate what is likely to happen next (data processing).

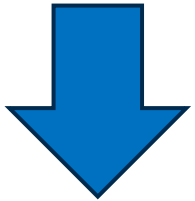
As a result, events that deviate from those learned patterns may go unnoticed. In this sense, many ML models operate more like forecasting models than instruments of measurement.

Kunak Calibration approach

1. **Environmental conditions effects:** Kunak embedded its own algorithm to convert the raw data of each sensor into concentration values (ppb or µg/m3), **locally and in real-time, without using or needing external reference data** to calculate them.

2. **Cross-sensitivities:** Kunak algorithm corrects the main cross-sensitivities in each gas sensor.

3. **Baseline and Sensitivity drift:** Gas calibration tool to re-adjust the gas sensors remotely.



Calibration model based on ISM apprach

Kunak AIR sensor systems

- Multipollutant monitoring
- Plug&Play cartridge system
- Algorithms to mitigate the influence of T and RH
- Remote operation and maintenance
- Data analysis and visualization tools

Kunak AIR Pro

Kunak AIR Lite

Smart Cartridges

Kunak Cloud Software

Independent Sensor Evaluations

AIRLAB Microsensors Challenge

https://airlab.solutions/en/actualites/resultats-du-challenge-airlab-microcapteurs-2023-203

2021 Challenge

- Winner “Most Accurate Multipollutant Sensor” (Pro)

2023 Challenge

- Winner “Most Accurate Multipollutant Sensor” (Pro & Lite)
- Winner “Best accuracy O_3” (Pro & Lite)
- Winner “Best accuracy PM2.5” (Lite)

MOST ACCURATE MULTI-POLLUTANT SENSOR

BEST ACCURACY FOR OZONE

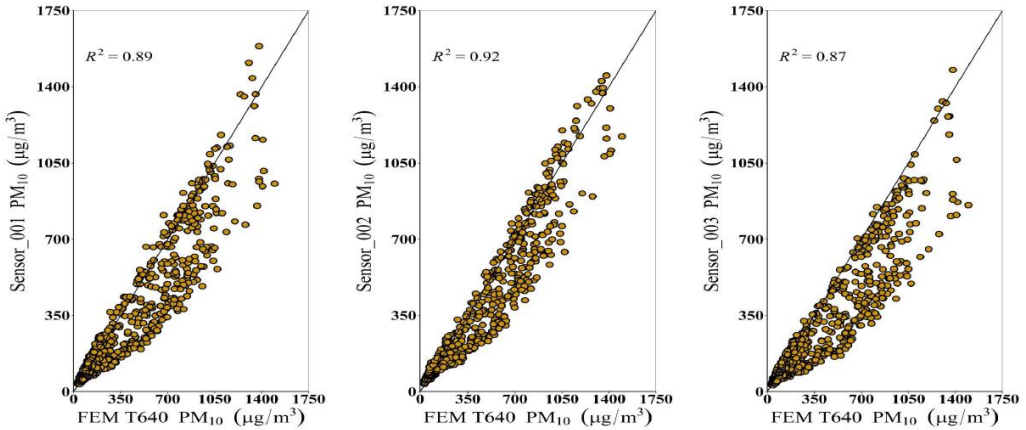
BEST ACCURACY FOR PM2.5

Independent Sensor Evaluations

AFRISET Evaluation

https://afriset.org/evaluations

KunakAir vs FEM T640 PM_{10} (Dry Period, 1 hour mean)



- Hourly PM_{10} data from all the KunakAir sensors exhibited a strong correlation (R^2 = 0.87 to 0.92) with the PM_{10} data from the FEM T640 monitor during the dry period

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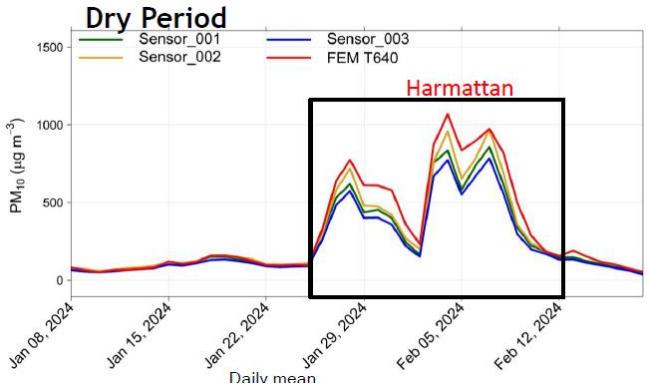


Gas sensors – Under evaluation

Independent Sensor Evaluations

USEPA Protocols

https://www.epa.gov/air-sensor-toolbox/air-sensor-performance-targets-and-testing-protocols

Laboratory Chamber Testing

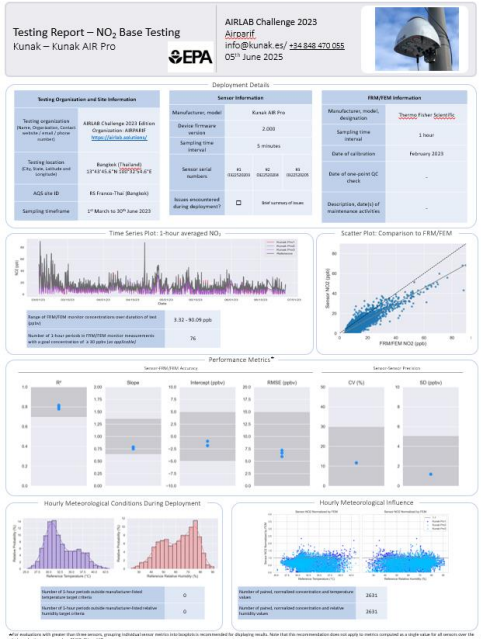
Enhanced Testing
Effect of Interferents
Effect of RH
Effect of T
Drift (Day 1)

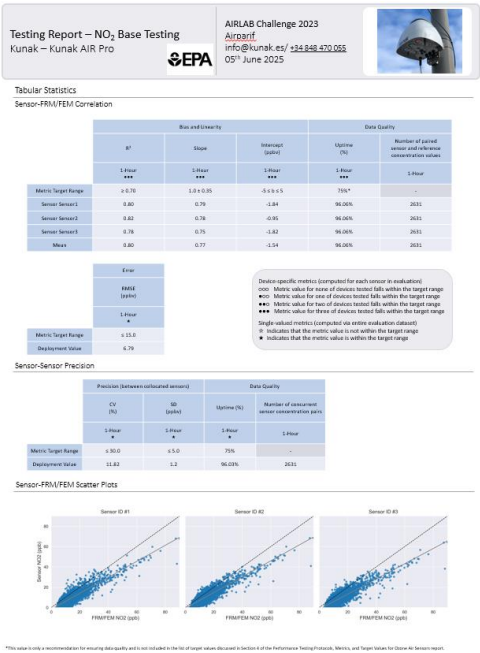
Enhanced Testing
Drift (Day 60)
Accuracy at high concentration

Outdoor Ambient Air Testing

Base Testing
Field Deployment 1

Base Testing
Field Deployment 2

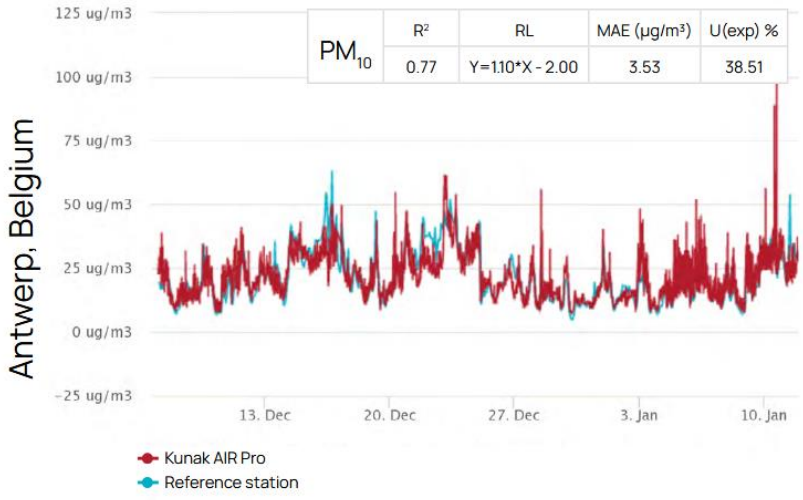


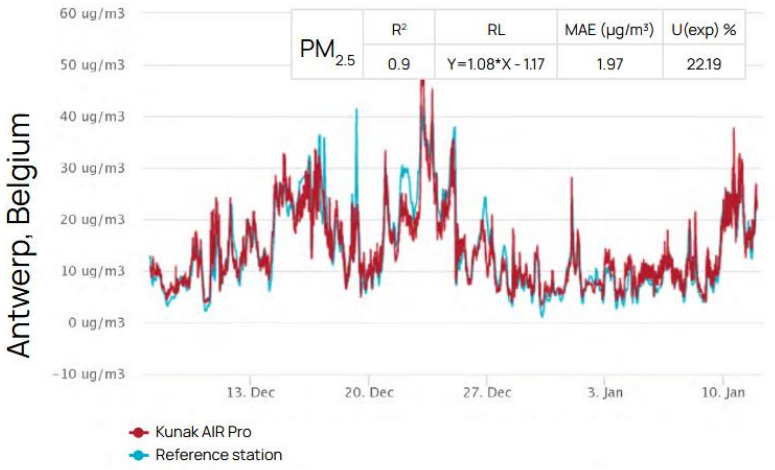


MCERTS Certification – PM sensor Indicative Measuremtns

https://www.csagroup.org/en-gb/services/mcerts/mcerts-product-certification/mcerts-certified-products/mcerts-certified-products-indicative-ambient-particulate-monitors/?srsltid=AfmBOorh1iHqmli_zPPBplT9OnsfeEvNRvTaGd3l6qyvLIT9DdHdTRkd

Kunak AIR Pro obtained MCERTS certification in 2023



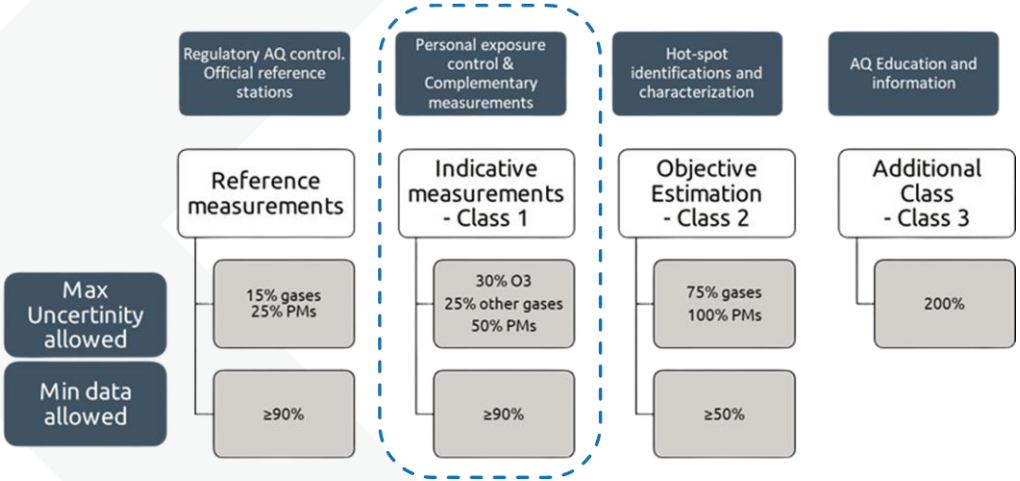


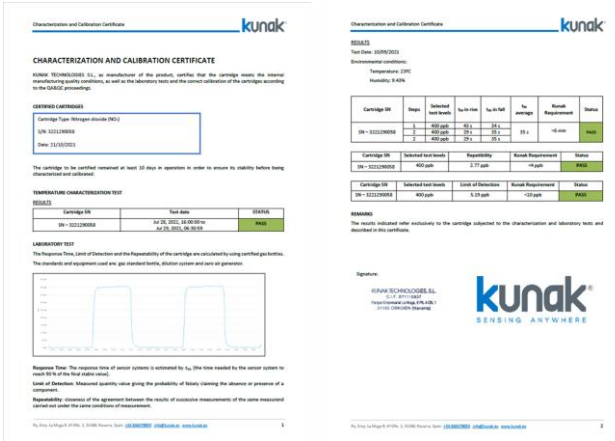
Independent Sensor Evaluations

CEN/TC264 – WG42

CEN/TS 17660-1:2021 “Air quality - Performance evaluation of air quality sensor systems - Part 1: Gaseous pollutants in ambient air”.

CEN/TS 17660-2:2024 “Air quality - Performance evaluation of air quality sensor systems - Part 2: Particulate matter in ambient air ».





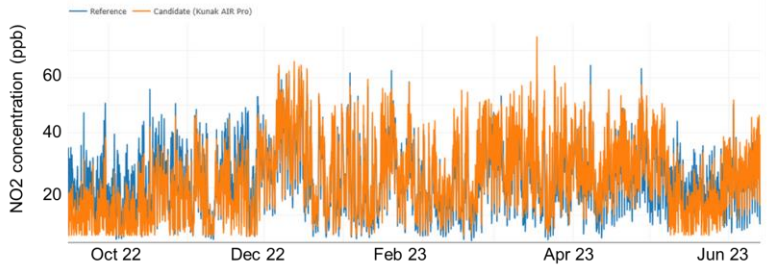
Kunak Calibration Certificate

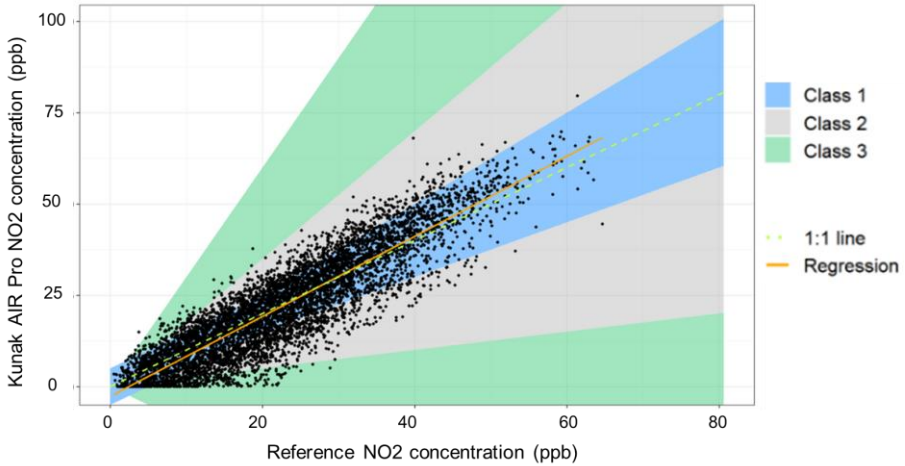
Independent Sensor Evaluations

RICARDO – Environmental Consultancy

CEN/TS 17660-1:2021 Metrics

Kunak AIR Pro and Lite: **NO_2, PM_{10} and $PM_{2.5}$** sensors would have been classified as **Class 1**





Key Takeaways

- Low-cost sensors can reach near-reference performance
- Deterministic, ISM-based calibration outperforms opaque ML models
- Kunak's ISM approach ensures *true measurement*, not prediction
- Proven performance through independent evaluations
- Reliable data → confident decision-making
- Continuous improvement and innovation remain essential

Looking for more insights?

Feel free to reach out!

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