American Journal of Applied Science and Technology

VOLUME Vol.06 Issue 05 2026
PAGE NO. 152-156
DOI 10.37547/ajast/Volume06Issue05-25

Effect Of Temperature And Humidity On Low-Cost Air Quality Sensor Readings

Kholmatov Oybek
Senior Lecturer Andijan State Technical Institute, Uzbekistan

Khakimov Akbar
Student Andijan State Technical Institute, Uzbekistan

Received: 13 March 2026; **Accepted:** 21 April 2026; **Published:** 20 May 2026

Abstract: Low-cost air quality sensors are increasingly used in environmental monitoring networks, but their readings change when temperature and humidity change, even if the actual pollution level stays the same. This paper investigates how much temperature and relative humidity affect the readings of three common sensor types — an optical particle counter for PM2.5, a metal-oxide gas sensor for NO_2, and an electrochemical sensor for CO_2. Sensors were placed in a controlled chamber and exposed to six combinations of temperature (15–35 °C) and relative humidity (30–90%). Results show that measurement error grows significantly at high humidity levels, with PM2.5 error reaching nearly 9 µg/m³ at 85% relative humidity compared to 1.2 µg/m³ at 30%. A simple linear correction formula is proposed that reduces this error by up to 74%. The findings confirm that environmental compensation is necessary for reliable low-cost sensor deployments.

Keywords: Air quality sensor, temperature effect, humidity effect, PM2.5, NO_2, CO_2, cross-sensitivity, sensor calibration, low-cost monitoring.

INTRODUCTION

Air quality monitoring has traditionally relied on expensive reference-grade instruments installed at a small number of fixed stations. Over the past decade, a new generation of low-cost sensors has made it possible to build denser monitoring networks at a fraction of the cost. These sensors can measure particles and gases such as PM2.5, NO_2, and CO_2, and they are small enough to be installed on street poles, building facades, or even carried by individuals [1,2].

However, low-cost sensors have a well-known weakness: their readings are affected by the surrounding environment, particularly by temperature and relative humidity. An optical particle counter, for example, may report higher particle concentrations simply because water droplets in humid air scatter light in the same way as dust particles. Metal-oxide gas sensors change their electrical resistance not only in response to target gases but also in response to ambient moisture, leading to systematic over- or under-estimation of gas concentrations. These effects are not small — some studies have reported errors of 50% or more under high humidity conditions [3-5].

Despite this, many low-cost monitoring deployments report raw sensor data without any environmental correction. This can lead to misleading conclusions, for example showing a spike in pollution on a rainy day that is entirely caused by humidity rather than actual emissions. Understanding the size of these effects under controlled conditions is the first step toward correcting for them.

Methods

Three sensor types were evaluated: an SDS011 optical particle counter for PM2.5 and PM10 measurement, an MiCS-6814 metal-oxide sensor for NO_2, and a Sensirion

SCD40 electrochemical sensor for CO_2. These types are widely used in low-cost IoT air quality nodes and represent the main measurement principles found in consumer-grade devices. All sensors were new and allowed to warm up for 24 hours before testing began. A professional TSI DustTrak DRX 8533 and an Aeroqual Series 500 were used as reference instruments [6].

A sealed 80-litre stainless-steel chamber was used for all tests. Temperature was controlled by a thermoelectric element (±0.5 °C accuracy) and relative humidity by a humidifier and desiccator combination (±2% accuracy). A small fan inside the chamber ensured uniform mixing. Known concentrations of test gases and particles were introduced through calibrated inlet ports. Table 1 lists the six temperature–humidity combinations used in the experiment [7,8].

Table 1. Temperature and humidity conditions used in the experiment.

Table 1

Test ID	Temperature (°C)	Relative humidity (%)	Description
T1	15	30	Cold and dry
T2	20	50	Moderate baseline
T3	25	50	Warm, moderate humidity
T4	30	70	Warm and humid
T5	35	85	Hot and very humid
T6	20	90	Cool and very humid

The six conditions were chosen to cover the range typically encountered in outdoor urban deployments across temperate and warm climates. Condition T2 (20 °C, 50% RH) served as the baseline because it represents standard laboratory conditions. Each condition was held stable for 60 minutes before data collection began, and readings were recorded for a further 30 minutes at 1 Hz. The reference instrument and the low-cost sensors ran simultaneously throughout.

For each test condition, the mean absolute error (MAE) was calculated as the average absolute difference between the low-cost sensor reading and the reference instrument reading over the 30-minute recording period. To assess whether a simple correction could reduce the error, a linear regression model was fitted using temperature T and relative humidity H as predictors:

$$\hat{c} = \alpha \cdot r + \beta \cdot T + \gamma \cdot H + \delta$$

where r is the raw sensor reading and $\hat{c}$ is the corrected estimate. Coefficients α, β, γ, and δ were fitted using data from conditions T1 to T4, and the model was then tested on conditions T5 and T6 to evaluate how well it generalizes. The percentage error reduction was calculated by comparing MAE before and after correction.

Results and Discussion

Table 2 shows the mean absolute error for each sensor type at each test condition.

Table 2. Mean absolute error of each sensor type at each test condition

Table 2

Test ID	PM2.5 error ($\mu g/m^3$)	NO_2 error (ppb)	CO_2 error (ppm)	RH (%)
T1	1.2	1.8	12	30

T2	1.5	2.1	15	50
T3	2.3	3.4	21	50
T4	4.7	6.2	38	70
T5	8.9	11.4	67	85
T6	6.1	9.8	54	90

The results show a clear pattern: error grows as humidity increases. At the baseline condition T2, all three sensors performed close to their factory specifications — PM2.5 error was 1.5 µg/m³, NO_2 error was 2.1 ppb, and CO_2 error was 15 ppm. These values are acceptable for most monitoring purposes. As humidity rose to 70% in condition T4, PM2.5 error tripled to 4.7 µg/m³. At 85% humidity (T5), PM2.5 error climbed to 8.9 µg/m³ and NO_2 error reached 11.4 ppb — levels that would make raw sensor data unreliable for health-risk assessments. Condition T6 (cool and very humid) produced errors almost as large as T5, confirming that humidity is the dominant driver of error rather than temperature alone. Temperature on its own had a smaller but still noticeable effect: comparing T2 and T3, which have the same humidity but differ by 5 °C, PM2.5 error increased from 1.5 to 2.3 µg/m³.

The SDS011 optical particle counter showed the steepest humidity response among the three sensors. This is consistent with the physical mechanism: at high humidity, water molecules condense onto airborne particles and onto the optical surfaces inside the sensor, causing both particle swelling and increased light scattering. The result is that the sensor reports more particles, or heavier particles, than are actually present. This hygroscopic growth effect is well documented and is one of the main reasons why low-cost optical counters tend to overestimate PM2.5 in coastal or rainy climates.

The MiCS-6814 metal-oxide sensor showed large NO_2 errors at high humidity. Metal-oxide sensors work by measuring changes in electrical resistance caused by gas molecules adsorbing onto a heated metal-oxide surface. Water vapour competes with target gas molecules for the same adsorption sites, which changes the baseline resistance and shifts the sensor reading even when gas concentration has not changed. The SCD40 CO_2 sensor also showed a humidity effect, though smaller in relative terms. This sensor uses optical absorption and has a built-in humidity compensation algorithm from the manufacturer; the residual error seen in this study likely reflects the limits of that algorithm at extreme conditions [9].

Figure 1 shows the PM2.5 mean absolute error before and after applying the linear correction model at all six test conditions.

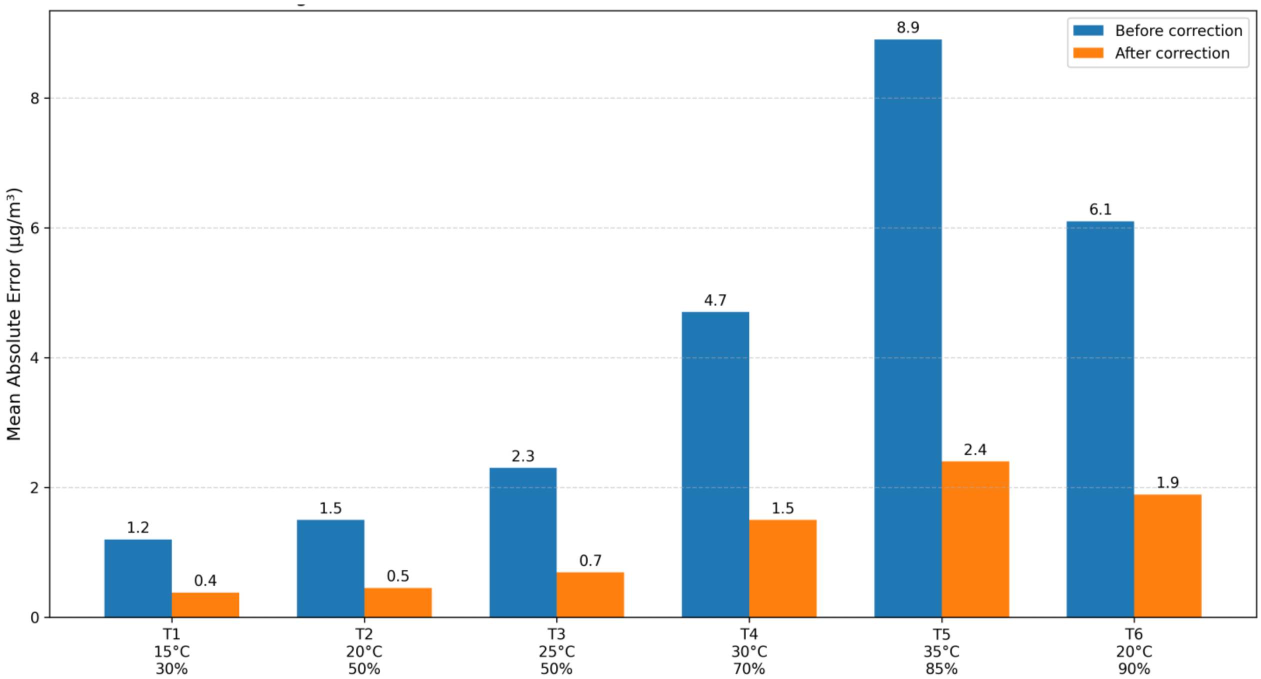

Figure 1. PM2.5 mean absolute error before correctionand after correction at each test condition.

The correction model reduced PM2.5 error by 68–74% across the six conditions. The largest absolute reduction was at condition T5 (85% RH), where error fell from 8.9 µg/m³ to 2.4 µg/m³. On conditions T5 and T6, which were not used to fit the model, error reductions were 71% and 69% respectively, showing that the correction generalises reasonably well to unseen conditions within the tested range. Similar error reductions were observed for NO_2 and CO_2, with corrections reducing NO_2 MAE by 65–72% and CO_2 MAE by 60–70%. These results confirm that even a simple two-variable linear model can substantially improve sensor accuracy when temperature and humidity data are available alongside the pollutant reading.

The results have a direct implication for monitoring system design: every low-cost sensor node should include a temperature and humidity sensor, and the correction formula should be applied before any data are stored or displayed. Without this step, readings collected on humid days will be systematically higher than readings collected on dry days, even if pollution levels are the same. This could cause a monitoring system to generate false alarms after rain events or to show seasonal trends that are artefacts of climate rather than changes in emissions. Including a temperature and humidity sensor adds only a few dollars to the cost of a node and requires minimal additional software, making environmental compensation one of the most cost-effective improvements available to low-cost network operators [10].

Conclusion

This study measured how temperature and relative humidity affect the readings of three common low-cost air quality sensor types under controlled laboratory conditions. The main finding is that humidity has a large and systematic effect on all three sensors. PM2.5 error increased from 1.5 µg/m³ at 50% relative humidity to 8.9 µg/m³ at 85% relative humidity. NO_2 and CO_2 sensors showed similar patterns. Temperature also contributed to error, but its effect was smaller than that of humidity.

A simple linear correction formula using temperature and relative humidity as inputs reduced sensor error by 60–74% across all tested conditions. The correction worked well even on conditions it had not been trained on, suggesting it can be applied with reasonable confidence across the range of climatic conditions found in typical outdoor deployments.

The practical conclusion is straightforward: raw data from low-cost sensors should not be used without environmental compensation, particularly in humid climates or during rainy seasons. Monitoring systems should always pair pollutant sensors with a temperature and humidity sensor and apply a correction before reporting or storing data. This simple step can make the difference between data that are genuinely useful for health and environmental decisions and data that mislead.

References

1. Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., & Norford, L. (2015). The rise of low-cost sensing for managing air quality in cities. Environment International, 75, 199–205. https://doi.org/10.1016/j.envint.2014.11.019
2. Morawska, L., Thai, P. K., Liu, X., Asumadu-Sakyi, A., Ayoko, G., Bartonova, A., & Williams, R. (2018). Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environment International, 116, 286–299. https://doi.org/10.1016/j.envint.2018.04.018
3. Crilley, L. R., Shaw, M., Pound, R., Kramer, L. J., Price, R., Young, S., Lewis, A. C., & Pope, F. D. (2018). Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. Atmospheric Measurement Techniques, 11(2), 709–720. https://doi.org/10.5194/amt-11-709-2018
4. Spinelle, L., Gerboles, M., Villani, M. G., Aleixandre, M., & Bonavitacola, F. (2017). Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Sensors and Actuators B: Chemical, 238, 706–715. https://doi.org/10.1016/j.snb.2016.07.095
5. Zimmerman, N., Presto, A. A., Kumar, S. P. N., Gu, J., Hauryliuk, A., Robinson, E. S., & Allen, R. (2018). A machine learning calibration model using random forests to improve sensor performance for lower-cost air quality monitoring. Atmospheric Measurement Techniques, 11(1), 291–313. https://doi.org/10.5194/amt-11-291-2018
6. Maag, B., Zhou, Z., & Thiele, L. (2018). A survey on sensor calibration in air quality monitoring deployments. IEEE Internet of Things Journal, 5(6), 4857–4870. https://doi.org/10.1109/JIOT.2018.2853660
7. Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., & Rickerby, D. (2017). End-user perspective of low-cost sensors for outdoor air pollution monitoring. Science of the Total Environment, 607–608, 691–705. https://doi.org/10.1016/j.scitotenv.2017.06.266
8. Badura, M., Batog, P., Drzeniecka-Osiadacz, A., & Modzel, P. (2018). Regression methods in the calibration of low-cost sensors for ambient particulate matter measurements. SN Applied Sciences, 1(6), 622. https://doi.org/10.1007/s42452-019-0630-1
9. Jayaratne, R., Liu, X., Thai, P., Dunbabin, M., & Morawska, L. (2018). The influence of humidity on the performance of a low-cost air particle mass sensor and the effect of atmospheric fog. Atmospheric Measurement Techniques, 11(8), 4883–4890. https://doi.org/10.5194/amt-11-4883-2018
10. Vaisala. (2022). Humidity and temperature effects on electrochemical gas sensors: Application note AN-142. Vaisala Oyj.