



1 **Community Air Sensor Network (CAIRSENSE) project:**
2 **Evaluation of low-cost sensor performance in a suburban**
3 **environment in the southeastern United States**

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20 **Abstract.** Advances in air pollution sensor technology have enabled the development of small
21 and low cost systems to measure outdoor air pollution. The deployment of a large number of
22 sensors across a small geographic area would have potential benefits to supplement traditional
23 monitoring networks with additional geographic and temporal measurement resolution, if the
24 data quality were sufficient. To understand the capability of emerging air sensor technology,
25 the Community Air Sensor Network (CAIRSENSE) project deployed low cost, continuous and
26 commercially-available air pollution sensors at a regulatory air monitoring site and as a local
27 sensor network over a surrounding ~2 km area in Southeastern U.S. Co-location of sensors
28 measuring oxides of nitrogen, ozone, carbon monoxide, sulfur dioxide, and particles revealed
29 highly variable performance, both in terms of comparison to a reference monitor as well as
30 whether multiple identical sensors reproduced the same signal. Multiple ozone, nitrogen
31 dioxide, and carbon monoxide sensors revealed low to very high correlation with a reference
32 monitor, with Pearson sample correlation coefficient (r) ranging from 0.39 to 0.97, -0.25 to
33 0.76, -0.40 to 0.82, respectively. The only sulfur dioxide sensor tested revealed no correlation
34 ($r < 0.5$) with a reference monitor and erroneously high concentration values. A wide variety
35 of particulate matter (PM) sensors were tested with variable results – some sensors had very
36 high agreement (e.g., $r = 0.99$) between identical sensors, however moderate agreement with a
37 reference PM_{2.5} monitor (e.g., $r = 0.65$). For select sensors that had moderate to strong



1 correlation with reference monitors ($r > 0.5$), step-wise multiple linear regression was
2 performed to determine if ambient temperature, relative humidity (RH), or age of the sensor in
3 sampling days could be used in a correction algorithm to improve the agreement. Maximum
4 improvement in agreement with a reference, incorporating all factors, was observed for an NO₂
5 sensor (multiple correlation coefficient $R^2_{\text{adj-orig}} = 0.57$, $R^2_{\text{adj-final}} = 0.81$); however, other sensors
6 showed no apparent improvement in agreement. A four-node sensor network was successfully
7 able to capture ozone (2 nodes) and PM (4 nodes) data for an 8 month period of time and show
8 expected diurnal concentration patterns, as well as potential ozone titration due to near-by
9 traffic emissions. Overall, this study demonstrates a straightforward methodology for
10 establishing low-cost air quality sensor performance in a real-world setting and demonstrates
11 the feasibility of deploying a local sensor network to measure ambient air quality trends.

12 **1 Introduction**

13 Air quality monitoring, including measurements of common gas-phase and particulate matter
14 pollutants, has traditionally been conducted by regulatory organizations using specific
15 instrumentation and protocols. For example, the United States Environmental Protection
16 Agency (EPA) monitors criteria pollutants under the National Ambient Air Quality Standards
17 (NAAQS) via a network of ambient monitoring sites operating Federal Reference Methods
18 (FRM) or Federal Equivalent Methods (FEM). FRM and FEM designation for instruments is
19 established through a strict testing protocol (Hall et al., 2014) and the overall network produces
20 very high quality data, however generally sparse in geographic coverage.

21
22 Meanwhile, numerous field studies have established that outdoor air pollution can vary
23 considerably at a fine spatial scale due to localized impacts of source emissions (e.g., Karner et
24 al., 2010). Recent and fast-paced technology development has brought to the market portable
25 and low-cost air sensor devices that may have potential to provide hyper-local air quality data
26 through individual use or application in a dense sensor network (Jovasevic-Stojanovic et al.,
27 2015;Kumar et al., 2015;Snyder et al., 2013). Low-cost sensor devices, defined here as below
28 \$2000 USD per pollutant (i.e., under \$4000 USD for a two-pollutant device, and so on),
29 typically utilizing electrochemical or metal oxide sensors for gas-phase pollutants such as
30 carbon monoxide (CO), nitrogen dioxide (NO₂), nitrogen oxide (NO), ozone (O₃), and to some
31 extent, total volatile organic compounds (VOCs). Commercially-available particle sensor
32 devices currently use laser-based or light-emitting diode (LED)-based optical detection of



1 particles. Currently, no direct-mass measurement of particulate matter is commercially
2 available, however ongoing research is in progress to develop a true mass measurement
3 (Paprotny et al., 2013).

4

5 Research groups have built custom devices using available original equipment manufacturer
6 (OEM) sensor components - such as the integration of the particulate PPD42NS sensor
7 (Shinyei) into field-ready devices (Gao et al., 2015;Holstius et al., 2014;Johnson et al., in
8 review) – which generally involves adding an enclosure, microprocessor, battery or AC
9 electricity connection, wireless communications and/or on-board data storage, and potentially
10 other environmental sensors. Most research groups working with low cost OEM sensors have
11 tested their sensor performance in field settings, with varying results. For particulate sensors,
12 PPD42NS sensor comparison at low to moderate ambient concentrations revealed good
13 correlation with a reference monitor (Holstius et al., 2014), however the same particle sensor at
14 very high concentrations had nonlinear response and authors used high-order model fits to
15 correct their data (Gao et al., 2015). A modified commercially available particle sensing device
16 (Dylos) was shown to compare closely with a research grade monitor in low ambient
17 concentrations (Northcross et al., 2013).

18

19 Results of gas-sensor performance in real-world environments have also had promising but
20 variable results. Spinelle et al. (2015) used multiple statistical approaches to maximize the data
21 quality from O₃ and NO₂ sensors, finding a simple linear regression for an electrochemical
22 ozone sensor was sufficient to achieve strong correlation with a reference monitor, however
23 even advanced supervised learning strategies were not able to achieve strong correlation for
24 NO₂ sensors. Mead et al. (2013) noted a 100% ozone interference issue for an electrochemical
25 NO₂ sensor, which could be corrected by sampling both parameters simultaneously.

26

27 Researchers are already employing low cost sensors in exploratory research, to assess spatial
28 variability of urban air quality (Gao et al., 2015;Heimann et al., 2015;Moltchanov et al., 2015),
29 and the growing number of commercially-available devices is anticipated to create an
30 exponential increase in air quality data. The consumer product potential has motivated a
31 number of new business ventures, some initiated through crowd-sourced funding (e.g.,
32 Kickstarter, Indiegogo). Sensor developers are also looking to engage directly with the public,
33 with one innovative group providing particle sensors at a public library for citizens to borrow



1 for their personal use (Page-Jacobs, 2015). While the public interest is quickly growing, the
2 quality of the air sensor data remains uncertain, particularly for commercial devices that may
3 be utilized by citizens and community groups without access to reference monitoring sites for
4 collocation. In order to better understand the performance of commercially available air sensor
5 devices, EPA established the Community Air Sensor Network (CAIRSENSE) project, which
6 involves testing the feasibility of a wireless sensor network application as well as extensive
7 collocation of multiple identical sensor devices with reference monitors over an extended
8 period of time. The CAIRSENSE project is a multi-year effort, involving field testing emerging
9 air quality sensors in multiple locations in the United States, including Decatur, Georgia;
10 Denver, Colorado; and Research Triangle Park, North Carolina. This paper presents the
11 CAIRSENSE testing results of a variety of particulate and gas sensors in a suburban
12 environment of Decatur, Georgia, which is located in the southeastern United States, from
13 August, 2014 to May, 2015.

14 **2 Methodology**

15 **2.1 Field study design**

16 Two main testing components –the sensor ad-hoc field testing (SAFT) and the wireless sensor
17 network (WSN) – were included in the CAIRSENSE project (Fig. 1). The SAFT involved a
18 minimum 30 day testing period of duplicate or triplicate sensors located at a state regulatory
19 monitoring site. Meanwhile, the WSN involved long-term (> 7 months) deployment of several
20 selected sensors in multiple locations over an approximately 1 mi² spatial range. With the
21 overarching goal to test sensors with potential near-term wide use, candidate sensors were
22 selected based upon several criteria and market research. Criteria pollutants – including
23 particulate matter (PM), carbon monoxide (CO), nitrogen dioxide (NO₂), sulfur dioxide (SO₂),
24 and ozone (O₃) – were given priority in sensor type selection. Other sensor selection criteria
25 included a general upper cost limit at \$2000 per pollutant (e.g., \$2000 for a single pollutant
26 sensor device, \$4000 for a two-pollutant sensor device, etc.), commercial availability,
27 continuous measurement, and low maintenance. The SAFT sensor set included five types of
28 PM sensors (Shinyei, Dylos, Airbeam, MetOne, and Air Quality Egg), three types of ozone
29 sensors, three types of NO₂ sensors, two types of CO sensors, and one SO₂ sensor (Table 1).

30



1 The SAFT component included two or three identical sensor devices co-located and operated
2 on 115 V AC power. The sensors were placed in a shelter providing full exposure to ambient
3 air while also protecting from rainfall (Fig. 1 A and D). To understand the basic sensor device
4 functionality, each SAFT sensor was operated according to manufacturer's recommendations
5 and data were output in their default format. For example, PM sensors reported concentrations
6 in a variety of units including $\mu\text{g}/\text{m}^3$, pt/0.01cf (particles per 0.01 cubic feet or 283 ml), and
7 hppcf (hundreds of particles per cubic feet). For one sensor – the Air Quality Egg – units were
8 unclear for gas measurements and the data output appeared to be raw voltage signals. All SAFT
9 sensor data were logged locally to the extent possible – for sensors which were designed to
10 transmit data primarily to an internet server (AirBeam, Air Quality Egg), a microprocessor code
11 variation was written to support local logging. One exception was the AQMesh, a commercial
12 system that utilizes multiple electrochemical sensors to measure gases and wirelessly transmits
13 the data to the manufacturer's server. In this case, the data were provided to the research team
14 from the manufacturer on a weekly basis during the field study. The AQMesh data analyzed
15 were already post-processed by manufacturer proprietary algorithms prior to analysis.

16

17 In addition, four WSN nodes plus one base communications station were deployed to test the
18 feasibility of deploying a local wireless sensor network. The CAIRSENSE network was
19 designed based on a star topology with the NCore (National Core) location serving as the base
20 station, while every other node connects to it. The design goal was for all of the nodes to
21 wirelessly report their data in near real time to the base station, then data subsequently were
22 transmitted to a server through cellular communication. Digi's Xbee-PRO 900HP 900 MHz 10
23 Kbps radios were chosen as the backbone of the WSN based on their relative low cost and
24 extended line-of-sight range. An omnidirectional antenna was selected for the base station while
25 directional Yagi antennas were chosen for the remote nodes. Prior to the field deployment, the
26 communication protocol and wireless range were tested between a remote node and the base
27 station. Range tests were conducted in a mixed suburban environment in North Carolina with
28 conditions similar to those found surroundings the NCore station. While the manufacturer lists
29 a line-of-sight range of up to 9 miles for the selected Xbee radios, actual tests indicated a
30 maximum communication range of approximately 1 mile with mixed open, forested, and
31 commercial buildings located between the radios.

32



1 The WSN nodes were designed to be small, weatherproof, and self-powered. The compact
2 size was important to facilitate deployment and minimize the installed footprint. Each WSN
3 node consisted of a weatherproof enclosure that was approximately a 0.4 x 0.4 x 0.15 m in
4 size, supporting several low cost (< \$1000) sensors (PM_{2.5}, O₃, NO₂), an Arduino based
5 microcontroller, micro SD card, Xbee wireless radio, Xbee antenna, solar panel, solar power
6 controller, and a 12 VDC battery. A photo of a typical node is shown in Fig. 1 with
7 components listed in Table 2. Like the remote nodes, the base station had an Arduino
8 microcontroller and Xbee radio to receive signals from the nodes and an SD card for on-board
9 data logging. The base node included a Sierra Airlink® GX440 cellular gateway and
10 associated antenna to connect the base node to the internet. Data were uploaded and stored on
11 a remote server in a Microsoft SQL database and displayed on private webpage that updated
12 every minute. The webpage displayed the data in a tabular format and supported direct data
13 downloading. The communication base station and the sensor node 4 collocated at the NCore
14 site used 120 V (nominal) AC electricity, while the remaining satellite stations (nodes 1-3)
15 operated on solar power with battery backup.

16

17 Preliminary review after WSN deployment revealed brief spurious PM readings (e.g., 10 to 50
18 times higher than FEM) that occurred during mid-day, which appeared to be caused by side-
19 scattered sunlight intrusion to the Shinyei sensor. As an experimental measure, aluminum foil
20 was placed surrounding the radiation shielding that encompassed the sensor to reduce light
21 penetration, while still allowing the sensor to have access to ambient air. After foil was
22 applied, very high values were greatly reduced (Fig. A-4); therefore, the foil covers were left
23 in place for the remainder of the WSN data collection.

24 **2.2 Study location**

25 The State of Georgia South Dekalb regulatory monitoring site is located in the suburban Atlanta
26 area Decatur (AQS ID: 130890002; Latitude/Longitude: 33.68808/-84.29018), The South
27 Dekalb station is operated year-round as an NCore multipollutant monitoring network site and
28 includes an extensive suite of measurements including criteria pollutants and precursors, air
29 toxics, and meteorology. The surrounding area has mature trees, single-family residential
30 houses, sports fields, and schools (Fig. 2). No known major point source emissions were located
31 nearby. A nearby highway (I-285; 145,000 annual average daily traffic) is located
32 approximately 400 m to the north of the site.



1

2 The SAFT component was located only at the NCore site. The WSN nodes were located in the
3 surrounding area. Node 1 (WSN-N1) was positioned at a nearby medical center (~1.2 miles
4 from the South Dekalb) and about 30 meters away from the major highway. Node 2 (WSN-N2)
5 was near a sports field (~0.5 mile from the South Dekalb). Node 3 (WSN-N3) was outside a
6 school property (~0.1 mile from the South Dekalb). Node 4 (WSN-N4) and the communications
7 base station were co-located with the NCore site.

8 **2.3 Analytical methods**

9 Sensor data were checked and analysed bi-weekly during the first three months to ensure all
10 sensors were working properly. Subsequently, data was recovered on a monthly basis. The
11 statistical software R (<http://www.r-project.org/>) version 3.2.1 with the “base” and “openair”
12 packages was used for all data processing and analysis. Multiple sensors reporting the same
13 pollutant of interest were compared against readings recorded by the NCore federal equivalent
14 methods (FEM). For duplicate or triplicate sensors evaluated in SAFT, readings were compared
15 between identical sensors to understand the reproducibility of sensor performance. Several
16 statistical measures are used to compare the co-located sensor measurements with the FEM
17 data, including: 1) the Pearson sample correlation coefficient (r) between individual sensor and
18 FEM; 2) the average values of sensor and FEM measurements in their original units; and, 3)
19 the slope, intercept, and coefficient of determination (r^2) of ordinary least squares (OLS)
20 regressions of individual sensor measurement on FEM. In addition, to enable basic comparison
21 of PM values with a reference monitor, data from PM sensors that had at least moderate
22 correlation ($r > 0.5$) were converted to $\mu\text{g}/\text{m}^3$ units based on upon an OLS regression equation.
23 Local meteorology was anticipated to be a driver of spatial variability in local pollutant trends
24 as well as potentially affecting sensor performance, as some sensors may have temperature
25 and/or humidity-based artifacts. The NCore wind, temperature, and humidity data were used as
26 the benchmark for comparison. In addition, sensor aging is another potential factor causing a
27 measurement factor – for example, solid-state gas sensors may undergo a loss of sensitivity
28 over time. Therefore, the sensor measurements were compared with FEM by number of days
29 measured to determine if an aging effect existed. Similar to the analysis by Holstius et al.
30 (2014), artifact effects are assessed by comparing the adjusted regression coefficients (R^2_{adj})
31 among multiple linear regressions of all possible variable combinations.

32



1 For the WSN, the first step of the analysis was to conduct an experimental approach at a network
2 calibration, where data were subset for a period presumed to be representative of similar
3 atmospheric conditions at all sites – namely, hours of 01:00-04:00 am and during periods with
4 wind upwind of the highway (wind direction from 75-235 degrees). For this study, all data
5 representing those conditions were grouped and compared with FEM, with OLS regressions
6 conducted by having FEM values as the dependent variable and sensor values as the
7 independent variable, which yielded a regression equation that was used to convert individual
8 sensor values to the corresponding FEM units. For sensors revealing at least marginal
9 agreement with FEM data ($r > 0.4$), exploratory analyses are presented showing node-to-node
10 comparison in trends.

11

12 While the EPA has a clearly defined method for approving technologies for use in a regulatory
13 application (e.g., Hall et al., 2014), there currently are no clearly defined nor universally
14 accepted criteria by which to provide a “pass” or “fail”, or alternative grading scheme,
15 judgement on a particular sensor model. Developing such criteria will be challenging, given
16 the diversity of research applications and related data quality objectives. In addition, sensor
17 performance may be affected by both the air pollutant mixture and concentration level, as well
18 as the environmental conditions. Therefore, the results in this paper are communicated
19 quantitatively by their correlation, or lack thereof, in comparison to regulatory-grade monitors.

20 **3 Results and Discussion**

21 Sensor field testing and the wireless sensor network were conducted over a wide range of
22 atmospheric conditions. The South Dekalb NCore site measured ambient temperature from -
23 12 to 33°C during the CAIRSENSE deployment, with an average of 14 °C. Meanwhile, the
24 RH varied from 11 to ~100%, with an average of 68%.

25 **3.1 Particle sensor evaluation**

26 All particle sensors evaluated detected particles via a light-scattering method. No sensors
27 directly measured particulate mass nor had defined size cuts preventing large particles from
28 entering the optical cell. Based on the project goal of understanding whether these types of
29 low cost sensor data could be indicative of fine particulate matter ($PM_{2.5}$) trends, a
30 comparison against the FEM $PM_{2.5}$ monitor, MetOne BAM 1020, is utilized. FEM monitors
31 are designed according to their application for use in determining compliance with the US



1 EPA National Ambient Air Quality Standards (NAAQS), which are at a 24-hour or annual
2 time basis. The beta-attenuation approach utilized in the MetOne requires having sufficient
3 particle mass deposited to the internal filter for an adequate signal to noise ratio. Given that
4 research applications of PM sensors may desire to use the data at a sub-daily time interval,
5 preliminary analysis was conducted to determine whether the raw MetOne BAM 1020 data
6 could be used at a faster time resolution than 24 hours, resulting in 12 hour averaging period
7 utilized for the FEM PM_{2.5} data comparisons.

8
9 Summarized in Table 3, the various particle sensors had widely variable initial output
10 quantities and correlation with the FEM monitor. The three collocated Air Quality Egg units,
11 with internal Shinyei PPD42NS sensors, had poor correlation with the FEM ($r = -0.06$ to
12 0.40). The three MetOne 831 monitors also had weak correlation ($r = 0.32$ to 0.41). The
13 three Shinyei PM sensors had moderate agreement ($r = 0.45$ - 0.60), followed by relatively
14 higher correlation by the AirBeam ($r = 0.65$ - 0.66), and Dylos units ($r = 0.63$ - 0.67 for the
15 PRO-PC version, $r = 0.58$). Comparison of identical sensors revealed generally highest
16 agreement (Fig. A-1) – for example, while the three MetOne monitors had weak correlation
17 with the FEM, they had nearly perfect correlation between identical units ($r = 0.99$). This
18 finding suggests that some sensor sets may have excellent precision supporting use to
19 evaluate relative concentration levels, however caution must be exercised in presuming the
20 resulting measurements are representative of PM_{2.5} reference measurements. Some factors
21 that likely contribute to the strong agreement among optical particle sensors, but weaker
22 agreement with PM_{2.5} FEM monitors, includes the following: differing physicochemical
23 properties between calibration aerosol and real-world aerosol mixtures, light-scattering signal
24 by particles larger than $2.5\ \mu\text{m}$, and for some sensors, particle count as the reported value
25 which generally emphasizes the numerous but smallest detected particles.

26

27 Several particle sensors with at least fair correlation ($r > 0.5$) were further investigated for
28 artifacts based upon temperature, humidity, or days of use. For three selected sensors that
29 showed the highest correlation with FEM among identical sensors– the Shinyei SAFT-2,
30 Dylos SAFT-2, and Airbeam SAFT-2 – incorporation of artifacts such as temperature, RH,
31 and number of measurement days made some minor improvements in agreement with the
32 FEM as indicated by R^2_{adj} values from the multiple linear regression analysis (Table 5). No
33 single factor provided much improvement to the Shinyei or Airbeam sensor agreement.



1 However, accounting for days of use significantly increased the Dylos unit R^2_{adj} by 0.11, but
2 incorporation of RH revealed no improvement and temperature revealed only minor
3 improvement (+0.03 in R^2_{adj}).

4 **3.2 Gas-phase sensor evaluation**

5 Gas-phase sensor measurements of O_3 , NO_2 , NO , CO , and SO_2 were compared with hourly
6 average NCore reference monitors (Table 4). Of all the sensors discussed, the CairClip NO_2/O_3
7 sensor is unique in having a single data value output that nominally represents the addition of
8 NO_2 plus O_3 . Therefore, CairClip NO_2 or O_3 values discussed represents the initial summation
9 minus a FEM reading (i.e., $\text{CairClip}_{\text{NO}_2} = \text{CairClip}_{\text{NO}_2/\text{O}_3} - \text{FEM}_{\text{O}_3}$; $\text{CairClip}_{\text{O}_3} = \text{CairClip}_{\text{NO}_2/\text{O}_3}$
10 $- \text{FEM}_{\text{NO}_2}$). Since CairClip readings were not calibrated with FEM, any negative values resulted
11 from the subtraction were kept in the correlation analysis. In addition, it should be noted that
12 two CairClip sensors at the SAFT site showed apparent operation failure at the outset of testing.
13 Sensor replacement was conducted in the mid-November for one sensor, which is included in
14 the analysis. The other failing sensor was deemed nonfunctional and is not incorporated into
15 further analysis.

16 **3.2.1 Ozone**

17 Of the ozone sensors tested, weak correlation was evident for two AQMesh units ($r = 0.39$ -
18 0.45), high for two CairClip sensors ($r = 0.82$ - 0.94), and consistently very high for three
19 Aeroqual SM50 sensors ($r = 0.91$ - 0.97) when compared to FRM/FEM measurements (Fig. A-
20 2). For the Aeroqual SM50 sensor, no apparent improvement in agreement was observed when
21 temperature, RH, or sampling day length factors were incorporated (Table 5). However,
22 incorporating RH appeared to provide some improvement (+0.07 in R^2_{adj}) to the CairClip sensor
23 agreement with a reference monitor.

24 **3.2.2 Nitrogen dioxide**

25 The CairClip, AQMesh, and Air Quality Egg measurements of NO_2 were highly variable
26 compared with a reference monitor, with r ranging from 0.42 to 0.76, 0.14 to 0.32, and -0.25 to
27 -0.22, respectively (Fig. A-3). Only one CairClip NO_2 sensor that had sufficient correlation
28 was further explored for artifact correction. Significant improvement was evident when
29 temperature and RH were incorporated as adjustment factors, with very slight additional
30 improvement by incorporating days of use (Table 5).



1 **3.2.3 Nitrogen oxide**

2 One sensor device – the AQMesh – was tested that reported NO measurements. The two
3 identical AQMesh units had very high agreement with the reference monitor ($r = 0.88-0.93$).
4 No apparent improvement in agreement was determined when incorporating environmental or
5 days of use as adjustment factors (Table 5). In absolute terms, the NO original sensor output
6 also agreed closely with mean FEM values (Table 4).

7 **3.2.3 Carbon monoxide**

8 The AQMesh and Air Quality Egg incorporated electrochemical and metal oxide CO sensors,
9 respectively. The AQMesh reported CO in ppb units, whereas the Air Quality Egg had no clear
10 indication of units. Good correlation ($r = 0.79-0.82$) was observed between the AQMesh and a
11 reference monitor. Incorporating days of use provided significant improvement in the AQMesh
12 CO data (Table 5), with a clear slope drift with time evident (Fig. 3). The Air Quality Egg CO
13 sensors had poor agreement with a reference ($r = -0.40$ to -0.14).

14 **3.2.4 Sulfur dioxide**

15 Only one sensor device was available that measured SO_2 – the AQMesh. The reported SO_2
16 values by the AQMesh were generally far higher than the reference monitor, on average a factor
17 of 172 and 163 higher. While the two AQMesh units had high correlation with one another for
18 SO_2 ($r = 0.94$), they had little correlation ($r = 0.13-0.17$) with a reference monitor.

19 **3.3 Sensor network**

20 **3.3.1 Data communications**

21 Based upon preliminary tests establishing an approximate 1 mile maximum range utilizing
22 XBee antennas for the direct point-to-point communication, the initial WSN installed
23 consisted of four nodes over a 1 mi^2 area transmitting data to the base node located at the
24 South Dekalb site. However, the location of several buildings and mature forest canopy in the
25 South Dekalb area limited the communication range of the network. Two of the WSN nodes
26 communicated reliably with the base station (nodes 3 and 4), whereas data from the more
27 distant Nodes 1 and 2 were not received. Therefore, data retrieval was conducted via manual
28 SD card downloads for Nodes 1 and 2. Some experimentation was conducted by adding a
29 repeater node mid-way between the base station and nodes 12, which had some success in



1 establishing communications between the two nodes but was unable to successfully transmit
2 data to the base station.

3 **3.3.2 Spatial and temporal trends**

4 Comparison of the hourly average WSN with FEM data during periods of time with
5 presumably similar pollution readings in all locations – hours of 01:00-04:00 AM and all sites
6 upwind of the highway – revealed moderate to good correlation between the WSN O₃ and
7 FEM O₃ (two nodes, $r = 0.62$ to 0.87) and WSN PM and FEM PM_{2.5} (four nodes, $r = 0.4$ to
8 0.45). While the CairClip total output compared well (two nodes, $r = 0.79$ to 0.9) with the
9 addition of FEM O₃ and NO₂ methods, the result was not replicated when isolating and
10 comparing the WSN NO₂ component. A simple subtraction of either the onboard O₃ sensor
11 data (SM50) or the FEM O₃ data from the CairClip total output revealed effectively no
12 correlation between WSN NO₂ and FEM NO₂ ($r < 0.1$). This finding indicates that the
13 CairClip NO₂/O₃ sensor readings may not be entirely additive and field performance may not
14 replicate the strong agreement observed in a laboratory evaluation (Williams et al., 2014).
15 Further evaluation is needed to understand how to separate the NO₂ portion of the signal.
16 Based on these results, analysis of spatial and temporal trends were constrained to O₃ and
17 PM_{2.5} sensor data sets.

18

19 After data were adjusted based upon linear regression analysis of WSN and FEM data sets
20 during the early morning and upwind time periods, wind directional plots indicated lower O₃
21 concentrations at the roadside site when air is transported from the highway (wind direction
22 from the N) with no directional signal observed at the site > 400 m from the highway.
23 Therefore, the O₃ sensors appear to have observed an ozone titration signal that has been
24 observed in other near-road field settings (Beckerman et al., 2008). Meanwhile, the PM
25 sensors had fairly uniform concentrations at all four sites and over the full range of wind
26 conditions (Fig. A-5). This finding is similar to past near-road studies, which generally see a
27 low signal change in particulate mass (Karner et al., 2010).

28

29 Diurnal signals of ozone revealed that the two sensor nodes replicated the typical afternoon
30 peak in ozone, however the amplitude of the cycle was smallest for the roadside site (Fig. A-
31 5). PM sensors had repeatable trends at all sites of maximum early morning concentrations



1 (06:00-08:00), which may attributed to lower atmospheric mixing and commute traffic
2 periods.

3 **4 Conclusions and discussion**

4 Emerging air sensor technology is of widespread interest to increase the spatial resolution of
5 air quality data sets and empower communities to measure air quality in their own
6 environments. The CAIRSENSE project is a multi-year, multi-city effort to assess emerging
7 ambient air quality sensors with existing or near-term commercial availability. Long-term
8 evaluation of duplicate or triplicate sensors in Decatur, Georgia, revealed widely variable
9 sensor performance under real-world conditions. The selected testing location represents a
10 generally low concentration, suburban environment (e.g., mean $PM_{2.5}$ ranging $\sim 9\text{-}12 \mu\text{g}/\text{m}^3$)
11 with temperate winters and hot, humid summers. As recently discussed in Johnson et al.,
12 (2016), sensor performance has been shown to vary with location and concentration regime.
13 Therefore, testing in multiple climates and air pollution mixtures is desirable to characterize
14 emerging air sensor technology.

15
16 At the Decatur testing site, some sensors were observed to have very strong agreement with
17 FEM over an extended period of time (e.g., SM50 O_3 sensor) and no artifact adjustment was
18 required to improve the agreement. Other sensors had good agreement with FEM (e.g.,
19 AQMesh CO sensor), that improved even further when days of use, temperature, or humidity
20 were incorporated as parameters in a multilinear regression equation. Other sensors had poor
21 or even negative agreement with FEM data sets; and, in some cases, substantially weaker field
22 performance than what had been shown in a laboratory setting. These results underscore the
23 importance of individual sensor performance testing prior to field use, and the corresponding
24 higher uncertainty in sensor datasets that do not incorporate field testing in their application.

25
26 Application of select sensors in a local wireless sensor network revealed useable ~ 8 month
27 data sets for both ozone and particulate matter. ZigBee-based network communications were
28 feasible over short ranges (e.g., 0.5 km), with the data communications range reduced from
29 the nominal ~ 1.5 km by the surrounding mature trees and several structures in the area.
30 Selecting early morning and upwind hours provided a means to adjust the data sets against the
31 nearby FEM data and subsequently investigate diurnal and wind-directional trends. Ozone
32 and PM trends were similar to repeatable past near-road field study observations.



1
2 Air quality sensor technology is quickly developing, with research efforts underway
3 worldwide to apply sensors for multiple uses including long-term outdoor monitoring, short-
4 term field studies, stationary and mobile applications, and personal monitoring. This field
5 study demonstrates a very wide range of sensor performance in an outdoor, suburban setting.
6 While the results of this study are likely transferable to environments that may have similar
7 pollution concentration ranges and environmental conditions, one complicating and
8 uncontrollable factor is the potential variability in the sensor manufacturing process. To
9 maximize the potential of this emerging technology, incorporating co-location with a
10 reference monitor into future field study designs is highly encouraged.

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15 was reviewed by EPA and approved for publication, it may not necessarily reflect official
16 Agency policy. Mention of any products or trade names does not constitute endorsement.

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1 **Table 1.** Sensors selected for collocation ad-hoc field testing (SAFT)
 2

Sensor/Manufacturer	Measured Pollutants/Internal Sensor (units)	Mechanism	N
PMS-SYS-1/Shinyei (Japan)	PM _{2.5} (µg/m ³)	Light scattering	2
Dylos Particle Counter (DC1100-PRO-PC)/Dylos Corporation (Riverside, CA, USA)	Particle ≥ 0.5 µm (pt/0.01cf)	Light scattering	2
Dylos Particle Counter, DC1100-PC/Dylos Corporation (Riverside, CA, USA)	Particle ≥ 1µm (pt/0.01cf)	Light Scattering	1
Airbeam/HabitatMap (Brooklyn, NY, USA)	PM _{2.5} /Shinyei PPD60PV (hppcf)	Light scattering	3
Aercet 831/MetOne (Grants Pass, OR, USA)	PM ₁ , PM _{2.5} , PM ₄ , PM ₁₀ and TSP (µg/m ³)	Light scattering	3
SM50/Aeroqual (New Zealand)	O ₃ (ppm)	Gas sensitive semiconductor (GSS)	2
Cairclip/Cairpol (France)	NO ₂ and O ₃ combined (ppb)	Electrochemical	2
Air Quality Egg/Wicked Device(Ithaca, NY, USA)	NO ₂ /e2v MiCS-2710, CO/e2v MiCS-5525, VOC/e2v MiCS-5521, PM/Shinyei PPD42 (pt/283ml)	Electrochemical for gases, light scattering for PM	3
AQMesh (Gen. 3)/AQMesh Corp. (UK)	NO, NO ₂ , CO, SO ₂ , O ₃ (all in ppb)	Electrochemical	2

3
 4 **Table 2.** Wireless sensor network components
 5

Parts/Manufacturer	Function	Node
PM Sensor/Shinyei (Japan)	Measures PM _{2.5} in µg/m ³	1, 2, 3, 4
CairClip/Cairpol (France)	Measures NO ₂ /O ₃ in ppb	1, 2, 3, 4
SM50/Aeroqual (New Zealand)	Measured O ₃ in ppm	1, 4
AM2315 temperature & humidity sensor/Aosong (China)	Temperature and humidity reading	1, 2, 3, 4
Arduino Mega 2560 microprocessor/Smart Projects (Italy)	On-board processing of data and transmission	1, 2, 3, 4
A09-Y11NF XBee antenna/Digi International (Minnetonka, MN, USA)	900 MHz directional wireless communication to base station via ZigBee network protocol	1, 2, 3, 4
A09-F5NF-M-ND XBee antenna/Digi International (Minnetonka, MN, USA)	900 MHz omnidirectional wireless communication via ZigBee network protocol	base
Solar panel and battery - SPM110P-FSW, SolarTech 55Ah battery ^a /SolarTech (Ontario, CA, USA)	Rechargeable power for system	1
Solar panel and battery - SPM055P-F, SolarTech 35 Ah battery ^a / SolarTech (Ontario, CA, USA)	Rechargeable power for system	2, 3
Airlink® GX440 cellular modem/Sierra (Canada)	Transmission of data to server	base

6 ^aA larger solar-power system was utilized for node 1, supporting the inclusion of the SM50 ozone sensor . The other location
 7 that included the sensor, node 4, was operated on landpower.



Table 3. Comparison Statistics for 12-hour Average PM Measurements at South Dekalb NCore Site

Manufacturer, Model	Name	Sampling Time (days)	Original Sensor Measurement			r > 0.5	Comparison with FEM				FEM Concentration ^c ($\mu\text{g}/\text{m}^3$)
			Mean	Unit	CV		OLS Regression (FEM = a×Sensor + b)		Converted to FEM unit ($\mu\text{g}/\text{m}^3$)		
Shinyei, PM Sensor	SAFT-1	251	8.31	$\mu\text{g}/\text{m}^3$	0.61	N	NA		NA		11.13
	SAFT-2	168	6.56	$\mu\text{g}/\text{m}^3$	0.69	Y	0.36	0.72	7.48	12.18	12.21
	WSN-N4 ^a	285	12.56	$\mu\text{g}/\text{m}^3$	1.51	N	NA		NA		10.81
Dylos	SAFT-1	108	423.1	pt/0.01cf	0.83	Y	0.33	0.0086	8.08	11.71	11.60
	SAFT-2	108	3054.04	pt/0.01cf	0.77	Y	0.45	0.0015	7.20	11.67	11.60
	SAFT-3	71	2948.3	pt/0.01cf	0.85	Y	0.40	0.0013	7.78	11.64	11.66
Airbeam (internal PM sensor: Shinyei, PPD60PV)	SAFT-1	251	2982.57	hppcf	0.62	Y	0.42	0.0020	5.24	11.20	11.13
	SAFT-2	168	2977.22	hppcf	0.58	Y	0.43	0.0018	6.01	11.48	12.22
	SAFT-3	168	3033.84	hppcf	0.61	Y	0.43	0.0017	6.40	11.45	12.22
MetOne, 831 ^b	SAFT-1	21	3.21	$\mu\text{g}/\text{m}^3$	0.67	N	NA		NA		9.60
	SAFT-2	21	3.12	$\mu\text{g}/\text{m}^3$	0.62	N	NA		NA		9.60
	SAFT-3	21	2.8	$\mu\text{g}/\text{m}^3$	0.62	N	NA		NA		9.60
Air Quality Egg (internal PM sensor: Shinyei, PPD42NS)	SAFT-1	121	277.59	n/a	0.53	N	NA		NA		13.81
	SAFT-2	196	3.31	n/a	0.46	N	NA		NA		11.90
	SAFT-3	115	89.42	n/a	0.89	N	NA		NA		11.11

a. With aluminum foil added after 2014/09/18

b. Short, discontinuous testing period from January-May, 2015

c. FEM PM_{2.5} instrument: MetOne, BAM 1020 (Grants Pass, OR, USA)



Table 4. Comparison Statistics for Hourly Gas Measurements at South Dekalb Ncore Site

Pollutant	Manufacturer, Model	Testing component ID	Sampling Time (Days)	Original Sensor Measurement			Comparison with FEM				Concurr ent FEM Concent ration ^d (ppb)	
				Mean	Unit	CV	r > 0.5	OLS Regression (FEM = a×Sensor + b)		Converted to FEM unit		
								r ²	Slope (a)	Interce pt (b)		
O ₃	Aeroqual, SM50	SAFT-1	251	0.0177	ppm	1.03	Y	0.94	888.26	2.56	18.3	18.3
		SAFT-2	168	0.0182	ppm	1.06	Y	0.94	811.52	2.84	17.6	17.6
	Cairpol, CairClip ^a	WSN-N4	281	0.016	ppm	0.93	Y	0.82	955.26	2.91	18.2	18.2
		SAFT-1 ^c	194	7.2	ppb	2.38	Y	0.88	0.851	12.451	18.6	18.6
		WSN-N4	285	6.3	ppb	2.67	Y	0.68	0.685	12.203	16.5	16.7
		SAFT-1	111	11.8	ppb	0.81	N			NA		14.9
NO ₂	AQMesh Corp, AQMesh	SAFT-2	110	11.6	ppb	0.71	N			NA		14.8
		SAFT-1 ^c	194	0.18	ppb	40	Y	0.57	0.955	11.391	11.6	11.7
	AQ Mesh Corp, AQMesh	WSN-N4	285	1	ppb	9.32	N			NA		11.2
		SAFT-1	111	17.5	ppb	0.80	N			NA		10.0
		SAFT-2	110	29.1	ppb	0.65	N			NA		10.0
		SAFT-1	121	31514.7	n/a	2.58	N			NA		10.6
Quality Egg (e2v MiCS- 2710)	SAFT-2	196	35927.7	n/a	2.1	N			NA		12.1	
	SAFT-3	115	32873.4	n/a	2.46	N			NA		11.3	
NO	AQMesh Corp, AQMesh	SAFT-1	111	19.4	ppb	1.84	Y	0.77	0.892	1.060	18.4	18.3
		SAFT-2	110	21.8	ppb	1.76	Y	0.87	0.883	-0.765	18.5	18.5
CO	AQMesh Corp, AQMesh	SAFT-1	111	318.3	ppb	0.70	Y	0.63	8.09E- 04	6.95E- 02	0.3272	326.2
		SAFT-2	110	345.4	ppb	0.68	Y	0.68	7.99E- 04	5.12E- 02	0.3272	326.3



Variable	SAFT-1		121	28500	n/a	0.25	N	NA	328.1
	Device, Air Quality Egg (e2v MiCS-5525)	SAFT-2							
SO ₂	SAFT-1	SAFT-2	196	25636.7	n/a	0.28	N	NA	328.1
	SAFT-2	SAFT-3	115	24882.8	n/a	0.31	N	NA	307.1
SO ₂	SAFT-1	SAFT-2	111	41.8	ppb	0.79	N	NA	0.243
	SAFT-2	SAFT-3	110	39.9	ppb	0.89	N	NA	0.245

- By subtracting the FEM NO₂ data
- By subtracting the FEM O₃ data
- After sensor replacement on 2014/11/15
- FEM instrument – O₃: Thermo Scientific, 491; NO₂: Thermo Scientific, 42C; NO: Thermo Scientific, 42C; CO: Thermo Scientific, 48C; SO₂: Thermo Scientific, 43i-TLE (Waltham, MA, USA)

Table 5. Comparison of Adjusted Regression Coefficients (R^2_{adj}) of Multiple Linear Regression Models between FEM Concentrations against Individual Sensor^a, Ambient Temperature, Humidity, and/or Number of Measurement Days

Variable Combination	PM (12-hr average)				O ₃ (hourly)		NO ₂ (hourly)		NO (hourly)		CO (hourly)	
	Shinyei SAFT-2	Dylos SAFT-2 Sm	Airbeam SAFT-2	Aeroqual SAFT-1	Cair-Clip SAFT-1 ^b	Cair-Clip SAFT-1 ^b	Cair-Clip SAFT-1 ^b	Cair-Clip SAFT-1 ^b	AQMesh SAFT-1	AQMesh SAFT-1	AQMesh SAFT-1	AQMesh SAFT-1
Sensor	0.36	0.45	0.43	0.94	0.88	0.57	0.77	0.63				
Sensor+T	0.36	0.48*	0.43	0.94*	0.90*	0.70*	0.77	0.71*				
Sensor+RH	0.40	0.45	0.46*	0.93	0.95*	0.64*	0.75	0.52				
Sensor+Day	0.37*	0.56*	0.46*	0.94*	0.88*	0.60*	0.77	0.75*				
Sensor+T+RH	0.41	0.50*	0.46	0.93	0.95*	0.81*	0.75	0.61				
Sensor+T+Day	0.37	0.56	0.46	0.94*	0.90*	0.70*	0.77	0.75*				
Sensor+RH+Day	0.42*	0.60*	0.51*	0.94	0.95*	0.68*	0.75	0.68				
Sensor+T+RH+Day	0.43	0.60	0.50	0.94	0.96*	0.82*	0.75	0.68				

- Representative sensors were selected when the correlation coefficient (r) between individual sensor and FEM ≥ 0.5 .
 - After the sensor replacement on 2014/11/15.
- *. Significant at p-value < 0.05.



Figure 1. CAIRSENSE field equipment, including: A: SAFT instrument enclosure; B and C: solar-powered WSN node; D: Interior of SAFT instrument shelter; and E: WSN node utilizing 120 V (nominal) AC electricity.



Figure 2. CAIRSENSE project Wireless Sensor Network (WSN) and Sensor Ad-hoc Field Testing (SAFT) locations.

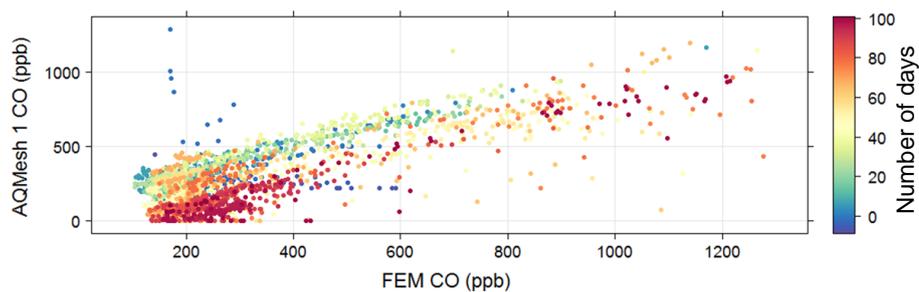
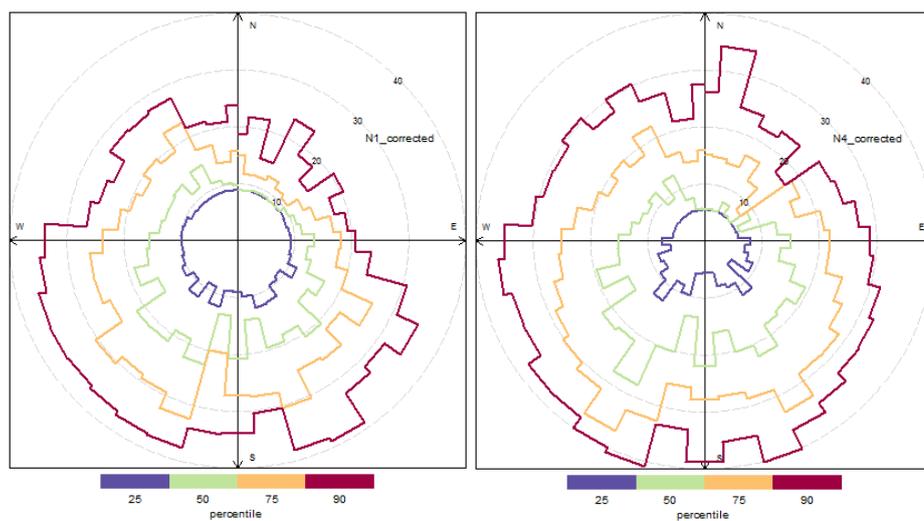


Figure 3. AQMesh vs. FEM carbon monoxide comparison, with markers colored by the number of days of sensor use.



(a) Near-road Node 1 Aeroqual O₃

(b) NCore co-located Node 4 Aeroqual O₃

Figure 4. Example Percentile rose plots between near-road sensor node (N1) and Ncore co-located node (N4) for hourly FEM-corrected ozone between August 2014 and early March 2015.