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MOMA: a field calibration method for air sensor networks

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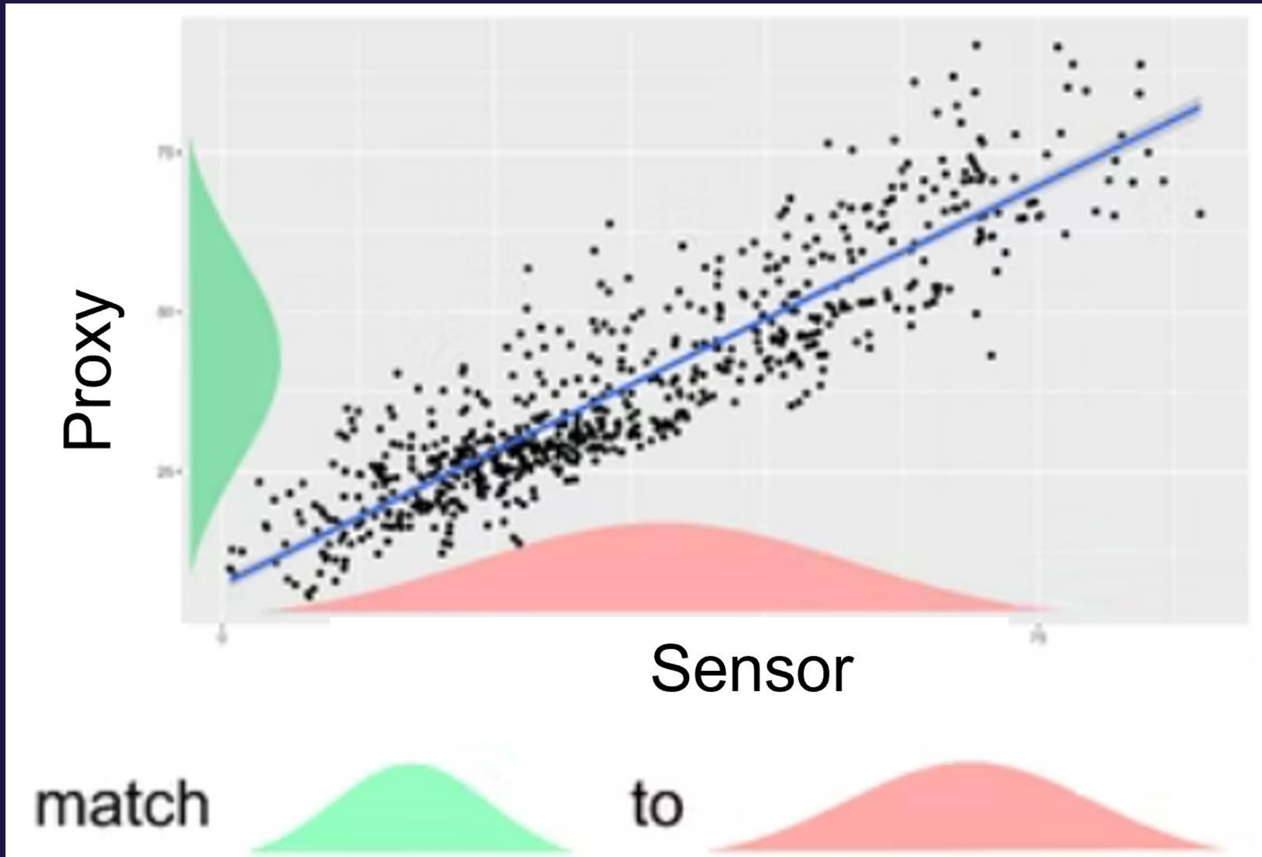
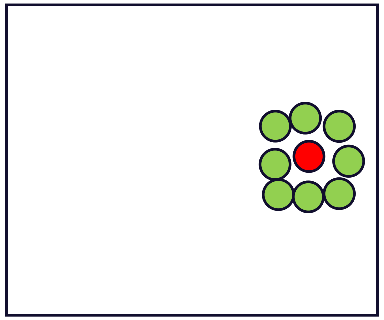


Approaches to field calibration of air sensor networks

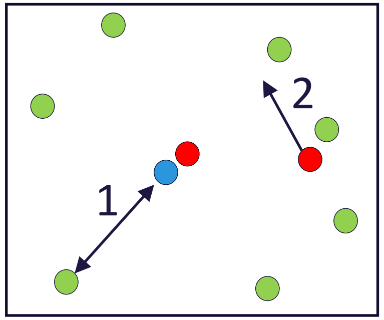
Co-location: calibrate sensors at a reference station.

- Good for short term projects and few sensors.
- Labor intensive for larger or longer running networks
- Data loss due to movement.



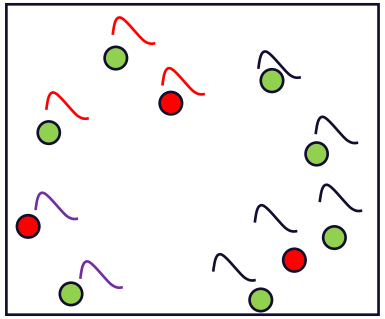
Mobile reference: reference moves around sensors in network.

- Requires sufficient range of measurement at each location to obtain a reliable zero and span (this can be challenging).



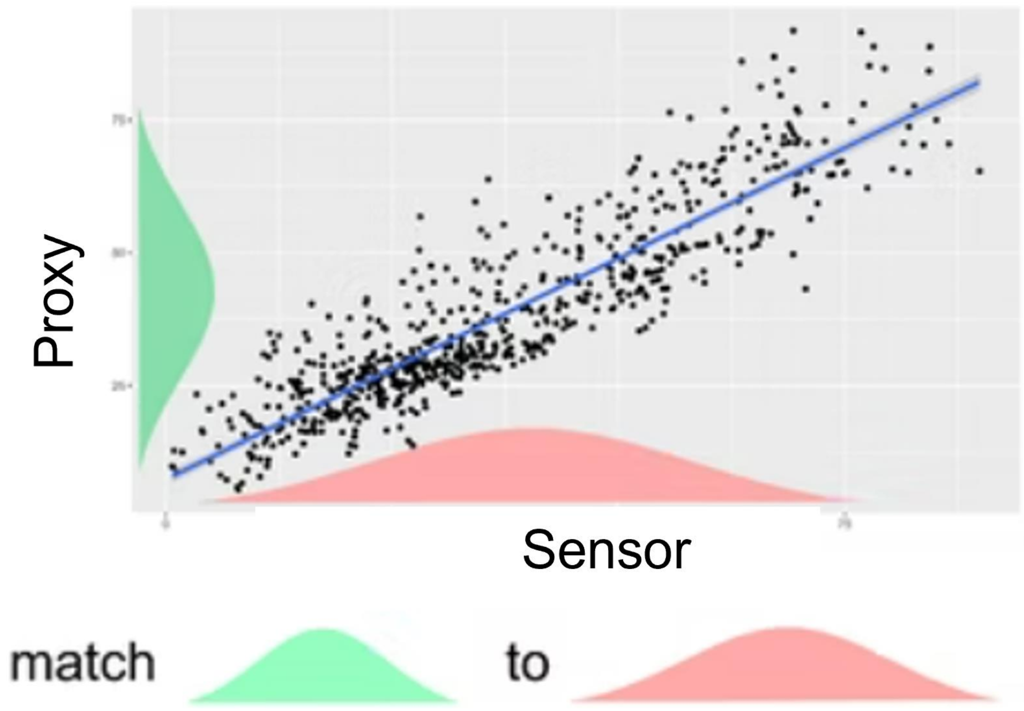
Remote calibration: Sensors remain fixed and reference data and/or atmospheric models used to construct a calibration.

- Transparency and reproducibility issues.
- How to validate ?



Remote calibration approach: MOMA (Moment Matching)

- Developed in 2017 with University of Auckland and South Coast Air Quality Management District.
- Uses a continuous monitoring reference in the airshed as a **Proxy** calibration standard.
- Assumes linearity of the sensor signal.
- Derives sensor slope and offset estimates by matching mean and standard deviations of the sensor distribution to values derived from Proxy distribution over the same time period.
- Device agnostic – can be applied to any outdoor air sensor e.g Aeroqual AQY, Clarity nodes, PurpleAir.
- Successfully applied to O_3, NO_2, $PM_{2.5}$ and PM_{10} measurements.
- Methodology is defined and published in scientific literature.



MOMA Calibration : Math!

1. **Sensor** concentration **at location *j*, time *t*** is a linear function of the **True** concentration.

True
Sensor

$$X_{j,t} = a_0 + a_1 Y_{j,t}$$

2. Select a **Proxy** whose concentration distribution over a period of time is statistically similar to the **True** concentration at the sensor site.

Proxy
True

$$\mathbb{P}\{X_j(t, t - t_d)\} \sim \mathbb{P}\{Z_k(t, t - t_d)\}$$

3. Calculate new estimates of sensor **gain** ($\hat{a}_1$) and **offset** ($\hat{a}_0$) by matching the **mean** and **variance** of the sensor data to the proxy data over the same time period.

Proxy
Sensor

$$\hat{a}_1 = \sqrt{\mathrm{var}\langle Z_k(t, t - t_d)\rangle / \mathrm{var}\langle Y_k(t, t - t_d)\rangle}$$

$$\hat{a}_0 = \mathrm{E}\langle Z_k(t, t - t_d)\rangle - \hat{a}_1 \mathrm{E}\langle Y_k(t, t - t_d)\rangle$$

References

1. Miskell, G., Salmond, J., Alavi-Shoshtari, M., Bart, M., Ainslie, B., Grange, S., McKendry, I.G., Henshaw, G.S., Williams, D.E., 2016. Data Verification Tools for Minimizing Management Costs of Dense Air-Quality Monitoring Networks. **Environ Sci Technol** 50, 835-846.
2. Miskell, G., Salmond, J.A., Williams, D.E., 2018a. Solution to the Problem of Calibration of Low-Cost Air Quality Measurement Sensors in Networks**. ACS Sensors** 3, 832-843.
3. Miskell, G., Alberti, K., Feenstra, B., Henshaw, G., Papapostolou, V., Patel, H., Polidori, A., Salmond, J.A., Weissert, L.F., Williams, D.E., 2019. Reliable data from low-cost ozone sensors in a hierarchical network. **Atmospheric Environment**, 214, https://doi.org/10.1016/j.atmosenv.2019.116870.

Proxy selection

The presence of suitable proxy references in the network area is a key element in successful application of MOMA calibration to sensor networks

The coverage of National Ambient Air Quality Monitoring Stations in most US urban areas is sufficient to support MOMA calibration for O_3, NO_2, $PM_{2.5}$, PM_{10}. CO and SO_2 are possible but regulatory networks are usually too sparse.

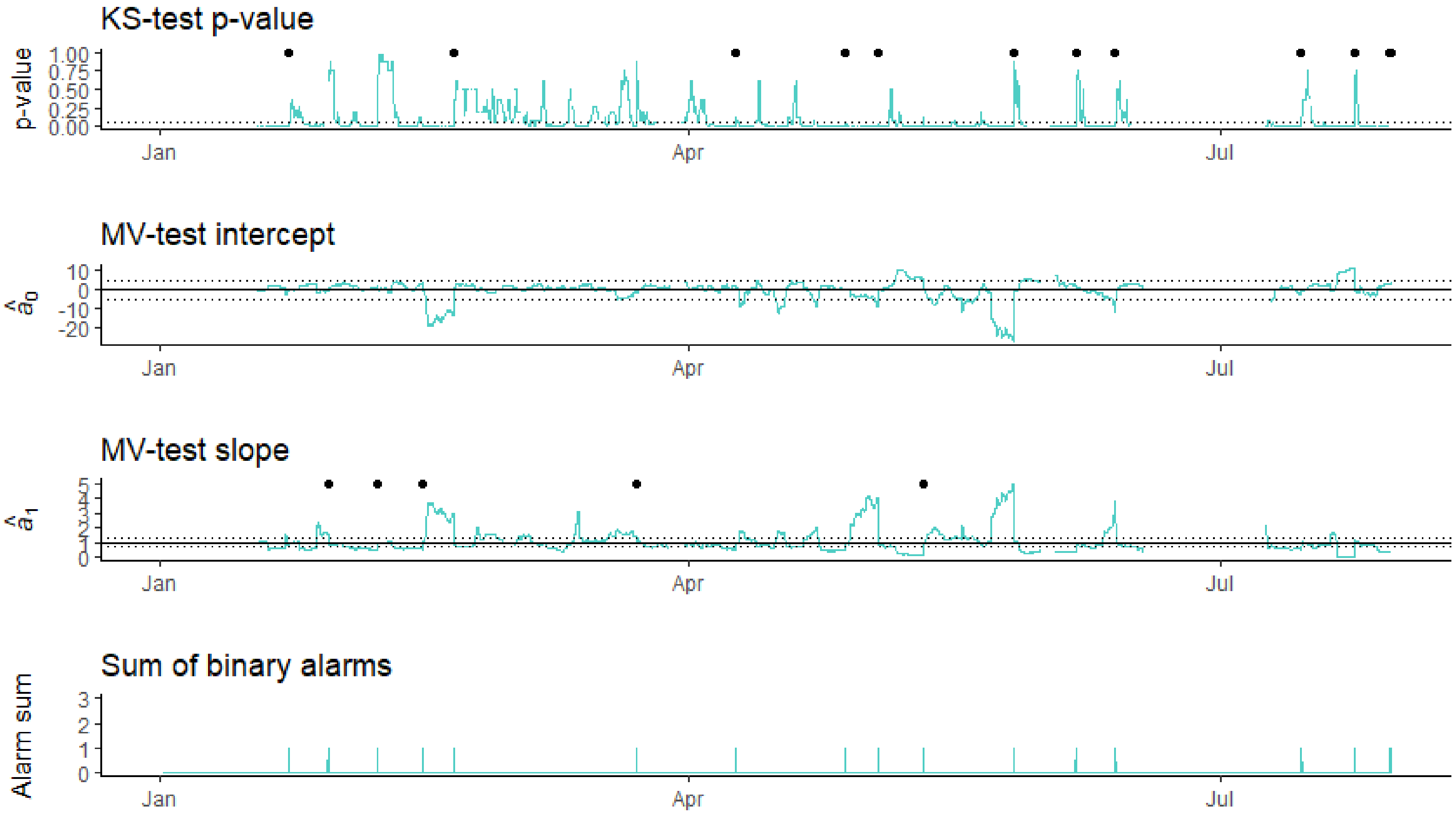
Studies(1-3) show proxy selection rules depend on the pollutant of interest:

Pollutant	Proxy selection rule
O_3	Distance
NO_2	Land use similarity
$PM_{2.5}$	Statistical analysis (r, distance, K-S test)
PM_{10}	Distance

1. Miskell, G., Salmond, J., Alavi-Shoshtari, M., Bart, M., Ainslie, B., Grange, S., McKendry, I.G., Henshaw, G.S., Williams, D.E., 2016. Data Verification Tools for Minimizing Management Costs of Dense Air-Quality Monitoring Networks. **Environ Sci Technol** 50, 835-846.
2. Weissert, L.F., Alberti, K., Miles, E., Miskell, G., Feenstra, B., Henshaw, G.S., Papapostolou, V., Patel, H., Polidori, A., Salmond, J.A., Williams, D.E. 2020. Low-cost sensor networks and land-use regression: Interpolating nitrogen dioxide concentration at high temporal and spatial resolution in Southern California. **Atmospheric Environment**, 223, https://doi.org/10.1016/j.atmosenv.2020.117287.
3. Weissert, L.F, Henshaw G.S, Williams D.E, Feenstra B., Lam R., Collier-Oxandale A., Papapostolou V., and Polidori A. Performance evaluation of MOMA – a remote network calibration technique for PM2.5 and PM10 sensors. **Atmospheric Measurement Techniques** (submitted)

Calibration frequency

Fixed interval: implement on a fixed schedule (eg monthly) or Drift detection: trigger calibration based on detection of sensor drift.



KS-test: theta: < 0.05

MV-test intercept: intercept threshold = +/-5ppb

MV-test slope: slope threshold = 1 +/- 0.25

Calibration triggered if >1 tests fail.

MOMA Test: setup

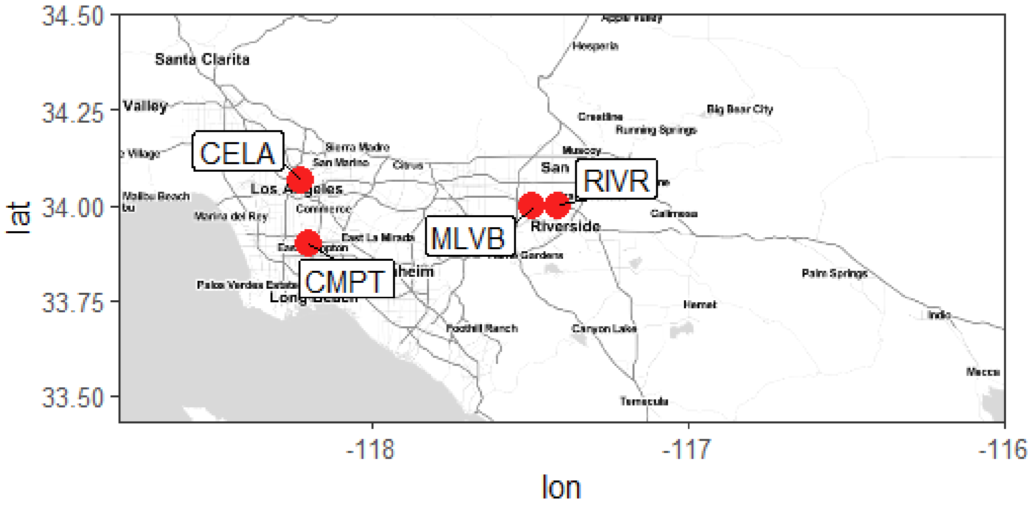
Sensor Network – South Coast AQMD

- **Low-cost Sensors**: Aeroqual AQY sensors measuring O_3, NO_2, $PM_{2.5}$ and PM_{10}
- **Reference Sites**: AirNow Reference (O_3, NO_2, $PM_{2.5}$, PM_{10})

MOMA test over a year (Jan to Dec 2021)

1. Sensors **collocated at Reference** sites are MOMA calibrated against a **Proxy at a different location**.
2. The MOMA calibrated sensor data is then compared with the collocated Reference data.

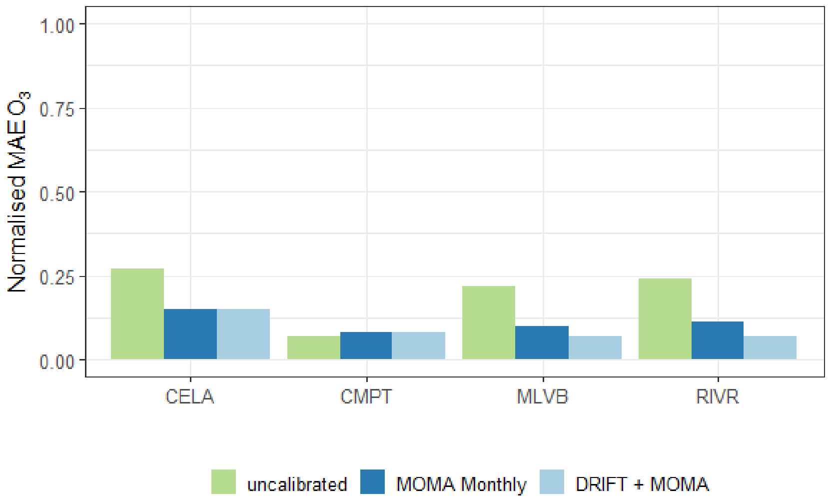
Collocation test sites: CELA, CMPT, MLVB, RIVR



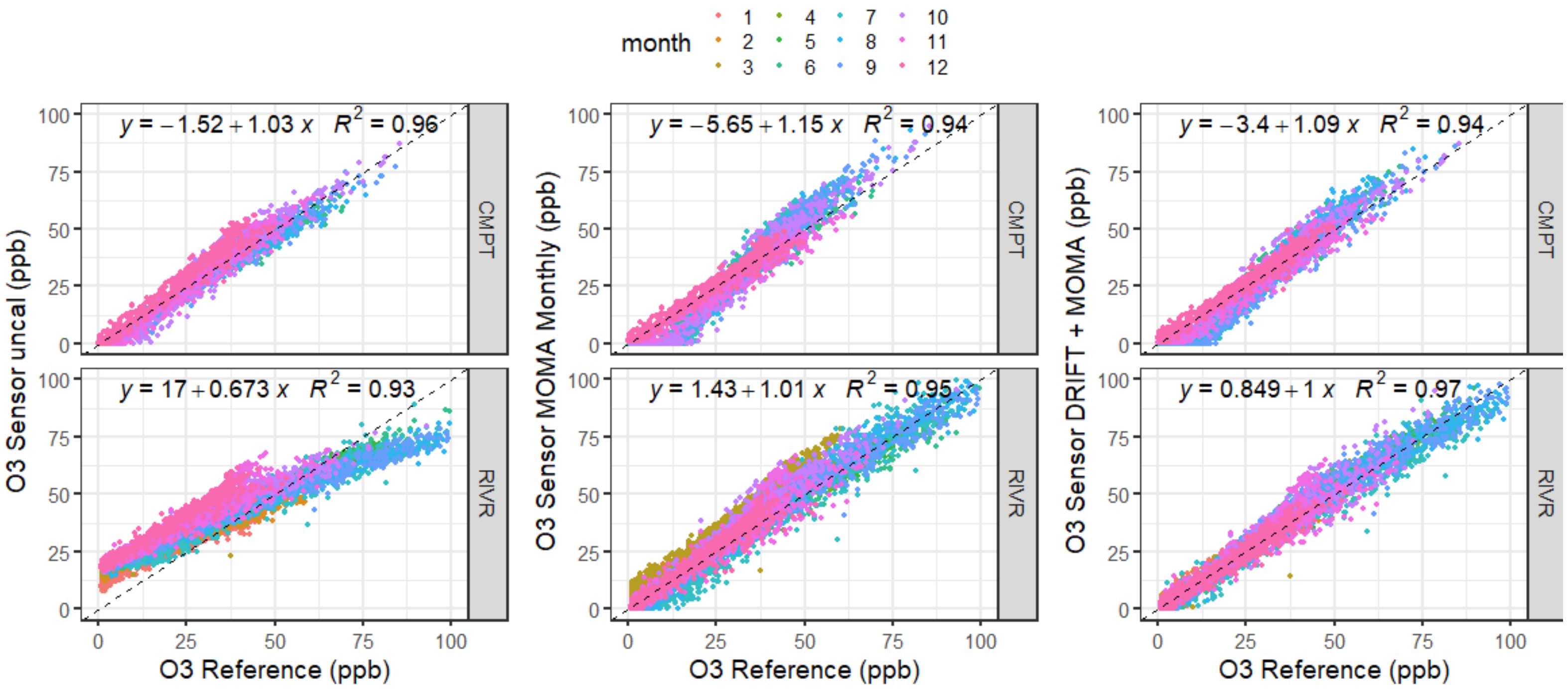
MOMA Test: O_3 Results

Metric used: Normalised MAE and Scatterplots

MOMA reduced the nMAE for the pollutants at most sites. Drift correction works better.



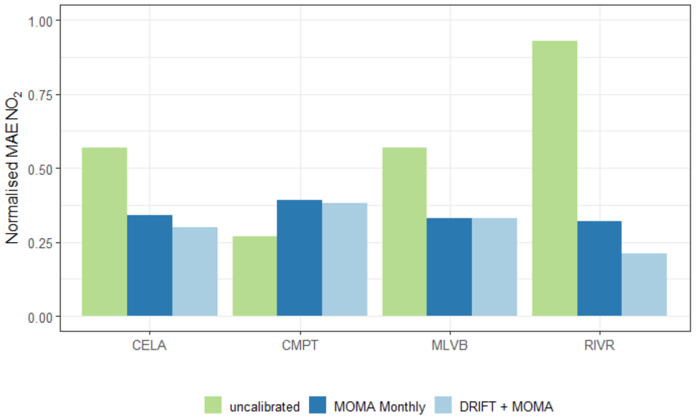
O_3 Sensor at RIVR shows instrumental drift over time as indicated by a decrease in the slope

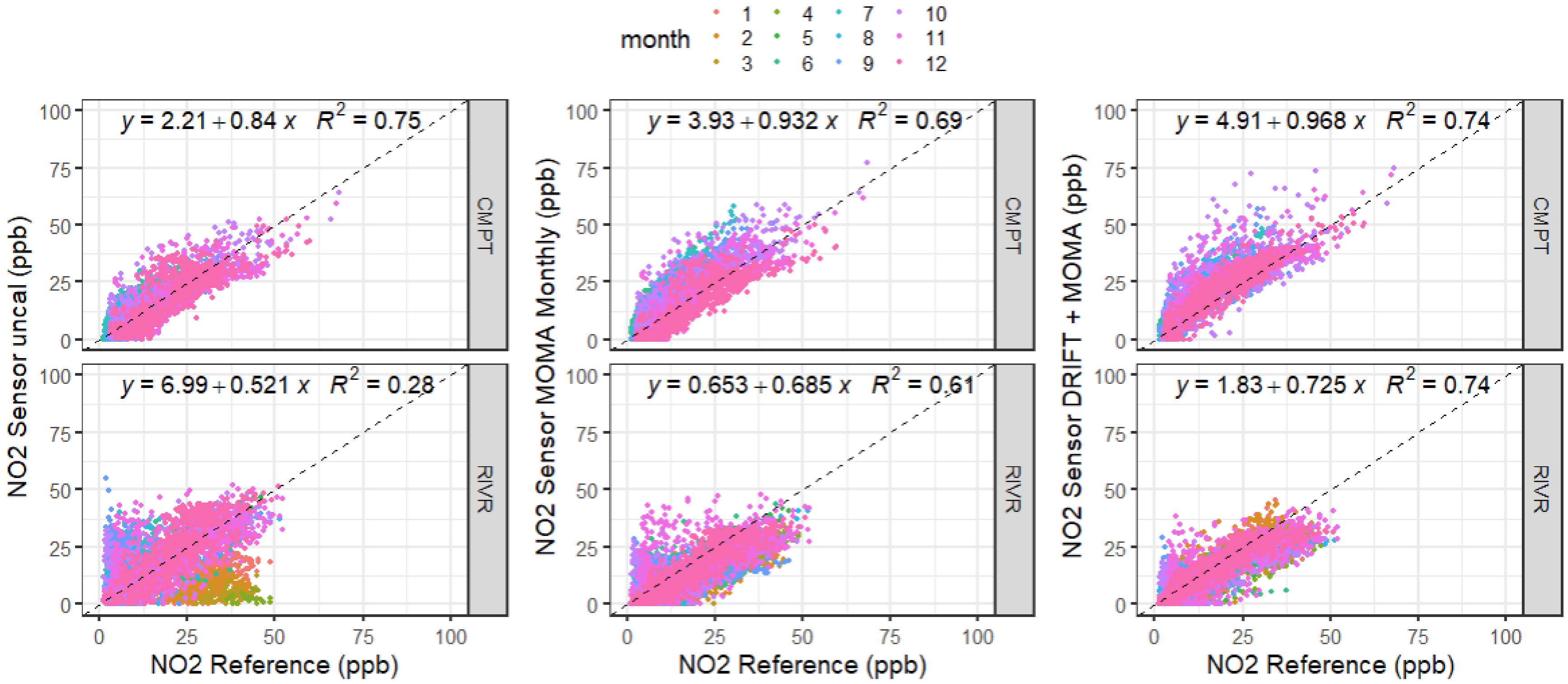


MOMA Test: NO_2 Results

Metric used: Normalised MAE and Scatterplots

MOMA reduced the nMAE for the pollutants at most sites. Drift correction works better.





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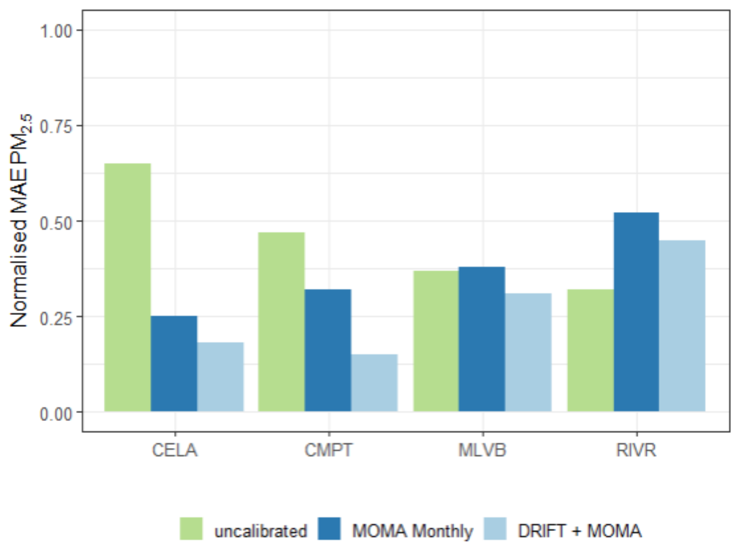
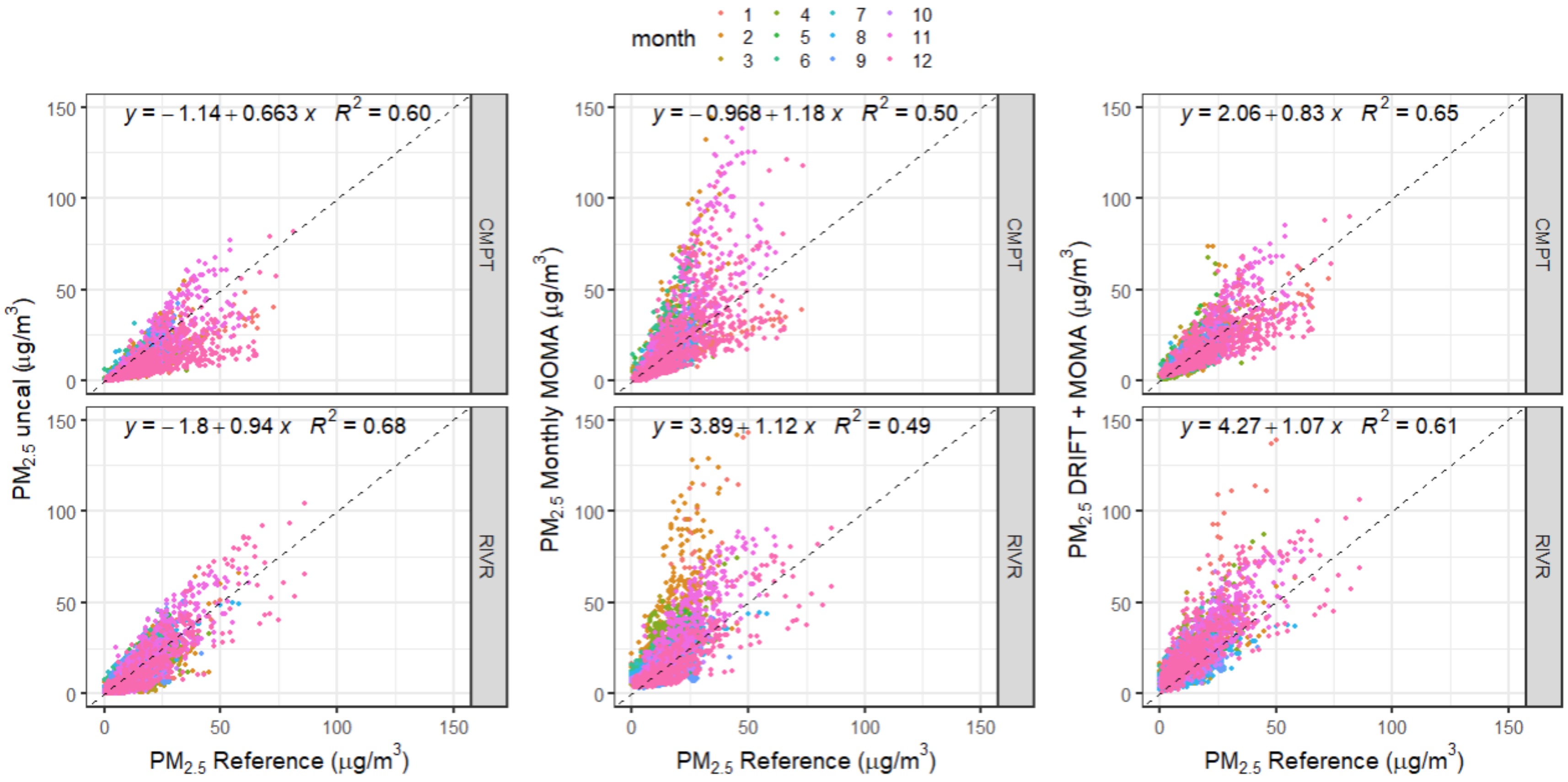
MOMA Test: $PM_{2.5}$ Results

Metric used: Normalised MAE and Scatterplots

MOMA reduced the nMAE for the pollutants at most sites. Drift correction works better.

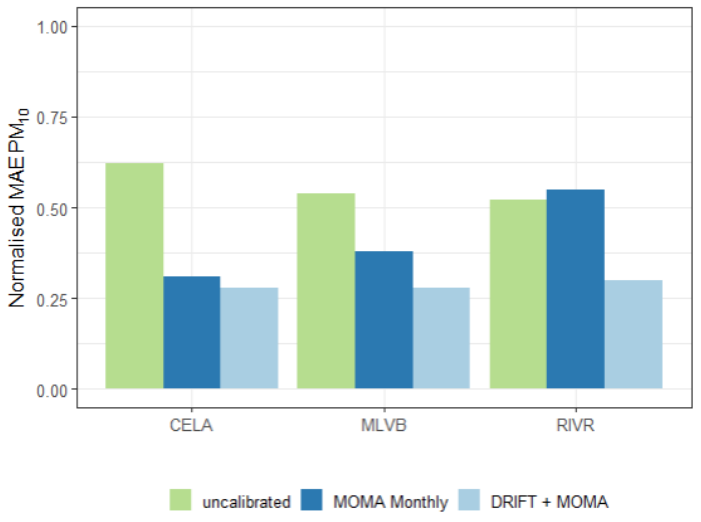


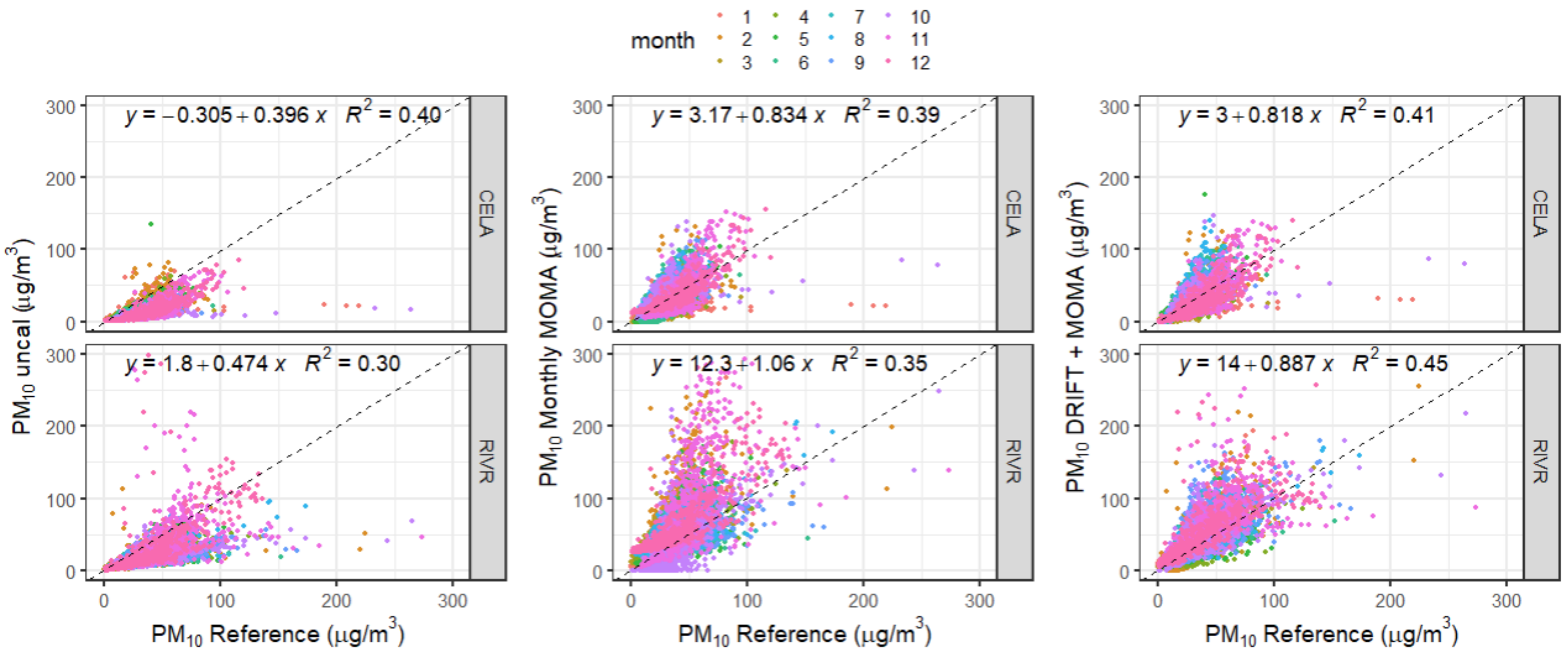


MOMA Test: PM_{10} Results

Metric used: Normalised MAE and Scatterplots

MOMA reduced the nMAE for the pollutants at most sites. Drift correction works better.

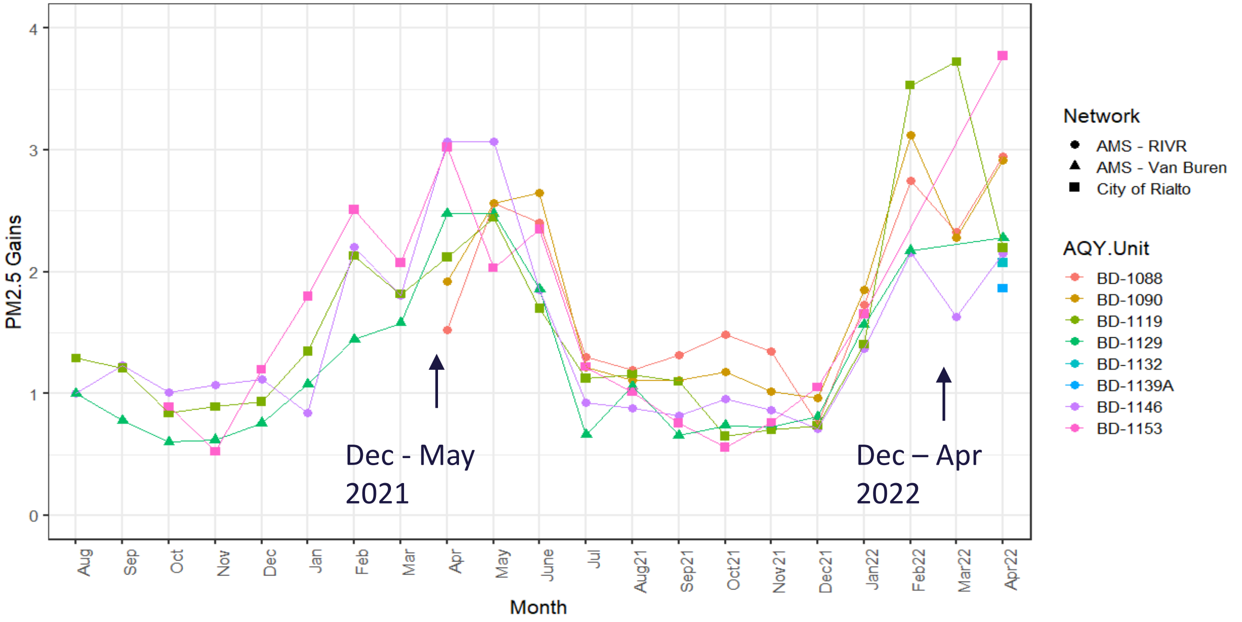




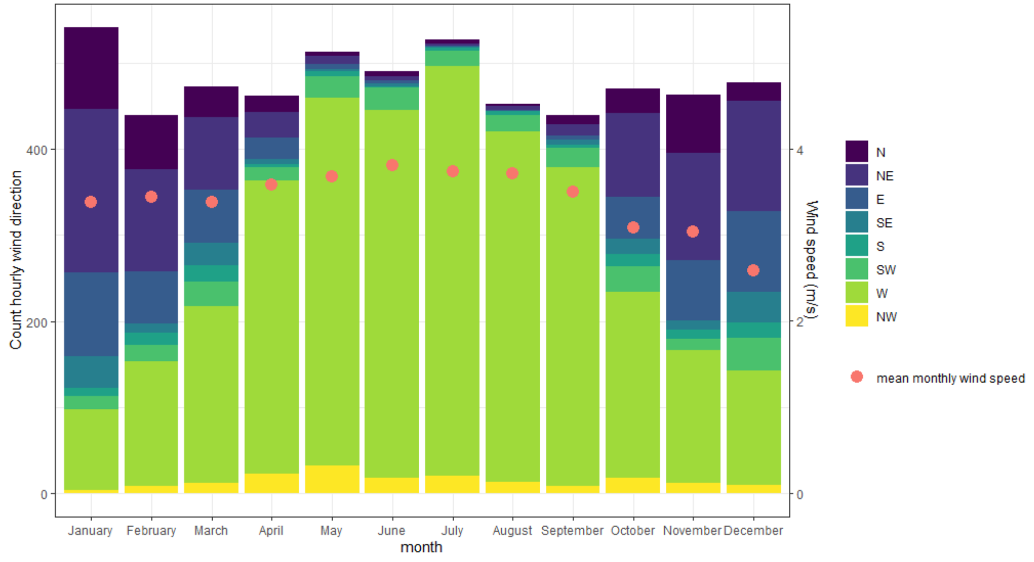
MOMA: PM calibration

MOMA calibrations of optical $PM_{2.5}$ sensors show **seasonal gains** across a year.

AQY $PM_{2.5}$ MOMA gains



Wind measurements – Riverside Airport



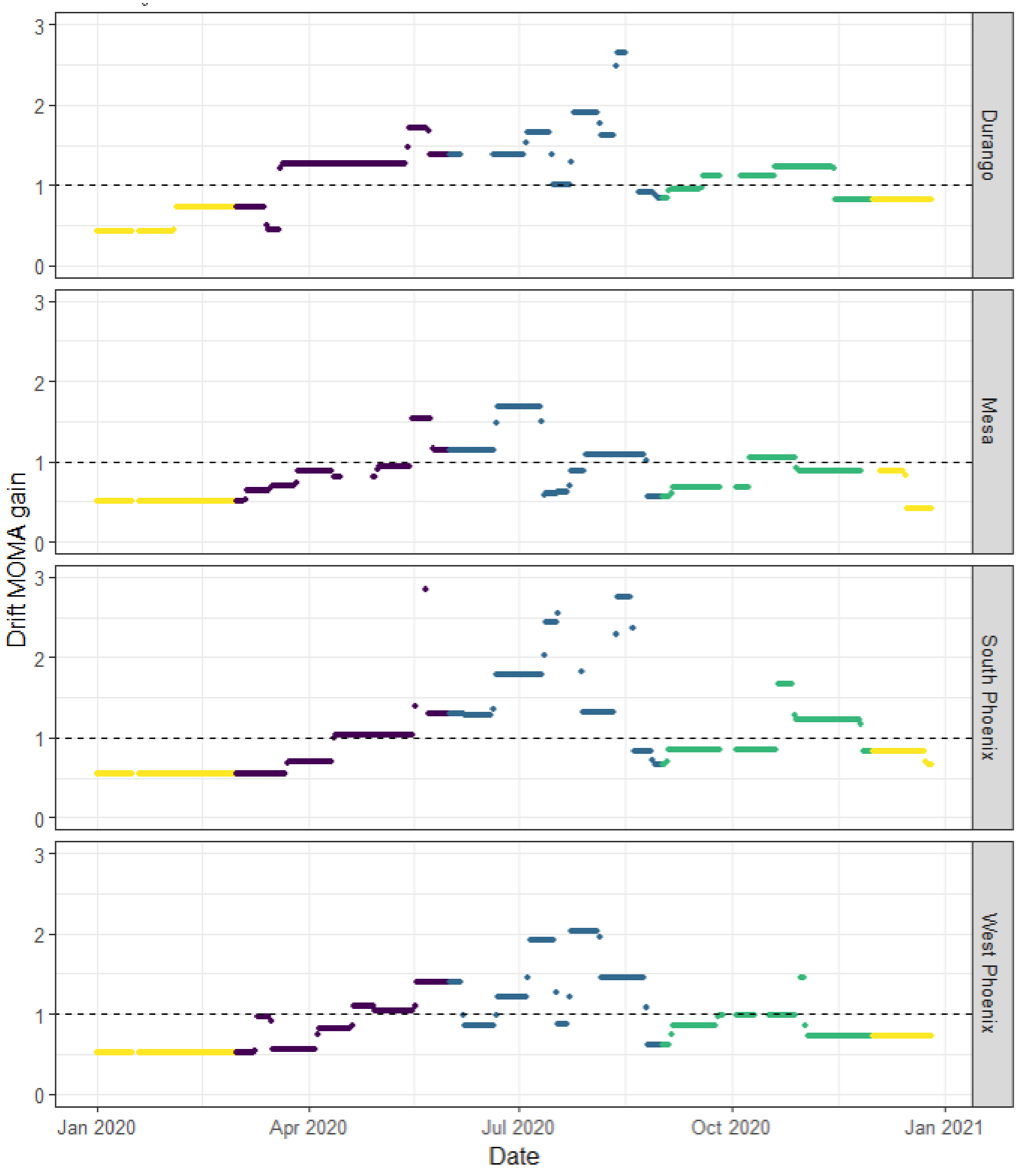
Why? Aerosol composition varies with seasonal winds and RH changes which impacts calibration of optical $PM_{2.5}$ sensors[1]

1. Weissert, L.F, Henshaw G.S, Williams D.E, Feenstra B., Lam R., Collier-Oxandale A., Papapostolou V., and Polidori A. Performance evaluation of MOMA – a remote network calibration technique for PM2.5 and PM10 sensors. **Atmospheric Measurement Techniques** (submitted)

PurpleAir sensors in Phoenix, AZ, through 2020

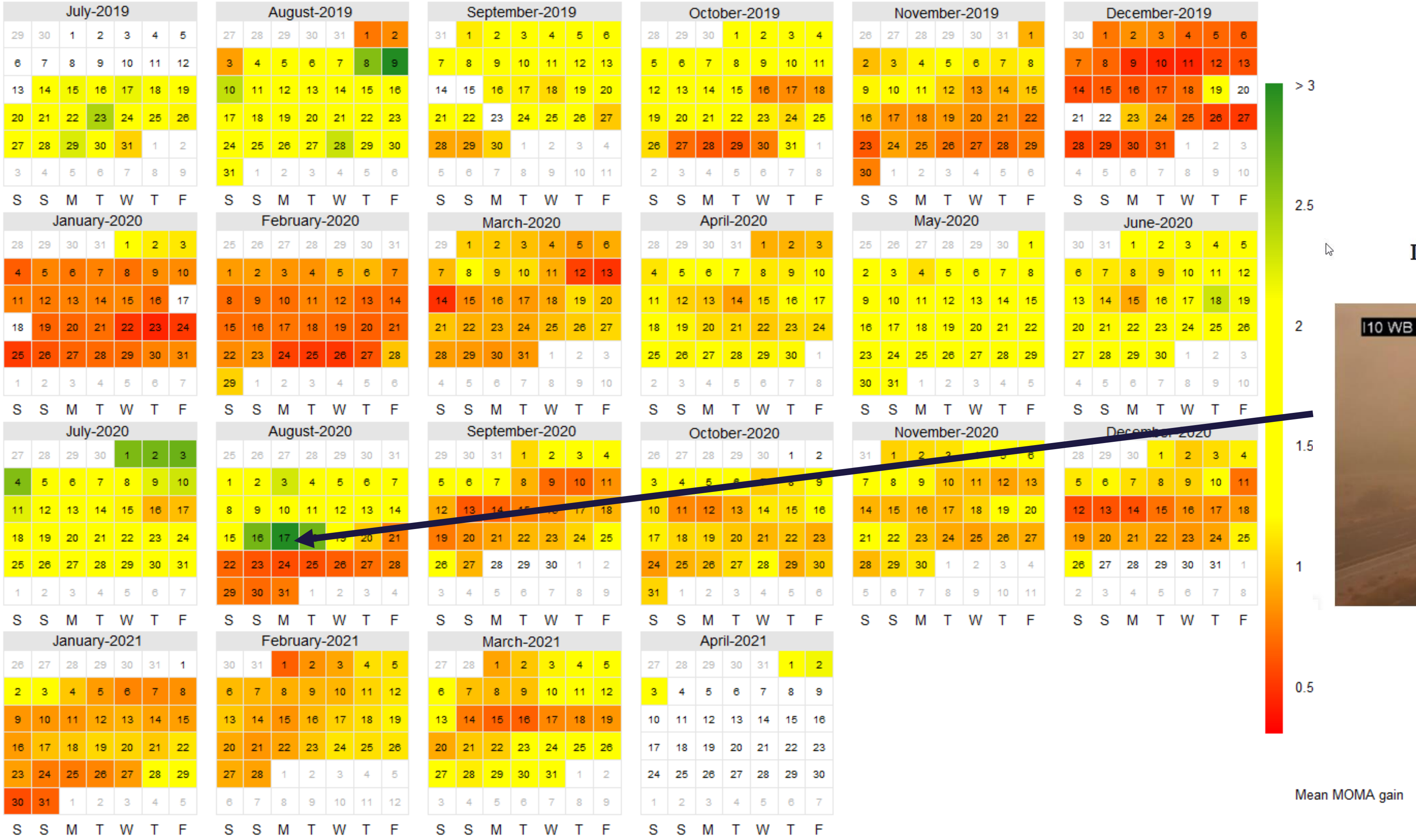
- The MOMA calibration gains vary across the year in a seasonal way but with some extreme values.
- As discussed, this suggests the calibration is correcting for changes in particle type rather than sensor drift.

Can we use the MOMA gain to detect specific $PM_{2.5}$ events ?



Daily MOMA gain for Phoenix PA $PM_{2.5}$ sensors

MOMA gain ~ 1	yellow	Sensor in agreement with the reference: spring/summer/autumn
MOMA gain > 2	green	Sensor under-reading: occasional days in July/August
MOMA gain < 0.7	orange/red	Sensor over-reading in winter months and August to September 2020



Summary

- A remote calibration technique called MOMA that can be applied to air sensor networks measuring O_3, NO_2, $PM_{2.5}$ and PM_{10} has been described.
- The MOMA technique is applicable to sensor networks in urban centres with existing regulatory ambient monitoring network.
- Tests show that drift detection triggered MOMA works better than a fixed interval, especially for PM measurement.
- MOMA generated gains appear to provide diagnostic information on PM sources and events.

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EPA

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HĪKINA WHAKATUTUKI

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