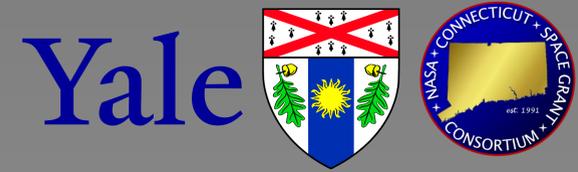


UAV deployment for CO₂ flux estimation in a mid-size city

Madeleine O'Brien; Natalie Schultz; Xuhui Lee
 Yale School of Forestry & Environmental Studies, New Haven, CT



Background

Urban areas produce a disproportionate amount of CO₂ emissions worldwide, and better understanding and quantifying these emissions is crucial to mitigating them. However, with current tools, **scientists possess limited ability to quantify CO₂ emissions on small scales and to resolve intra-city variation in CO₂ flux.**

Existing satellites that measure atmospheric column CO₂ lack spatial resolution to de-aggregate CO₂ patterns within cities.

Municipal emission inventories present difficult-to-quantify uncertainties, and many inventory methodologies do not account for carbon sinks (like green spaces) that may affect a city's CO₂ flux.

Gas flux models based upon eddy covariance (EC) calculations often assume homogenous surfaces, which clearly does not hold in complex urban topography. Perhaps as a result, EC data are most often collected on undeveloped land.

Calibration of Low-Cost CO₂ Sensor

Calibration data collection: The K30 was placed adjacent to a high-precision CO₂ analyzer (Los Gatos Research analyzer) and a meteorological instrument (iMet XQ2) and left undisturbed in an unoccupied room for 13 days to record ambient air from a propped-open window. K30 values appeared *lower* than LGR values by 8.61ppm on average in this period.

Calibration correction equation: Raw K30 data were fed into a multivariate regression model ($K30_{raw} \sim LGR + Pressure + Air\ Temp + Relative\ Humidity$) to quantify offset from the LGR and how weather factors affect instrument performance. Coefficients from the linear model were used to assemble a "correction equation" that could be applied to future K30 data collected in the field.

$$K30_{corrected} = \frac{[K30_{raw} - 606.364 - (0.581 * Pressure) - (0.712 * AirTemp) - (0.328 * RelHumidity)]}{0.942}$$

Conclusions

- When compared to a high-precision CO₂ sensor, our low-cost sensor originally exhibited a RMSE of 5.453 ppm. Factory-stated accuracy of the low-cost sensor is +/- 3% or 30 ppm.
- By calibrating our low-cost sensor against the high-precision LGR, and accounting for sensor response to weather variables, we reduced the RMSE of recorded CO₂ values to 3.806 ppm.
- Determining proper sensor placement on UAVs is high-priority for anemometers and temperature sensors, medium-priority for CO₂ sensors, and lower priority for humidity and pressure instruments.
- We observed a gradient of ~20 ppm between 10 and 25 meter altitude.

Instrument Testing & Placement

Anemometer: TriSonica Mini Wind + Weather Sensor

Rotor wind can interfere with measurements, but mounting an instrument on a boom too far from UAV's center of gravity may present safety hazards. Anemometer was mounted atop UAV on an adjustable-height platform. Wind speeds were recorded for 5 min intervals at 13 heights. 30 cm above the drone presented the best compromise.

CO₂: K30 Fast Response Sensor

To estimate effect of rotor wind, sensor was mounted on a grounded UAV, and CO₂ data were collected while alternating rotors on-and-off for 5 min and 20 min intervals. Rotor wind increased the SD of CO₂ values (5.9 to 9.1), but mean CO₂ values were not significantly different with or without rotors (P=0.08).

Temp, Humidity, & Pressure: iMet XQ2

Placed on the side of the UAV, pressure and humidity do not significantly differ when rotors are on (p=0.62 and 0.41). Air temperatures were significantly cooler with rotors-on (p=0.00), but this requires re-testing.

Experimental Flights

Urban park adjacent to university campus

Trafficked intersection during lunchtime

Influence of measurement height: Mean CO₂ concentrations were lower on average over urban parkland. The measured CO₂ gradient was smaller than expected—concentrations at 10m were ~20ppm higher than at 25m.

Relative humidity decreases with height, while temperature responds less linearly.

Measurement variation with wind:

Measured CO₂ concentrations exhibited more stability in higher ambient wind (SD 4.87 at the batting cages vs. 19.5 at the parking lot).

Both flights still produced very similar mean CO₂ values (411.9 vs. 412.1 ppm).

Future Work

- Fly transects over different land cover types, at different times of day, to compare CO₂ values
- Refine the assumptions used in calculating CO₂ flux from CO₂ concentrations
- Deploy platform adjacent to eddy covariance tower to directly compare flux estimates
- Estimate flux footprint areas, to examine what mix of land cover types are included in the platform's source area



Acknowledgements

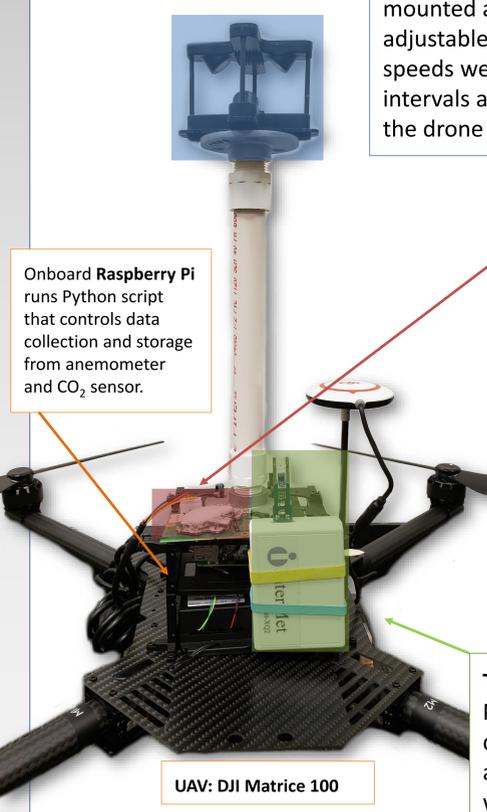
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Onboard Raspberry Pi runs Python script that controls data collection and storage from anemometer and CO₂ sensor.