



Using in-situ CO₂, PM₁, PM_{2.5}, and PM₁₀ measurements to assess air change rates and indoor aerosol dynamics

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ABSTRACT

A common technique to assess indoor air quality is to estimate a space's air change rate by quantifying the decay of a tracer species, such as metabolic carbon dioxide (CO₂). However, CO₂ decay does not fully represent the complexities of aerosol dynamics. In this study, low-cost sensors (QuantAQ/Aerodyne Research ARISense v200 and QuantAQ MODULAIR-PM) were used for continuous measurements of size-resolved particulate matter (PM₁, PM_{2.5}, PM₁₀) and CO₂ in a university classroom across >5 months in 2021. Occupant-generated emissions from classroom activity and cleaning (fogging aerosols) events were used to determine the decay time constant of each pollutant, which varied substantially (e.g., 25–86 min for CO₂, 14–66 min for class PM₁₀ and 24–103 min, 25–82 min, and 18–56 min for fogging PM₁, PM_{2.5}, and PM₁₀, respectively across 3 months in the Spring). The range of measured CO₂ and PM decay rates was comparable, indicating that quantifying metabolic CO₂ decay is a viable method to estimate the timescale of indoor aerosol decay, and that both species provide comparable air change rate estimates. However, the effect of deposition on PM decay was evident and uncertainties in using occupant-generated tracer decay to determine air change rates should be considered. These results provide insights into the practicality and limitations of using in-situ CO₂ and PM decay measurements to assess ventilation, and of using CO₂ decay to estimate aerosol decay. This work also highlights the importance of performing continuous measurements over extended periods of time to quantify a range of air change rates.

1. Introduction

The COVID-19 pandemic has brought increased attention upon the importance of evaluating indoor air quality in public spaces [1–3]. The surge in public motivation to assess indoor air quality, combined with a steady increase in commercially available low-cost air quality sensors over the past years, has led to individuals and organizations alike monitoring indoor air [4,5]. Measuring indoor pollutant levels provides a first look at indoor air quality, but a more comprehensive metric to understand indoor air quality and pollutant exposure is the air change rate, or air changes per hour (ACH) [6–8]. Historically, to empirically evaluate ACH, controlled amounts of tracer gasses such as sulfur hexafluoride (SF₆) or helium (He) are released in a room, and ACH is then assessed through a variety of techniques based on mass balances [9]. Human-emitted carbon dioxide (CO₂) may also be used as a tracer gas, and quantifying the decay of metabolic CO₂ levels after the space is vacated is arguably the most accessible and common method to assess

ventilation [10,11]. This process has been performed in many indoor spaces including residential buildings [8], university dorm rooms [12–14], and classrooms [15–18]. However, when considering particulate matter (PM) exposure and virus transmission risks, it is important to understand the timescale that aerosols (e.g., respiratory particles) remain in the air, and neither ACH nor CO₂ decay directly reflect indoor aerosol dynamics. In both controlled test environments [19,20] and in ventilated residential rooms [21,22], it has been shown that PM decay is impacted by particle loss processes other than ventilation, such as through deposition onto surfaces. An added complexity is that particle deposition varies with particle size [20,22,23]. A potential alternative to using CO₂ measurements to approximate ACH and aerosol timescales is using PM sensors to directly evaluate aerosol decay rates [24]. However, due to the low mass loading of human aerosol production events (i.e., coughing, speaking, etc.) [23,25] and fluctuations in background PM levels, it can be difficult to quantify the decay of particles emitted from human activities in many indoor environments. As air quality monitors

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are increasingly installed in public spaces [26,27], it is important to provide data-driven recommendations to the public on how to effectively assess and understand indoor air quality using in-situ measurements [1,2,6,28].

An increasing number of studies have compared the dispersion [28, 29] or decay [21,30] of PM and tracer gasses indoors. For example, a recent collaborative study by McNeill et al. [1] discussed characterizing classroom ACH using a variety of tracer decay analysis methods, from controlled release of particles or gasses to in-situ CO₂ monitoring. However, most studies that compare particle and gas decays in the same space use either controlled release of generated gasses and particles or numerical modelling methods [16,31], and thus are not practical for general use. A study by Tran et al. [17] assessed room ventilation using metabolic CO₂ decay and used occupancy-based PM changes to estimate particle deposition in a naturally ventilated classroom. However, the study did not compare the decays of CO₂ and PM. To understand the practicality of using PM sensors to monitor indoor air change rates and assess how well CO₂ decay represents indoor aerosol decay, there is a need to comprehensively evaluate and compare the decay rates of in-situ CO₂ and PM of different sizes generated by human activities in various indoor spaces.

In this study, we conducted size-resolved PM measurements with low-cost sensors to compare the decay rates of CO₂ and a range of PM sizes (<1 µm (PM₁), <2.5 µm (PM_{2.5}), and <10 µm (PM₁₀)) generated from human activities in a mechanically ventilated university classroom in Spring and Fall 2021. Instances of high aerosol mass concentrations were regularly observed during both class and cleaning (fogging aerosols) events, providing a valuable opportunity to measure in-situ indoor aerosol decay. Both CO₂ and PM decays were then characterized and fit to an exponential decay curve to assess the decay time constant (τ). τ was, in turn, used to understand the room ventilation dynamics, as well as to compare the decays of CO₂ and PM. Results from this work provide insights into the practicality and limitations of using in-situ CO₂ and PM decay measurements to assess room ventilation.

2. Experiments and methods

2.1. Space studied and instrumentation

Continuous indoor air quality monitoring was performed in a 180.9 m² × ~3.7 m tall lecture hall at the Georgia Institute of Technology (Georgia Tech) during two semesters, from March–May 2021 (Spring) and August–September 2021 (Fall) using two QuantAQ low-cost sensors (QuantAQ/Aerodyne Research ARISense v200, hereafter referred to as QuantAQ/ARI v200, and QuantAQ MODULAIR-PM, hereafter referred to as MODULAIR-PM) [32–34]. The QuantAQ/ARI v200 detects various gas species including CO₂. It uses an NDIR CO₂ sensor (Alphasense IRC-A1) to measure CO₂, and it can measure in the range of 0–5000 ppm. The MODULAIR-PM uses both an optical particle counter (OPC) and nephelometer to report mass concentrations (0–2000 µg m⁻³) of PM₁, PM_{2.5}, and PM₁₀, and provides size-resolved particle number concentration measurements between 350 nm and 40 µm. Both sensor models have a time resolution of 1 min and record environmental conditions including temperature, pressure, and relative humidity. Both sensors were calibrated by the manufacturer prior to use and do not require user calibration. A recent study by Yang et al. [32] performed source apportionment analysis of urban air pollution with the QuantAQ sensor data (also using the QuantAQ/ARI v200 and MODULAIR-PM) and resolved similar source factors to those determined from research grade instrument data. Results from Yang et al. [32] indicate that the MODULAIR-PM can be used to assess PM mass concentration trends.

One factor to consider when using low-cost sensors is the impact of environmental conditions on sensor performance. The QuantAQ/ARI v200 and MODULAIR-PM are rated for use in environments with temperature from –20 to 60 °C, and relative humidity from 5 to 95%. Throughout the measurement period in this study, temperature was

observed to range between 21 and 27 °C, while relative humidity ranged between 18 and 55%. Prior investigation of OPCs and nephelometers by Hagan and Kroll [35], as well as Hagan et al. [33], indicated that values of relative humidity observed in this study should have had a negligible effect on the sensor particle size distribution measurements.

The sensors were installed ~0.3 m apart and at a height of ~2.1 m above the floor on the wall. The classroom investigated is situated in a building built in 2000 and contains one permanently sealed window to the outside. A schematic of the classroom is displayed in Fig. 1. The room is part of a multizone space, and is supplied with a Minimum Efficiency Reporting Value 13 (MERV 13) filtered mixture of roughly 70% indoor air recirculated from neighboring classrooms and 30% outdoor air, though these percentages change based on outdoor air conditions and economizer settings. The MERV 13 filter for the room is replaced quarterly. The room is equipped with a fully automated variable air volume mechanical heating and ventilation (HVAC) system that is CO₂ demand-controlled. The HVAC supply air flowrates can change several times within an hour to maintain indoor conditions (e.g., temperature, relative humidity, and CO₂ levels) within a set range of values that are dependent on the HVAC occupancy mode. For both Spring and Fall, the HVAC system was set to run in Occupied Mode from 6 AM to 9 PM every weekday, and in Unoccupied Mode from 9 PM to 6 AM every weekday and all weekend. During Occupied Mode, ventilation is set to increase the supply air flowrates once CO₂ levels exceed 1200 ppm and return to previous flowrates once levels drop back below 800 ppm. In Occupied Mode, the HVAC system additionally attempts to maintain temperatures between 20.7 and 23 °C, providing heated or cooled air when temperatures leave this range, and to maintain humidity below 50%. During Unoccupied Mode, this range is more broad, with ventilation set to maintain temperatures below 26 °C, and to not respond to elevated humidity nor CO₂ levels. These different set points often lead to lower HVAC ventilation rates during Unoccupied Mode [36].

The room studied was occasionally (not often more than one time per day) fogged with aerosols for disinfection. During the fogging procedure, the fogging personnel sprayed the fogging aerosols, spending a total of 1–2 min in the room. It is noted that fogging was carried out after classes ended for the day, when no one else was in the room, and the personnel performing the fogging wore personal protective gear.

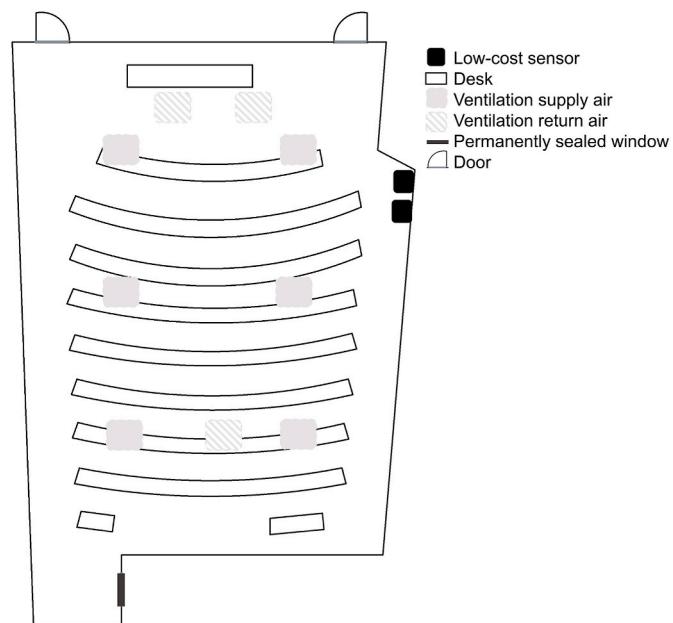


Fig. 1. Schematic (top view) of the room studied, indicating the locations of the low-cost sensors, furniture, doors, permanently sealed window, and ventilation supply and return air (on ceiling).

2.2. Data analysis and model fitting

Fig. 2 displays the timeseries of temperature, relative humidity, CO₂, PM₁, PM_{2.5}, and PM₁₀ measured in both Spring and Fall. In the classroom, three types of human occupancy events led to elevated levels of CO₂ or PM concentrations. For each event, once the source of the CO₂ or PM emission (i.e., occupants) vacated the room, the pollutant concentration subsequently decayed (primarily due to ventilation and, for PM, also deposition processes). The three human occupancy events observed are displayed in **Fig. 3**: 1) Throughout class, metabolic CO₂ levels built up until class ended and students left the classroom (hereon referred to as class CO₂) (**Fig. 3a**). 2) At the end of class, PM₁₀ (though not so much PM_{2.5} nor PM₁) levels were observed to spike (referred to as class PM₁₀). These spikes in PM₁₀ were attributed to particle resuspension and student movement at the end of class [15,22,37–40] since they appeared at the end of class time (rather than building up throughout) (**Fig. 3a**). 3)

Outside of class activities, the room was occasionally fogged. Fogging resulted in a sharp increase in PM₁, PM_{2.5}, and PM₁₀ (**Fig. 3b**). Since the personnel performing the fogging left the room immediately after fogging (remaining in the room for under 2 min), there was no corresponding increase in or decay of CO₂ during the fogging events.

There are two main approaches to using metabolic CO₂ as a tracer gas to evaluate room ventilation, described in depth in review papers by Batterman et al. [41] as well as Persily [7]. One is the steady state or equilibrium method: once CO₂ levels are constant, an estimated rate of CO₂ generation from occupants can be used to determine the ventilation rate required to maintain CO₂ at a steady state level. In this study, since the number of occupants was not known for each class, and since this method is not applicable to the types of instantaneous PM events we observed, our analysis is focused on the second method: assessing the decay rate of the tracer species. To do this, the species decay following each individual event was fit to an exponential decay model. In order to

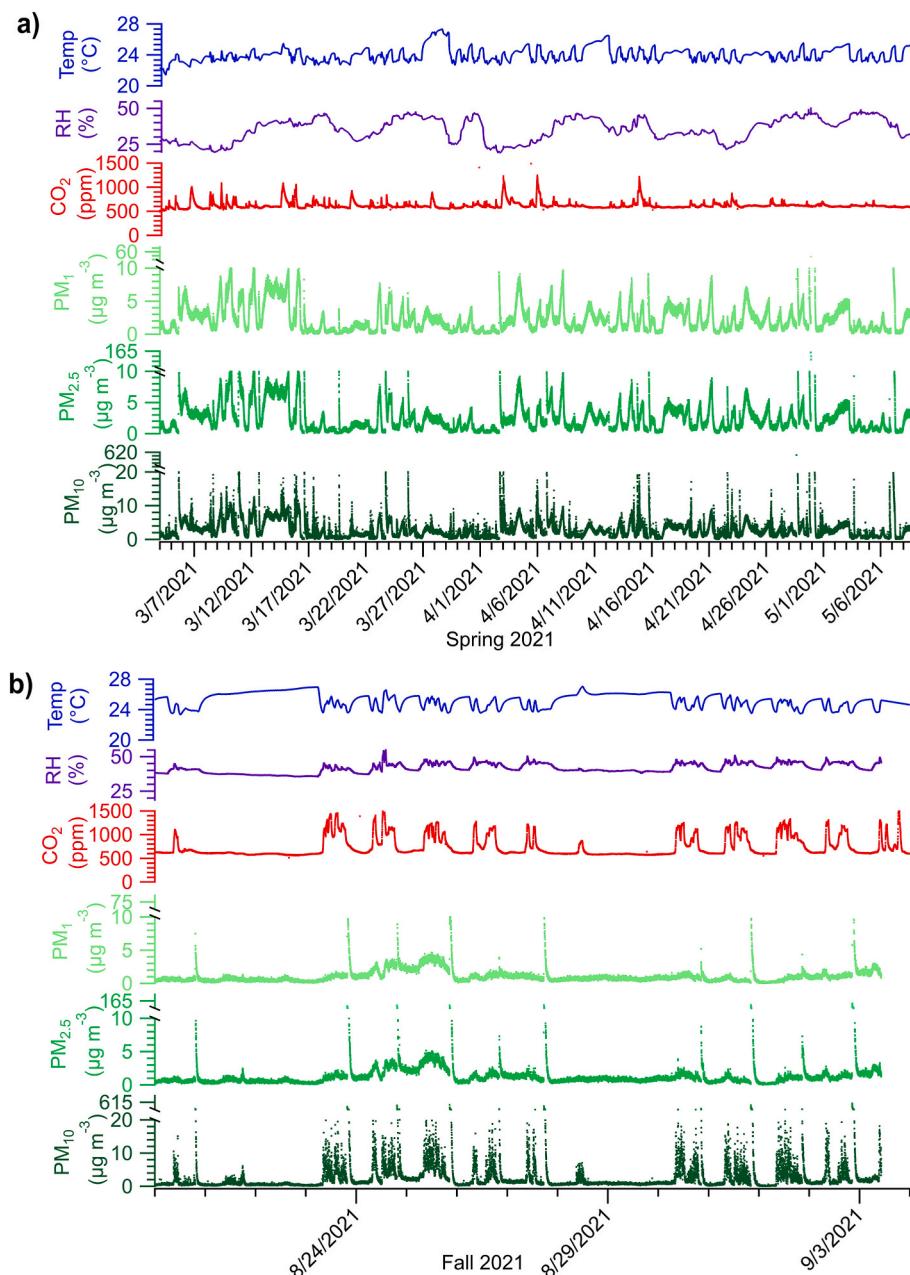


Fig. 2. **a)** Timeseries of temperature (Temp), relative humidity (RH), CO₂, PM₁, PM_{2.5}, and PM₁₀ in Spring 2021. Large spikes in PM mass concentrations indicate fogging events. **b)** Timeseries of temperature (Temp), relative humidity (RH), CO₂, PM₁, PM_{2.5}, and PM₁₀ in Fall 2021.

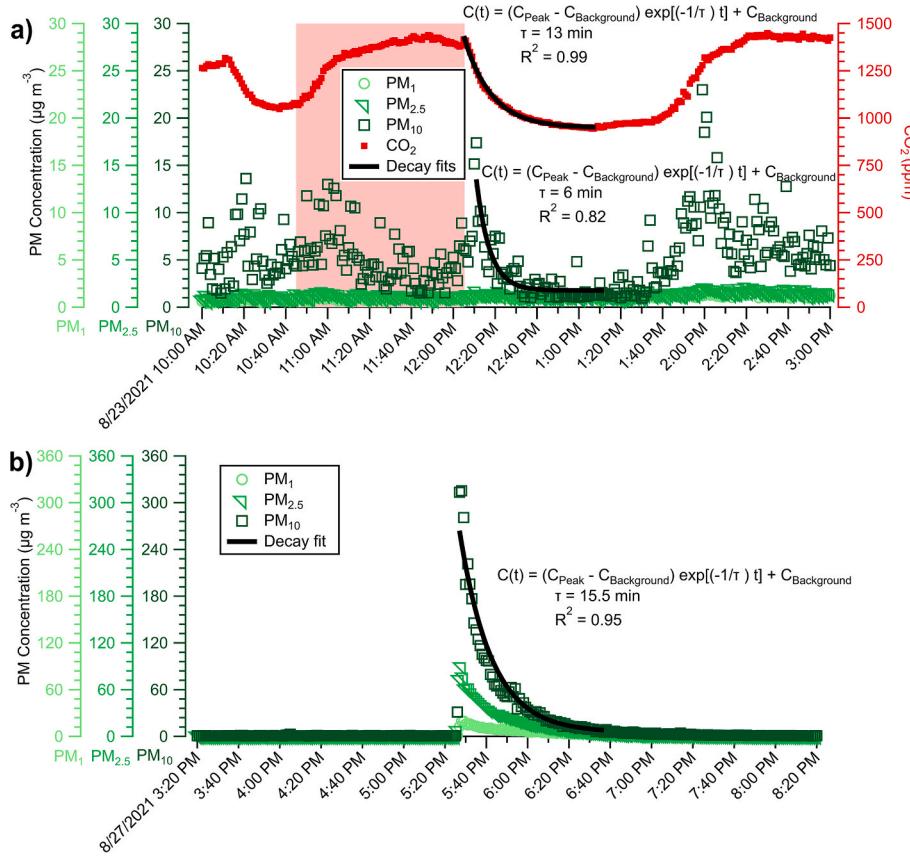


Fig. 3. a) Example of class CO₂ and class PM₁₀ (08/23/2021, during Fall 2021). Exponential decay fits (Equation (2)) shown in solid black lines. Class time is highlighted in pink. b) Example of fogging PM. Exponential decay fit (Equation (2)) for PM₁₀ is shown in a solid black line. R² values shown are derived from linear fits performed on natural log transformations of the same data sets, which can be found in the SI Section 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

apply the decay model, a number of assumptions must be made: 1) The air is well-mixed, and there is a homogenous concentration of the species throughout the room. This criterion is difficult to confirm without deployment of multiple sensors, and presents a primary limitation of any tracer decay technique that does not check homogenous tracer dispersion. However, it has previously been reported that non-homogeneity may lead to tracer decay analysis errors of only around 7% [42]. 2) The air change rate is constant throughout the decay period. 3) For CO₂, that there is no deposition of CO₂. 4) For PM, that coagulation effects are negligible [20]. 5) There is no source of the species during the decay period. Specifically, for class CO₂ it was assumed that the only CO₂ source during class time was the occupants, and that once occupants left there was no source of CO₂ in the classroom. For class PM₁₀, it was assumed that the only PM₁₀ source was particle resuspension from student movement, and that there was no PM₁₀ emission once students left the room. For fogging PM (PM₁, PM_{2.5}, and PM₁₀), it was assumed that the only PM source was fogging spray, that the fogging did not initiate significant aerosol chemistry, and that there was no other PM emission source once fogging was completed.

The mass balance of each species is given as:

$$\frac{dC}{dt} = -\frac{1}{\tau} [C(t) - C_{Background}] \quad (1)$$

and integrated to:

$$C(t) = (C_{Peak} - C_{Background}) * \exp\left(-\frac{1}{\tau} * t\right) + C_{Background} \quad (2)$$

where $C(t)$ is the concentration of the species; τ is the decay time constant; $C_{Background}$ is the background concentration of the species in the room, which was considered equivalent to the species concentration in incoming supply air (at steady state the background concentration in the room = concentration in incoming air); and C_{Peak} is the peak species

concentration (before decay). Fig. 3 shows an example fit for each type of event. When $t = \tau$, $C(\tau) = C_{Peak} * \exp(-1)$, and τ represents the time that it takes for 63% of the peak concentration to decay, or the amount of time a full room's volume of air is changed with new incoming air (here, a filtered mix of outdoor and recirculated air supplied by mechanical HVAC ventilation and/or infiltrating through other openings in the room) [7]. As the room studied here does not have openable windows, air change rate was attributed mainly to HVAC ventilation. Then, ACH can be estimated by taking $1/\tau$. It is important to note that the τ calculated for PM decay from Equation (2) accounts for all particle loss processes (i.e., including both HVAC ventilation and particle deposition) and could lead to an overestimation of ACH if used to calculate ventilation. To directly compare the timescale dynamics of CO₂ and PM, subsequent discussion will be centered on τ (i.e., τ_{CO_2} and τ_{PM}).

Another important note is that, when determining ACH values, one must consider if the room studied is single or multizone (that is, if HVAC supply air includes air recirculated from other rooms in the building). If the room is multizone, and if the rest of the building air does not maintain a constant concentration of the tracer, the calculated ACH may vary from the true ventilation rate provided by the HVAC ventilation system [7,41], due to interference from variations of species concentrations in the incoming supply air. However, calculating species decay rates still holds value since they represent the timescale for occupant-generated species (such as CO₂ or PM such as virus particles) to lower to steady state background levels [7]. Corresponding ACH estimates can also provide context for ventilation rates.

Statistical analysis to compare different sets of measurements was performed using a two-sample *t*-test, and differences were considered significant at p-value <0.05.

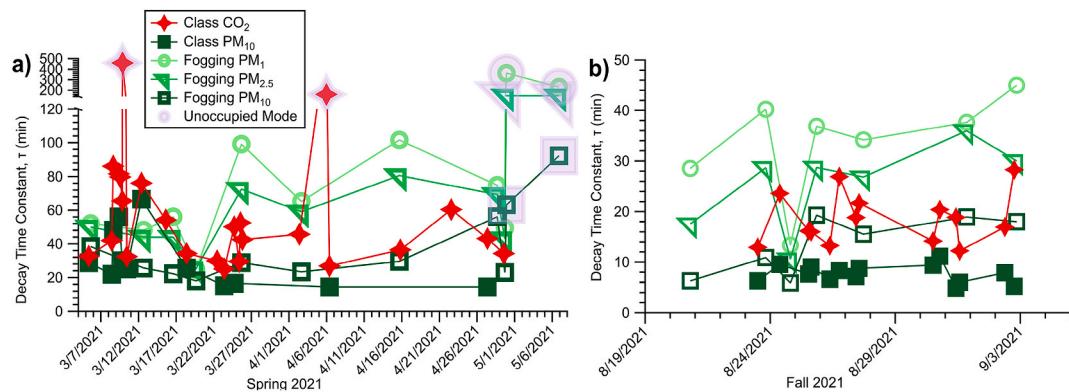


Fig. 4. a) Timeseries of τ_{CO_2} , τ_{PM_1} , $\tau_{\text{PM}_{2.5}}$, and $\tau_{\text{PM}_{10}}$ in Spring 2021. Decay time constants from events that occurred when the HVAC was in Unoccupied Mode are highlighted in lavender. b) Timeseries of τ_{CO_2} , τ_{PM_1} , $\tau_{\text{PM}_{2.5}}$, and $\tau_{\text{PM}_{10}}$ in Spring 2021.

3. Results & discussion

3.1. Variation in decay time constants

Fig. 4 displays the timeseries of all τ values for Spring and Fall class and fogging events. It can be observed that τ varied substantially. One pattern of variation was that τ values were substantially lower in Fall than in Spring. Since there were no changes in mechanical HVAC ventilation settings between the Fall and Spring, this change is mainly attributed to the difference in classroom occupancy in the Spring vs. Fall. In response to the COVID-19 pandemic, in-person Spring classes were held at reduced capacity (under ~20 students) with appropriate social distancing and health and safety precautions in place [43]. In Fall, classes had full in-person instruction (with occupancy ranging from ~20 to 75 students). As can be seen in the timeseries of Fig. 2 and in a direct comparison of class times between the Spring and the Fall in Fig. 5, higher classroom occupancy in the Fall led to CO_2 levels almost two times as high as levels during the Spring. Full classroom occupancy in the Fall also led to higher class time temperatures, which was attributed to the increase in body heat production. A combination of elevated class time temperatures (triggering ventilation cooling) and elevated CO_2 levels (triggering the CO_2 demand-controlled ventilation once levels exceeded 1200 ppm), led to higher HVAC supply air flowrates during the Fall. It is also possible that seasonal variables such as outdoor temperature led to a difference in HVAC supply air flow between the semesters [7,44].

Another source of variation in τ was HVAC occupancy mode. In Spring, events that occurred when the HVAC was in Unoccupied Mode (highlighted in lavender in Fig. 4) led to high τ values. Class τ_{CO_2} and fogging τ_{PM_1} were over 3 and 4 times higher during Unoccupied Mode than Occupied Mode, respectively. Though the effect of HVAC

occupancy mode was less pronounced on fogging $\tau_{\text{PM}_{2.5}}$ and $\tau_{\text{PM}_{10}}$, the PM decay profiles of two separate fogging events that occurred in different HVAC occupancy modes (but on the same day) indicated that the effect was still clear (Fig. 6a). Interesting to note in Fig. 6a is also the decrease in all PM levels at 6 AM. This decrease is due to the switch of the HVAC from Unoccupied Mode to Occupied Mode. Unoccupied Mode settings allowed temperatures to rise overnight above the Occupied Mode maximum set point of 23 °C. When the HVAC switched back to Occupied Mode at 6 AM, increased air flowrates were introduced back to the room to lower the temperature. To identify if any other daily trends systematically affected τ , all Spring and Fall class and fogging events were plotted by time of day in Fig. 6b and c, respectively. No other diurnal trend in τ was observed. These results emphasize the strong impact of mechanical HVAC settings (i.e., CO_2 demand-control and occupancy mode) on species decay.

Figs. 4 and 6 also demonstrate that the τ values of each species varied substantially from day to day, even during Occupied Mode and around the same time of day. The variation within Occupied Mode is clearer in Fig. 7, which shows box plots of τ values for all class and fogging events that occurred during Occupied Mode in both Spring and Fall. Spring τ values ranged from 25–86 min for class CO_2 , 14–66 min for class PM_{10} , and 24–103 min, 25–82 min, and 18–56 min for fogging PM_1 , $\text{PM}_{2.5}$, and PM_{10} , respectively. Fall τ values ranged from 12–28 min for class CO_2 , 5–11 min for class PM_{10} , and 13–45 min, 11–36 min, and 6–19 min for fogging PM_1 , $\text{PM}_{2.5}$, and PM_{10} , respectively. When converted to ACH estimates, the class CO_2 values ranged from 0.69–2.40 hr⁻¹ in the Spring, averaging at 1.37 ± 0.53 hr⁻¹; and 0.91–4.91 hr⁻¹ in the Fall, averaging at 3.00 ± 1.13 hr⁻¹. These results from the Spring are very similar to the ACH reported for a mechanically ventilated university classroom by You et al. [13], which also used metabolic CO_2 decay to estimate ACH. The Fall ACH estimates observed here were significantly higher (p-value

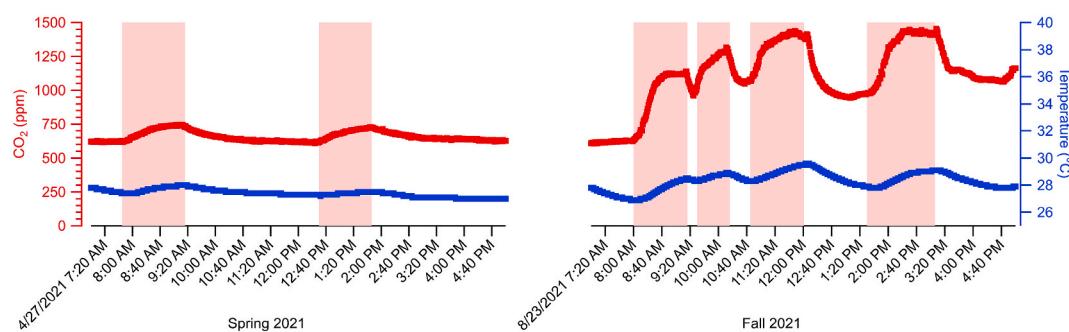


Fig. 5. CO_2 timeseries from a day in Spring and a day in Fall 2021. Class times are highlighted in pink. Peak CO_2 levels on the Fall day reached up to 2X higher than on the Spring day (1500 ppm vs. 750 ppm). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

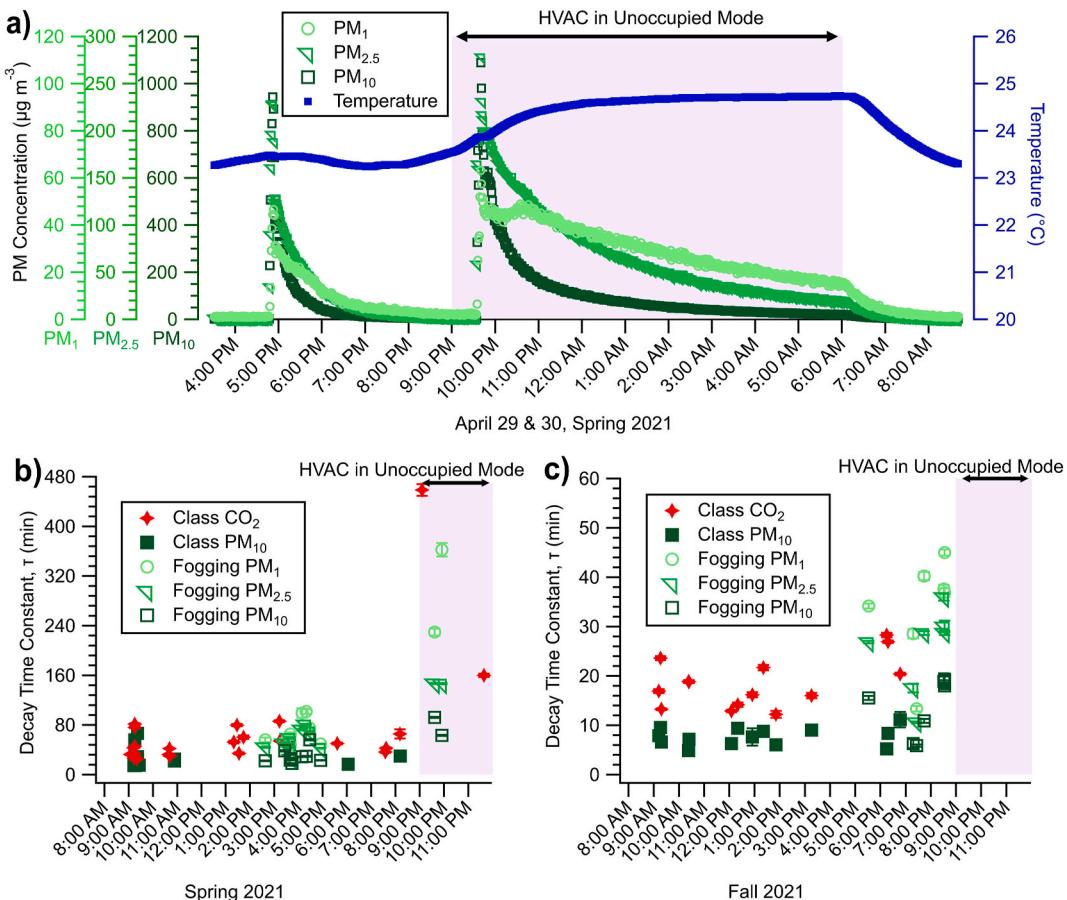


Fig. 6. **a)** Timeseries of two fogging events that occurred a few hours apart, one when HVAC was in Occupied Mode and one when HVAC was in Unoccupied Mode. It is noted that the y-axis scale is different for each PM size. The decrease in PM levels at 6 AM corresponds to HVAC switching back to Occupied Mode. **b)** Diurnal of τ_{CO_2} and τ_{PM} in Spring 2021. **c)** Diurnal of τ_{CO_2} and τ_{PM} in Fall 2021.

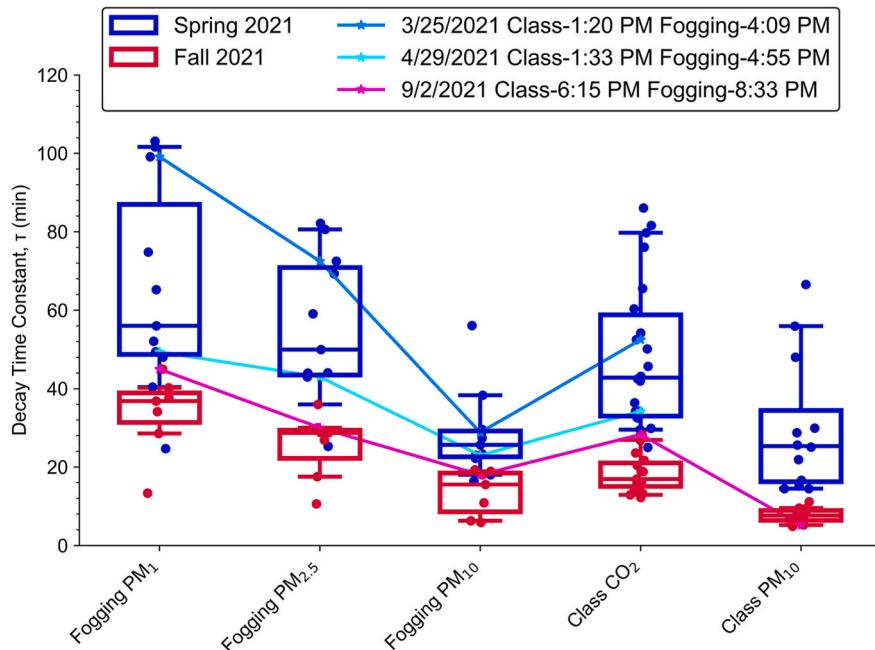


Fig. 7. All CO₂, PM₁₀, PM_{2.5}, and PM₁ decay time constants from events that occurred when the HVAC was set to Occupied Mode. The whisker box plots represent the following statistics: lower-whisker: 5th percentile; box: lower quartile, median, and upper quartile; upper-whisker: 95th percentile; solid circle: single value. Class and fogging events that occurred within a few hours of each other are connected by lines. It is noted that the events on 3/25/2021 and 4/29/2021 do not include class PM₁₀ measurements due to insufficiently clear PM₁₀ data to fit to a decay.

<0.05) than those in the Spring, but were still at the lower end of ACH values reported for mechanically ventilated classrooms in the study by McNeill et al. [1]. As noted in McNeill et al. [1], this difference could be in part due to different measurement techniques (where other universities performed controlled release of tracer gasses), and/or room or HVAC setup (with the room in this study potentially using lower percentages of outdoor air in ventilation due to economizer settings).

In addition to the subset of ACH estimations made from data collected in the room presented in this study, ACH estimates from classrooms in four other Georgia Tech buildings were presented in McNeill et al. [1]. Of the other classrooms presented, three were also mechanically ventilated, and the ACH values determined were comparable to the values presented in this work. The sole exception was for a building built in 1958 and equipped with an older mechanical ventilation system, which presented significantly lower ACH (p -value <0.05). The results from these data, as well as the broader work presented in McNeill et al. [1], highlight the importance of building designs and HVAC ventilation system type on air change rates and indoor air quality.

It was hypothesized that, other than regular changes in room mechanical HVAC ventilation (e.g., HVAC triggered by changes in indoor conditions like temperature), daily variations in class τ_{CO_2} could also be attributed to changes in incoming concentrations of CO₂ in the HVAC supply air during the decay period. In Equation (2), it was assumed that $C_{background}$ was equal to the species concentration in the incoming supply air. Incoming supply air CO₂ levels can vary due to changes in the percentage of outdoor air in supply air, changes in outdoor air CO₂ levels, or CO₂ concentrations in neighboring classrooms that share recirculated air [41]. To explore the extent to which changes in incoming concentrations of CO₂ may have affected the calculated τ , the CO₂ decays following two classes held on the same day (3/25/2021) were analyzed. Based on the class CO₂ decays, τ_{CO_2} was determined to be 30 min and 52 min (which would correspond to ACH values of 2 hr⁻¹ and 1.15 hr⁻¹, respectively), a difference of 22 min (or 0.85 hr⁻¹). A simple sensitivity analysis revealed that a change in incoming CO₂ concentration of 15 ppm during the CO₂ decay period after one of the classes could explain this difference in decay measurement (SI Section 2). A similar sensitivity analysis on PM decay indicated that changes in incoming PM levels of up to 3 $\mu\text{g m}^{-3}$ would have little effect on the fogging τ_{PM} , but greater effect on class $\tau_{PM_{10}}$ due to the lower PM₁₀ mass concentrations of class events (SI Section 2). These changes in incoming CO₂ and PM levels are possible considering the background fluctuations displayed in Fig. 2.

These results highlight a primary limitation—changes of species levels in incoming supply air—of using CO₂ or PM decay to determine ACH [8,45]. Although changes in incoming CO₂ or PM levels could change the calculated ACH, it is worth noting that this impact is dependent on the ventilation rate. In rooms with higher air change rates, any spike in CO₂ or PM concentration due to human occupancy events will decay more quickly. If the decay period is shorter, there may be fewer fluctuations in incoming species concentrations, which would lead to a smaller impact of changes in incoming concentration levels on calculated ACH values. It is hypothesized that this could help explain why τ varied less in the Fall than in the Spring (Fig. 7). Specifically, in the Fall, air change rates were almost two times higher than the Spring. Thus, the decay periods were almost two times shorter and there was only half as much time for incoming species concentrations to fluctuate. Therefore, the τ calculations from the Fall could have been less impacted by incoming species fluctuations. Also to note is that the mixing of room air (affected by student movement or open doors) and the HVAC supply air flowrates to the room (affected by changes in room conditions like temperature or CO₂ levels after occupants leave) [41] may have changed in the time following class dismissal [7,11]. In such cases, τ determined from occupant-generated species decay after class dismissal may not represent the ventilation conditions that students were exposed to during class. When evaluating room ventilation conditions, in order to

minimize the effect of these uncertainties and the variation in calculated τ , it is recommended to perform continuous measurements over extended periods of time and to characterize a range of air change rates.

For PM, another important cause of τ variation was particle size. For each fogging event, PM₁₀ decayed the quickest, followed by PM_{2.5} and then PM₁ (Figs. 4 and 7). This is expected since larger particles have higher gravitational settling rates and thus decay, or deposit, faster than smaller particles [19,20,22,46]. To roughly quantify the deposition of PM, a brief analysis of particle decay and deposition rates was performed. Equation (2) was adjusted to explicitly include a term accounting for particle deposition, and a non-linear least squares method was used to fit the equation to each fogging decay (for each PM) and return the optimized parameters of deposition rate (k) and ventilation rate, or ACH. Results from this analysis (SI Section 2) resolved k values ranging from $k = 0.0\text{--}0.8$, $0.0\text{--}2.1$, and $1.4\text{--}4.6 \text{ hr}^{-1}$ for fogging PM₁, PM_{2.5}, and PM₁₀, respectively. It is noted that there are only a few incidents in which $k = 0 \text{ hr}^{-1}$ (and mainly for PM₁) which can be interpreted as ventilation largely outweighing deposition to the point that model fits resolved negligible contributions of deposition to the particle decay. The maximum values observed were similar to the deposition rates from kitty litter suspension PM events reported by Howard et al. [22] and within the range of indoor deposition rates reported by Thatcher et al. [19], though were slightly higher than the deposition rates of classroom PM reported by Tran et al. [17]. A potential source of the variation in results is that the method of calculating fogging PM deposition rates in this study involved fitting two parameters (both ACH and k) to the PM decay, which differs from the methods used by Howard et al. [22] and Tran et al. [17] that only fit k .

This deposition analysis provides insights into the relative importance of air change rate vs. particle deposition on PM decay, which depends on the air change rate value and characteristics of the emitted aerosol, such as aerosol size distribution. The low deposition rates of fogging PM₁ confirmed that its decay was primarily air change rate dominated (i.e., $k \ll \text{ACH}$), consistent with the observation that fogging τ_{PM_1} was the most affected by changes in HVAC settings, while $\tau_{PM_{2.5}}$ and $\tau_{PM_{10}}$ were comparably more controlled by deposition. Class PM₁₀ k values were resolved with a similar method to the one used to find fogging PM k values, but by setting the ACH parameter to be the value found from the corresponding τ_{CO_2} (i.e., setting ACH = $1/\tau_{CO_2}$) and solving for only the parameter k (following the same method as Tran et al. [17]). Deposition rates were found to be $0.2\text{--}3.9 \text{ hr}^{-1}$ in the Spring (within a similar range to those of fogging PM₁₀), but significantly higher (p -value <0.05) in the Fall at $1.6\text{--}8.9 \text{ hr}^{-1}$ (Fig. S3). It has been observed in prior studies that increased room air mixing can increase PM deposition rates due to increased interactions between particles and room surfaces [19,20,22,29]. Therefore, it is possible that in the Fall both the higher HVAC ventilation rates and increased student movement (due to higher class attendance) increased deposition rates, further contributing to the decreased class τ_{PM} values in the Fall.

3.2. Using CO₂ decay rate as a proxy for aerosol decay rate

CO₂ sensors have been used to collect in-situ data for metabolic CO₂ decay analysis in many previous studies [1,8,16,21,41], and they remain widely recommended for use in indoor air quality monitoring [4,25]. They are also more available to the public than low-cost PM sensors that provide size-resolved particle measurements (particularly for PM₁) [11,47]. Thus, it is of interest to assess how metabolic CO₂ decay compares to occupant-generated PM decay. Fig. 7 reveals that the range of calculated τ_{CO_2} was generally comparable to that of τ_{PM} . Within each semester, there was no significant difference between the means of the distributions of τ_{CO_2} and τ_{PM} .

Class CO₂ and class PM₁₀ events provided an opportunity to directly compare CO₂ and aerosol decays that occurred at the same time (and thus under the same air change rate). For every paired class CO₂ and class PM₁₀ event, the τ_{CO_2} was 1.4–3 times higher than the $\tau_{PM_{10}}$. If these

values were used to calculate room ACH, they would result in an ACH estimation of $\sim 1.9\text{--}2.6 \text{ hr}^{-1}$ higher if based on PM_{10} decay than if based on CO_2 decay. This discrepancy is expected due to the additional effect of particle deposition on class PM_{10} decay. Unlike class PM_{10} , because fogging was not performed when the room was occupied, there were no simultaneous fogging PM and class CO_2 decays available for direct comparison. Marked in Fig. 7 are three sets of events (3/25/2021, 4/29/2021, and 9/2/2021) for which class and fogging events took place within a few hours of each other. Once again, class τ_{CO_2} values were higher than the fogging $\tau_{\text{PM}_{10}}$ values. Overall, while it is expected that PM_1 and $\text{PM}_{2.5}$ should decay faster than CO_2 due to particle deposition, in these three events this trend was not apparent. We hypothesize that the τ_{CO_2} were lower than the τ_{PM} due to different HVAC ventilation rates during the class and fogging events, changes in incoming CO_2 concentrations, and a difference in room air mixing due to student movement and opening doors at the end of class [19,20,22,29].

Since a main reason to directly quantify PM decay instead of CO_2 decay is to improve estimations of airborne aerosol timescales (particularly respiratory aerosols), it was of interest to consider how well the τ_{PM} values presented in this work may represent human respiratory particle decays. Though the size distribution of exhaled respiratory aerosols varies, previous studies have reported that the number concentrations of respiratory aerosols peak at $<1 \mu\text{m}$ and are primarily $<5 \mu\text{m}$ [22,23,48–51]. Size distribution analysis from the MODULAIR-PM sensor data (shown in Fig. 8) of class PM_{10} and fogging PM_{10} events revealed that both consisted of an increase in particles $<5 \mu\text{m}$, so the size-dependent decay rates of respiratory particles were somewhat represented in the decays of PM studied in this work. The size

distribution of class PM_{10} revealed that the increase in particle mass concentration at the end of class was due to a small number of large particles ($>2.5 \mu\text{m}$), supporting the initial assumption that class PM_{10} events were due primarily to particle resuspension. The size distribution of fogging PM_{10} specifically had a more evenly distributed increase in particles across the $0.4\text{--}4 \mu\text{m}$ range, with a peak number concentration of particles sized under $1 \mu\text{m}$, similar to the size distribution of respiratory aerosols reported by Johnson et al. [51].

4. Conclusions and implications

In this work, CO_2 and PM from human occupancy events were used to assess air change rates over extended periods of time in Spring and Fall 2021. This is one of the first studies in literature [17] to explore how in-situ PM monitoring—a method more easily accessible to the general public than measuring controlled releases of particles—can be used to measure occupant-generated PM decay in a classroom and assess indoor aerosol decay timescales. To our knowledge, this is also the first study that comprehensively evaluates and compares the decay rates of occupant-generated CO_2 , PM_1 , $\text{PM}_{2.5}$, and PM_{10} in a mechanically ventilated university classroom using in-situ measurements. Overall, it was observed that both τ_{CO_2} and τ_{PM} varied substantially throughout the study period. Part of the variation was attributed to changes in the HVAC ventilation schedule between the day and night, as well as from a change in class attendance levels from Spring to Fall and subsequent response of the CO_2 demand-controlled ventilation system. Decay rates were also observed to vary throughout the day, even under similar HVAC settings, potentially due to changes in incoming species levels. The results in this work indicate that to fully understand a room's ventilation, continuous and long-term measurements to quantify a range of room air change rates should be performed. This is particularly true for mechanically ventilated rooms, where continuous in-situ measurements can bring notice to any changes—or failures—in a room's HVAC ventilation system.

In comparing the decay rates of CO_2 and PM, τ_{CO_2} values were generally comparable to τ_{PM} values, indicating that CO_2 measurements can be used to estimate the timescale that human-emitted aerosols remain in the air, though deposition effects should not be assumed negligible. CO_2 monitors are more widespread and often less costly than PM sensors, with many building HVAC systems already monitoring CO_2 . The results from this work support the continued use of CO_2 monitoring to gain a general understanding of occupant-generated aerosol decays and potential virus exposure timescales when PM sensors are not available.

In this study, PM deposition analysis was limited, and future work should be done to characterize the consistency and repeatability of PM deposition and decay rates from various emission sources in different classroom settings. Moreover, since low-cost sensors vary in PM size resolving capabilities, future work is needed to further assess the accuracy of PM measurements of various PM sensor designs, which could in turn affect the calculated τ_{PM} values and air change rates. Further recommendations for general use of low-cost sensors to monitor indoor air quality in classrooms include: 1) Placing multiple sensors throughout the classroom to assess how decay and deposition vary throughout the space, including near the supply air to account for changes in incoming species levels. 2) Recording the number of students in the room during each class. 3) Performing tracer decay analysis with an independent (not commonly existing in classroom air) tracer gas, for direct comparison with in-situ CO_2 and PM tracer decay rates.

In reality, there are many situations in which someone wishing to use a PM or CO_2 sensor to evaluate the risk of a virus transmission will only have access to a single sensor and limited other resources. The analysis provided in this work presents a case for the feasibility of using either a low-cost CO_2 or PM sensor to do so. Although occupant-generated CO_2 or PM tracer decay calculations may not provide true ventilation rates (depending on the validity of the assumptions for the decay model

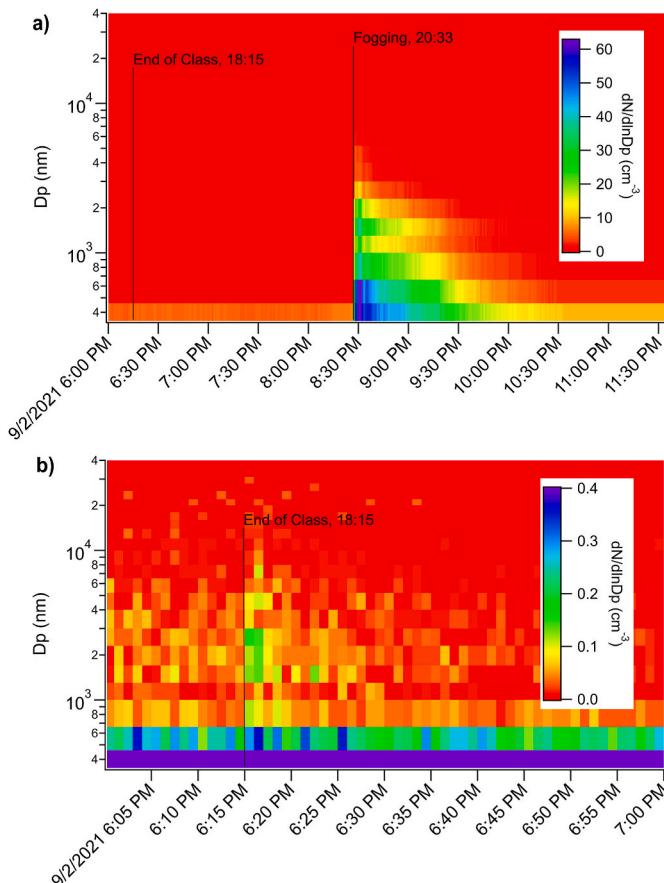


Fig. 8. a) Particle number size distribution for a class event and a fogging event on 9/2/2021. b) Particle number size distribution for the same class event, with re-scaled x-axis and z color scale. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

discussed in the Experiments and methods Section and throughout the paper), the estimated ACH from the analysis provides a decent benchmark when none other is available. When using this technique, if the average calculated ACH falls below recommended ACH values (such as the range of ACH values, per person, recommended by ASHRAE [52]), it is a good indication that room ventilation or particle removal methods should be improved (such as installing portable air filtration units). Moreover, when using a PM sensor, the calculated decay time constant represents the timescale that aerosols remain in the air. This information can be useful when assessing room usage; for example, if there is a 15 min transition time between classes, τ_{PM} should ideally be under 15 min. If this is not the case, consider increasing the time between classes.

As low-cost sensors of all types continue to be tested and become more widely available, it will become more feasible to continuously monitor a wider number of indoor environments. Results from this study highlight that continuous indoor air quality monitoring is both a necessary and increasingly viable method of assessing and improving our understanding of indoor aerosol and ventilation dynamics.

CRediT authorship contribution statement

Sabrina Westgate: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Funding acquisition. **Nga Lee Ng:** Supervision, Resources, Project administration, Funding acquisition, Conceptualization, Methodology, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.buildenv.2022.109559>.

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