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An assessment of residence scale residential $PM_{2.5}$ exposure inaccuracy with a measurement-constrained theoretical model approach

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ABSTRACT

Residences are an important micro-environment for human exposure to $PM_{2.5}$ mass. Existing measurement and simulation methodologies can return residence scale estimates of residential $PM_{2.5}$ mass concentration by averaging over the individual rooms of a residence. Such methods can be advantageous, however accuracy may be lost through averaging over rooms. Recent measurements allow the presented assessment of accuracy in exposure to residential $PM_{2.5}$ mass when using the residence scale. For multiple residences, measurements were taken in the kitchen, a child's bedroom and either the living or dining room. Here we set a theoretical ground-truth for exposure of inhabitants to residential $PM_{2.5}$ mass by combining the measurements resolved across the three rooms with multiple plausible and informative occupancy schedules. Against this reference were compared three types of averaging over rooms for quantification of their accuracy: (i) equal-weighted and (ii) volume-weighted arithmetic means of multi-room measurements, and (iii) use of the living or dining room as representative of the whole residence. The error in residence scale estimation can lead to all residences found to have time-integrated $PM_{2.5}$ mass exposure above 100 μg m^{-3} through room-resolved estimation being miscategorised as having $PM_{2.5}$ less than 100 μg m^{-3}. Consequently, depending on the objective of work, room-averaging in deterministic studies may be deemed inappropriate. The median error in $PM_{2.5}$ daily exposure for typical room and residence occupancy schedules was 0 μg m^{-3}, and the median error for relative risk to all-cause mortality was 0, suggesting that room-averaging may be appropriate for population-level studies. A key implication for field studies and simulations is that researchers can combine this assessment with study objectives to identify whether the residence scale is sufficiently accurate or whether the room scale is required.

1. Introduction

It is known that the mass concentration of particulate matter with diameter less than or equal to 2.5 μm (hereafter $PM_{2.5}$) in residences is positively associated with health burden (Morawska et al., 2013; Lewis et al., 2022; Buonanno and Kumar, 2025; Chamseddine et al., 2025). Two factors make residential $PM_{2.5}$ particularly important: the relatively high concentrations compared to other micro-environments, and the high fraction of time spent in residences (Thomas et al., 2022; Ferguson et al., 2023).

Fixed-site measurement and modelling studies assuming a spatially uniform $PM_{2.5}$ concentration within residences are common approaches to investigating residential $PM_{2.5}$ exposure. Practical, financial and computational expense is less for both measurement and modelling if residence scale resolution can be used rather than if room scale resolution needs to be used. That is to say, for a given time in a given

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residence, a single value to represent the entire residence exposure to residential $PM_{2.5}$ is cheaper to gain and apply than values per room.

An important question for identifying appropriate methodologies is therefore: what inaccuracy is introduced when using residence scale estimates of exposure to residential $PM_{2.5}$?

Empirical studies have previously addressed this issue, through comparison of fixed site measurement of residential $PM_{2.5}$ (as the residence scale estimate) against exposure estimated by personal monitoring. Results from studies without distinction between times spent in residences versus other locations are challenging for accurately quantifying the representativeness of the fixed point residential measurement (Özkaynak et al., 1996; Pellizzari et al., 1999; Lai et al., 2004; Turpin et al., 2007), and are therefore not reviewed here.

Lung et al. (2021) compared $PM_{2.5}$ personal exposure measurements when the subject was only present in a residence against coincident fixed site living/dining room measurements. Measurements were independently calibrated against a reference instrument and the study considered residences with $PM_{2.5}$ typically greater than 5 $\mu g\,m^{-3}$. Considering residences in New Taipei City (Taiwan), they found a $p < 0.001$ and r^2 of 0.74 between personal exposure when at home and living room fixed site measurements.

For Kousa et al. (2002) and Mohammadyan and Ashmore (2005), personal monitoring after returning home from work until leaving home from work was distinct from other times, though it includes leisure time outside the residence. Both Kousa et al. (2002) and Mohammadyan and Ashmore (2005) compared personal monitoring results against measurements from a single fixed site monitor placed in the living room for Mohammadyan and Ashmore (2005) and in an unspecified location in the residence for Kousa et al. (2002). Kousa et al. (2002) found a statistically significant ($p < 0.001$) correlation between personal monitoring and fixed site measurement for participants in Basel, Helsinki and Prague. Measurements from multiple cities returned a linear regression with r^2 of 0.76 (Kousa et al., 2002). Mohammadyan and Ashmore (2005) find a statistically significant ($p < 0.01$) correlation between personal monitoring and fixed site measurement for participants in Bradford (UK), with r^2 of 0.38.

Kousa et al. (2002), Mohammadyan and Ashmore (2005) and Lung et al. (2021) therefore show that the variance in measurement of $PM_{2.5}$ from an indoor fixed site has significant predictive ability for the variance in personal exposure to residential $PM_{2.5}$, though the effect of the inaccuracy that can be introduced through the fixed site measurement was not investigated.

The computational modelling studies of Petrou et al. (2024, 2025) returned an underestimate of $PM_{2.5}$ exposure for inhabitants when using the living room concentration or an equal-weighted arithmetic mean of kitchen, living room and bedrooms to estimate $PM_{2.5}$ exposure, respectively. For the living room representation, the bias was greatest for the individual responsible for cooking, at around 60%, decreasing to negligible for inhabitants spending almost no time in the kitchen. The result was similar when using the equal-weighted room arithmetic mean. Whilst the study is simplistic in treating cooking as the only source of indoor-generated $PM_{2.5}$, it suggests substantial inaccuracy when using residence scale $PM_{2.5}$ exposure for inhabitants regularly in close proximity to indoor $PM_{2.5}$ sources. Similarly, the modelling study of McGrath et al. (2017) reports more than a factor of 10 difference in $PM_{2.5}$ exposure between different room occupancy schedules in the same residence, indicating that a residence scale value would give substantial inaccuracy for some inhabitants.

The study of Serrano et al. (2023) is the only one we are aware of to compare residential PM exposure between personal monitoring and multi-room fixed site monitoring. This study design is in principle a powerful way to quantify inaccuracy in residence scale resolution for residential $PM_{2.5}$ exposure. However, interpretation of results is undermined by most studied residences having $PM_{2.5}$ below 5 $\mu g\,m^{-3}$, compromising application to more concerning residences with orders of magnitude higher $PM_{2.5}$ (Du et al., 2024; Cheung et al., 2025). Also undermining the study is the lack of independent calibration of the low cost sensors, since similar sensors (Nothhelfer et al., 2025) have shown compromising error for comparable field evaluations (Westgate et al., 2025).

In terms of observational study, none of the studies above address the accuracy of equal-weighted or volume-weighted averages over rooms, and none investigate the effect of residence scale $PM_{2.5}$ inaccuracy on categorising residences by $PM_{2.5}$, nor on health effect. Meanwhile, the modelling studies above are based on case studies and therefore difficult to extend across larger samples. These gaps in quantification of the inaccuracy of residence scale exposure to residential $PM_{2.5}$ is concerning since many field campaigns and computational models assume that the residence scale is representative. For example, the volume-weighted arithmetic mean over rooms is the assumption (either explicitly or implicitly applied) in single zone computational simulation (a.k.a. 0D or box models) (Milner et al., 2011), such as: Logue et al. (2015), Thomas et al. (2022), Du et al. (2024) and Carslaw et al. (2025). Whilst the equal-weighted arithmetic mean over rooms is important, because it is an intuitive method for reporting results from multi-room campaigns (e.g. Ikeda et al., 2023; Cheung et al., 2025; Varaden et al., 2025). Finally, the living/dining room representation of the residence scale is regularly used in field studies such as Nishihama et al. (2021) and Riveron et al. (2025). Furthermore, without knowledge of the inaccuracy of residence scale estimates, the evaluation of exposure studies that have room scale representation through comparison with residence scale estimates is questionable (e.g. Ferguson et al., 2023).

The shortage of spatial resolution evaluation for residential $PM_{2.5}$ is in part attributable to the challenge of practically delivering a field study that combines fixed site and personal monitors, as this not only requires substantial researcher time, but is also demanding for participants.

An alternative to the personal monitoring method for exposure is the indirect method for exposure estimation that combines fixed site measurement by micro-environment with time-activity diaries containing the times at which the assessed individual is present in each micro-environment (for residences, micro-environments are rooms of a residence) (Klepeis, 1999). For room-resolved residences, the indirect method is valid if the fixed site monitoring per room reproduces the personal monitoring per room.

Spatial heterogeneity of $PM_{2.5}$ mass concentration across rooms of residences has been demonstrated theoretically and empirically. For example, residence-averaged values for the kitchen and bedroom vary by up to a factor of two in the empirical results of Cheung et al. (2025). Additionally, within a room, studies indicate that concentrations can vary by an order of magnitude during a localised emission event (Acevedo-Bolton et al., 2014; Jones et al., 2024; Liu et al., 2025). Heterogeneity arises from the local nature of indoor emission of $PM_{2.5}$, e.g. cooking, candle burning, smoking, coupled with a time delay before the emitted $PM_{2.5}$ is either transferred to other rooms or removed (e.g. by egress or deposition to surfaces) (e.g. Shen et al., 2021; Xiang et al., 2021).

To test whether the local nature of indoor residential emission sources significantly affects personal exposure to $PM_{2.5}$, we must consider personal exposure measurements. The "personal cloud" phenomenon that elevates pollutant levels in close proximity to individuals was reported in previous studies with no distinction between micro-environments (e.g. Turpin et al., 2007). It is not found in Kousa et al. (2002), Mohammadyan and Ashmore (2005), Cattaneo et al. (2010) and Lung et al. (2021), which do distinguish exposures between micro-environments. Additionally, measurement (Shen et al., 2021; Xiang et al., 2021) and modelling (Lakey et al., 2021) find that $PM_{2.5}$ becomes spatially homogenised within a room of an inhabited residence. Furthermore, following prescribed standards for placement of fixed site indoor monitors assists in avoiding local sources and sinks of $PM_{2.5}$ (e.g. Cheung et al., 2025).

Whilst a robust evaluation of the validity of the indirect method using multi-room measurement for residential $PM_{2.5}$ exposure remains outstanding, the above review is evidence in favour of its validity. Therefore, here we constrain the indirect method by the multi-room, multi-residence fixed site measurements of inhabited residences from the INGENIOUS (understandING the sourcEs, traNsformations and fate of IndOor air pollUtants) (Ikeda et al., 2023; Carslaw et al., 2025; Cheung et al., 2025) study. We also combine population-level survey-constrained inhabitant time-activity diaries with theoretical diaries to set room and residence occupancy schedules. The occupancy schedules are rationalised so as to cover the range of plausible exposures per residence, allowing distinction between exposure variation due to occupancy schedules and variation due to spatial scales for $PM_{2.5}$ representation.

The study here therefore relies on the theoretical model that fixed site monitors represent exposure, and on the theoretical model that plausible room and residence occupancy schedules can provide meaningful exposure estimates. Whilst further evidence to test these theoretical models is needed, we next describe why our study represents an important advance for investigating residence scale inaccuracy within the constraints of currently available empirical data.

Our assessment of the inaccuracy of residence scale $PM_{2.5}$ estimates is novel because the review above shows a dearth of studies constrained by measurements and directly addressing the residence scale inaccuracy question. It is significant because of its precision compared to past studies (detailed above), specifically, only using residential measurements that synchronise with occupancy. Significant because it considers a relatively large cohort (258 residences), with most breaching the WHO annual guideline of 5 $\mu g\,m^{-3}$ (WHO, 2021; Cheung et al., 2025), and therefore of particular concern for health burden, an advance on past studies. Significant because of the investigation of various types of averaging over rooms and of the inclusion of independent sensor calibration. The study is timely because developments in low cost sensor technology and application are allowing multi-room fixed site monitoring of residential $PM_{2.5}$ (e.g. Ikeda et al., 2023; Varaden et al., 2025) and because residence scale spatially uniform concentrations of residential $PM_{2.5}$ are being applied in the use and evaluation of exposure models (e.g. Logue et al., 2015; Thomas et al., 2022; Ferguson et al., 2023; Du et al., 2024).

Our study aim is therefore to quantify the inaccuracy introduced to residential $PM_{2.5}$ exposure through use of residence scale estimations by comparison with a reference residential $PM_{2.5}$ exposure based on the indirect method constrained to room-resolved fixed site measurements of inhabited residences. We aim to deliver this evaluation in a manner helpful to those deciding whether the residence scale is suitable for their work. To do this our objectives are: (1) quantify $PM_{2.5}$ error across systematically selected occupancy schedules, (2) quantify the tendency to miscategorise residences, (3) quantify error in the relative risk of all-cause mortality and (4) quantify error variation within and between residences.

2. Method

The experimental methods adopted for INGENIOUS are detailed in Ikeda et al. (2023) and Cheung et al. (2025), with key points repeated here. 321 inhabited family residences in Bradford (UK) were considered. Monitoring was conducted at five minute intervals, and the sampling duration for each study residence was two weeks. The total period of monitoring was March 2023-April 2024. Simultaneous observations of $PM_{2.5}$ were obtained for three rooms per residence: kitchen, living or dining room (hereafter living/dining room) and child's bedroom. $PM_{2.5}$ observation was made by placement of a separate sensor in each room. Where practical, sensor placement in a room followed international standard BS ISO 16000-37:2019 (ISO, 2026), which recommends a height corresponding to the breathing zone, otherwise a height as close as possible to this was used.

Sensors were Plantower PMS5003 inside AirGradient units. $PM_{2.5}$ outputs were calibrated through coincident and collocated observations with a FIDAS PALAS 200 S. Analysis of sensor bias showed an average over measurements and an average across instruments of ±5% (Cheung et al., 2025). Therefore, to capture the effect of measurement bias we include in our analysis data synthetically adjusted to represent bias. Data were adjusted to give two cases, one with kitchen measurements increased by 5% whilst bedroom measurements were decreased by 5%, acting to give a maximum error to the residence scale estimate as it enhances the difference between rooms for the average residence (Cheung et al., 2025). In the second case, kitchen measurements decreased by 5% whilst bedroom measurements were increased by 5%, acting to give a minimum error to the residence scale estimate as difference between rooms was reduced for the average residence.

The three considered rooms are meaningful because:

(1) they include the typical maximum (kitchen) and minimum (bedroom) locations of $PM_{2.5}$ (Wigzell et al., 2000; Bhangar et al., 2011; Hegde et al., 2020; Abdel-Salam, 2021; Singh et al., 2024; Cheung et al., 2025);

(2) collectively, they represent the locations that inhabitants typically spend most time when in the residence (Fig. A.13, Ferguson et al. (2023))

(3) they are commonly used locations for residential airborne pollution studies (e.g. Wigzell et al., 2000; Bhangar et al., 2011; Hegde et al., 2020; Abdel-Salam, 2021; Singh et al., 2024; Cheung et al., 2025; Varaden et al., 2025).

We assume that the measurement in the child's bedroom is representative of all bedrooms in a given residence.

A visual summary of the measured $PM_{2.5}$ is provided in Fig. A.7. We note in this figure that relative standard deviations are typically around 200% (standard deviations double that of the arithmetic mean measurement) for the kitchen and living/dining room, with values typically around 150% for the bedroom, indicating substantial differences between residences and/or days per residence. However, relative standard deviations when considering variation over just rooms per residence on a given day are smaller, with arithmetic means around 30%.

2.1. Residence characteristics

Following data processing (detailed in Section 2.7) 258 study residences remained for analysis, providing 1278 days of measurement. The volume and layout of analysed residences varied considerably, from one to four storeys, with total volume of the measured rooms (kitchen, living/dining room and bedroom) varying from 60 to 220 m^3. Histograms of storeys and volume are provided in Appendix Figs. A.8 and A.9, respectively.

Inhabitants were aware of the measurement, but were otherwise assumed to behave as normal. Statistics on the distribution of several variables (ranges provided here) for the sample are contained in Cheung et al. (2025): season (all), cooking appliance (electric and gas), type of residence (detached, semi-detached, terraced and flat), year residence built (<1914–>1991), pets (present and absent), smokers (present and absent), housing tenure (rented and owned) and ethnicity (varied). The standard deviation of daily averages reported for our sample in Cheung et al. (2025) of 25.7 $\mu g\,m^{-3}$ is notably more than the 15.4 $\mu g\,m^{-3}$ reported in the study of 5000 Japanese residences by Nishihama et al. (2021).

The average $PM_{2.5}$ inside sampled residences is more than twice as high as the average outdoor $PM_{2.5}$ (Fig. S5 of Cheung et al., 2025), indicating that indoor sources are the primary contributor to $PM_{2.5}$.

Ventilation rate is a primary determinant of the decay rate of $PM_{2.5}$ in residences, and we show in Fig. A.10 that the daily arithmetic mean for this value varies considerably, with a geometric standard deviation of 1.7, indicating a broad range of ventilation when compared against the Nazaroff (2021) review of residential ventilation rate.

In our sample, residences were skewed towards higher levels of deprivation relative to those typical of the UK, as demonstrated in Fig. A.11. Cheung et al. (2025) report a statistically significant decreasing trend of $PM_{2.5}$ with decreasing deprivation in our sampled residences, however they also show $PM_{2.5}$ levelling off at the lower deprivation categories, questioning whether sampling of residences with even lower deprivation would have significantly different $PM_{2.5}$ and $PM_{2.5}$ determinants, such as indoor activity. We note that since residences of higher deprivation tend to have higher $PM_{2.5}$, the sample analysed here is well aligned with epidemiological interest.

Given the relatively large spread in observed $PM_{2.5}$ compared to previous study, and the spread of variables defining residence character described above, there is reason to consider the sample as relevant to most UK residences in terms of $PM_{2.5}$ determinants.

2.2. Exposure estimation

24-hour (midnight to midnight) exposure to $PM_{2.5}$ mass concentration ($PM_{2.5}$) on a given residence day (rd) for a given occupancy schedule (k) was defined as:

$$\mathrm{PM}_{2.5rd,k} = \frac{\Sigma_{t=1}^{t=n}\mathrm{PM}_{2.5t,rd,k}\Delta T_t}{\Sigma_{t=1}^{t=n}\Delta T_t}, \tag{1}$$

where t denotes a given time on that residence day, n is the total number of observed times that residence day, and ΔT is the time interval represented by the observation.

$PM_{2.5}$ in Eq. (1) is found by two approaches in this study. First, the room scale reference exposure is represented by resolving $PM_{2.5}$ over the observed rooms, hereafter referred to as the room-resolved method. Second, the residence scale comparison exposure, is represented by one of several methods to gain a residence scale average, hereafter referred to as room-averaged methods. Both methods are detailed below.

2.3. Occupancy

Information on room occupancy and residence occupancy with time per resident were not obtained for INGENIOUS. Here two types of rationalised time-activity diaries set room and residence occupancy schedules. First, we set schedules based on the UK Time Use Survey 2014-15 (Gershuny and Sullivan, 2017), second we set theoretical schedules to cover the plausible range of exposures possible in each residence.

We take a systematic approach to room and residence occupancy to allow the variation in exposure by occupancy schedule to be distinguished from the variation in exposure by spatial representation (room-averaged vs. room-resolved). As such, four room occupancy schedules were defined, with timings given in Fig. A.12:

- Synchronised with room of maximum $PM_{2.5}$ (Ro1),
- Typical adult survey-constrained schedule (Ro2),
- Typical child survey-constrained schedule (Ro3),
- Always in bedroom (Ro4).

The first and last schedules will give the maximum and minimum exposures for the average residence, since Fig. A.7 shows the bedroom having the lowest $PM_{2.5}$ at all times, when averaged over residences. The survey-constrained schedules are useful for providing an exposure representative of the typical adult (Fig. A.13) and child (Ferguson et al., 2023). For synchronisation with room of maximum $PM_{2.5}$, many sources of indoor residential $PM_{2.5}$ do require an inhabitant to initiate the emitting activity, and it is plausible that the initiator will remain in the same room during elevated $PM_{2.5}$, therefore whilst it is also plausible that the inhabitant moves to another room during elevated $PM_{2.5}$, this theoretical schedule is useful.

Four residence occupancy schedules were defined, with the timings of occupation given in Table A.1:

- All day presence (Re1),
- Relatively short daytime absence (Re2),
- Relatively long daytime absence (Re3),
- Night absence (Re4).

By combining all possible room and residence occupancy schedules, 16 occupancy scenarios are generated, allowing a systematic assessment of exposure variation by occupancy schedule. Hereafter, a room and residence occupancy combination is provided in shorthand by combining their codes, e.g., always in bedroom all day is Ro4Re1.

Since this study focuses on the residence micro-environment, when occupancy schedules set absence from residence, $PM_{2.5}$ exposure is not considered for that time.

To quantify the difference in exposure error between occupancy schedules (Occ), the following equations were used:

$$BE_{ra,rd,k} = \mathrm{PM}_{2.5ra,rd,k} - \mathrm{PM}_{2.5rr,rd,k}, \tag{2}$$

$$Occ_{MADra,kj} = \frac{1}{m}\Sigma_{rd=1}^{rd=m}|BE_{ra,rd,k} - BE_{ra,rd,j\neq k}|, \tag{3}$$

$$Occ_{NMADra,kj} = \frac{Occ_{MADra,kj}}{\frac{1}{2m}\Sigma_{rd=1}^{rd=m}(|BE_{ra,rd,k}| + |BE_{ra,rd,j\neq k}|)}, \tag{4}$$

where ra is room-averaged, rr is room-resolved, k and j are occupancy schedules, m is the total number of residence days (rd). BE represents bias error, $(N)MAD$ represents (normalised) mean absolute difference. Therefore, the bias error was first found for each occupancy schedule for each residence day for a given room-averaging approach (Eq. (2)), then the mean absolute difference between two occupancy schedules was found by averaging over residence days (Eq. (3)), and this was finally normalised by the mean absolute bias error of the two occupancy schedules. The result is a comparison between the errors of two occupancy schedules relative to the errors typical of those schedules.

2.4. Reference exposure

The reference exposure provides a theoretical ground-truth of the exposure of an individual to residential $PM_{2.5}$. Here, reference exposure is provided by treating the observations from the three rooms separately, giving a room-resolved approach. We have reviewed the limited evidence around the validity of the theory that room-resolved fixed-site monitors represent personal exposure to residential $PM_{2.5}$ in Section 1, finding evidence in support. Additionally, the occupancy schedules we employ will not exactly reproduce the schedules of real inhabitants, however through systematic representation of schedules, we cover the plausible range and can consider the inaccuracy of the residence scale estimate per occupancy schedule.

For the reference exposure, time-weighted arithmetic means of $PM_{2.5}$ were found per half hour per room. Then room occupancy schedules were applied to estimate the $PM_{2.5}$ exposure per half hour. Finally, the $PM_{2.5}$ daily exposure was found by the arithmetic mean over the half hours that an individual was present in the residence.

For each of the 16 occupancy schedules described in Section 2.3, box and whisker plots of $PM_{2.5}$ daily exposures through the room-resolved reference method are provided in Fig. A.14. Although not the focus of this study, comparing Fig. A.14 with the simulated results for $PM_{2.5}$ exposure in McGrath et al. (2017), there is indication that in the sampled residences, internal doors tended to be open, not closed, at least during periods of elevated $PM_{2.5}$.

2.5. Exposure when averaging over rooms

Three methods for averaging over rooms were investigated through comparison with the reference exposure, with implications for field study design and application, and modelling design and application:

(1) Equal-weighting to the three observed rooms for an arithmetic mean at a given time;

(2) Use of the living/dining room observation to represent an average state of the residence at a given time;

(3) Volume-weighting to the three observed rooms for an arithmetic mean at a given time.

None of the room-averaging methods requires a room occupancy schedule, thereby simplifying field study and computational simulation. The equal-weighted room average approach is useful to investigate as, in the interests of multi-room field study efficiency, it is the study method requiring least data collection (e.g. no data on room volume needed). Using the living/dining room $PM_{2.5}$ to represent the whole residence $PM_{2.5}$ was investigated, since this location is often used in single room studies (e.g. Mohammadyan and Ashmore, 2005; Riveron et al., 2025), whilst multi-room studies indicate it has a typically moderate $PM_{2.5}$ compared with other rooms (e.g. Cheung et al., 2025).

Finally, the volume-weighted room average approach was investigated as it is the approach of a zero-dimensional, or single zone, box model (Milner et al., 2011). Here the volume fraction representation of the total residence per observed room is approximated by assuming that a measurement on a given floor (ground, first, etc.) of a residence represents the value on that floor. If multiple measurements were available for one floor, they were weighted by the room volumes on that floor (room volumes were measured for INGENIOUS), to gain an arithmetic mean value for that floor. If there were floors that were not measured on, the closest measurement(s) was used for that floor. It was assumed that each floor had the same volume of air. For example, for a three storey residence, with the observed kitchen and living/dining room on the ground floor, with a volume ratio of 0.4 to 0.6, and the observed bedroom on the first floor, the calculation for volume-weighted arithmetic mean $PM_{2.5}$ at a given time would be:

$$PM_{2.5t} = \frac{0.4}{3}PM_{2.5t,kitchen} + \frac{0.6}{3}PM_{2.5t,living/dining\ room} + \frac{2}{3}PM_{2.5t,bedroom}, \quad (5)$$

since the kitchen and living/dining room measurement make a volume-weighted contribution to the ground floor, whilst the bedroom measurement represents the first and second floors.

For the room-averaged exposures, averaging was done over rooms at individual times first. Then, time-weighted arithmetic means of $PM_{2.5}$ were found per half hour. Finally, the $PM_{2.5}$ daily exposure was found by the arithmetic mean over half hours that an individual was present in the residence.

2.6. Accuracy of the room-averaged exposure

The accuracy of the room-averaged exposure was characterised for each of the 16 occupancy schedules described in Section 2.3 through pairing the daily room-resolved and room-averaged estimated exposures. A key metric in characterising the inaccuracy generated by room-averaging was the bias error (BE) for a given occupancy schedule on a given residence day (Eq. (2)). Additionally, the absolute error (AE) was also considered:

$$AE_{ra,rd,k} = |(PM_{2.5ra,rd,k} - PM_{2.5rr,rd,k})|. \quad (6)$$

Correlation analysis was conducted through pairing daily room-averaged and room-resolved estimates. Normal distributions were best approached with $\log_{10}$ of estimates, with untransformed estimates positively skewed, as indicated in Fig. A.14. To allow comparison with previous studies, the sample Pearson correlation coefficient (r_p) was found for $\log_{10}$ transformed estimates and the Spearman rank correlation coefficient (r_s) was found for untransformed estimates. Their respective coefficients of determination (r^2) were also found. For Pearson, the p-value for a hypothesis test whose null hypothesis is that the slope is zero, using Wald Test with t-distribution of the test statistic (p_p) was found. For Spearman's rank, the p-value for a hypothesis test whose null hypothesis is that two samples have no ordinal correlation (p_s) was found. Furthermore, the y-intercept (c) and gradient (m), found from linear least-squares regression on the $\log_{10}$ transformed estimates, were reported. r_p, r_p^2, p_p and linear regression were performed using the linregress function of the scipy.stats package (scipy v1.15.3) (Virtanen et al., 2020). r_s, r_s^2 and p_s were calculated through the spearmanr function of scipy.stats package (scipy v1.15.3).

For health effect, we employed the form of concentration–response function for $PM_{2.5}$ and relative risk of all-cause mortality (RR) described in Burnett et al. (2014) and Apte et al. (2015):

$$RR_{ra,rd,k} = 1 + \alpha(1 - exp(-\gamma(PM_{2.5ra,rd,k} - C_0)^{\delta})), \quad (7)$$

where C_0 (the threshold above which risk exceeds 1) was set to zero following the recommendation of Chen et al. (2023). α, γ and δ were respectively set to 1.0, 0.003 and 1.2 to achieve a relative risk function that compromises between that analysed for relatively low $PM_{2.5}$ by Chen et al. (2023) and that at relatively high $PM_{2.5}$ by Burnett et al. (2014) (the latter plotted in Apte et al. (2015)). The resulting function is plotted in Fig. A.15.

We also investigated the variation of inaccuracy in $PM_{2.5}$ exposure across all residence days, between residences and between days of a residence by calculating the normalised bias error NBE per residence day:

$$NBE_{ra,rd,k} = \frac{BE_{ra,rd,k}}{PM_{2.5rr,rd,k}}100, \quad (8)$$

where $BE_{ra,rd,k}$ is given in Eq. (2). The standard deviation for NBE was found for:

- all residence days,
- the arithmetic mean per residence,
- days per residence.

Variation across all residence days was characterised by the standard deviation of NBE over all residence days. Variation between residences was found by first calculating the arithmetic means of NBE over observed days per residence, then the standard deviation of these means over residences was found. Variation within residences was limited to residences with multiple days of observation and was found by first calculating the standard deviation of NBE over days per residence, then taking the arithmetic mean of the resulting standard deviations over residences. The variation in error was investigated because it is beneficial to know whether a given residence is likely to achieve an acceptable error over all observed days. For such a residence, room-averaging could be acceptably accurate even when it is unacceptable for other residences. This is important for deterministic studies which may focus on case study residences.

A mean normalised bias error ($MNBE$) was used to provide a single value summary of the bias errors per occupancy schedule and room-averaging method over all residence days:

$$MNBE_{ra,k} = \frac{\Sigma_{rd=1}^{rd=m} NBE_{ra,rd,k}}{m}, \quad (9)$$

where m is the total number of residence days. Eqs. (2), (6) and (9) with $PM_{2.5}$ replaced by RR (Eq. (7)) provided characterisation of accuracy for the relative risk of all-cause mortality.

For categorisation of residences by their $PM_{2.5}$, arithmetic means of $PM_{2.5}$ over observed days were found for each residence using the room-resolved and room-averaged methods. Then, using room-resolved estimates, residences were categorised into four $PM_{2.5}$ intervals based on WHO guidelines (WHO, 2021): <5, ≥5 <15, ≥15 <100, ≥100 $\mu g\,m^{-3}$ for each occupancy schedule. The fraction of residences in a category that were not correctly placed in that category by the room-averaged estimate was found.

2.7. Data processing

Days in residences without a calculable volume weight of the individual rooms were omitted. Times when a sensor returned an invalid result were omitted, likewise times when a sensor returned a result close to the limit of detection (≤0.5 $\mu g\,m^{-3}$) were omitted. Then, if

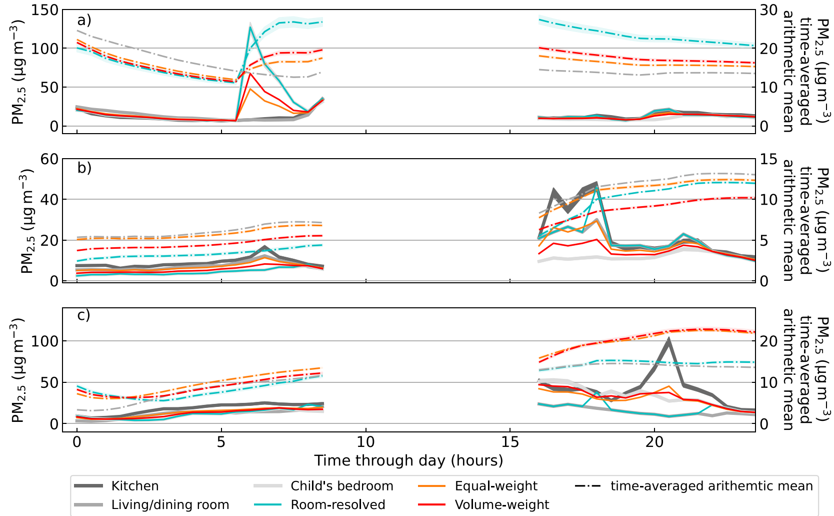

Fig. 1. Time profiles of $PM_{2.5}$ for three example residence days at the 10th (a), 50th (b) and 90th (c) percentile of bias error (Eq. (2)) for the equal-weight room-averaging approach when considering the typical adult room occupancy schedule with a relatively short daytime absence (the absence period is empty in plots). Besides the equal-weight result, demonstrations are also provided for the room-resolved, living/dining room and volume-weight results. The left ordinate, relating to solid lines, refers to $PM_{2.5}$ at different times, for observations in individual rooms and for room-resolved and room-averaged estimates. The right ordinate, relating to dashed lines, refers to $PM_{2.5}$ time-averaged arithmetic means (time since beginning of day), where the values at the end of day are those considered for accuracy characterisation such as in Eq. (2). For clarity, uncertainty ranges arising from measurement bias, as described in Section 2, are provided around room observations and time-averaged arithmetic means only.

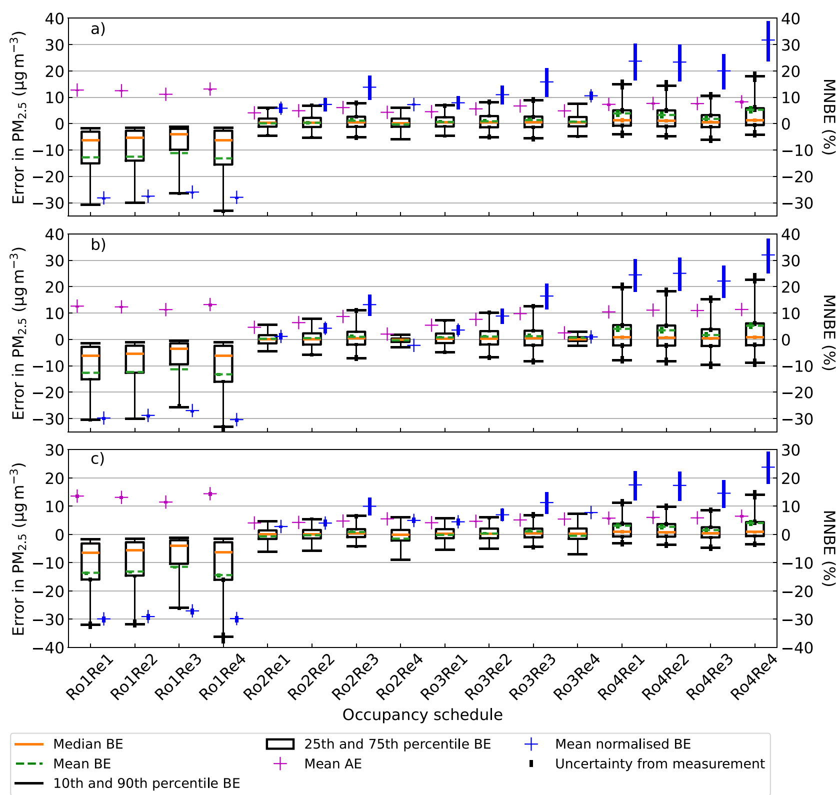

Fig. 2. Bias error (BE) and absolute error (AE) results for (a) equal-weight arithmetic mean, (b) living/dining room and (c) volume-weight arithmetic mean methods for room-averaging for all occupancy schedules. The left ordinate is for non-normalised bias errors and absolute errors. The right ordinate is for the mean normalised bias error only. Vertical bars for the range in estimates generated by measurement uncertainty are given for all metrics, but the range is not sufficiently large to be readily visible for all cases.

coincident $PM_{2.5}$ measurements across the three observed rooms were unavailable for more than 50% of a single hour, that day in that residence was omitted. Taking this approach left a total of 258 residences, covering 1278 days of measurement.

3. Results

The different occupancy schedules generated a range of errors when room-averaged estimates were compared with the room-resolved estimates, with results based on Eq. (4) given in Tables A.2, A.3 and A.4. The minimum difference between occupancy schedules (Eq. (4)) was 15%, which was for the living/dining room approach when comparing the typical child room occupancy against the typical adult room occupancy, both with a relatively long daytime absence. All occupancy schedules are therefore retained for analysis to ensure variation due to occupancy differences is captured.

For the equal-weight room-averaging approach when considering the typical adult room occupancy schedule with a relatively short daytime absence, residence days at the 10th, 50th and 90th percentile of bias error (Eq. (2)) were identified and their temporal profiles as examples of how inaccuracy is introduced to varying degrees by room-averaging is presented in Fig. 1. Focussing on the dashed lines in Fig. 1, which show the development of time-averaged arithmetic means for the room-resolved (reference exposure) and room-averaging approaches, subplots (a) and (c) exemplify how the equal-weight, volume-weight and living/dining room-averaging methods can under- and overestimate exposure after 24 h between 5 and 10 $\mu g\,m^{-3}$. In contrast, in subplot (b), the room-averaged estimates are within 2.5 $\mu g\,m^{-3}$ of the room-resolved after 24 h.

Considering the error in room-averaged $PM_{2.5}$ estimates, results for all residence days are shown in Fig. 2, where the bias error is found through Eq. (2), absolute error is found through Eq. (6) and mean normalised bias error is found through Eq. (9).

Fig. 2 demonstrates similar trends in error profiles per room occupancy schedule across the three room-averaging methods. A relatively large tendency to underestimate $PM_{2.5}$ exposure is shown for the room occupancy synchronised with room of maximum $PM_{2.5}$, with MNBE typically around -30%. A relatively moderate tendency to overestimate when always in bedroom is shown, with MNBE typically between 20 and 30%. A relatively low error when room occupancy is constrained against surveys for the typical adult and child is shown, with MNBE typically between 0 and 15%.

Whilst the median bias error is typically around −5 $\mu g\,m^{-3}$ for room occupancy synchronised with room of maximum $PM_{2.5}$, for other room occupancies it is typically around 0 $\mu g\,m^{-3}$. For these zero bias errors, the 50th percentile point for bias error must be relatively close to the 1:1 line for room-averaged vs. room-resolved estimates. However, the mean bias error tends to be positive for these room occupancies, indicating that greater biases occur on the overestimation side of the 1:1 line for room-averaged vs. room-resolved estimates.

Living/dining room bias error results for the room occupancy schedule synchronised with maximum $PM_{2.5}$ in Fig. 2b span across those given by Petrou et al. (2024), agreeing with Petrou et al. (2024) that living/dining room averages can underestimate $PM_{2.5}$ exposure for inhabitants present in the room of emission. The same is true when comparing equal-weight results in Fig. 2a with those in Petrou et al. (2025).

Correlation results based on linear least-squares regression of the $\log_{10}$ transformed estimates are shown for synchronised with room of maximum $PM_{2.5}$, typical adult and always in bedroom room occupancies for the relatively short absence residence occupancy and living/dining room method in Fig. 3. The relatively short absence (for which 70% of time is in the residence) was chosen as residents in the Lung et al. (2021) study spent on average 70% of time in the monitored residence, whilst sampled residents in Kousa et al. (2002) and Mohammadyan and Ashmore (2005) were working adults and therefore also frequently out of residence during the day. Tables containing linear regression statistics for all averaging methods and occupancy schedules are provided in Tables A.5, A.6 and A.7.

For the room occupancy following maximum $PM_{2.5}$ rooms, Fig. 3a supports Fig. 2b in showing a tendency to underestimate when room-averaging, and has r_p^2 0.84. The living/dining room has a tendency to overestimate daily $PM_{2.5}$ exposure for both the typical adult (Fig. 3b) and always in bedroom room occupancies (Fig. 3c). The correlation is stronger for typical adult room occupancy (r_p^2 0.84) than for

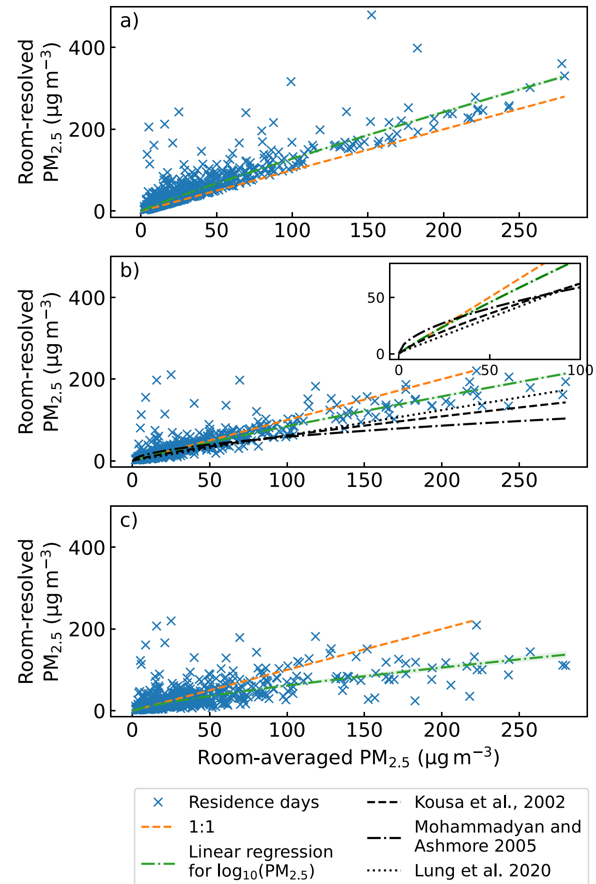

Fig. 3. Correlation analysis between the room-resolved and living/dining room representation of the residence scale $PM_{2.5}$ for three different room occupancies: (a) synchronised with room of maximum $PM_{2.5}$, (b) typical adult survey-constrained schedule and (c) always in bedroom, all for the residence occupancy of relatively short absence from home. All axes show $PM_{2.5}$ on a linear scale. The linear regressions for results of this study are for $\log_{10}(PM_{2.5})$ and is least-squares regression. The inset plot in (b) shows only regression results, with formats corresponding to the legend and only for the lower values of $PM_{2.5}$ in (b) (axes titles are the same as for the main plot in (b)) to provide more clarity for comparison between regressions.

always in bedroom room occupancy (r_p^2 0.66). Tables A.5, A.6 and A.7 show these characteristics are true across room-averaging methods, however they also show generally stronger correlations (higher r_p^2) for the equal-weight and volume-weight methods than for the living/dining room method, for example, typical adult room occupancy with relatively short absence has r_p^2 0.93 for equal-weight and r_p^2 0.94 for volume-weight.

As in Kousa et al. (2002) and Lung et al. (2021) statistically significant correlations ($p < 0.001$) were found between room-resolved and room-averaged estimates of exposure (Tables A.5, A.6, A.7). The r_s^2 of 0.74 of Lung et al. (2021) is less than the r_s^2 of 0.84 reported in Table A.6 for typical adults with relatively short daytime absence. Considering the living/dining room method for the typical adult with either relatively short or relatively long absence from residence (comparable to the working adults sampled in Kousa et al. (2002) and Mohammadyan and Ashmore (2005)), Table A.6 shows r_p^2 values of 0.84 and 0.73 for these occupancy schedules, bounding those in Kousa et al. (2002) (0.76) and higher than in Mohammadyan and Ashmore (2005) (0.38).

The regression lines on Fig. 3b, including the inset plot show that above time-integrated $PM_{2.5}$ exposures of 50 $\mu g\,m^{-3}$, the regression of this study finds less overestimation by the living/dining room fixed-site

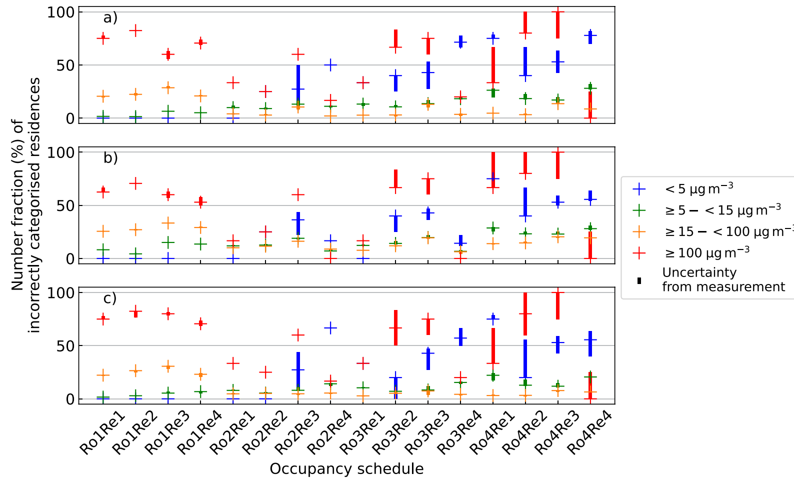

Fig. 4. The number fraction of residences belonging to the categories of $PM_{2.5}$ shown in the legend according to room-resolved estimates that are not identified in that category by room-averaging estimates, with equal-weight in (a), living/dining room in (b) and volume-weight in (c).

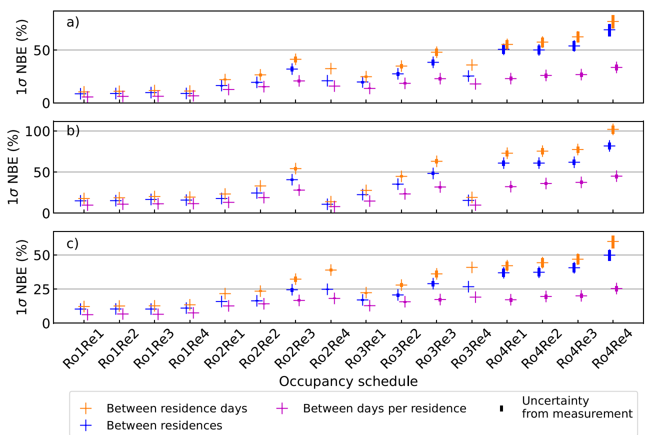

Fig. 5. Variation, expressed as one standard deviation (σ) (Section 2.6) in normalised bias error (Eq. (8)), across all residence days, between residences and between days per residence for: (a) equal-weight, (b) living/dining room, and (c) volume-weight room-averaging.

measurement than in previous studies. Below 25 µg m^{-3} the regression here does not reproduce the underestimation of the Mohammadyan and Ashmore (2005) regression, but does follow the regression of Kousa et al. (2002) relatively closely.

The fraction of residences in a category that were not correctly identified in that category through the room-averaged method is shown in Fig. 4. It is shown that for the most concerning category of ≥100 µg m^{-3}, up to 100% of identified residences are wrongly identified as being in less concerning categories when room-averaging is used. Inaccuracy is also relatively high for the least concerning category of <5 µg m^{-3}, whilst for the intermediate categories inaccuracy is typically less than 20%.

Next is investigation of how error in $PM_{2.5}$ exposure varies, specifically whether variation is generated by inter-residence or intra-residence variability. Standard deviations in normalised bias error (Eq. (8)) were used to quantify variation across all residence days, between residences and within residences as described in Section 2.6, with results shown in Fig. 5.

Fig. 5 shows that, averaged over residences, the variation in bias error between days per residence is between 5% and 45% of the room-resolved $PM_{2.5}$ daily exposure, depending on the occupancy schedule and the room-averaging method. Fig. 5 also shows the variation in error between residences to be greater than the variation between days per residence for all occupancy schedules, though of the same order of magnitude.

Next, results consider the effect of $PM_{2.5}$ error on the direction and magnitude of bias for relative risk of all-cause mortality (Eq. (7)). Comparing room-averaged and room-resolved estimates, box plots of bias error, the mean absolute error and mean normalised bias error, as described in Section 2.6 are shown in Fig. 6.

As in Fig. 2, Fig. 6 shows similar inaccuracy between room-averaging methods for a given room occupancy schedule. For example, median errors in relative risk are around −0.02 when occupancy synchronises with the room of maximum $PM_{2.5}$ and 0.0 for other room occupancies, which is true for all room-averaging methods. The maximum deviation of MNBE from zero for relative risk of mortality in Fig. 6 is 5%, less than the 32% maximum MNBE for $PM_{2.5}$ in Fig. 2. The cause of this difference is the non-linear (asymptotic) concentration–response function for $PM_{2.5}$ and all-cause mortality relative risk (shown in Fig. A.15). With reducing change in response per unit $PM_{2.5}$ at greater $PM_{2.5}$, the spread in estimates across residence days is less for relative risk than for $PM_{2.5}$, as exemplified in Fig. A.17. Consequently, the error relative to room-resolved estimate is reduced for relative risk compared to for $PM_{2.5}$.

4. Discussion

As described in Section 1, there are two theoretical model constructs employed in this study. First, the theory that room-resolved fixed-site monitors represent personal exposure to $PM_{2.5}$ in residences. In Section 1 we report evidence in favour of this model, however we also noted that the theory has not been directly investigated. Further studies, we suggest with designs comparable to Serrano et al. (2023), should investigate whether this theory is valid.

The second theory is that the employed occupancy schedules allow a meaningful characterisation of accuracy of residence scale residential $PM_{2.5}$ exposure estimates. The study took a systematic approach to setting occupancy schedules, allowing inaccuracy of the residence scale (room-averaged) representation of $PM_{2.5}$ and its effects to be quantified across the range and intermediate values of residential $PM_{2.5}$ exposure (Section 2). The resulting quantification of inaccuracy is useful because it represents the likely range and intermediate values of inaccuracy for residence scale estimates of $PM_{2.5}$ exposure.

Within the current constraints on our understanding of $PM_{2.5}$ exposure, the results presented in Section 3 should assist work around residential $PM_{2.5}$ exposure. For example, work to characterise the exposure to residential $PM_{2.5}$ on an individual residence (deterministic)

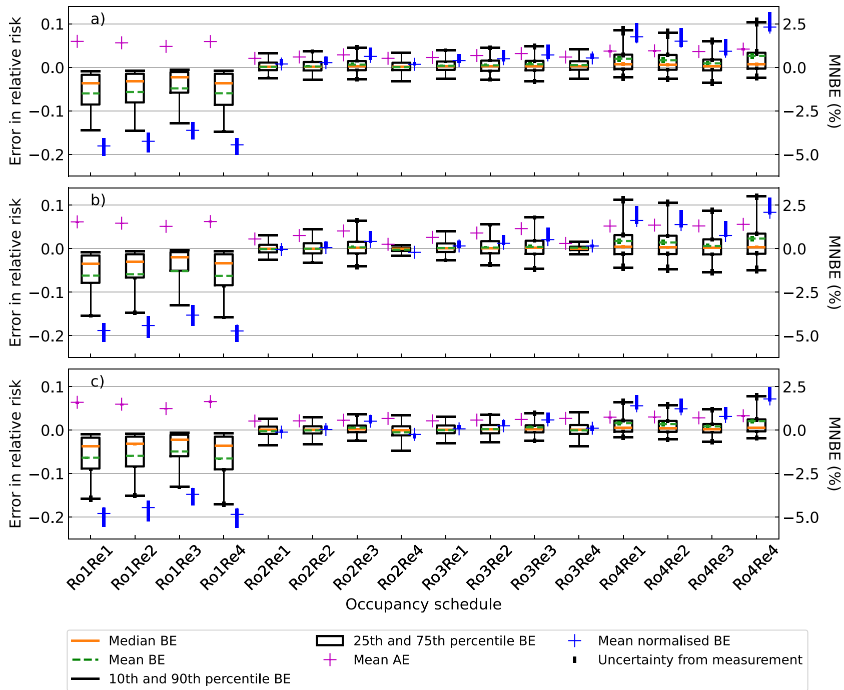

Fig. 6. On the left ordinate, the errors in relative risk of all-cause mortality for all occupancy schedules for (a) equal-weight, (b) living/dining room and (c) volume-weight. On the right ordinate is the mean normalised bias error.

basis may chose to measure and/or model using room scale resolution since Fig. 4 indicates that relatively very low and relatively very high $PM_{2.5}$ exposure residences have a high likelihood of being miscategorised, as even for typical room occupancies, 50% of such residences are miscategorised.

Fig. 5 indicates that a day of room-averaging error characterisation in a single residence can determine whether that residence is suitable for room-averaging, since the variation in NBE is within ±30% for all occupancy schedules other than bedroom all day. For example, if the residents in question are adults or children with relatively short absence and following typical room occupancy schedules, and a day of inaccuracy characterisation using the equal-weight approach returns a NBE of 10% (the $MNBE$ given in Fig. 2), then Fig. 5, which gives 15% for one standard deviation of NBE, demonstrates we would expect the NBE to range between −20 and 40% on most days. Given that the difference between the 10th and 90th percentiles for daily $PM_{2.5}$ exposures for these occupancies is a factor of 10 (Fig. A.14), such an error range may be acceptable, depending on study objectives.

On a population-level, comparison with the regressions of previous studies that used personal monitors to measure personal exposure in Fig. 3, indicates that the median adult does not have a room occupancy synchronised with room of maximum $PM_{2.5}$. Considering only the other room occupancies then, the median bias error for $PM_{2.5}$ daily exposure in Fig. 2 is 0 $\mu g\,m^{-3}$ for all room-averaging methods, and is 0 for relative risk of all-cause mortality in Fig. 6. These results indicate that for population-level studies, residence scale estimation of $PM_{2.5}$ is valid when considering the median over residence days. The maximum arithmetic mean of normalised bias errors is 32% for $PM_{2.5}$ in Fig. 2 (for the always in bedroom room occupancy), whilst the maximum $MNBE$ for room occupancies other than synchronised with maximum $PM_{2.5}$ for relative risk of all-cause mortality is 2.5% in Fig. 6 (for the always in bedroom room occupancy). Whether these means of error are acceptable depends on the study objectives. Other chronic health responses to $PM_{2.5}$ mass concentration also show asymptotic behaviour (Logue et al., 2012), indicating that the decrease in NBE from $PM_{2.5}$ to relative risk is not limited to all-cause mortality.

For population-level study, and particularly for the equal-weight and volume-weight room-averaging methods, many of the occupancy schedules in Tables A.5 and A.7 have r^2 values greater than 0.9. Therefore, a correction factor could be applied to the room-averaged estimates to decrease the average inaccuracy, so as to better represent daily personal exposure to $PM_{2.5}$.

Comparing the three methods for room-averaging, the absolute $MNBE$ values for $PM_{2.5}$ (Fig. 2) and relative risk of all-cause mortality (Fig. 6) found here for the volume-weight method are typically 25% lower than for the equal-weight and living/dining room methods. If volume-weight is not possible, then comparing the equal-weight and living/dining room methods, the spread in errors is generally greater for the living/dining room, with standard deviations for NBE of $PM_{2.5}$ in Fig. 5 typically between 5 and 10 percentage points greater for living/dining room. Additionally, r^2 values are lower for the living/dining room for all occupancy schedules except for the night absence (Tables A.5 and A.6).

Considering Fig. 3b, it should be noted that the regressions found in Kousa et al. (2002) and Mohammadyan and Ashmore (2005) include no $PM_{2.5}$ measurements above 100 $\mu g\,m^{-3}$. Similarly, the arithmetic mean (standard deviation) of living room $PM_{2.5}$ in Lung et al. (2021) was 15 (13) $\mu g\,m^{-3}$, less than the 27 (35) $\mu g\,m^{-3}$ for the living/dining room in the INGENIOUS sample in Fig. 3b. However, Fig. A.16 indicates that, for the sample here, the tendency for the living/dining room method to overestimate $PM_{2.5}$ exposure compared to the room-resolved estimate increases with increasing $PM_{2.5}$ exposure. Therefore, limiting regression analysis to sampled residences of lower $PM_{2.5}$ would act to widen the separation between the INGENIOUS regression and those of past studies.

In Section 2 and particularly Section 2.1, we provide information on the character of the sampled residences. Caution should be applied when applying these results to residences with characteristics beyond the range of the sample here, including those where the outdoor source of $PM_{2.5}$ dominates residential $PM_{2.5}$.

Future work should evaluate the validity of room-resolved fixed site measurements for representing personal exposure to residential $PM_{2.5}$. Such evaluation has significant implications given the relative ease of deploying fixed site measurements compared to personal monitoring.

5. Conclusion

With a relatively large sample of residential $PM_{2.5}$ measurements, this study has quantified the inaccuracy introduced by the residence scale representation of residential $PM_{2.5}$. The study is significant as it is based on independently calibrated, multi-room measurements in residences dominated by $PM_{2.5}$ levels above the WHO annual guideline and it assessed three commonly employed room-averaging methods. The study went beyond previous assessments by considering: the inaccuracy variation between days of a given residence, the effect of inaccuracy on categorisation of residences by $PM_{2.5}$ and the effect of inaccuracy on the relative risk of a health effect, namely, all-cause mortality.

Median bias error for daily exposure to residential $PM_{2.5}$ mass concentration and for relative risk of all-cause mortality from residential $PM_{2.5}$ for typical room and residence occupancies was 0 $\mu g\,m^{-3}$ and 0 relative risk, respectively. The mean normalised bias error for $PM_{2.5}$ exposure was ±30%, and the mean normalised bias error for relative risk of all-cause mortality was ±5%, depending on occupancy schedule. In the worst case, $PM_{2.5}$ error led to all residences with $PM_{2.5}$ above 100 $\mu g\,m^{-3}$ being miscategorised as having $PM_{2.5}$ below 100 $\mu g\,m^{-3}$. Although dependent on the objectives of work, application of residence scale estimation of $PM_{2.5}$ to population-level studies therefore appears more likely to introduce acceptable inaccuracy than general application to deterministic studies.

For residences with characteristics comparable to the sample here, the results here should be useful for identifying if residence scale resolution is acceptable, and, if it is, for quantifying the error for the residence scale estimate of residential $PM_{2.5}$ exposure.

CRediT authorship contribution statement

Simon P. O'Meara: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lia Chatzidiakou:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Data curation. **David R. Shaw:** Writing – review & editing, Supervision, Software, Resources, Project administration, Data curation. **Rachael W. Cheung:** Writing – review & editing, Data curation. **Tiffany C. Yang:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation. **Dagmar Waiblinger:** Resources, Data curation. **Salma Chopdat:** Resources, Data curation. **Athina Ruangkanit:** Data curation. **Thomas Warburton:** Data curation. **Yunqi Shao:** Data curation. **Matthew L. Thomas:** Writing – review & editing. **Jacqueline F. Hamilton:** Supervision, Resources, Project administration, Funding acquisition, Data curation. **Gordon McFiggans:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Rosemary R.C. McEachan:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation. **Nicola Carslaw:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Data curation.

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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.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.aeaoa.2026.100471.

Data availability

The datasets used and/or analysed during the current study are available from Born in Bradford on reasonable request. Applications can be made via an expression of interest form available on the study website (https://borninbradford.nhs.uk/our-data/how-to-access-data/) which also includes details on data access fees.

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