Imperial College London

HEI Health Effects Institute

5 May 2025

Measurement error and the "true" personal exposure to ambient air pollution: Problems and remedies

Main results and lessons learnt from the MELONS project

Klea Katsouyanni (PI), Dimitris Evangelopoulos, Dylan Wood, Ben Barratt, Hanbin Zhang, Barbara Butland, Evi Samoli, Heather Walton, Audrey de Nazelle, Vangelis Evangelou, Sean Beevers and Joel Schwartz

Health Effects Institute Annual Conference 2025

Imperial College London

MELONS overview:

| Title: Investigating the consequences of **M**easurement **E**rror of gradually more sophisticated long-term personal exposure models in assessing health effects: The **LON**don **S**tudy (MELONS).

| Timetable: Initial duration 3 years (July 2020 – June 2023); no-cost extension until December 2023. Report accepted in November 2024.

| Collaborators:

- Imperial: K Katsouyanni (PI); D Evangelopoulos, D Wood (project management, data harmonisation and epi analysis); B Barratt, H Zhang, A de Nazelle (personal exposure campaigns/analysis); S Beevers (surrogate exposures); V Evangelou (UK Biobank); H Walton (Policy implications)
- St George's: B Butland (simulation study)
- University of Athens: E Samoli (simulation study)
- Advisor: Joel Schwartz, Harvard TH Chan School of Public Health

MELONS overview:

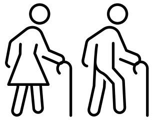
| Background: The use of surrogate exposure assessment methods (measured or modelled) introduces measurement error (ME) which can lead to biases in health effect estimation, usually to the null

| Previous studies*: It has been shown that these biases can range in magnitude, based on the definition of true exposure to air pollution

| Overall Aim: Are increasingly detailed estimates of long-term individual exposure to air pollution useful and effective in yielding better health effect estimates, especially in large-scale epi studies?

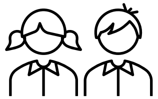
| Personal exposure campaigns: Multi-pollutant exposure measurements in London (12,901 person-days)

COPE



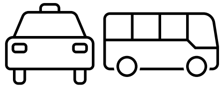
76 older adults with COPD

BLW



164 schoolchildren

DEMIST



66 professional drivers

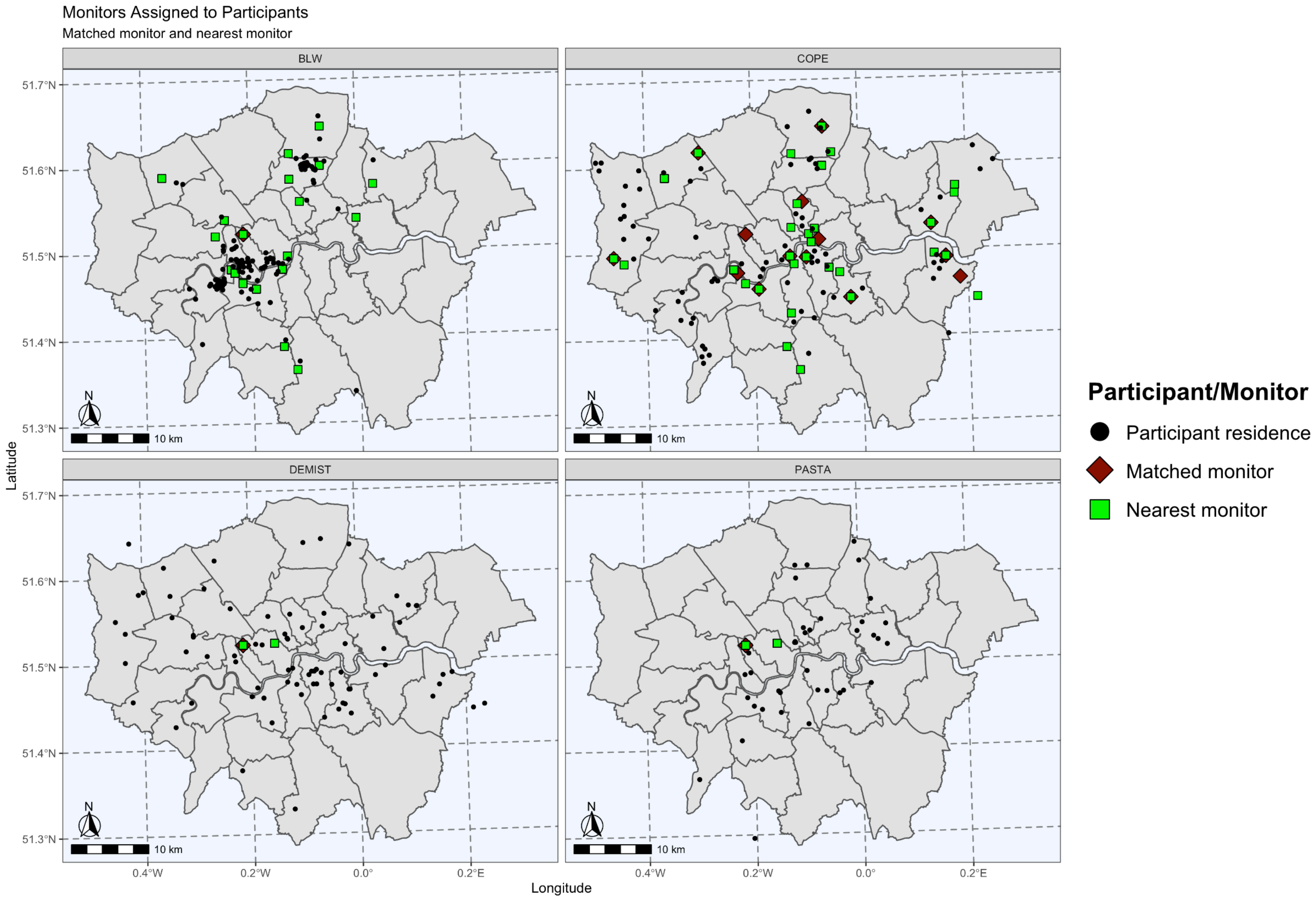
PASTA

38 healthy adults

*Bergen et al. 2016; Butland et al. 2020; Samoli et al. 2020; Wei et al. 2022

Imperial College London

MELONS overview:

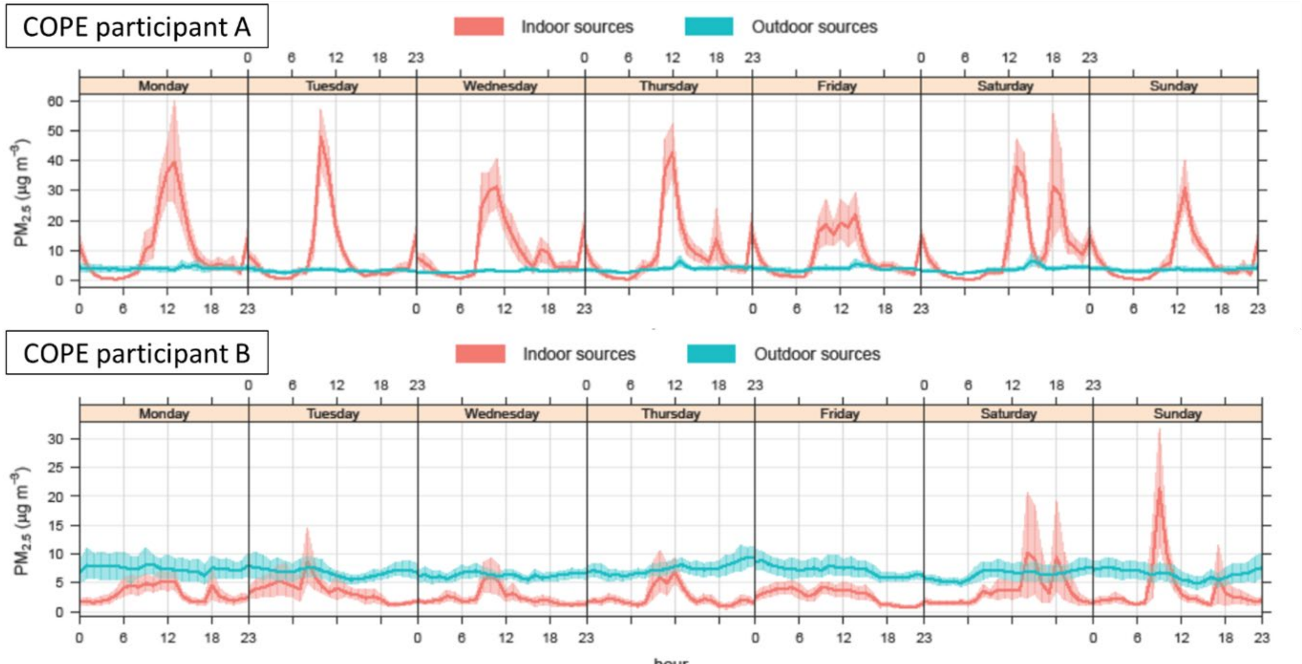


Objective 1: Develop long-term estimates of personal exposures to outdoor air pollution

| "True" exposure: We combined measurements, GPS data, exposure separation (indoor/outdoor) techniques and a behaviour prediction algorithm to predict annual estimates of outdoor-generated personal exposures.

| Findings: In COPE, **49%** and **41%** of their NO_2 and $PM_{2.5}$ total exposure derived from ambient sources, respectively

Proportion of time spent at home and outdoors		
Dataset	Home	Outdoors
COPE	93%	6%
BLW	55%	9%
DEMIST	51%	29%
PASTA	55%	10%



<u>Lessons learnt</u>:

Estimating "true" exposure is not straightforward and is based on several assumptions.

People are exposed to outdoor-generated pollution even if they spend most of their time at home.

Zhang et al. "Estimating exposure to pollutants generated from indoor and outdoor sources within vulnerable populations using personal air quality monitors: A London case study." *Environment International* (2025): 109431.

Imperial College London

Objective 2a: Compare personal exposures and surrogate estimates for outdoor air pollution

| Surrogates: Nearest monitor, spatiotemporal models (STEAM for NO_2, $PM_{2.5}$, O_3 & ELAPSE for BC) and models based on typical time activity patterns (London Hybrid Exposure Model-LHEM)*

| Findings:

Table 1. Mean (SD) in μg/m³ for personal and surrogate exposures

Exposure assessment method (Mean (SD))	NO_2 (COPE)	$PM_{2.5}$ (BLW)	O_3 (COPE)	BC (PASTA)
Predicted annual personal from outdoors	4.5 (1.5)	5.0 (1.7)	2.9 (1.1)	1.4 (1.0)
Nearest monitor from London network	44.5 (18.1)	10.0 (1.7)	32.6 (7.9)	4.0 (1.7)
Modelled estimates (STEAM/ELAPSE)	40.1 (18.7)	16.4 (1.4)	60.0 (7.2)	2.2 (0.3)
Mobility-adjusted STEAM (only NO_2 & $PM_{2.5}$)	13.5 (4.3)	10.0 (0.9)	-	-

Table 2. Spearman correlation with predicted annual personal exposure

Spearman correlation with personal exposure	NO_2 (COPE)	$PM_{2.5}$ (BLW)	O_3 (COPE)	BC (PASTA)
Nearest monitor	0.11	-0.07	0.02	0.17
STEAM/ELAPSE	0.20	-0.11	-0.15	0.00

Lessons learnt:

By quantifying MEs, we can identify the error types (classical/Berkson) and explore the error determinants.

Personal exposures are on a different scale compared to ambient levels. Their correlations can be very low.

*Dimakopoulou et al. 2022; de Hoogh et al. 2018; Wood et al. 2025

Objective 2b: Estimation of measurement error – Inputs for simulation analysis

Table 3. NO_2 error parameters used as inputs for our simulation analysis for the quantification of measurement error bias.

NO_2 error parameters	Pearson Correlation (surrogate, personal)	Variance ratio (surrogate /personal)	% Classical error	% Berkson error
Nearest monitor	0.13	154.3	100.0	0.0
STEAM/ELAPSE	0.16	165.0	100.0	0.0
Mobility-adjusted STEAM	0.25	8.9	97.0	3.0

Table 4. $PM_{2.5}$ error parameters used as inputs for our simulation analysis for the quantification of measurement error bias.

$PM_{2.5}$ error parameters	Pearson Correlation (surrogate, personal)	Variance ratio (surrogate /personal)	% Classical error	% Berkson error
Nearest monitor	0.10	1.30	57.3	42.7
STEAM/ELAPSE	0.08	0.53	33.4	66.6
Mobility-adjusted STEAM	0.04	0.25	18.8	81.2

Lesson learnt:

Based on the validation datasets used in MELONS and the estimation of predicted annual personal exposure from outdoor sources as “true” exposure, we identified extreme scenarios for the error parameters (i.e. low correlations and variance ratios much different than 1).

Imperial College London

Objective 3: Quantifying measurement error bias using simulations

| Inputs: (A) Theoretical (for testing correction methods), (B) Based on MELONS, (C) Literature-based

| Framework: Cohort of n=10,000 with simulated survival time using concentration-response functions from the literature, and incorporating ME based on different scenarios for A, B and C.

Figure 1. Bias in the log hazard ratio before and after correction by SIMEX/regression calibration using theoretical scenarios for measurement error

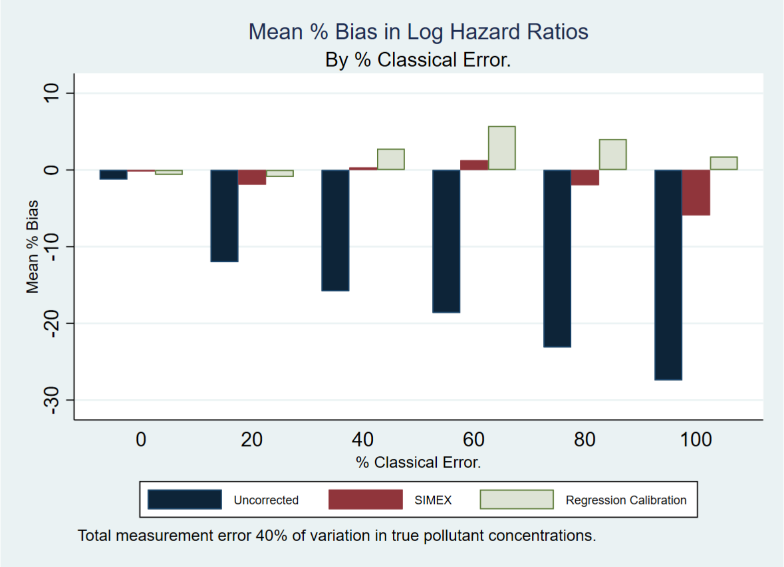
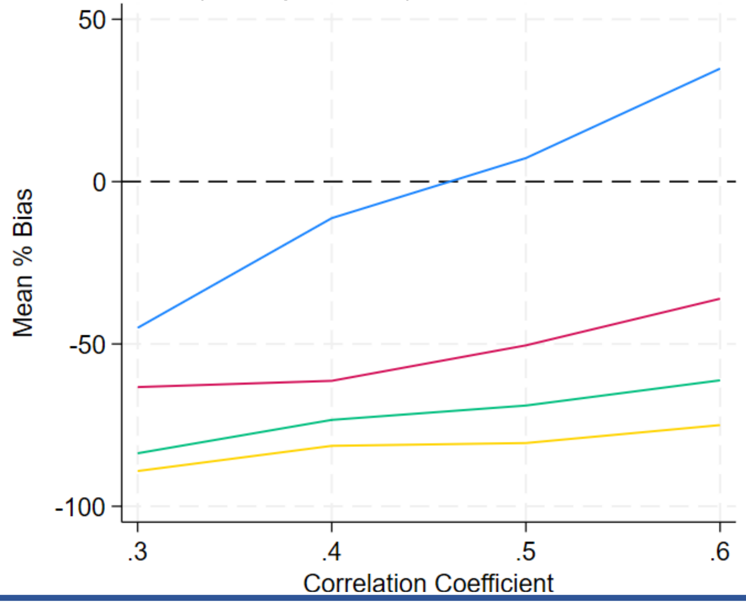


Table 5. Measurement error bias using error inputs from MELONS

$PM_{2.5}$ Surrogate exposure	Bias in logHR (%)	Coverage (%)
Nearest monitor	-90.5	43.7
STEAM	-88.7	74.1
Mobility-adjusted STEAM	-96.3	83.6

Figure 2. Bias in the log hazard ratio using measurement error inputs derived from the previous systematic reviews. Variance ratios (surrogate/true): 0.2 / 1.0 / 2.9 / 6.3



Lessons learnt:

Even in low/moderate ME scenarios, downward bias in health effect estimation can be substantial.
ME correction methods can be utilised, but they rely on the presence of validation data.

Imperial College London

Objective 4: Apply ME correction in the UK Biobank cohort

| Setting: 60,528 Greater London residents aged 40-69 years when recruited in 2006-10

| Analysis: $NO_2/PM_{2.5}/O_3$ and multiple health endpoints associations were investigated using Cox PH models and SIMEX/RCAL, controlling for age, sex, smoking status, BMI, employment, ethnicity, income

| ME estimation: Personal exposures from COPE were used as an external validation dataset

Table 6. Hazard ratios of the association between natural-cause mortality and NO_2 per IQR* increase

NO_2 Surrogate exposure	Uncorrected model	SIMEX-corrected	RCAL-corrected
Nearest monitor	0.992 (0.945, 1.040)	0.990 (0.923, 1.063)	0.983 (0.894, 1.081)
STEAM	1.028 (0.983, 1.074)	1.063 (0.998, 1.134)	1.077 (0.955, 1.215)
Mobility-adjusted STEAM	1.032 (0.991, 1.075)	**1.066 (1.004, 1.131)**	1.055 (0.985, 1.131)

*IQRs (μg/m^3): Nearest monitor: 22.42; STEAM: 14.54; STEAM LHEM-adjusted = 4.71.

Table 7. Hazard ratios of the association between COPD incidence and NO_2 per IQR* increase

NO_2 Surrogate exposure	Uncorrected model	SIMEX-corrected	RCAL-corrected
Nearest monitor	1.017 (0.951, 1.088)	1.039 (0.943, 1.146)	1.035 (0.904, 1.184)
STEAM	**1.087 (1.022, 1.155)**	**1.192 (1.093, 1.301)**	**1.254 (1.061, 1.482)**
Mobility-adjusted STEAM	1.051 (0.993, 1.112)	**1.101 (1.016, 1.194)**	1.088 (0.988, 1.198)

*IQRs (μg/m^3): Nearest monitor: 22.42; STEAM: 14.54; STEAM LHEM-adjusted = 4.71.

Lessons learnt:
Measurement error correction resulted in higher health effect estimates, in some cases 2/3-fold increase. ME correction methods can be utilised, but they rely on the presence of validation data.

Imperial College London

Air pollution exposure measurement error in epidemiological studies: problems and remedies

| True exposure: Is personal exposure to outdoor generated pollution the “gold (or silver) standard”?

| Indoor/outdoor exposures: Outdoor generated pollution is an issue even for people spending most of their time indoors.

| Future studies: Set standards for personal exposure campaigns as validation datasets in epidemiology? Personal measurements should be coupled with residential outdoor levels to estimate infiltration.

| Bias in effect estimates: Exposure measurement error leads to large underestimation of the effect estimates, even with moderate errors. The biases might be higher in multi-pollutant models.

| Policy: Should we use corrected concentration-response functions in health impact assessments? These may result in greater impacts which can justify more ambitious policies for improved air quality.

Imperial College London

Acknowledgements:

| Disclaimer: This work was conducted under contract to the Health Effects Institute (HEI), an organization jointly funded by the United States Environmental Protection Agency (EPA) (Assistance Award CR 83998101) and certain motor vehicle and engine manufacturers. The contents of this article do not necessarily reflect the views of HEI, or its sponsors, nor do they necessarily reflect the views and policies of the EPA or motor vehicle and engine manufacturers. HEI retains a non-exclusive license to publish material from work funded by the HEI.

DE, DW, BB, HW were part funded by the NIHR HPRU in Environmental Exposures and Health, a partnership between the UK Health Security Agency (UKHSA) and Imperial College London. DE was also funded by the MRC Centre for Environment and Health, Imperial College London. The views expressed are those of the author(s) and not necessarily those of the NHS, NIHR, UKHSA, HSE, Department of Health and Social Care, or Imperial College London.

Thank you