Environment, Natural Resources and Agriculture Strategic Research Programme 2022-2027

RESAS

Rural & Environmental Science and Analytical Services

END OF PROJECT REPORT

Purpose of End of Project Report

SRP 2022-27 projects provide quarterly progress reports and annual narrative summaries as well as research outcomes throughout the term of the project via the Researchfish platform. This end of project report provides additional information when a project finishes that can be used to summarise what the project has delivered, lessons learned and next steps. This report will be published on the SRP 2022-27 project webpages of SEFARI Gateway or on the Scottish Government website.
All sections must be completed

Project Researchfish ID	SRUC-D1-2		
Project Name	Air quality: domestic biomass burning and fine particle emissions.		
Lead Principal Investigator	John Newbold		
Start Date	1 Apr 2022	**Completion Date**	31 Mar 2025 (project terminated)

Purpose of the project
Burning biomass (wood, coal and manufactured solid fuels (MSF)) for domestic heating can release fine particles and noxious gases, causing respiratory and cardiovascular disease. This project sought to answer three questions: 1. How much domestic biomass burning takes place in Scotland? 2. How much pollution does this cause? 3. Does this impair human health? The project addressed these questions using novel measurement methods as well as modelling. The project was needed because of uncertainty surrounding each question, with results expected to inform future policy and priority-setting in this area (e.g., identifying areas where restrictions on domestic biomass burning might be justified on grounds of human health).

Objectives achieved/not achieved

Questions 1 and 2

1. *How much domestic biomass burning takes place in Scotland?*
2. *How much pollution does this cause?*

Questions 1 and 2 were addressed in Work Package (WP) 1, which was sub-contracted by SRUC to UKCEH (UK Centre for Ecology and Hydrology). The methodology and results are comprehensively described and discussed in the draft report provided to RESAS by UKCEH on 1st June 2025 (hereafter cited as Di Marco et al., 2025; Appendix 1). We consider the objectives of WP1 to have been achieved in full.

Task 1.1	*Biomass burning inventorying*
Task 1.2a	*Measurement quantification of biomass burning contribution to PM2.5[1] in village/ small town*
Task 1.2b	*Measurement quantification of biomass burning contribution to PM2.5 for understudied smoke-controlled area*
Task 1.2c	*Analysis of Scottish Black Carbon network sites for biomass burning aerosol*

Methods and Results from Tasks 1.2a, b and c are described in Chapter 2 of Di Marco et al. (2025). For practical reasons, measurements were first made in an area of central Edinburgh (Task 1.2b, winter of 2022/2023) and then in a rural location in Fife (Task 1.2a, winter of 2023/2024). Methods of choice were aerosol mass spectrometry and multiwavelength aethalometry, as described in report sections 2.1.2 and 2.1.3. The latter section also describes the derivation of estimates of black carbon (soot) produced during domestic biomass burning.

Results in Task 1.2b (section 2.3) confirmed some intuitive expectations, such as the diurnal distribution of biomass burning (peaking in the evening) and its relatively even spatial distribution across the city (compared with emissions from traffic, concentrated in the city centre). A novel finding was the relatively large contribution from cooking, likely arising from restaurants and hospitality venues. Aethalometer data showed that domestic biomass burning accounted for 16% of black carbon emissions, with the remainder generated by traffic.

Results in Fife (Task 1.2a, section 2.4) showed that, compared with Edinburgh, there was less of an evening peak in emissions from traffic (less of a rush-hour) and an absence of emissions from cooking (lack of nearby restaurants). Emissions from domestic coal and wood burning could be distinguished: both showed peaks in the evening, as expected. Of black carbon (soot), 27% was due to wood burning (a higher proportion than in Edinburgh) and the rest to traffic. The timings of peaks in emissions from biomass burning suggest more regular use throughout the week, as a primary source of domestic heat, compared with the urban pattern suggesting greater use of wood and coal fires at the weekend.

In Task 1.2c (section 2.5), results from the two sites used in this project (Edinburgh and Fife) were compared with data from two other sites in Scotland (rural Auchencorth Moss and urban Glasgow Townhead) that are part of a long-term DEFRA study. Black carbon emissions from biomass burning accounted for between 4 and 6% of the concentration of $PM_{2.5}$, across all four

[1] Fine particulate matter with a diameter of 2.5μm or smaller

sites. Concentrations of black carbon (‘c_{wood}’) were higher from Nov-Mar, coinciding with the season of biomass burning.

Task 1.3 Model quantification of biomass burning contribution to PM2.5

After generating new data for the contribution of biomass burning to PM2.5 at two specific locations in Task 1.2, the objective of modelling this contribution, at high resolution (1km^2), across Scotland was pursued in Task 1.3. This work is described in Chapter 3 of Di Marco et al. (2025).

Compared with the original project plan, this task was delayed[2], in agreement with RESAS, in order to take advantage of a DEFRA fuel survey conducted in 2022/23 and published in 2024, which repeated a similar survey conducted in 2018/19. Compared with the 18/19 survey, the 22/23 survey suggests an increase of 260% in the estimate of domestically burned wood, and an increase in Scottish wood burning from 7% to 12% of the UK total. Use of the 22/23 survey in this project will therefore inevitably mean an increase in the estimate of PM2.5 from domestic burning.

Emission Factors were derived for specific combinations of fuel type (separating, for example, seasoned and unseasoned wood) and burning device (e.g., different ages of wood burning stove). Several surprising observations were made based on this work, for example low emissions for seasoned wood (<20% moisture) compared with dried wood, and lack of lower emissions from modern stoves compared with their immediate predecessors.

The distribution of domestic biomass burning (all solid fuels burnt indoors) is mapped at 1km^2 scale in Figure 3.3 of Di Marco et al., (2025). Hot spots not surprisingly coincide with locations with high population density.

Results from this mapping exercise were compared with two other published sources. Several differences are noted (e.g., Table 3.9). Compared with the National Inventory (2021), total PM2.5 emissions in Scotland from the domestic burning of wood, coal and MSF, as estimated in this project, are 22% higher, while emissions from wood are 30% lower.

Finally, bringing all the preceding work in Task 1 together, the impact of these new estimates of emissions on air pollution was modelled using the EMEP4UK model[3], as described in Chapter 4 of Di Marco et al., (2025). Perhaps the most salient excerpt is: *‘…the magnitude of PM2.5 contributions from Scottish domestic solid fuel burning is generally small (<0.5 μg/m^3, compared to total concentrations 4-8 μg/m^3) except in hotspots around small towns such as Dumfries, Fort William and Ayr.’*

The validity of the EMEP4UK model, as used in this project, was checked by comparing its predictions with the measurements made at the sites used in this project (Edinburgh and Fife) and in the DEFRA (2024) report (Auchencorth moss and Glasgow). As described in section 4.3,

[2] through Project Change Requests dated 8Sep23 and 22May24
[3] EMEP = European Monitoring and Evaluation Programme, a co-operative programme for monitoring and evaluation of the long-range transmission of air pollutants in Europe (https://www.emep.int/). EMEP4UK is a UK application of this Atmospheric Chemistry and Transport Model. Full references are included in the Di Marco et al. (2025).

the model performed well in 3 of these 4 sites, the exception being Edinburgh, where the model may overpredict emissions from coal and MSF. Model uncertainties are discussed in Chapter 5 of Di Marco et al. (2025).

Question 3. Does domestic biomass burning affect human health?

This question was due to be addressed by SRUC in Work Package 2.

Much of the work anticipated in WP2 was dependent on WP1 and was therefore affected by the same delays (e.g., availability of relevant DEFRA data for Task 1.1 and Task 1.2c). Loss of staff resource then coincided with the decision of RESAS to terminate the project. This objective was not achieved, and the question remains unanswered.

Task 2.1 Identification of the spatial distribution of life expectancy, and respiratory or coronary diseases in Scotland

A background report (Degiovanni, 2025; Appendix 2) on methodologies that could be used to model the spatial distribution of life expectancy and respiratory and coronary diseases was prepared as part of Task 2.1. However, these models were not applied to available health data, and Task 2.1 was not completed.

Task 2.2 Identification of the spatial distribution of sources of air pollution (other than those associated with biomass burning) across Scotland

UKCEH ran the EMEP4UK model six times to separate and spatially map different sources of air pollution (see Chapter 4 of Di Marco et al., 2025):
1. Reference run with all emissions included.
2. Rest-of-the-UK run with domestic solid fuel emissions for non-Scottish UK sources removed (i.e. England, Wales & N. Ireland).
3. No-wood run with all wood and wood product emissions removed for Scotland
4. No-coal run with all house coal/lignite/peat emissions removed for Scotland
5. No-MSF run with all MSF emissions removed for Scotland
6. No solid fuel run with all solid fuel emissions removed for Scotland

Results (annual and winter averages for the pollutants PM2.5, NOx, NO_2 and SO_2) are shown in Figures 4.3 to 4.10 of the UKCEH report. These model runs provide the data required for completion of Task 2.2. Run 1 (panel (a) in Figures 4.3 to 4.10) minus Run 6 (panel (f) in Figures 4.3 to 4.10) represents the spatial distribution of sources of air pollution other than those associated with domestic biomass burning.

Task 2.3 Measurement of the effect of PM2.5 concentration levels due to biomass burning on health outcomes in Scotland

This task would have used existing information on the spatial distribution of life expectancy and the incidence of respiratory and coronary disease (gathered and modelled in Task 2.1) and information on the magnitude and spatial distribution of pollutants from biomass burning (WP1 and Task 2.2) to assess the possible impact of biomass burning on health.

Little progress had been made before the project was closed at the end of March 2025.

Task 2.4 Evaluation of the effect of the Low Emissions Zones (LEZ) on health outcomes in Scotland

The intention of this task was to assess the impact of LEZ on health outcomes and to use the spatial distribution of emissions and health outcomes (from Tasks 1.3, 2.1 and 2.2) to identify opportunities for new LEZ. In the final project proposal, it was anticipated that this task would be performed in the fourth year of the project (2025-2026), by which time LEZ were expected to have been fully geographically identified and their effects on emissions computed.

Scotland's LEZs were introduced on 31 May 2022 with Glasgow beginning enforcement on 1 June 2023, Dundee on 30 May 2024, and Aberdeen and Edinburgh on 1 June 2024 (https://lowemissionzones.scot/about).

No work was undertaken on this task before the project was closed at the end of March 2025. Given their relatively recent dates of introduction, more time may be needed before impacts of existing LEZ on emissions are sufficiently well quantified. However, the opportunity to use the work done in this project on the spatial distribution of air pollutants as a baseline when evaluating effects of LEZ and opportunities for future LEZ, is clear.

References:
Degiovanni, H (2025) Task 2.1.1 Review of Methodological Approaches
Di Marco CF (2025) The contribution of indoor domestic solid fuel burning to Scotland's air pollution. Draft final report to Scottish Government

Outcomes

1. The estimate of Scottish PM2.5 emissions from solid fuel burning made in this project is higher than previous estimates (e.g., National Inventory 2021), due partly to higher estimates of the quantity of solid fuels used, and partly to higher emission factors describing the emissions per unit of fuel
    a. An exception is the burning of wood, where a reduction in the emission factor outweighs a higher estimate of the amount burned, resulting in a reduction in national emissions from this fuel type

2. A number of observations challenge assumptions about PM2.5 emissions from domestic biomass burning, such as:
    a. New emission factors show limited benefit of switching from coal to MSF
    b. Modern stoves may not have lower emissions than older stoves, although more data are needed

c. Seasoned wood may have lower emissions than pre-dried wood

3. The project provides insights into the spatial and temporal (diurnal and seasonal) distribution of emissions from domestic biomass burning. These insights arise from direct measurement in two specific locations and from application of an atmospheric chemistry and transport model (with a high degree of temporal and spatial granularity) to the whole of Scotland:
   a. From direct measurements, the proportional contribution of biomass burning to PM2.5 emissions was greater in rural Fife (17%) than in urban Edinburgh (8%). Restaurant cooking was identified as an underappreciated source of emissions in Edinburgh.
   b. From application of the model, the largest local values (for PM2.5 concentration from domestic biomass burning) are in the central belt between Bathgate and Livingston (with a major contribution from MSF). The contribution from wood burning was proportionally greater in small towns in rural areas, such as Fort William.

4. There was generally good agreement between modelled and measured estimates of emissions except for:
   a. Modelling accounted for secondary PM2.5 formed from gases generated by solid fuel burning which are not included in the measurements
   b. The model may overestimate the amount of coal and MSF burnt in Edinburgh

5. The contribution to PM2.5 in Scotland from biomass outside Scotland is relatively small and confined to the Scottish Borders (most likely originating from Carlisle and vicinity).

6. The contribution of biomass burning to NO_2 (of concern to human health) is very small (around 1%)

7. There is evidence of long-term decline in PM2.5 concentration (Glasgow, from DEFRA statistics)

Project Insights

UK-wide surveys of domestic fuel usage and domestic biomass burning practices conducted by DEFRA added great value to the project (e.g., making project outputs of greater value to the next National Inventory) but also caused delay. The rationale for this change was identified early by UKCEH and accepted by RESAS.

Closer involvement of SRUC scientists responsible for WP2 in the later stages of work by UKCEH scientists on WP1 (in late 2024) would have allowed a faster start to work to explore relationships between PM2.5 emissions and human health.

The decision to terminate the project (therefore not answering the question of whether emissions of air pollutants from domestic biomass burning affect human health) should not detract from the high value of work conducted by UKCEH in WP1 and WP2 Task 2.2. This work represents a major advance in our understanding of the spatial and temporal distribution of air pollutants, particularly PM2.5, in Scotland, and the contribution of domestic biomass burning to those pollutants. This work adds value to future National Inventory calculations and asks questions of practical relevance to the significant proportion of the Scottish population who use wood, coal and MSF in domestic settings.

The opportunity to use the outputs of WP1 to pursue the questions not answered by the aborted WP2 (associations with human health and evaluation of LEZ) remains.

Next Steps/ Future Plans
The logic of co-mapping air pollutants and health outcomes remains and could lead to targeted, impactful actions to reduce emissions to deliver improvements in human health. It is recommended that new projects are initiated to complete the work not delivered by this project.

Appendix 1: Di Marco et al 2025 Scottish Solid Fuel Burning Final Report Draft 1June2025

Di Marco et al 2025
Scottish Solid Fuel Bur

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Appendix 2: Task 2.1 Identification of spatial distribution of life expectancy, and respiratory or coronary diseases in Scotland

Task 2.1.1 Review of Methodological Approaches

Hernan Degiovanni

Executive Summary

This document outlines key methodologies for analysing health disparities in Scotland, focusing on the spatial link between life expectancy, respiratory and coronary diseases, and air pollution. The primary challenge is to account for the geographic and temporal complexity of air pollution and its lagged effects on public health, while also considering socioeconomic and lifestyle factors.

The report explores four main approaches:

- **Spatial Durbin Models (SDM):** This method is well-suited for a dataset of cities or local authorities. It accounts for "spillover effects" where air pollution in one area can influence health outcomes in neighbouring regions. The approach requires rigorous statistical tests to ensure the robustness of the findings.
- **Spatial Autocorrelation Models:** These models address the fact that nearby locations tend to have similar health outcomes and pollution levels. This approach uses techniques like spatial lag or spatial error models to ensure accurate effect estimates by adjusting for spatial dependencies.
- **Spatial Cluster Detection (SCD):** This method identifies "hotspots" where health outcomes are disproportionately high and determines if they align with areas of high air pollution. This is particularly useful for generating hypotheses, targeting specific public health interventions, and finding localized effects that might be lost by broader models.
- **Multilevel and Hierarchical Models:** These models are designed to handle data with different population groups (e.g., age, social class) and are a good way to understand the general impact of air pollution without focusing on fine-grained spatial effects.

The choice of methodology depends heavily on the granularity of the available data from UKCEH. This document provides a framework for the next phase of the project, which is to identify and map the spatial distribution of air pollution sources across Scotland.

Contents

1.0 Introduction

Health disparities remain a major concern in public health research, particularly in regions with variable socio-economic, environmental, and lifestyle factors, such as Scotland. Measuring and identifying the spatial distribution of health outcomes, including life expectancy and disease prevalence, is crucial for effective health policy formulation.

Air pollution is spatially distributed, and this needs to be accounted for in any modelling approach and complicates attribution, as well as socio-economic and lifestyle factors.

The purpose of this document is to outline methodologies used to attribute health outcomes to the spatial distribution of life expectancy, and respiratory or coronary diseases in Scotland. As such it provides the basis for Task 2 which is to identify the spatial distribution of sources of air pollution (other than those associated with biomass burning) across Scotland.

2.0 Methodology

This report explores various quantitative methodologies employed to measure the spatial distribution of health outcomes, specifically life expectancy, respiratory diseases, and coronary diseases, within Scotland. There are a variety of approaches that have been used to identify impact. Generally econometric approaches need to recognise the spatial heterogeneity of health indicators and the lag effect of impact. This leads to a range of studies that include regression modelling, spatial analysis, spatial autocorrelation and spatial clustering approach. Each has a level of complexity but ultimately is driven by the granularity of data methods.

2.1. Spatial Durbin Model

Chen et al. (2017) employed the spatial Durbin Model (SDM) to assess air pollution and spillover effects on the public health of China. They employed data on public health in 116 cities of China over 2006 to 2012. A panel data set on lung cancer mortality and respiratory diseases mortality to measure public health was used and the statistical data of industrial emissions of sulphur dioxide and soot from the corresponding cities to measure air pollution.

The SDM approach is widely used in spatial econometrics to account for spatial dependence by including both spatially lagged independent variables and spatially lagged dependent variables.

These can be relatively easily developed in both R and Stata statistical frameworks. The approach to developing an SDM for applying a Spatial Durbin Model (SDM) to study health impacts of air pollution would be to define the outcome variables and assemble the panel. Given Chen et al (2017) using cities data exists at a local authority level for Scotland[4]. The key to SDM is to test for spatial dependence – effectively to robustly assess that outcomes are dependent on pollutants. Given the significant autocorrelation that is implicit in air pollution, these are essential and usually rely on specifying Moran's I (Li et al.,2021).

This approach is ubiquitous within the literature this is worth exploring, but requires a number of tests to establish robust estimation, e.g. to assess for endogeneity. There are direct and indirect spillovers from air pollution – given the lack of granularity in some data, e.g. the lagged impact of pollution incidents, some of this will be captured in the error term and therefore tests are needs to assess the sensitivity of responses.

[4] https://www.environment.gov.scot/our-environment/air/air-pollution-and-air-quality/

Papers which demonstrate the approach and could be used

Chen, Shao, Tian, Xie & Yin (2017), *Journal of Cleaner Production*
Studied 116 Chinese cities; used an SDM to quantify both local and spatial spillover impacts of air pollution on public health, explicitly decomposing direct and indirect effects. Frequently cited in later spatial-health work.

Zhang et al. (2019), *International Journal of Environmental Research and Public Health*
"Spatial-Temporal Effects of $PM_{2.5}$ on Health Burden: Evidence from China." SDM on 29 regions (2008–2017) showing significant spatial clustering, temporal lags, and sizable spillover effects on outpatient visits/expenses; includes multi-WW robustness and spatial GMM checks.

Peng, Ma, Chen & Coyte (2021), *Environmental Science and Pollution Research*
Combined CHARLS micro-health data with provincial pollution and estimated an SDM for ill-health; found neighbours' pollution measurably worsens local health (clear spillovers). Good model-building and diagnostics.

Scientific Reports (2021): Effect of $PM_{2.5}$ on Perinatal Mortality in China
Provincial panel (2002–2015) using FE and SDM; detects strong spatial autocorrelation and finds both local and neighbouring $PM_{2.5}$ significantly raise perinatal mortality, with interpretable elasticities. Useful as a mortality-focused exemplar.

2.2. Spatial Autocorrelation Models

Air pollution and many health outcomes are spatially structured: nearby locations tend to have similar exposures and disease rates. Ignoring that violates independence assumptions, biases standard errors, and can produce misleading effect estimates. Spatial autocorrelation essentially means the correlation of a variable with itself through space.

Spatial Regression Models These models bring together health outcome: counts (hospital admissions, deaths), rates, or continuous measures (lung function). Exposure surface: particulate matter (PM2.5), NO_2, ozone — often estimated with monitors, kriging, or land-use regression (LUR). Covariates: age, SES, smoking proxies, healthcare access, urban/rural indicators. Spatial support: point addresses, grid cells, or administrative areas — choice drives model class[5].

This approach comprises a suite of models which account for spatial autocorrelation.

Key regression models include the Spatial lag model (SAR) — accounts for spatial dependence in the dependent variable, where a spillover effect is adding (reflecting neighbouring outcomes affecting a local respiratory based outcome). Spatial error models, focuses on the residual (error term) to assess for spatial autocorrelation.

Key conditional autoregressive (CAR) / intrinsic CAR (iCAR) models tend to reflect Bayesian disease mapping and small-area health studies; used as area-level random effects in Poisson or logistic models to model residual spatial structure[6].

Overall, whilst these work with a granular panel of data over time, there are elements of spatial confounding, effectively modelling spatial random effects can reduce bias but may also absorb part of a

[5] Clark, L. P., Zilber, D., Schmitt, C., Fargo, D. C., Reif, D. M., Motsinger-Reif, A. A., & Messier, K. P. (2025). A review of geospatial exposure models and approaches for health data integration. *Journal of Exposure Science & Environmental Epidemiology*, *35*(2), 131-148.
[6] https://link.springer.com/book/10.1007/978-94-015-7799-1

true exposure effect if exposure is itself spatially structured. A paper with an approach that could be mimicked is Beelan et al. (2014) [7] but this requires fine grained data to fully implement the test.

Papers which demonstrate the approach and could be used

Keshtkar, M., Heidari, H., Moazzeni, N., & Azadi, H. (2022). Analysis of changes in air pollution quality and impact of COVID-19 on environmental health in Iran: application of interpolation models and spatial autocorrelation. *Environmental Science and Pollution Research*, *29*(25), 38505-38526.

Lee, D., & Mitchell, R. (2014). Controlling for localised spatio-temporal autocorrelation in long-term air pollution and health studies. *Statistical methods in medical research*, *23*(6), 488-506.

Havard, S., Deguen, S., Zmirou-Navier, D., Schillinger, C., & Bard, D. (2009). Traffic-related air pollution and socioeconomic status: a spatial autocorrelation study to assess environmental equity on a small-area scale. *Epidemiology*, *20*(2), 223-230.

Jerrett, M., Burnett, R. T., Ma, R., Pope III, C. A., Krewski, D., Newbold, K. B., ... & Thun, M. J. (2005). Spatial analysis of air pollution and mortality in Los Angeles. *Epidemiology*, *16*(6), 727-736.

2.3. Spatial Cluster Detection

SCD helps identify *where* health outcomes (e.g., respiratory admissions, mortality, asthma incidence) occur in excess relative to expectation and whether those excesses spatially coincide with higher pollution levels or sources (traffic corridors, industrial zones). Hence these are useful for hypothesis generation (hotspots for further study), targeting public-health interventions, and checking for spatially localised effects that global regression might miss[8].

Most studies use a combination of approaches, e.g. global spatial autocorrelation tests for clustering of values, e.g. around a particular incident. Then local indicators of spatial association (LISA) identify localised high-value or low-value clusters and spatial outliers (e.g., high asthma rates surrounded by high rates). Useful for mapping cluster “hotspots”.

Spatial regression / cluster detection hybrids — spatial lag/error models, geographically weighted regression (GWR), or spatially varying coefficient models test associations while accounting for spatial dependence; residual cluster detection can reveal unexplained spatial hotspots.

Papers which demonstrate the approach and could be used

Zou, B., Peng, F., Wan, N., Mamady, K., & Wilson, G. J. (2014). Spatial cluster detection of air pollution exposure inequities across the United States. *PLoS One*, *9*(3), e91917.

Qian, Z., Chapman, R. S., Hu, W., Wei, F., Korn, L. R., & Zhang, J. J. (2004). Using air pollution based community clusters to explore air pollution health effects in children. *Environment international*, *30*(5), 611-620.

Aggarwal, A., & Toshniwal, D. (2019). Detection of anomalous nitrogen dioxide (NO2) concentration in urban air of India using proximity and clustering methods. *Journal of the Air & Waste Management Association*, *69*(7), 805-822.

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[7] Beelen, R., et al. (2014). *Effects of long-term exposure to air pollution on natural-cause mortality: analysis of 22 European cohorts (ESCAPE).* Lancet. — major multi-cohort study using fine spatial exposure models and small-area exposure assignment in air pollution epidemiology.

[8] Jerrett, M., Burnett, R. T., Pope III, C. A., Ito, K., Thurston, G., Krewski, D., ... & Thun, M. (2009). Long-term ozone exposure and mortality. *New England Journal of Medicine*, *360*(11), 1085-1095.

2.4. Multilevel and Hierarchical Models

Multilevel models accommodate for variation within the population. Thus, it can pool information across locations and estimate the variance between populations for particular characteristics, e.g. different ages, social classes and health outcomes. As such it provides a parsimonious approach to understanding the impact of air pollution on outcomes at a more general level, e.g. not accounting for more granular spatial effects.

Key references on the approach

Dominici, F., Samet, J. M., & Zeger, S. L. (2000). Combining evidence on air pollution and daily mortality from the 20 largest US cities: a hierarchical modelling strategy. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *163*(3), 263-302.

Shaddick, G., Thomas, M. L., Green, A., Brauer, M., Donkelaar, A., Burnett, R., ... & Prüss-Ustün, A. (2018). Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. *Journal of the Royal Statistical Society Series C: Applied Statistics*, *67*(1), 231-253.

Bobb, J. F., Dominici, F., & Peng, R. D. (2013). Reduced hierarchical models with application to estimating health effects of simultaneous exposure to multiple pollutants. *Journal of the Royal Statistical Society Series C: Applied Statistics*, *62*(3), 451-472.

Blangiardo, M., Pirani, M., Kanapka, L., Hansell, A., & Fuller, G. (2019). A hierarchical modelling approach to assess multi pollutant effects in time-series studies. *PLoS One*, *14*(3), e0212565.

3.0. Summary

Dependent on the data that is delivered through UKCEH there are a variety of approaches that can be used. Key issues are the granularity of data delivered but also the choice of parsimony in informing policy solutions.