



Full length article

Quantifying the health impact of PM_{2.5} with various chemical transport models and for different years – A case study for Poland

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ABSTRACT

Poland is in the group of European countries with the most severe air quality and specific emission structure (over 80 % of PM_{2.5} emitted in residential combustion). In this work, we quantify the health impacts of PM_{2.5} concentrations in Poland using two chemical transport models (CTMs), WRF-Chem and EMEP4PL. The models were run for two years (2017 and 2018), which differed in meteorological conditions. The results show that the total number of premature deaths that could be avoided if the PM_{2.5} concentrations do not exceed the WHO recommended value of 5 µg m⁻³ exceeds 22,000 deaths for all model runs and meteorological years considered, with the lowest estimate at 22,447 (WRF-Chem model run for the year 2017; 95 % confidence intervals CI (95 % CI) 17121–25045) and the highest at 29,227 (95 % CI 22343 – 32572; EMEP4PL for the year 2018). These numbers are underestimated, as both CTMs underestimate the measured PM_{2.5} concentrations at site locations. The underestimation is the highest during the heating seasons and can be reduced if the emission of primary PM_{2.5} from residential combustion increases. The total number of estimated premature deaths is sensitive to chemical transport model selection and meteorological year. The selection of the meteorological year for the analysis may change the estimated number of premature deaths by 10 %. This change is significant compared to the estimated change in health impact due to the envisaged implementation of the Clean Air Program in Poland.

1. Introduction

Population health and life quality are strongly affected by atmospheric pollution. World Health Organization (WHO) estimates that 4.2 million premature deaths are attributed to ambient air pollution worldwide in 2019 (WHO 2022). A recent study by Lelieveld et al. (2019) estimates that the annual excess mortality rate from ambient air pollution in Europe is 790,000 for the year 2015 (28 countries of the European Union and Iceland, Norway, Switzerland, Balkan countries, Belarus, Moldova and Ukraine). 48 % of these deaths are due to cardiovascular events. Lelieveld et al. (2019) use new hazard ratio functions given by the GEMM (Global Exposure Mortality Model) of (Burnett et al. 2018), which is based on 41 cohort studies in 16 countries. These functions relate hazard ratios to ambient air pollution concentrations, being dependent on age and geographical location (usually country level). The GEMM accounts for a much larger range of air pollution concentrations than the GBD (Global Burden of Disease) of 2015, by

including new cohort data from China, where air quality tends to be poorer than in Europe and North America from where epidemiological data have dominated former GBD assessments. Im et al. (2018), using an ensemble of chemical transport models for PM_{2.5} concentrations, estimated that the economic costs of low air quality in Europe are EUR 300 billion (for the year 2010 for EU27 countries, both morbidity and mortality effects included, monetary year 2013).

Poland belongs to a group of European countries with the poorest air quality (EEA 2024). The main issue is related to high coal consumption and low quality of stoves used in residential combustion. This leads to significant emission of primary particulate matter and exceedances of PM_{2.5} and PM₁₀ recommended values during the heating seasons. These exceedances are observed each year at various locations (Górka and Lewicka-Szczepak 2013; Reizer and Juda-Rezler 2016; Czernecki et al. 2017; Rogula-Kozłowska et al. 2018; Adamkiewicz et al. 2021). Adamkiewicz et al. (2022), for the year 2019, have shown that the PM_{2.5} annual mean recommended value (20 µg m⁻³) was exceeded at

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40 % of monitoring stations in Poland in the year 2019. [Lelieveld et al. \(2019\)](#) have estimated that the reduction of mean life expectancy in Poland is 2.8 years, compared to 2.2 for the European mean value. According to the study by [Khomenko et al. \(2021, 2023\)](#) there is a substantial variability in sectoral and spatial contributions to mortality among the European cities. For $PM_{2.5}$, the main sectoral contributors to premature mortality were the residential and agricultural sectors, followed by industry, transport, energy, and shipping. Overall, for $PM_{2.5}$, contributions to premature mortality from the residential sector were the highest in eastern and northern Europe (including Poland and Czech Republic). The contributions from agriculture were the highest in Germany, the Netherlands, Belgium, and the UK. Contributions from industry were widespread, with the highest estimates for cities in the UK, Spain, Portugal, Germany, France, and Romania. Transport contributions were the highest in western and central Europe and northern Italy. [Adamkiewicz et al. \(2022\)](#) emphasize that there is a significant association between hospital admission and particulate matter concentrations in Poland. This relation is especially strong during heating seasons. [Ratajczak et al. \(2021\)](#) have linked the upper respiratory tract symptoms in children with increased $PM_{2.5}$ or PM_{10} concentrations, while [Lindner-Cendrowska and Bröde \(2021\)](#) have successfully connected the incidence of influenzas-like illnesses in Warsaw with low air quality. All these findings well document the air quality problems in Poland and Europe and indicate the broad range of health, environmental, and economic effects.

This paper aims to quantify the health impacts of $PM_{2.5}$ concentrations using two different chemical transport models (WRF-Chem and EMEP4PL) for two years (2017 and 2018) with various meteorological conditions. We keep the same emission inventory for both models and years. With this data set, we address the following question: how many premature deaths could be avoided if annual mean $PM_{2.5}$ concentrations in Poland are reduced to the WHO recommended value of $5 \mu g m^{-3}$ ([WHO 2021](#)), and how year-to-year changes in meteorological conditions may affect this estimate? We also show how the population-weighted mean concentration changes between rural, suburban, and urban areas for two years with various meteorological conditions.

2. Data and methods

The general concept of this study is presented in [Fig. 1](#). We have used $PM_{2.5}$ concentrations calculated with two different chemical transport models, WRF-Chem and EMEP4PL, for two years: 2017 and 2018. The modelled $PM_{2.5}$ concentrations were compared with measurements of daily $PM_{2.5}$ concentrations. For each year, the EMEP4PL and WRF-Chem modelled $PM_{2.5}$ were averaged (multi-model mean value) to form a third dataset. Finally, for each year, three datasets with $PM_{2.5}$ annual mean concentrations were used to calculate the number of premature deaths for a population exceeding 30 years old using the WHO AirQ+ software ([Miri et al. 2017; Brito et al. 2022](#)).

2.1. Differences in meteorology for the years 2017 and 2018

The main meteorological variables (air temperature at 2 m, wind speed and direction at 10 m, and precipitation) were compared to show the differences in meteorology between the selected years and to better understand the model's performance. Years 2017 and 2018 were also compared with long-term mean values (2011–2020). For this comparison, we used the meteorological observations gathered at 69 SYNOP stations in Poland, operated by the Institute of Meteorology and Water Management – National Research Institute in Poland.

There are substantial differences in air temperatures between 2017 and 2018 in the first six months ([Fig. 2](#)). January was colder in 2017 than in 2018, but February and March were significantly warmer. These are the months with substantial emissions from residential combustion, and ambient air temperature is linked with heat demand and influences this emission. The period from April to October 2018 was warmer than in 2017, and 2017 was very similar to the long-term mean for these months.

If wind speed and direction are compared, there are significant differences between 2017 and 2018 ([Fig. 3](#)). Westerly wind was much more frequent in 2017 compared to 2018 and the long-term mean. Also, the wind speed in 2017 was higher compared to 2018 and the long-term mean, with a lower frequency of calm periods. Year 2018 was similar to the long-term mean conditions.

Precipitation in year 2017 was higher if compared to the year 2018 and the long-term mean ([Fig. 4](#)). The differences are especially large for April and September to November. More rainfall in 2018, compared to 2017, was measured in July and December. May for both years was drier if compared to the long-term mean.

2.2. Chemical transport models configurations

The details of the WRF-Chem and EMEP4PL configurations are provided below. For each year and the model, one simulation was run with a 5-day spin-up time, similar to ([Kryza et al. 2020](#)). The models were configured using two one-way nested domains. The outer domain covers Europe with a $12 km \times 12 km$ spatial resolution ([Fig. 5](#)). The nested domain, which is used in this study, covers the area of central Europe with a $4 km \times 4 km$ spatial resolution. Both domains use 35 vertical levels, with the lowest layer top at about 30 m.

Both models used the same anthropogenic emission inventory for the year 2018. The emission inventory was fixed for each year, as the focus was on the effect of meteorology and the model on population exposure estimates. While this affects the model evaluation results, a similar approach has been applied before, e.g., by [Im et al. 2018](#). EMEP emission was used for the outer domain, available at $0.1^\circ \times 0.1^\circ$ spatial resolution. The EMEP emission inventory was also used for the nested domain for all the countries except Poland. For Poland, we used the emission provided by the Chief Inspectorate of Environmental Protection (CIEP), available

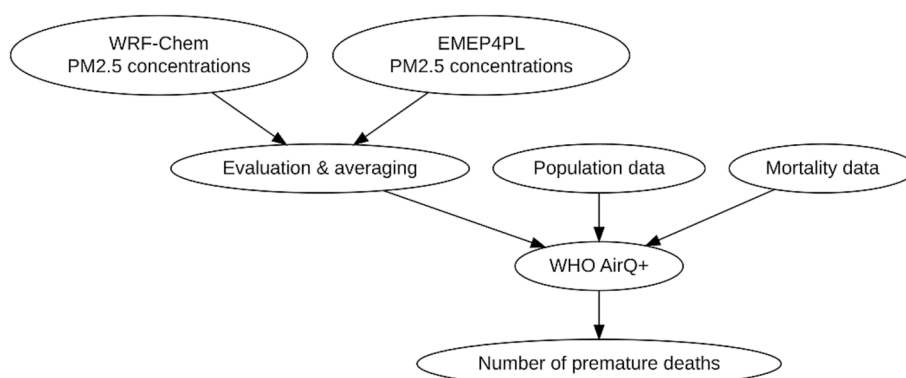


Fig. 1. Flowchart summarizing the modelling framework.

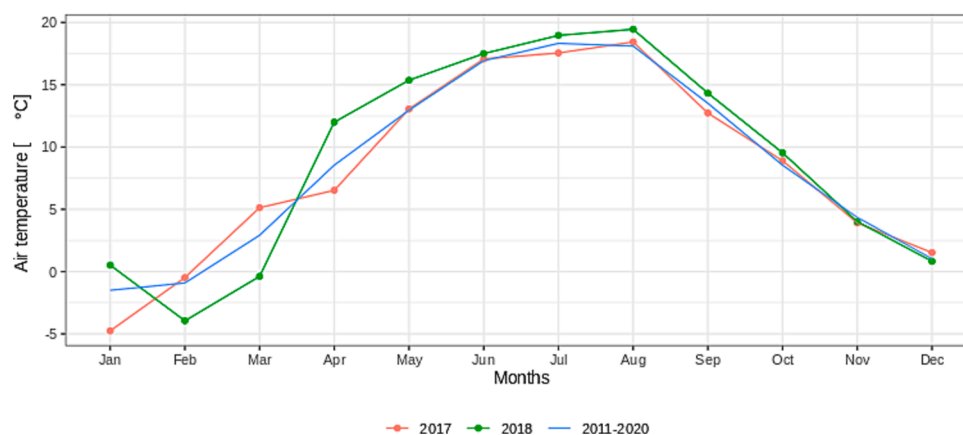


Fig. 2. Monthly mean air temperatures at 2 m in Poland (mean values from 69 SYNOP stations).

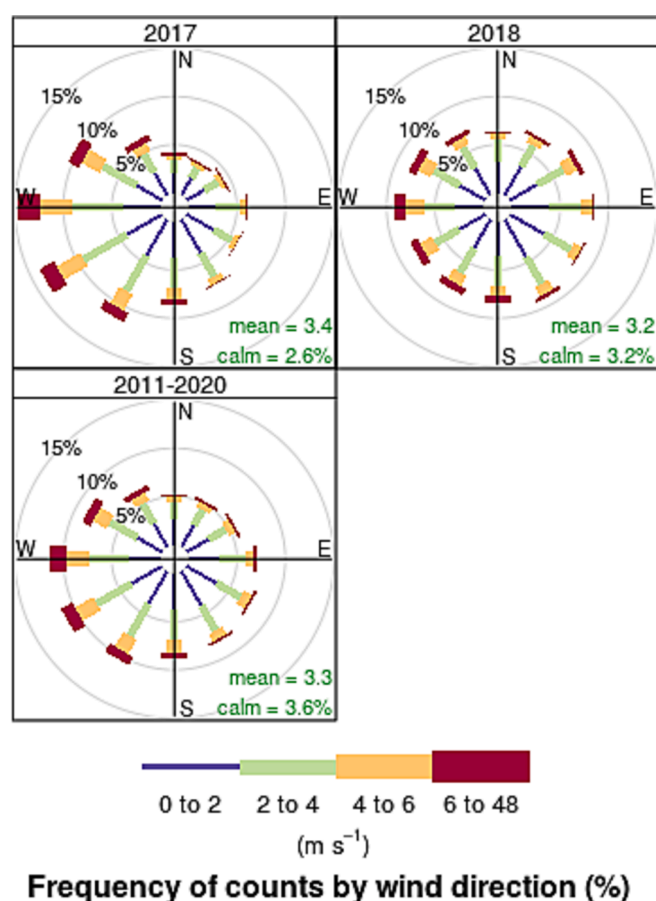


Fig. 3. Wind speed and direction in Poland (data from 69 SYNOP stations).

at a high spatial resolution of 1 km x 1 km (Gawuc et al. 2021). None of the models used data assimilation.

2.2.1. The WRF-Chem model configuration

The Weather Research and Forecasting model with Chemistry (WRF-Chem) version 3.9.1 was used in this study. The WRF-Chem model is an online integrated model with fully coupled chemistry and meteorology (Grell et al. 2005). Both chemical and meteorological components use the same transport scheme, horizontal and vertical grid, time step, and physical parameterization for subgrid-scale transport. The model configuration applied in this study is similar to the configuration used by, e.g., Werner et al. (2019b, a) and Kryza et al. (2020). The model

configuration options used were the Noah Land Surface Model (Chen and Dudhia 2001), the YSU scheme for boundary layer physics (Hong et al. 2006), RRTMG long and short wave radiation schemes (Iacono et al. 2008), Grell 3D convection parameterization scheme and Morrison 2-moments scheme for microphysics (Morrison et al. 2009). We used the Regional Atmospheric Chemistry Mechanism (RACM) for gas phase chemistry. For aerosols, the MADE-VBS scheme was applied (Ahmadov et al. 2012). NCEP's final analysis of meteorological data was used to determine initial and boundary conditions. This information was available every 6 h, with 1° x 1° spatial resolution. PM_{2.5} concentrations from the lowest model layer were used in this study (c.a. 15 m).

2.2.2. The EMEP4PL model configuration

The EMEP MSC-W model is an offline Eulerian CTM used by the Meteorological Synthesizing Centre-West (MSC-W) within the European Monitoring and Evaluation Program (EMEP). The model is one of the key tools supporting the European air pollution policy assessment and was described in detail by Simpson et al. (2012). The model has several national implementations, e.g., EMEP4UK is used for the United Kingdom (Vieno et al. 2010; Lin et al. 2017; Oxley et al. 2023), EMEP4NL for the Netherlands (van der Swaluw et al. 2021; Verweij et al. 2023). Application of the EMEP model for Poland (EMEP4PL) was described by Werner et al. (2018).

We used the EMEP4PL model version 4.34 offline coupled with meteorology from the WRF-Chem model simulations described above. The EMEP4PL and WRF-Chem share the same domain setup, so no interpolation was necessary. The Em-Chem09 chemical scheme was used. The scheme has been extensively validated for Europe, as described by Simpson et al. (2012). In this study, we present the PM_{2.5} concentrations from the surface of the lowest model layer (c.a. 3 m).

We have also averaged the annual mean PM_{2.5} concentrations estimated by the WRF-Chem and EMEP4PL models for each year considered. This formed the third dataset for the estimation of population exposure with the AirQ + software. We refer to this data set as EnsMean further in the manuscript. The EnsMean data set was calculated as both models have distinct strengths that can complement each other (e.g. the EMEP4PL model outperforms the WRF-Chem model during winter, while the opposite relation is observed for summer). By averaging their outputs, we aim to balance their individual biases, reduce uncertainty, and enhance the robustness of our population exposure estimates.

2.3. Evaluation of the modelled PM_{2.5} concentrations

The modelled PM_{2.5} 24 h mean concentrations were compared with site measurements. The measurements were gathered at the national air quality network operated by the Chief Inspectorate of Environmental

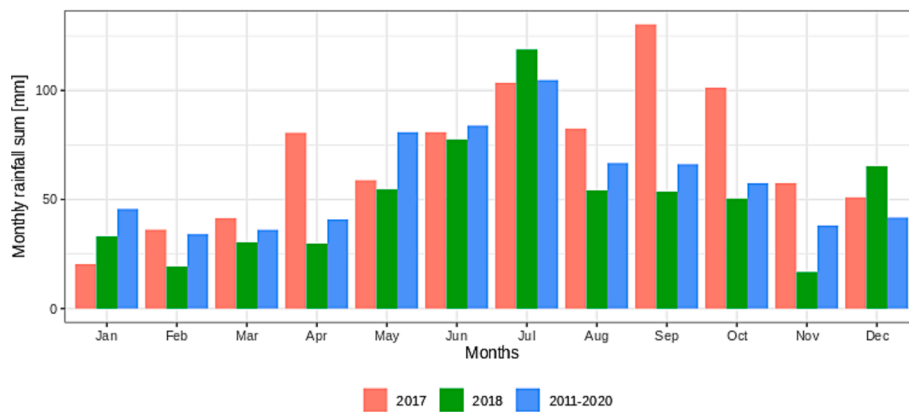


Fig. 4. Monthly precipitation sums in Poland (data from 69 SYNOP stations).

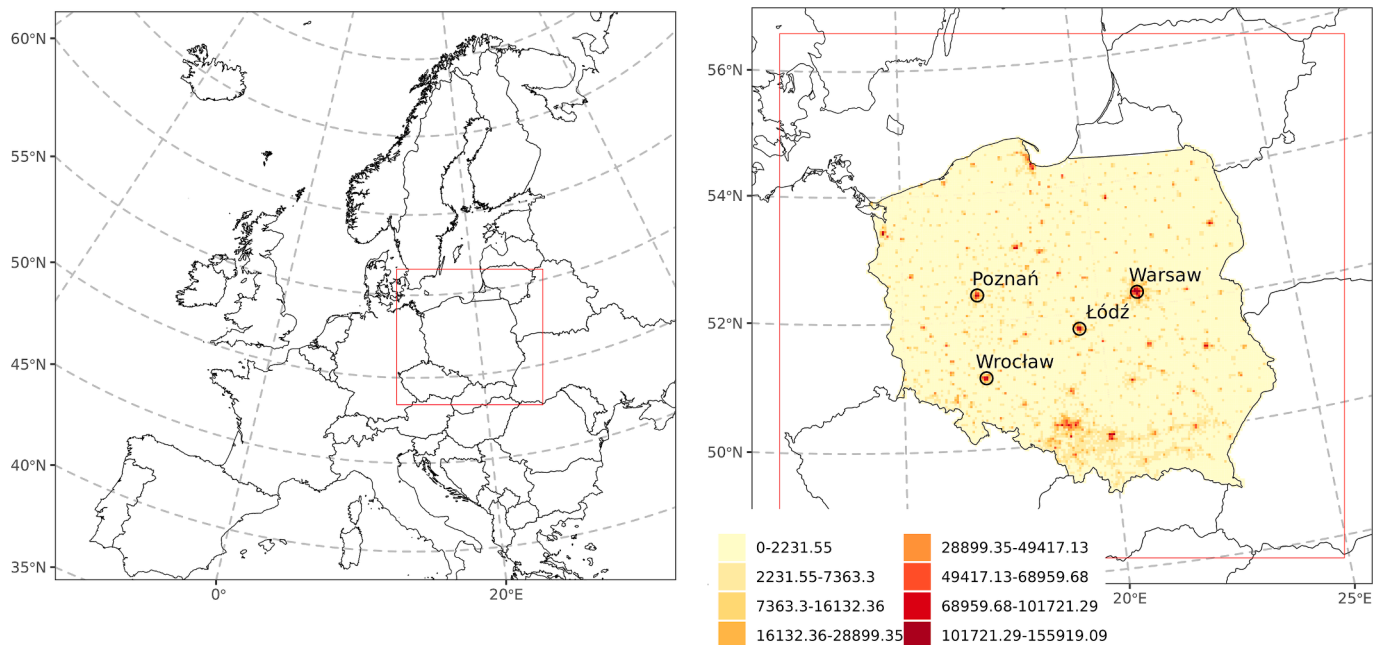


Fig. 5. Model domains (left; nested domain as a red rectangle) and gridded population data [number of persons; 4 km x 4 km grid] used for exposure estimates in Poland. The cities mentioned in text are marked with circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Protection in Poland. For 2017, 98 sites with PM_{2.5} measurements were available (85 urban sites, 13 suburban and rural). For 2018, data from 101 sites (89 urban, 12 suburban and rural) were used. The WRF-Chem, EMEP4PL, and EnsMean model performance was summarized using three statistics: Mean error (ME; eq (1); (Emery et al. 2017)), Index of Agreement (IOA; eq (2); (Willmott 1982)), correlation coefficient (COR; eq (3)) and normalized mean bias (NMB; eq (4); (Carslaw and Ropkins 2012)).

$$ME = \frac{\sum_{i=1}^N (M_i - O_i)}{N} \quad (1)$$

$$IOA = \frac{\sum_{i=1}^N (O_i - M_i)^2}{\sum_{i=1}^N (|M_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (2)$$

$$COR = \frac{\sum (O_i - \bar{O})(M_i - \bar{M})}{\sqrt{\sum (O_i - \bar{O})^2 \sum (M_i - \bar{M})^2}} \quad (3)$$

$$NMB = \frac{\sum_{i=1}^N M_i - O_i}{\sum_{i=1}^N O_i} \quad (4)$$

where M is the modelled value, O is the observed value, N is the number of observations and $\bar{M}$ and $\bar{O}$ are modelled and observed mean values, respectively. ME is expressed in $\mu\text{g m}^{-3}$, while the IOA and COR are unitless. NMB is in range from -1 to +1.

2.4. Estimation of population exposure and health effects

We used AirQ + software (version 2.1.1) developed by the WHO Regional Office for Europe to calculate all-cause mortality due to PM_{2.5} in Poland. The details of the AirQ + software are provided by Miri et al. (2016, 2017) and Brito et al. (2022). The AirQ + model estimates the attributable proportion (AP) of a given health endpoint, the attributable excess incidence (EI) per 100,000 population at risk, and the attributable excess cases (EC) associated with exposure to a given pollutant at a given concentration X, using the equation (Brito et al. 2022):

$$RR_X = e^{\beta(X-X_0)} \quad (5)$$

where RR_X is the relative risk, β is an empirical parameter used to describe the change in RR_X for a given change in concentration X (typically $10 \mu\text{g m}^{-3}$ (Brito et al. 2022)) and X_0 is the cut-off level below which the health effect is considered negligible. The model requires as input also the change in RR_X per $10 \mu\text{g m}^{-3}$, the baseline incidence (BI) of the specific health endpoint per 100,000 population at risk and the size of the population at risk (population over 30 years old). The model estimates the Attributable Proportion (AP) and Excess Incidence (EI) using the following equations:

$$AP = (RR_X - 1) / RR_X \quad (6)$$

$$EI = AP * BI \quad (7)$$

In this study, we used the relative risk (RR) provided by Chen and Hoek (2020), with a relative risk of 1.08 (95 % CI = 1.06, 1.09) per $10 \mu\text{g m}^{-3}$ (–|–) increment in PM_{2.5} concentration. The cut-off value was set to $5 \mu\text{g m}^{-3}$ to answer the question: how many premature deaths could be avoided (for adults over 30 years old) if the PM_{2.5} concentrations are reduced to the new WHO recommended value of $5.0 \mu\text{g m}^{-3}$ (annual mean PM_{2.5} concentrations)?

The National Statistical Office in Poland provided information on BI (for the population at risk, all-cause natural mortality, and the mean value for the year 2017–2018 for both years considered) for each commune in Poland. This information was gridded into the 4 km x 4 km model mesh (Fig. 5), in which data on PM_{2.5} was available. The gridding from vector to raster data model was done using a dedicated R script to ensure that the country's total BI does not change during this process. We have also used National Statistical Office data for population structure to calculate the share of the population above 30 years old. This information was combined with gridded population data from the National Statistical Office (National Census of Population and Housing, 2011) at a 1 km x 1 km grid cell and regridded into the model mesh (Fig. 5). Population at risk (N_{risk}) was calculated by multiplying the share of the population at risk and the total population. With data on

BI, N_{risk} , and PM_{2.5} concentrations in the same 4 km x 4 km mesh, the AirQ + model was applied for each grid cell covering Poland using the multiple areas option.

The information on the number of premature deaths is completed by the information on population-weighted mean concentration (ApSimon et al., 2021; PPMC). PPMC is calculated using the following formula (eq (8)):

$$PPMC = \sum_{ij} (P_{ij} \times C_{ij}) / \sum_{ij} P_{ij} \quad (8)$$

Where the summation is over grid cells i, j in Poland or urban/rural areas, with population P_{ij} and concentration C_{ij} . Urban and rural regions are delineated using the National Statistical Office TERYT number methodology (<https://eteryt.stat.gov.pl/eTeryt/english.aspx>).

2.5. Case study on residential heating emission

Previous studies show a significant underestimation of the modelled PM_{2.5} concentrations by various chemical transport models (Struzewska et al. 2015; Werner et al. 2019b; Kryza et al. 2020). This underestimation increases the uncertainty related to the exposure studies (Im et al. 2018). It is, therefore, necessary to better understand the reasons for this underestimation. We have undertaken a case study to address this issue for one selected year (2018) and the EMEP4PL model. Residential heating is the primary emission sector in Poland, except for the main cities (district heating systems and significant role of traffic emission) and along the main roads, contributing over 80 % of the total PM_{2.5} primary emission (Fig. 6). For the case study, we have increased the SNAP sector two (Non-industrial combustion plants) emissions by 25 %, run the model with increased emissions for the year 2018, and compared the results with the original EMEP4PL run described above. We have then calculated the differences in ME and COR for each station

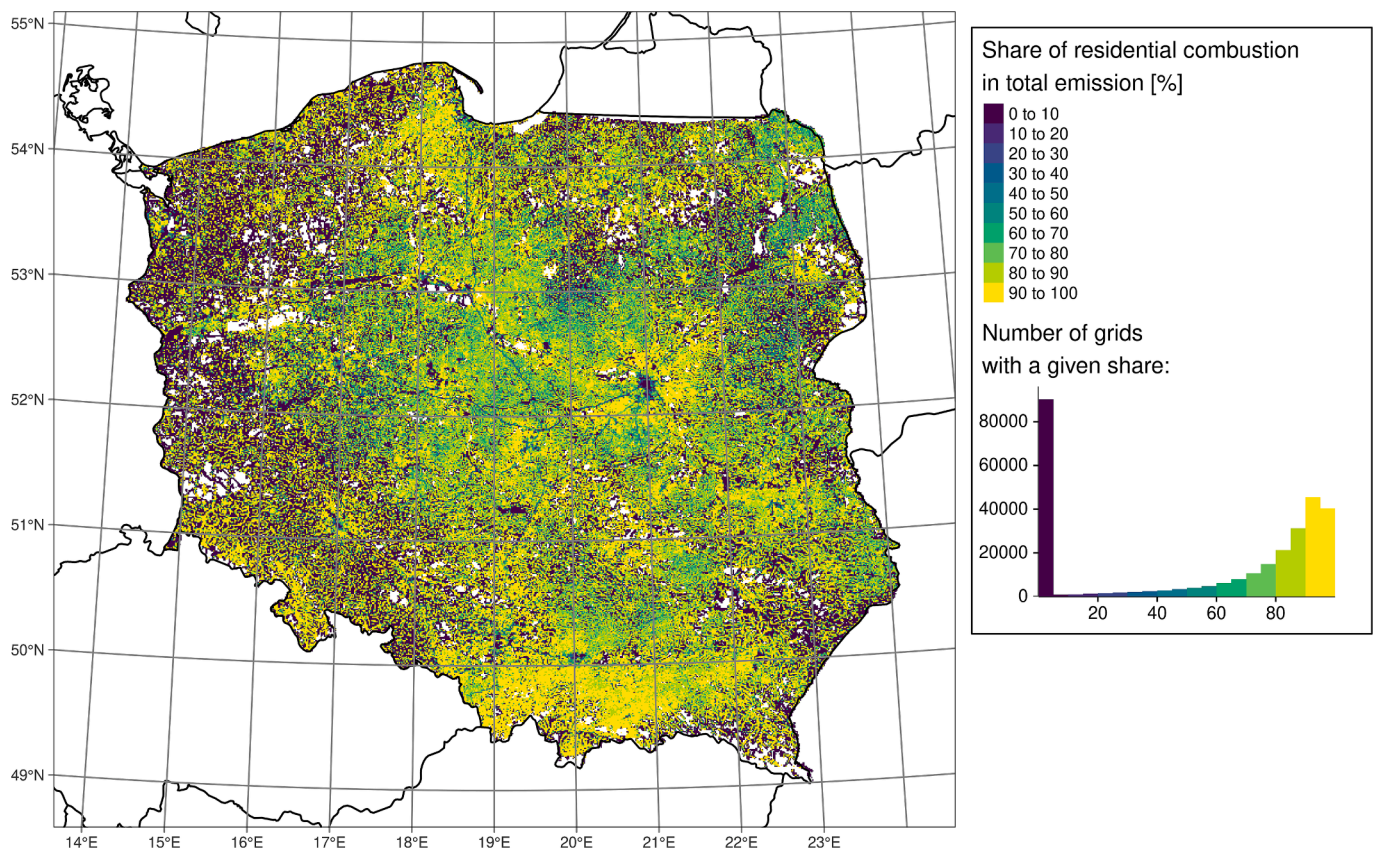


Fig. 6. Share of the SNAP sector 2 PM_{2.5} emission in the total emission of PM_{2.5} in a grid (emission year 2018 as used in this study).

to see if the increase in ME, related to higher PM_{2.5} emission, does not deteriorate the correlation coefficient significantly. If the ME is reduced and COR is at the same level or increased in this additional model run, it might suggest that the residential heating emission is correctly spatially distributed but is underestimated.

3. Results

This section is organized as follows. First, we address the CTMs model performance and compare the modelled PM_{2.5} with observations. Second, we compare the spatial distribution of PM_{2.5} modelled with WRF-Chem, EMEP4PL and EnsMean. Finally, we present the AirQ + estimates of the health effects and case study on impact of residential combustion emission on EMEP4PL model performance.

The statistical summary of the model's performance for daily mean PM_{2.5} concentrations are summarized in Table 1 for both years analyzed. All three datasets underestimate the observed PM_{2.5} levels. This underestimation is the strongest for the WRF-Chem model. The WRF-Chem model performance also has smaller NMB, IOA and COR values.

The ME changes from year to year and from season to season (Fig. 7). In the year 2017, the ME values were larger (in terms of the absolute values) in January, compared to the year 2018, contrary to March. This correlates well with the meteorological conditions (January 2017 was colder than January 2018, and February and March were colder in 2018; Fig. 2) and increased domestic combustion in winter. However, we must also consider that the emission inventory was fixed for both years, and other factors, such as deposition velocity, dilution rates, and wind patterns, likely contributed to the observed differences. Lower air temperatures lead to increased heat demand and emissions from the residential sector. None of the models applied in this study used temperature-dependent emissions for the residential sector. Both models used constant monthly and daily emission profiles. The increased model errors for cold months might support the hypothesis of the significant impact of residential heating on air quality. For both years and models, heating season PM_{2.5} concentrations are underestimated. If the normalized errors are analyzed, the highest underestimation is also observed for the cold season, except for the EMEP4PL model, which also shows large values for the summer months (Fig. 7).

Both models and their averages show the highest annual mean PM_{2.5} air concentrations over the area of Upper Silesia and Kraków (south of Poland; Fig. 8). This is a region with a historical tradition of coal mining and with a large share of coal in residential combustion. High PM_{2.5} concentrations are also modelled for other populated areas, including the largest cities of Wrocław, Poznań, Łódź or Warsaw.

For all three data sets and years considered, all the grid cells have annual mean PM_{2.5} concentrations above the WHO recommended value of 5 $\mu\text{g m}^{-3}$ (Fig. 8). Over half of the Poland territory has annual mean concentration of PM_{2.5} above 10 $\mu\text{g m}^{-3}$. This is true for all the models and years considered, and it also means that the earlier WHO guidelines have been exceeded (set to 10 $\mu\text{g m}^{-3}$ (World Health Organization 2006)). The EMEP4PL usually shows higher PM_{2.5} concentrations compared to the WRF-Chem model results. This agrees with the model evaluation results presented above, where EMEP4PL was described with the lower ME. The models react similarly to the changes in

meteorological conditions. Both WRF-Chem and EMEP4PL show higher PM_{2.5} concentrations for the year 2018 if compared to the year 2017. However, it is not only the overall statistical distribution of annual mean PM_{2.5} that differs between the models. The spatial distribution of PM_{2.5} concentration changes if different models are compared. Grid to grid correlation matrix (Fig. 8) shows that the correlation between the EMEP4PL and WRF-Chem for the same meteorological year is smaller than the correlation for the same model and different years.

Table 2 summarizes the population-weighted mean exposure for all three datasets and two years, together with the mean concentration of PM_{2.5} in Poland. PPMC was higher in 2018 compared to 2017 for all three datasets considered and the entire area of Poland. As expected, the population in urban areas has higher exposure than in rural or suburban areas. The differences in PPMC between rural and suburban areas are minor, especially for the year 2017.

The spatial distribution of the number of attributable premature deaths due to PM_{2.5} exceeding the WHO recommended value of 5 $\mu\text{g m}^{-3}$ is presented in Fig. 9. The number of attributable premature death is also summarised, by area type, in Table 2. Again, the areas of high coal consumption for residential heating, located in the south of Poland, have the highest number of premature deaths per 100 k population. Large cities show up as hotspots – this includes, e.g., Łódź and Poznań. Northwest and southeast areas of Poland have the lowest number of premature deaths per 100 000 population at risk. All these hot spots have large primary PM_{2.5} emissions and the emission of aerosol precursors coming from residential combustion. The spatial correlation between the models for the same year is smaller compared to the same model for different years (Fig. 9).

The total number of attributable deaths exceeds 22,000 according to each model and for both years considered (Fig. 9), with the maximum value of 30,000 deaths calculated with the EMEP4PL model for year 2018. Lower values calculated with WRF-Chem modelled PM_{2.5} concentrations are related to this model's stronger underestimation of PM_{2.5}. This value is significantly higher for the year 2018 than for 2017 for all three datasets considered.

As demonstrated in Fig. 6, the EMEP4PL and WRF-Chem models consistently underestimate the observed PM_{2.5} concentrations, particularly during the winter when residential heating emissions are high. The case study EMEP4PL model run, with residential emissions of PM_{2.5} increased by 25 %, shows that for most of the stations, the correlation coefficient for the run with increased emission is very similar to the base run (Fig. 10). This means that spatial distribution of the PM_{2.5} emission has not deteriorated. On the other hand, mean bias is reduced for most of the stations. This comparison might suggest that the underestimation of the emission from the residential sector is the main reason for the negative bias in our study. This is supported by the temporal variability of the bias, which was especially large during the heating season when residential emissions were high.

4. Discussion

All model runs underestimate the measured PM_{2.5} concentrations for both meteorological years considered. This underestimation was reported earlier by, e.g. Werner et al. (2018) and Kryza et al. (2020) with the WRF-Chem and EMEP4PL models. The underestimation is usually linked with considerable uncertainty related to residential emissions and low fuel quality used for heating (Gawuc et al. 2021; Jagiełło et al. 2023). The model underestimation of PM_{2.5} is more significant if the ME is compared with the EMEP4UK model (Lin et al. 2017). However, if the normalized errors are compared, the values are similar (−0.38 for the UK, as reported by Lin et al. 2017 and −0.39 for Poland, as calculated in our study using all the PM_{2.5} measuring sites). The model's performance for various countries should be done carefully, as there are differences in the total number of stations, station types (urban, rural, suburban), or sensors used.

Residential combustion emissions are responsible for over 80 % of

Table 1

Overall model performance for years 2017 and 2018 (daily mean PM_{2.5} concentrations, all stations; n – number of observations, ME – mean error, NMB – normalized mean bias, IOA – Index of Agreement, COR – Pearson correlation coefficient).

model	n	ME [$\mu\text{g m}^{-3}$]	NMB [-]	IOA [-]	COR [-]
WRF-Chem	69,253	−9.19	−0.40	0.59	0.58
EMEP4PL	69,253	−9.06	−0.39	0.69	0.70
EnsMean	69,253	−9.13	−0.39	0.65	0.70

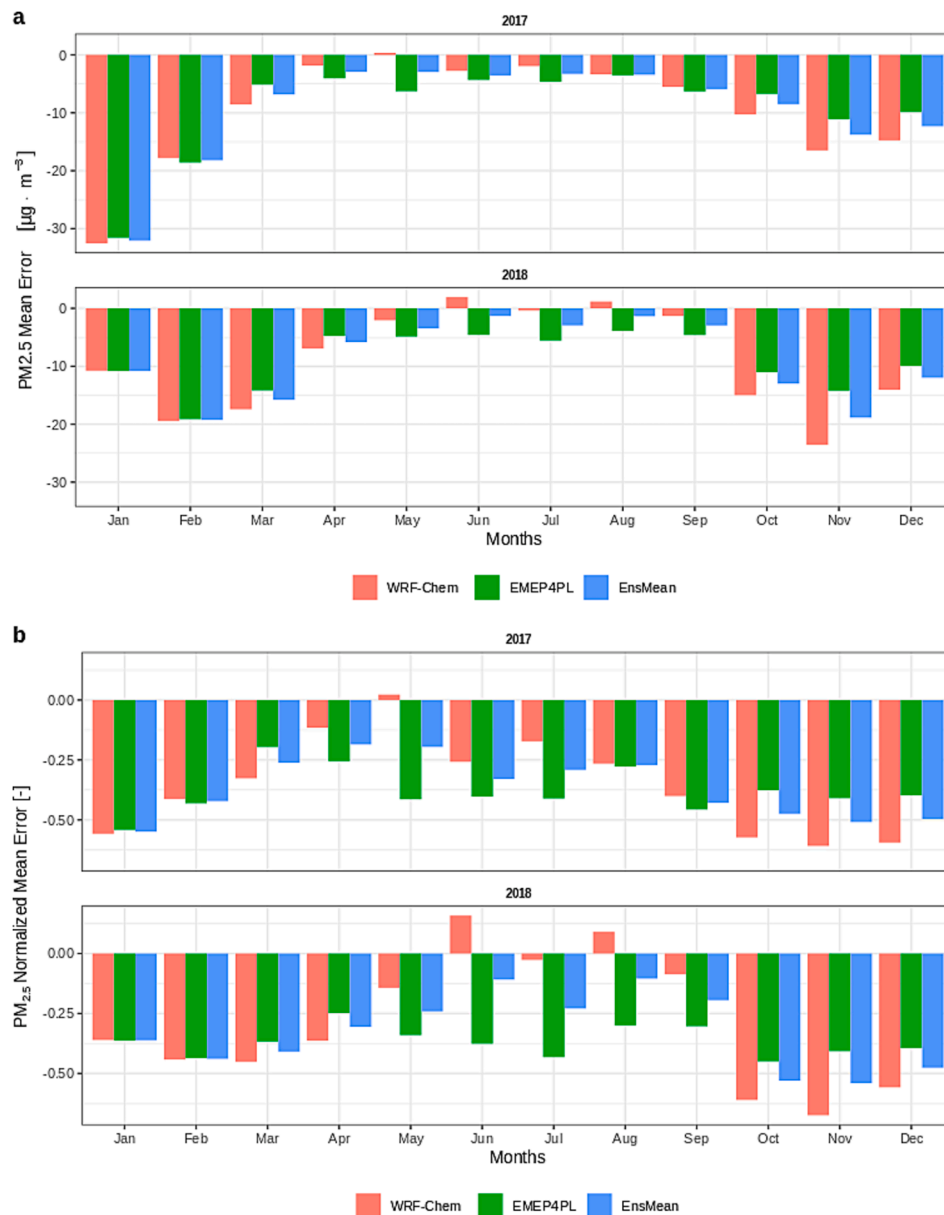


Fig. 7. PM_{2.5} mean error and normalised mean error summarized by models, months, and years considered.

the country's total primary PM_{2.5} emissions. The comparison of the baseline EMEP4PL run and a case study run for which the primary PM_{2.5} emissions were increased by 25 % supports the hypothesis that the residential heating emissions could be underestimated in Poland. The uncertainty related to emission inventory is also identified as a key element affecting the CTM's performance in other geographical areas. For example, (Zhang et al. 2023) have reported large differences in emission inventories for the Beijing-Tianjin-Hebei Region for PM_{2.5} and other pollutants. Similar findings were reported by Paisi et al. (2023) for Europe. As we show in our study, uncertainty related to emission may lead to e.g. underestimation of modelled PM_{2.5}. Data assimilation could partly address this problem and decrease the bias (Werner et al. 2019c, a). Hybrid CTMs – machine learning approach also shows promising results (Gouldsbrough et al. 2024; Vovk et al. 2024).

Despite the overall underestimation of PM_{2.5}, the model results for Poland show that the annual mean PM_{2.5} concentrations are above the WHO-recommended value of $5 \mu\text{g} \cdot \text{m}^{-3}$ for Poland, affecting health and quality of life. Annual premature mortality attributed to PM_{2.5} concentrations exceeding $5 \mu\text{g} \cdot \text{m}^{-3}$ estimated in this work exceeds 22,000

deaths and reaches the highest value in the case of the EMEP4PL model run for the year 2018 (c.a. 29,200 deaths). The multi-model mean value is c.a. 28,000 and c.a. 27,400 deaths for 2017 and 2018, respectively. These numbers are conservative, as both models underestimated observed PM_{2.5} because of the abovementioned reasons. However, the World Bank report estimated the total number of premature deaths in Poland for year 2016 to be c.a. 44,800 deaths (World Bank 2019). The estimate of the European Environmental Agency (EEA) for the year 2016 (cut-off value $0 \mu\text{g} \cdot \text{m}^{-3}$) suggests that over 44,000 premature deaths are attributed to PM_{2.5} (European Environmental Agency 2019), and more recently, Global Burden of Disease estimates for the year 2021 reported 34,000 deaths (Global Burden of Disease 2024). Jagiello et al. (2023), using the GEM-AQ modelled PM_{2.5} concentrations for year 2019 and AirQ+ methodology, estimate the number of premature deaths to c.a. 19300, but with the cut-off value of $10 \mu\text{g} \cdot \text{m}^{-3}$ ($5 \mu\text{g} \cdot \text{m}^{-3}$ is used in our work). It must be emphasized that these numbers are not easy to compare directly, as there are differences in health impact assessment methodologies and air quality assessments. For example, the EEA study and the World Bank report use air quality measurements from

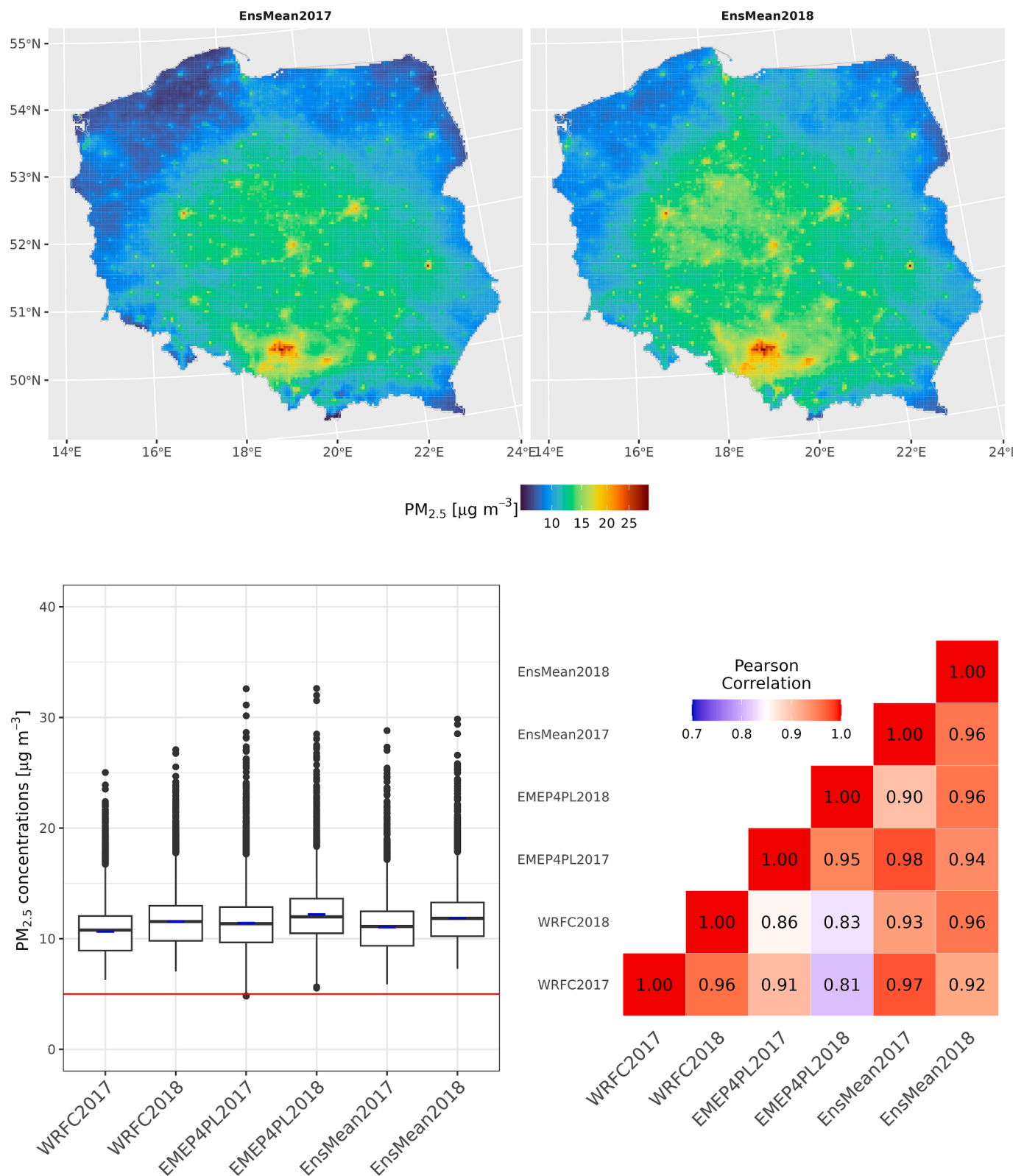


Fig. 8. Modelled PM_{2.5} annual mean concentrations (ensemble mean, A), statistical summary for each model run (boxplot calculated using all the grid cells; in blue – 95 % confidence intervals). Red line shows WHO recommended value of 5 $\mu\text{g m}^{-3}$, (B) and spatial correlation (grid to grid) matrix (C). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

monitoring stations for health impact assessment (HIA), combined with model or satellite observations. Despite using the same year, both studies use different risk models (EEA report uses WHO relative risk to calculate health impacts, while the World Bank Report employs integrated exposure–response functions). The health impact assessment estimates are done for different years, with various input data on the population. Jagielo et al. (2023) use different meteorological years and cut-off values compared to our study. Only after careful harmonization

Table 2

Annual mean PM_{2.5} concentration (MC), population-weighted mean concentration (PVMC) and total number of premature deaths attributable to PM_{2.5} exposure (TNAD, with 95% CI in square brackets).

	WRFC2017	WRFC2018	EMEP4PL2017	EMEP4PL2018	EnsMean2017	EnsMean2018
Poland						
MC	10.6	11.5	11.4	12.2	11.0	11.9
PVMC	12.9	14.1	14.7	15.4	13.8	14.7
TNAD	22,447 [17121; 25045]	25,479 [19453; 28413]	27,088 [20693; 30200]	29,227 [22343; 32572]	24,775 [18911; 27632]	27,358 [20901; 30499]
Urban areas						
MC	13.1	14.4	14.7	15.4	13.9	14.9
PVMC	14.4	15.6	17.1	17.9	15.7	16.8
TNAD	12,339 [9436; 13752]	13,907 [10625; 15495]	15,783 [12083; 17530]	16,811 [12853; 18641]	14,072 [10766; 15653]	15,365 [11747; 17067]
Suburban areas						
MC	10.4	11.4	11.2	12.2	10.8	11.8
PVMC	11.7	12.8	12.6	13.5	12.2	13.1
TNAD	4392 [3347; 4901]	5088 [3867; 5653]	4979 [3776; 5521]	5530 [4180; 6105]	4683 [3563; 5212]	5308 [4024; 5881]
Rural areas						
MC	10.6	11.4	11.3	12.0	10.9	11.7
PVMC	11.6	12.6	12.4	13.1	12.0	12.8
TNAD	5716 [4357; 6381]	6484 [4931; 7212]	6326 [4802; 7024]	6886 [5213; 7619]	6020 [4580; 6704]	6685 [5073; 7418]

of methodologies can the total number of premature deaths in Poland be compared. For instance, adjusting the EEA estimates for the year 2016 to the cut-off of $5 \mu\text{g m}^{-3}$ would reduce the number of premature deaths from over 44,000 to c.a. 33000. The EEA study uses the annual mean PM_{2.5} concentration of $20.6 \mu\text{g m}^{-3}$, which is c.a. two times higher than our study (based on modeled data only). Adjusting the annual mean PM_{2.5} concentration would reduce the EEA results to c.a. 24000. This estimate aligns with our study, considering other differences (meteorological year, input data).

The spatial pattern of PM_{2.5} concentrations is generally similar to the results presented by Jagielło et al. (2023) with the GEM-AQ model. The areas of high PM_{2.5} concentrations are in the south and central Poland and are co-located with the areas of increased emission from residential coal combustion. Population-weighted mean concentrations are higher for urban areas than suburban and rural areas. This is noticeable for both meteorological years. The year-to-year meteorological changes influence the PM_{2.5} concentration spatial pattern less if compared to the differences between the models for a given year. This is shown by the grid-to-grid correlation coefficients calculated for the WRF-Chem and EMEP4PL, which are smaller than the correlation coefficient for the same model and different years.

The spatial pattern of the number of attributable deaths is similar to the spatial distribution of PM_{2.5}. High numbers are calculated for the emission source areas, especially Upper Silesia and Kraków. This pattern is generally consistent with the findings published by Jagielło et al. (2023) for counties and by Cakaj et al. (2023) for the major cities. All these papers consistently indicate the same hot spot areas despite using different data and methods: models, measurements, meteorological years, and emission inventories.

If the different meteorological years are compared for the same model, the central estimates for the number of attributable deaths vary by approximately 10 % for the EnsMean dataset and are the highest for the online integrated WRF-Chem model (12 %). This difference increases to 30 % when comparing the lowest central estimate (WRF-Chem model for 2017) with the highest (EMEP4PL for 2018). These differences highlight the sensitivity of health impact estimates to meteorological variability and the choice of model. Noticeably, these differences due to meteorology alone are more significant if compared to the impact of the envisaged implementation of the Clean Air Program in Poland, which supports renovations and heat source replacements in single-family houses (Jagielło et al. 2023). This highlights the relative influence of two distinct factors on air quality and associated health outcomes: natural meteorological variability and planned policy

interventions aimed at reducing air pollution. While the Clean Air Program represents a significant step towards reducing air pollution from residential heating, the influence of meteorological variability on air quality and health outcomes is substantial. These results are not directly comparable due to the differences in methodology (e.g., different cut-off values for PM_{2.5} concentrations and differences in exposure, as discussed above). However, these differences due to meteorology alone can have a significant impact on the envisaged implementation of the Clean Air Program in Poland, supporting renovations and heat source replacements in single-family houses.

5. Summary and conclusions

This paper aimed to quantify the health impacts of PM_{2.5} concentrations in Poland using two air quality models applied for selected years, which were different regarding meteorological conditions affecting pollutant dispersion. The main conclusions are:

1. Both models used in this study underestimate PM_{2.5} concentrations. The WRF-Chem model's underestimation is larger and most significant during the heating season (for both models). We suggest that the main reason for this underestimation is too low emissions from the residential sector.
2. The total number of premature deaths that could be avoided if the concentrations of PM_{2.5} do not exceed the WHO recommended value of $5 \mu\text{g m}^{-3}$ exceeds 22,000 deaths for all model runs and meteorological years considered. The number of deaths varies from c.a. 24,800 to 27,400 for multi-model mean for years 2017 and 2018, respectively. The spatial distribution shows the hotspot areas in large cities and the south of Poland.
3. The total number of estimated premature deaths is sensitive to the choice of chemical transport model and the selected meteorological year. The estimated number of premature deaths can vary due to the meteorological year used in the analysis by approximately 10 % for the ensemble model and 14 % for WRF-Chem. This highlights the significant role of natural meteorological variability in health impact estimates. The Clean Air Programme (CAP), which aims to reduce air pollution through renovations and heat source replacements, may have less immediate impact on reducing premature deaths compared to year-to-year variations caused by meteorological factors (Jagielło et al. 2023). However, it is essential to emphasize that the CAP provides long-term health benefits, with the cumulative reduction in air pollution expected to yield significant, sustained decreases in

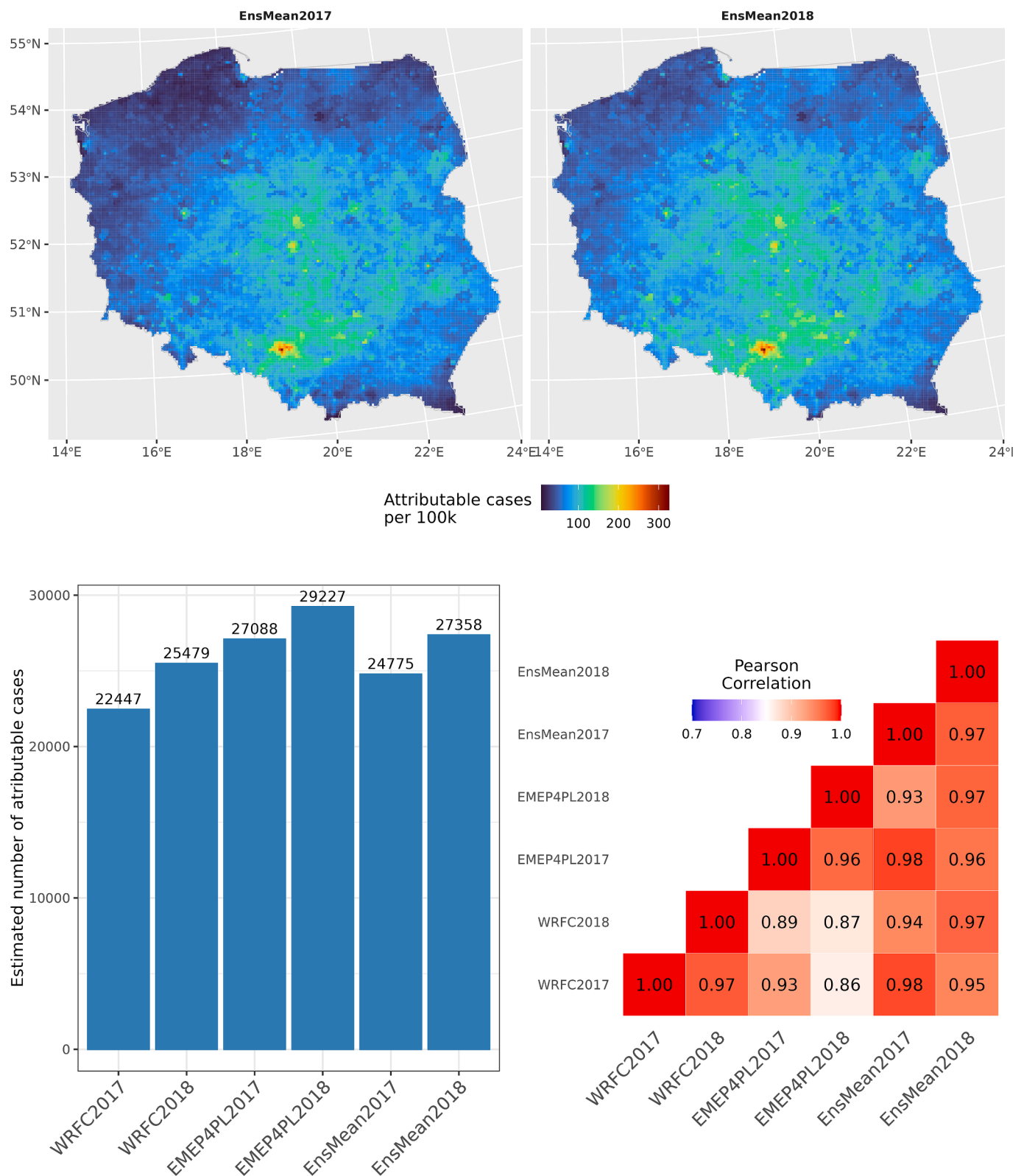


Fig. 9. Attributable deaths per 100,000 population (ensemble mean, A), a total number of attributable deaths (B), and grid-to-grid correlation matrix (C) for the attributable deaths calculated for each model run.

health burdens over time. In contrast, the effects of meteorological variability are transient and do not contribute to lasting improvements in air quality or health outcomes.

The manuscript shows that the EMEP4PL and WRF-Chem model

performance differs despite the fact that both models share the same meteorological and emission input data. Moreover, the model performance changes with, e.g., season and location, which emphasizes that evaluation of the model carried out for another year or geographical location will not be valid for other regions or periods. Additionally, the

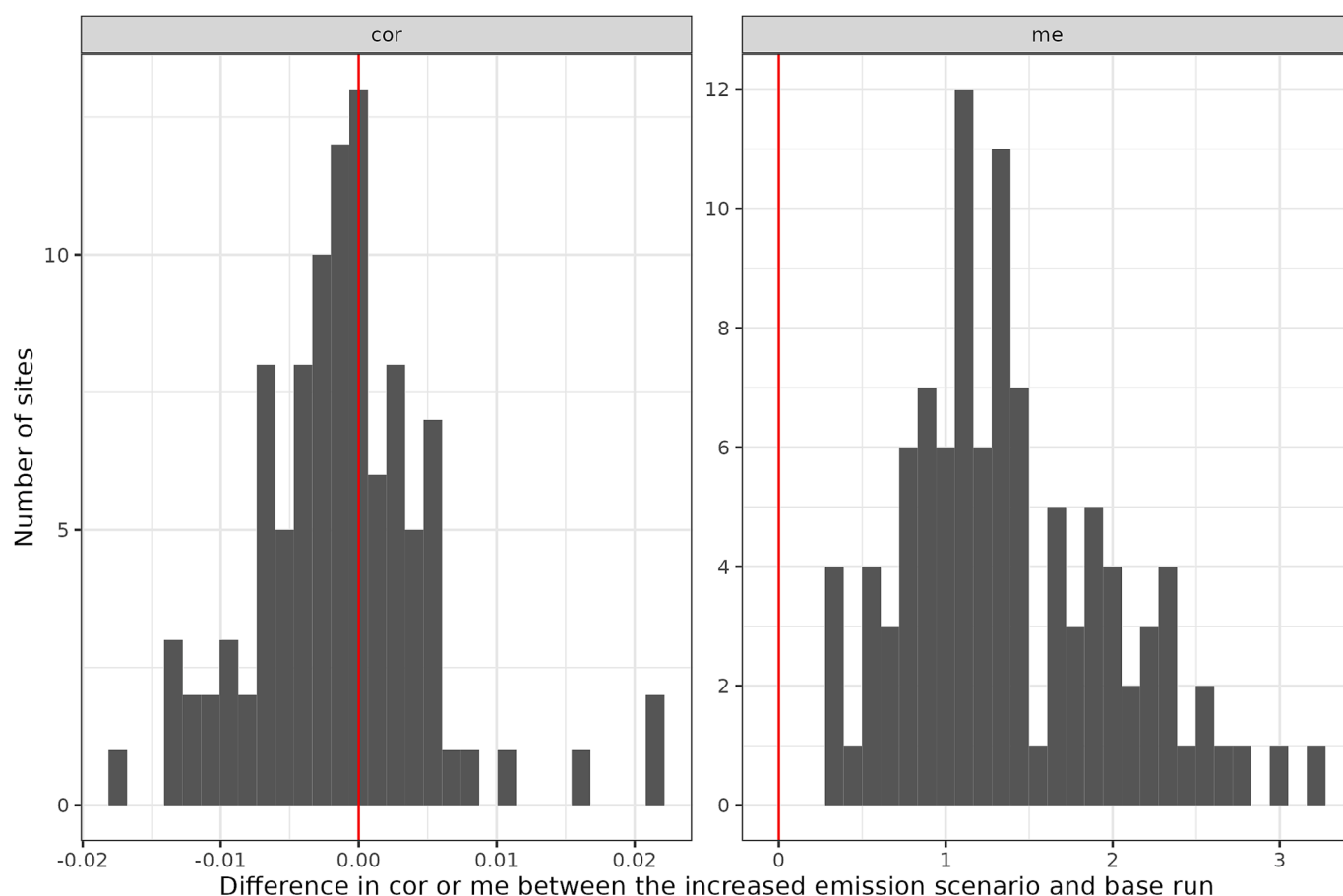


Fig. 10. Differences correlation coefficient (left) and mean error (right) between the increased emission scenario test run and a base run with the EMEP4PL for the year 2018.

single dispersion model usually has several chemical mechanisms and physical parameterizations that can be used in the simulation. Different parameterizations lead to different results of air pollution concentrations, which concludes that the model evaluation should accompany each HIA study.

Our study relies on modelled PM_{2.5} concentrations from WRF-Chem and EMEP4PL to assess health impacts in Poland, providing a consistent framework for evaluating spatial variability and meteorological influences. However, both models tend to underestimate PM_{2.5} levels, particularly during the heating season, which is likely due to limitations in the emission inventory for residential heating, a significant source of PM_{2.5} in Poland. This underestimation implies that our health impact estimates may be conservative. While observational data from monitoring stations could improve exposure accuracy for densely sampled areas, this study focuses on modelled data to maintain consistent, grid-level coverage and assess model-specific and meteorological influences on country-wide exposure. Observational data, in contrast, is spatially limited and does not capture the full geographic extent needed for a nationwide assessment.

Future work could reduce model bias through data assimilation of observational data or hybrid approaches that integrate machine learning, potentially enhancing the accuracy of modelled PM_{2.5} concentrations. Improvements in emission inventories, such as temperature-dependent emissions or updated data on fuel use, especially for the residential sector, would also enhance exposure estimates, which have been initially shown/tested in this study. Although our estimates align with other health impact assessments in Poland, such as those by the EEA and World Bank, methodological differences (e.g., use of observational data, differing cut-off values) make direct comparisons

challenging, emphasizing the need for harmonized approaches to quantify the health burden of air pollution.

CRediT authorship contribution statement

Maciej Kryza: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Małgorzata Werner:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Data curation. **Michael Holland:** Writing – review & editing, Supervision, Software. **Helen ApSimon:** Writing – review & editing, Supervision, Methodology, Investigation.

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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Data availability

Data will be made available on request.

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