

Impact of agricultural interventions on ammonia emissions and on PM_{2.5} concentrations in the UK: a local and regional modelling study

Matthieu Pommier¹, Robert Benney², Jamie Bost¹, Becky Jenkins³, Joe Richardson⁴, Liam Rock⁴,
5 Olivia Blythe⁴, Oliver Marshall², Alexandra Spence²

¹Ricardo Energy & Environment, 18 Blythswood Square, Glasgow G2 4BG, UK.

²Ricardo Energy & Environment, Bright Building, Manchester Science Park, Pencroft Way, Manchester M15 6GZ, UK.

³Ricardo Energy & Environment, The Gemini Building, Fermi Avenue, Harwell, Didcot OX11 0QR, UK.

⁴Ricardo Energy & Environment, 30 Eastbourne Terrace, London W2 6LA, UK.

10

Correspondence to: Matthieu Pommier (matthieu.pommier@ricardo.com)

Abstract. The contribution of agricultural emissions of fine particulate matter (PM_{2.5}) poses significant health and environmental challenges, particularly in the UK where intensive farming activities contribute to elevated pollutant levels. This contribution includes direct emissions and PM_{2.5} formed through chemical reactions from precursors such as ammonia (NH₃). The study aims to analyse the impact of series of mitigation measures through emission scenarios (low, medium, high uptake) on dairy, pig and poultry sectors in 2030 and mainly focusing on NH₃ emissions. Under the high uptake scenario, NH₃ emissions could decrease by up to 13% nationally, with reductions reaching as high as 20% in certain regions. The Community Multiscale Air Quality (CMAQ) and the Atmospheric Dispersion Modelling System (ADMS) models were used. CMAQ allows to understand the contribution made by agricultural NH₃ to secondary PM_{2.5} at a regional scale, while ADMS is used to better understand near-field dispersion and dilution of primary pollutants. Despite the impact of the changes in emissions due to the mitigation measures compared to the future baseline scenario, changes are not reflected on regional scale PM_{2.5} concentrations since the maximum modelled decrease was around 1-1.5%. This finding is explained by an NH₃-rich atmosphere reducing the impact of these reductions in NH₃ emissions on mitigating PM_{2.5} concentrations. Results from ADMS show that the NH₃ and PM_{2.5} concentrations are quickly dispersed near the farms, highlighting the usefulness of local modelling in addressing impact studies on PM_{2.5} formation near these sources. Indeed, for the five studied livestock farms, it has been found that 50% of maximum NH₃ and PM_{2.5} concentrations are located within a distance between 100 and 400m and up to 90% of concentrations have decreased within 700m. The study also demonstrates the complementary use of local and regional modelling in understanding PM_{2.5} dispersion near agricultural areas. The comparison with ground-based measurements might suggest a non-representation of atmospheric processes in the PM_{2.5} formation by CMAQ (with an underestimation of PM_{2.5} concentrations by approximately 50%). It underscores the need for integrated modelling approaches to guide mitigation strategies for both primary and secondary PM_{2.5}, as well as to improve understanding of the chemical atmospheric processes involved in the secondary inorganic aerosols.

35 1 Introduction

Air pollution from PM_{2.5} (fine particulate matter with a mass median aerodynamic diameter <2.5 μm) has been estimated to cause millions of premature deaths annually in recent years (Burnett et al., 2018; Kiesewetter et al., 2015; Lelieveld et al., 2015). PM_{2.5} poses significant environmental and public health problems due to its ability to penetrate deep into the respiratory system, causing various health issues, including respiratory and cardiovascular diseases (Pope and Dockery, 40 2006). Therefore, mitigating this PM_{2.5} pollution is a high priority for environmental protection in many areas such as the European Union (EU) and in the United Kingdom (UK).

Among the various components contributing to PM_{2.5} concentrations, ammonia (NH₃) has an important role in secondary particulate formation. In the atmosphere, NH₃ reacts with acidic compounds such as sulfuric acid (H₂SO₄) and nitric acid (HNO₃), forming ammonium sulphate ((NH₄)₂SO₄) and ammonium nitrate (NH₄NO₃), which are significant constituents of 45 PM_{2.5} (Seinfeld and Pandis, 2016; Wyer et al., 2022).

The UK presents a significant case for examining the influence of NH₃ on PM_{2.5} levels due to its varied agricultural practices, transport-related emissions, and industrial activities. NH₃ emissions in the UK primarily originate from agricultural sources, particularly livestock waste and the application of fertilizers (Misselbrook, et al., 2023). Indeed, the most recent figure from the UK National Atmospheric Emissions Inventory (NAEI) shows that agriculture accounted for nearly 87% of total ammonia emissions in 2023 (NAEI, 2025). Direct soil emissions account for 52.7% of total NH₃ emissions, followed by 50 cattle at 25.9%, waste at 9.5%, other livestock at 4.8%, poultry at 3.7%, and combustion and production processes at 3.4%. These emissions have been shown to vary seasonally and spatially, influencing the formation and distribution of airborne PM_{2.5} concentrations (e.g. Wyer et al. 2022). Various mitigation measures (i.e. farm practices) have been developed to mitigate emissions of NH₃, such as covering slurry stores, or using automatic scrapers in housing, however, reducing air 55 pollution from agriculture remains challenging (Jenkins and Wiltshire, 2025).

Previous studies have highlighted the importance of understanding the interaction between NH₃ and PM_{2.5} to inform regulatory measures and mitigate adverse health effects. For instance, the work by Vieno et al. (2014) demonstrated that reductions in NH₃ emissions could lead to significant decreases in PM_{2.5} levels, especially in areas with large nitrogen oxides (NO_x) concentrations, suggesting that targeted strategies in NH₃ emission control could be effective in improving air quality. 60 These results were confirmed by the study of Ge et al. (2023), since they showed NH₃ reductions are more effective for regions or countries with better air quality, such as in the UK (compared to Asia, for example) to mitigate PM_{2.5} concentrations. The impact of NH₃ emissions reduction is significantly more efficient with large emission reduction measures (Bessagnet et al., 2014) and abating NH₃ emissions can even be more cost-effective than NO_x for mitigating PM_{2.5} air pollution (Gu et al., 2021). Conversely, other work such as Ge et al., (2022) and Pay et al. (2012), suggested NH₃ 65 emissions reduction may only lead to minor improvements in airborne PM_{2.5} concentrations, especially in the UK since the UK is characterized by a NH₃-rich atmosphere. A study in the United States also showed controlling NH₃ became significantly less effective for mitigating PM_{2.5} in rural areas (Pan et al., 2024).

Due to the complexity of atmospheric chemistry, numerical air quality models such as Chemistry Transport Models (CTMs) are commonly used to simulate these processes and assess the effectiveness of potential emission control strategies. CTM

70 such as the Community Multiscale Air Quality (CMAQ) model (Appel et al., 2021), developed and distributed by the US Environmental Protection Agency (EPA) is a cutting-edge numerical air quality model that comprehensively represents the emission, formation, destruction, transport, and deposition of numerous air pollutants, including PM_{2.5} and its precursors. CTMs such as CMAQ are designed to calculate background concentrations, i.e. air pollutants' concentrations at a km scale spatial resolution (De Visscher, 2014).

75 Local dispersion models like Atmospheric Dispersion Modelling System (ADMS) (Carruthers et al., 1994) can be utilized to provide detailed simulations of pollutant dispersion at a finer scale such as 1m. ADMS is particularly effective for assessing the impact of emissions from specific sources and understanding local air quality variations (Zhong et al., 2023). The combination of local dispersion models such as ADMS with CTMs allows a more comprehensive understanding of both regional and local air quality dynamics. Indeed, local modelling studies have shown their accuracy in determining the

80 dispersion of pollution (Hood et al., 2018; Porwisiak et al., 2024; Zhong et al., 2023). ADMS is by default a steady state (non-reactive) Gaussian plume model that predicts pollutant concentrations based on the assumption that both the vertical and horizontal dispersion of the continuous plume is represented by normal distribution around the plume centreline. However, due to the steady state assumption, short range estimates within 10km are recommended (Environmental Protection Ireland Agency, 2020).

85 The aim of the study was to understand the impact of mitigation measures relating to livestock housing and the storage and spreading of manures and slurries on PM_{2.5} concentrations and was part of an interdisciplinary project named AIM-Health which included stakeholder engagements, measurement campaigns, air quality modelling, health impact assessment, economic study and ecosystem impact assessment. A companion study has already presented the impact of these policies on NH₃ concentrations and nitrogen deposition at a regional scale (Pommier et al., 2025). This study primarily focussed on

90 measures to reduce emissions from housed dairy, pigs and poultry, while emissions from other sources such as manufactured fertilisers were not within its scope. Three intervention scenarios were developed to model the impact on PM_{2.5} concentrations nationally based on differing uptake levels of the mitigation measures across the UK, ranging from low, medium and high. Additionally, local modelling was done to show how primary emissions of NH₃ and PM_{2.5} disperse within the local vicinity (10km) of farms included in this study.

95 Section 2 of this paper describes the methodology used for the scenario development and the air quality modelling (regional and local). The analysis on the modelled PM_{2.5} concentrations is presented in Section 3. Section 4 discusses the results and Section 5 gives the conclusions and perspectives.

2 Method

100 A series of mitigation measures related to livestock diet, livestock housing and improved storage and spreading of manures and slurries were modelled to understand the impact on emissions from housed dairy, pigs and poultry across the UK. The mitigation measures were modelled through scenarios which represented various levels of uptake (low-high) on these farms across the UK in 2030.

105 Whereas the regional modelling assumes a progressively higher national adoption of measures across these low to high scenarios, the local modelling applies only those mitigation strategies that are relevant to each individual farm. This approach is summarised in Figure 1.

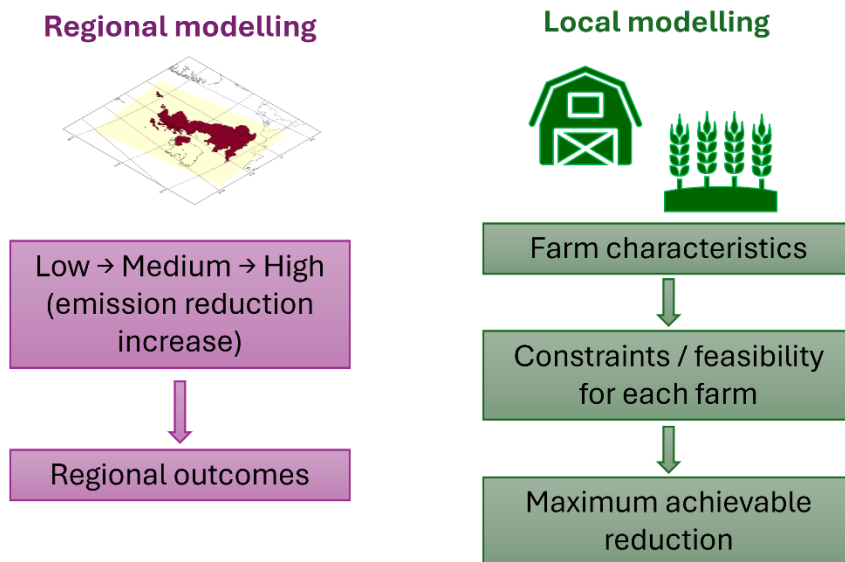


Figure 1: Schematic workflow for designing the emission scenarios.

To undertake the study, the CMAQ model, has been used for the regional modelling and evaluated. CMAQ is a 3D Eulerian model, incorporating the effects of meteorology, emissions, land use, chemistry and aerosol processes on modelled air pollution. It has been developed to represent the emission, transport, formation, destruction, and deposition of many air pollutants, including nitrogen dioxide (NO₂), ozone (O₃) and PM_{2.5}. The version used in this study is 5.4 (US EPA Office of Research and Development; <https://zenodo.org/records/7218076>, 2022a). This chemical-transport model requires input from a weather model, emissions and the background atmospheric composition. For our work, the CMAQ model has been driven by meteorological fields from the Weather Research and Forecasting (WRF) model version 4.5 (NCAR, 2022).

115 For the local modelling, ADMS version 6 (CERC, 2024) has been used. ADMS is steady-state Gaussian air dispersion model that incorporates air dispersion based on planetary boundary layer turbulence structure and scaling concepts, including treatment of both surface and elevated sources, and both simple and complex terrain. This model allows calculation of

concentrations of atmospheric pollutants emitted both continuously from point, line, volume and area sources, or intermittently.

2.1 Scenario development

120 The list of 20 mitigation measures were identified by European Commission's Best Available Techniques (BAT) reference
document for the intensive rearing of poultry or pigs (European Commission. Joint Research Centre., 2017) and Defra's
Code of Good Agricultural Practice (COGAP) for Reducing Ammonia Emissions (DEFRA, 2024b). The year 2030 was
chosen due to being 10-years in the future from the start of the research study, therefore establishing a realistic timeline for
practical implementation of new activities on farms. These measures mainly focus on controlling NH₃ emissions and not on
125 mitigating the primary PM_{2.5} emissions from farming activities.

Three scenarios have been considered: low, medium and high uptake and compared to a baseline in 2030 and defined in the
rest of the document as low2030, medium2030, high2030 and base2030, respectively. The uptake scenarios were developed
through stakeholder engagement with farmers and stakeholders (i.e. farm advisers, academics and farmer representatives) to
assess realistic implementation of specific mitigation measures.

130 Each scenario includes all 20 mitigation measures, however with varying percentages of uptake, a table presenting levels of
uptake is presented in Appendix A and a table with descriptions of the mitigation measures is in Appendix B. The number of
measures listed in Tables A1 and B1 differ because each measure appears only once in Table B1, whereas Table A1 includes
measures multiple times when they apply to more than one livestock sector. The uptake rates were unique to each mitigation
measure in each sector and were reflective of feedback received through engagement activities. The engagement activities
135 included an online survey, focus groups and one-to-one interviews with participants from the dairy, pig and poultry sectors
and those in other sectors which utilise manure or slurry. A total of 161 people took part in the activities. Full results and
methodology are detailed in Jenkins and Wiltshire (2025).

Discussions in these activities were centred around understanding the current level of uptake and the benefits and barriers
associated with the mitigation measures to determine a potential future uptake. If a mitigation measure was received
140 positively, it was estimated to have a higher uptake compared to measures that were received negatively by participants. This
was determined in the final level of uptake for each scenario. The future uptake did not take account of any potential changes
to legislation that may have an impact as this information is not known, additionally there were no different uptakes for each
part of the UK due to a lack of data.

To determine the emission reduction associated with each mitigation measure, the Scenario Modelling Tool (SMT) was used
145 (Ricardo EE, 2021). The SMT is a model for the management and analysis of complex scenarios of mitigation of air quality
and greenhouse gas emissions from agricultural sources in the UK. In this work, the model implements a mass flow model to
track pollutant transfer between each of the locations on a farm, to correctly reflect the cascade of mitigation effects along
the manure management chain.

The SMT calculates the effect on emissions of each scenario by adding measures with emission reduction values and uptake rates. It allows designing mitigation measures using the effect on emissions (as a percentage reduction), cost, and targeting (the point in the agricultural system/manure management chain at which the effect on emissions is felt). Uptake rates are used in the SMT, allowing for the uptake of each measure to be reflected as a percentage of a cohort of farms (e.g., fixed slurry cover can be applied to 15% of dairy farms). It is worth noting that the cost impact of the measures is not discussed in this study.

There are different ways that the various types of measures are calculated within the SMT. In this study, ‘Emission’ and ‘Reduction’ measures were used. ‘Emission’ measures directly reduce the pollutant emission factor at a location on a farm. This type of measure represents changes in practice or technical solutions and is not typically used where a measure represents a change in the overall management system. ‘Reduction’ measures reduce the quantity of a source of emissions (e.g. the number of animals in housing or the quantity of excreta in housing). This reduction is reflected in emissions occurring at all associated locations. In this study, the only ‘Reduction’ measures used related to extended grazing on dairy farms and low protein diets in dairy, pig, and poultry farms. For the low protein diet measures the quantity of excreta was reduced, while for the extended grazing the quantity of managed solid and liquid manure was reduced. All other measures were implemented as ‘Emission’ measures; directly reducing the emission factors at relevant locations.

The SMT comes with a default library of mitigation measures and associated emission reduction factors. These emission reduction factors have been calculated based on empirical evidence and published scientific literature; primarily UK based, and with reference to relevant international studies and the UNECE Task Force for Reactive Nitrogen Ammonia Abatement Guidance Document (Bittman et al., 2014). The mitigation impact of these measures from the SMT is verified for accuracy by comparison with data from the Agricultural Ammonia and Greenhouse Gas Inventory (AAGHGI) (Misselbrook, et al., 2023).

Eleven measures that were included in the modelling in this project were not included in the pre-defined measure library. To determine how to reflect these eleven measures in the SMT (including what stage(s) in the agricultural system the measure is relevant to and if it is an ‘Emission’ or a ‘Reduction’ measure), as well as the emission reduction potential of these measures, COGAP, BAT, and expert knowledge was used. This information was added to the SMT using the ‘Measure’ function as outlined above.

The calculation of measure effect takes account of measure interactions, including the order of implementation and exclusivity, and employ the principal of maximum overlap of uptake and a multiplicative effects model, in line with similar, earlier models such as National Ammonia Reduction and Strategies Evaluation System (NARSES) (Webb et al., 2006; Webb and Misselbrook, 2004). Baseline emission data comes from the AAGHGI (Misselbrook, et al., 2023). The data set for the year 2019 was used as baseline as it was the most recent submission at the time of running the scenarios.

180 2.2 Regional modelling: CMAQ

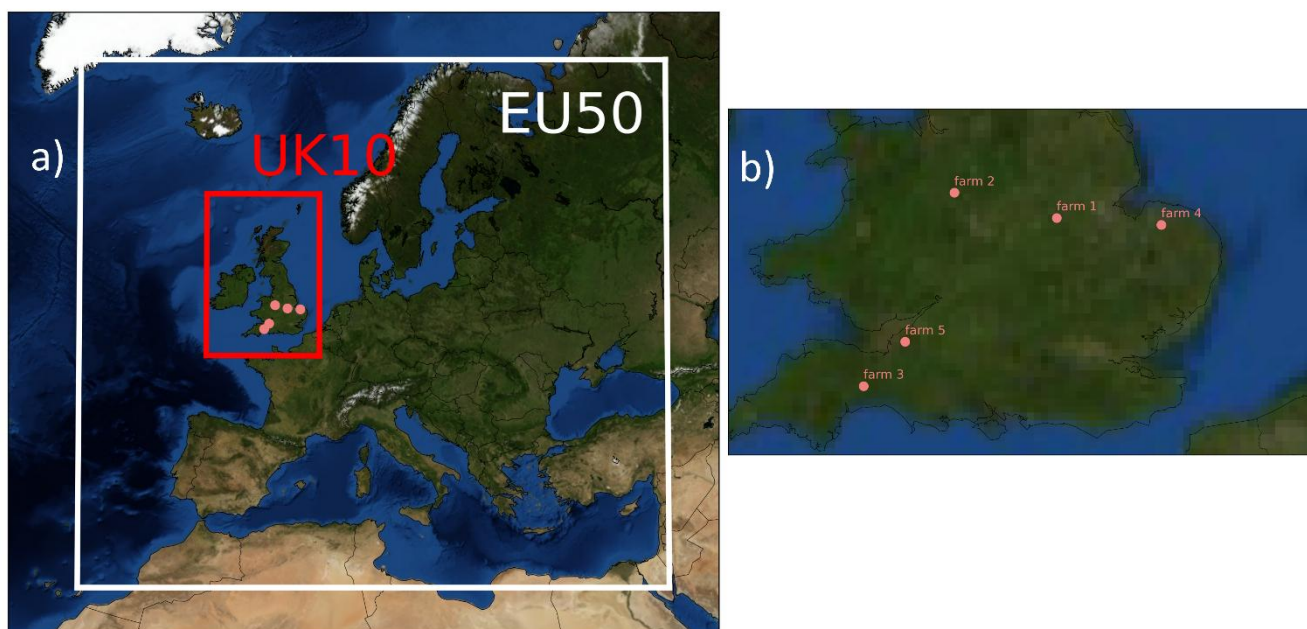
2.2.1 Model set-up

The CMAQ model, calculating the pollutants' concentrations and depositions at an hourly resolution, was setup using the same vertical and horizontal grid structure as for WRF, modelling the meteorology. Atmospheric chemistry was simulated using the carbon bond mechanism (CB06r5) (Luecken et al., 2019) combined with the aerosol mechanism using the 7th generation aerosol module (AERO7) (Pye et al., 2017). Dry deposition of gaseous species is simulated utilizing deposition velocity and the M3Dry aerosol deposition parameterization (Hogrefe et al., 2023). The configurations of the WRF and CMAQ models are given in Table 1.

Table 1: Summary of WRF and CMAQ modelling settings

WRF configuration – version 4.5	Scheme
Longwave radiation	Rapid Radiation Transfer Model Global (Iacono et al., 2008)
Shortwave radiation	Dudhia (Dudhia, 1989)
Planetary boundary layer	ACM2 (Pleim, 2007)
surface layer	Pleim (Pleim, 2006)
Land-Surface	Rapid Update Cycle (RUC) (Smirnova et al., 2016)
Cumulus	Kain-Fritsch (Kain, 2004)
Land use classification	Noah-modified 21-category IGBP-MODIS (Friedl et al., 2002)
Vertical layers	24 eta levels (1.000, 0.998, 0.993, 0.986, 0.976, 0.960, 0.930, 0.900, 0.820, 0.700, 0.650, 0.600, 0.550, 0.500, 0.450, 0.400, 0.350, 0.300, 0.250, 0.200, 0.150, 0.100, 0.050, 0.000)
CMAQ configuration - version 5.4	Scheme
chemistry	Cb6r5 (Luecken et al., 2019)
aerosol	Aero7 (Pye et al., 2017)
aerosol deposition parameterization	M3Dry (Hogrefe et al., 2023)

190 A nested modelling approach has been employed, dividing the broader geographic area into smaller domains to enhance spatial resolution. This hierarchical structure enables more accurate representation of variations in emissions and meteorological conditions. The outer domain, covering Europe, uses a horizontal resolution of 50 km (EU50), while the inner domain focuses on the UK with a finer resolution of 10 km (UK10), as illustrated in Figure 2.



195 **Figure 2: a) Regional nested modelling domains and location of the studied farms shown with the matplotlib NASA Blue Marble image used as an illustration. The white box corresponds to the European domain at 50 km × 50 km horizontal resolution (EU50) and the red box to the UK domain at 10 km × 10 km horizontal resolution (UK10). Each farm is shown with a pink coral circle. b) Zoom on the location of each studied farm with their corresponding id. The details on the farms are provided in Table 2.**

The air quality simulations were carried out using meteorological data from 2019. This year was selected as the reference
 200 because it is classified as a typical meteorological year in the UK (see Pommier et al. 2025 and references within) and 2019 was also the most recent UK emissions year at the beginning of the project. This historical 2019 simulation has been used for model performance evaluation prior the analysis of the future predictions with the scenarios. The future scenarios solely focused on change in emissions and no climate projection has been undertaken. Consequently, there is no analysis on changes in meteorological conditions.

205 The regional simulation started with a spin-up period of 2 weeks. The simulation setup follows a 'forecast-cycling' approach, where the output fields from each run were used to initialize the simulation for the following day. This process has been applied continuously throughout the entire year of 2019 for both the EU50 and UK10 domains. The initial and boundary conditions for the outermost domain (EU50) were created using hemispheric CMAQ outputs for the year 2016 provided by the US EPA (US EPA Office Of Research And Development, 2022b). Subsequently, the CMAQ concentrations computed
 210 within the EU50 domain were used as boundary conditions for the nested UK10 domain.

2.2.2 Emissions

The anthropogenic emissions data from the European Monitoring and Evaluation Programme (EMEP) (CEIP, 2022) were post-processed into 50×50 km to populate our EU50 domain in CMAQ. The UK anthropogenic emissions, including from agriculture, were based on the gridded emissions from the UK National Atmospheric Emission Inventory (NAEI) for 2019 (Churchill et al., 2021). The NAEI provides gridded emissions data at a $1 \text{ km} \times 1 \text{ km}$ resolution, which was post-processed to match the $10 \text{ km} \times 10 \text{ km}$ resolution of the UK10 domain. Additionally, the 2019 large point source emission inventory was used to vertically distribute emissions within the CMAQ grid.

The baseline 2030 future scenario for the EU50 domain was based on the EMEP gridded emissions for 2019 and scaled with the factors provided by the GAINS ECLIPSE (Greenhouse Gas and Air Pollution INteractions and Synergies - Evaluating the Climate and Air Quality Impacts of Short-Lived Pollutants) V6b Baseline CLE scenario (IIASA, 2019).

With the exception of the UK base2030 scenario, all UK scenarios incorporate the same set of measures. The increasing adoption of these measures across the low2030, medium2030, and high2030 scenarios reflects progressively higher ambition in reducing air pollutant emissions as described in Section 2.1.

Figure 3 shows the total UK anthropogenic emissions as used in CMAQ and highlights the main changes in these emissions for the different scenarios. Since the mitigation measures mainly tackle the NH_3 emissions, this explains the large decrease calculated for this pollutant. As explained in Pommier et al. (2025), the reduction in NH_3 emissions could reach up to 20%, 22%, and 24% in certain regions under the low2030, medium2030, and high2030 mitigation scenarios, respectively. It is noteworthy that the UK NH_3 emissions are mainly dominated by the February-April period as shown in Figure S1 and in Hellsten et al. (2007). Marais et al. (2021) reported an additional July peak associated with dairy cattle farming, based on satellite observations, alongside the spring peak. In contrast, the Emissions Database for Global Atmospheric Research (EDGAR) applies a uniform temporal profile for agricultural NH_3 emissions in the UK in its latest inventory version (EDGARv8.1: https://edgar.jrc.ec.europa.eu/dataset_ap81#p1m, last access on 02.11.2025).

A constant decrease in carbon monoxide (CO) is predicted across all scenarios. Unlike other pollutants, this trend is influenced not only by the selected mitigation measures but also by the scope of the SMT model, which does not fully capture all future CO emission sources. Slightly larger reductions in emissions are calculated for the high2030 scenario for volatile organic compounds (VOCs) and the coarse PM (PM_{10} , PM with an aerodynamic diameter lower than $10 \mu\text{m}$), while the changes in NO_x and $\text{PM}_{2.5}$ remain limited, and null for sulphur dioxide (SO_2).

CMAQ also calculates biogenic emissions with an online module incorporated in the model. This uses the Model of Emissions of Gases and Aerosols from Nature (MEGAN) (version 3.2) (Guenther et al., 2020). CMAQ also calculates windblow dust (Foroutan et al., 2017) and sea spray emissions (Gantt et al., 2015; Kelly et al., 2010) with online modules. These emissions are identical in all scenarios.

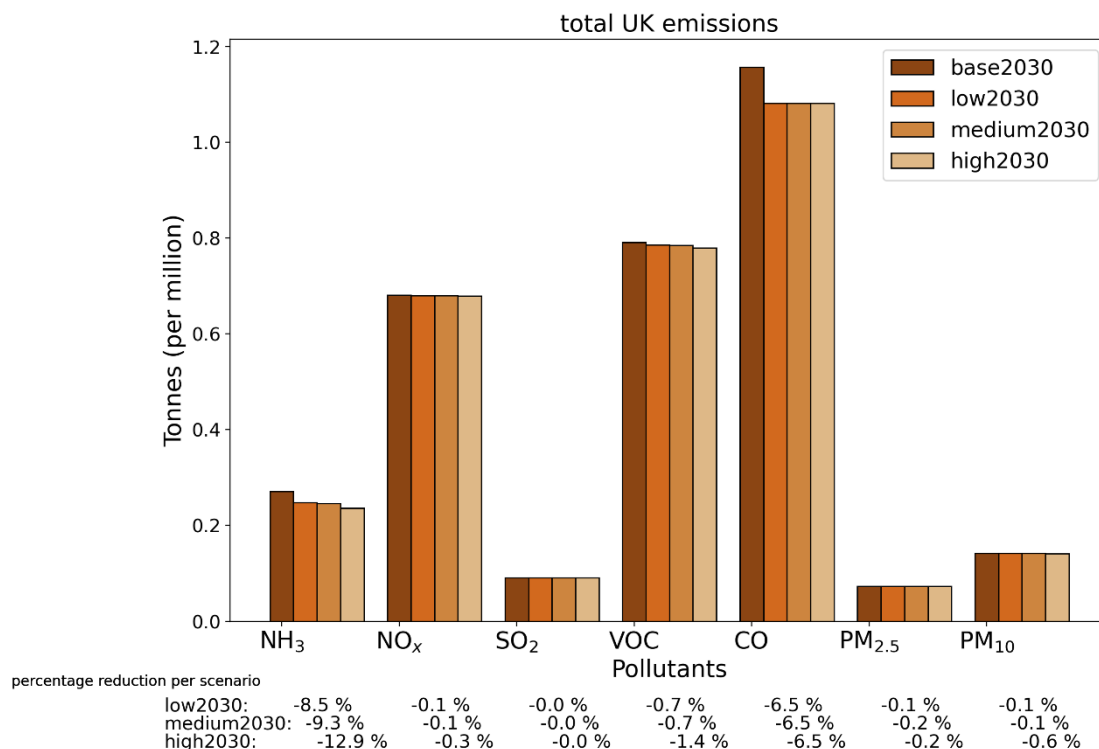


Figure 3: Total UK anthropogenic emissions in tonnes for the different scenarios used by CMAQ for NH₃, NO_x, SO₂, VOC, CO, PM_{2.5}, and PM₁₀. The relative difference for the low2030, medium2030 and high2030 scenarios compared to the base2030 are given below each corresponding bar.

245 2.3 Local dispersion modelling: ADMS

2.3.1 Model setup

For the local modelling, meteorological datasets were procured from National Oceanic and Atmospheric Administration (NOAA) weather stations ranging from 6km to 25km from farms in this study. Where data capture was insufficient, gap-filling was performed to ensure coverage exceeded 85% for all parameters, including wind speed, wind direction, cloud cover, temperature, and precipitation. Data filling involved selecting the most representative NOAA station for each farm, and where gaps were present in its dataset, missing values were supplemented using data from the next most representative station. This approach ensured a complete and more reliable dataset for modelling. 2019 was selected as this year is consistent with the existing baseline year of the regional model.

Each farm, situated in a different region of the UK (Fig. 2), away from major roads and industrial areas, had a 15km-by-15km points grid centred at the farm with a 100m resolution. This was overlaid with the CORINE Land Cover 2018 100m data (European Environment Agency, 2019) to extract map codes for each grid point. The land use classifications were associated with a surface roughness ranging between 0.04025 (water) and 1.3 (urban areas) in Aermot, the meteorological pre-processor for Aermot (Support Center for Regulatory Atmospheric Modeling, 2017 Appendix W Final Rule). NH₃

deposition was considered by using deposition velocities that vary depending on the surface. The deposition velocity values
260 used for NH₃ vary between 0.02 m/s for lower plants (lowland shrubs, grassland) and 0.03 m/s for higher plants (woodlands)
(Natural Resources Wales, 2021). Plume depletion was turned on in ADMS, this means that atmospheric concentrations of
NH₃ and PM_{2.5} decrease due to dry and wet deposition.

The requirement for complex terrain was established using the Environment Agency's 1m Lidar data (DEFRA, 2023) to see
if it met Defra's Local Air Quality Management modelling requirement (> 1:10) (DEFRA, 2022) for any of the farms. None
265 of the farms displayed a terrain of 1:10 or above and so complex terrain was omitted from the model.

ADMS can include buildings to simulate the impact of building downwash for point sources only, air recirculation leeward
(downwind) of the building. Buildings within a distance three times the mechanical ventilation stack height were included to
estimate the potential of increased concentrations very close to the source. This distance is a more conservative threshold
than the Good Engineering Practice (GEP) criteria to allow for differences in building shape, wind direction, and wake
270 effects, improving the accuracy of near-field dispersion modelling. The US Clean Air Act (USEPA, 1985) sets a threshold at
2.5 times the height of the nearest structure, measured from ground level at the base of the stack.

The CMAQ modelled concentrations for the corresponding grid cells of the UK10 domain were used as background
concentrations for NH₃ and PM_{2.5}. Indeed, the concentrations calculated by CMAQ or other CTMs with a somewhat-coarse
resolution are mostly representative of the background conditions.

275 2.3.2 Emissions

The emissions in the regional modelling have been calculated with the SMT, based on national emissions, whereas the local
modelling has used a combination of emission rates derived from measurements undertaken as part of this project (Leonard
and Wiltshire, 2025) and in the absence of measured emissions the Simple Calculation of Atmospheric Impact Limits
(SCAIL) agricultural emission inventory (Hill et al., 2014) has been used.

280 The local modelling has focused on five farms, chosen to represent the locations covered by the measurement campaign.
These farms have remained anonymous for the study. Details on the farms included in local modelling such as livestock
type, number of sources, those that include measured or SCAIL emission inventories and mitigation have been detailed in
Table 2.

These farms have very high reductions in emissions because of their nature and the impact of specific measures (Table 2).
285 However, overall, at a national level, the reductions are on average more modest, even if these farms are located were larger
reduction in national NH₃ emissions were calculated (Pommier et al., 2025). In the local modelling, the emission reduction
scenario reflects the maximum achievable reduction at the individual farm level depending on their characteristics, whereas
the regional modelling evaluated a range of progressively increasing reduction scenarios (Figure 1).

It is noteworthy the measurement campaign was conducted during a challenging period, beginning with the onset of the
290 COVID-19 pandemic at the beginning of the project, which significantly affected the recruitment of farms for fieldwork.
Engagement with pig farms was particularly difficult due to severe abattoir delays—partly linked to the UK's departure from

the European Union—which led to overcrowding on farms. These factors caused substantial delays in recruitment, further compounded by the withdrawal of two participant farms that had to be replaced, and operational issues at another farm that prevented the collection of usable data. Additionally, concerns about infection risks - both from COVID-19 and general biosecurity - limited access to measurement equipment. This led focusing the study on these five farms. While some farms had data collected for only part of an animal cycle—requiring assumptions about how representative the results were—the study still gathered high-quality, comprehensive data from these five distinct locations.

The local dispersion modelling for all studied farms uses the same methodology, except for the development of the emission rates which was unique to each farm depending on availability of activity and monitoring data from farms. However, farm activity and monitoring data were consistently reviewed across each farm with the final data used varying to reflect level of detail available.

Table 2: Farms included in local dispersion modelling.

Farm	Type of livestock	Sources	Measured or SCAIL sources	Mitigation measure and emission reduction
One	Pig	Two mechanically ventilated housing units with 4 fans each and 2 slurry lagoons	Measured at both housing units. SCAIL emission rate for slurry lagoon.	Housing - ventilation scrubber 80% NH ₃ reduction (SMT) 60% PM _{2.5} reduction (European Commission. Joint Research Centre., 2017) Slurry lagoon Floating cover 60% NH ₃ (SMT)
Two	Pig	One naturally ventilated housing unit, 11 Mechanically ventilated housing units with 25 fans and 2 manure piles	SCAIL at naturally ventilated, 1 mechanically ventilated and 2 manure piles. Measured at 10 mechanically ventilated.	Housing - ventilation scrubber 80% NH ₃ reduction (SMT) 60% PM _{2.5} reduction (European Commission. Joint Research Centre., 2017) Manure piles Manure cover 60% NH ₃ (SMT)
Three	Poultry, broilers	Eight mechanically ventilated housing units	Measured at 8 mechanically ventilated housing units	Housing - ventilation scrubber

				80% NH ₃ reduction (SMT) 35% PM _{2.5} reduction (European Commission. Joint Research Centre., 2017)
Four	Poultry, broilers	Three mechanically ventilated housing units	Measured at 3 mechanically ventilated housing units	Housing-ventilation scrubber 80% NH ₃ reduction (SMT) 35% PM _{2.5} reduction (European Commission. Joint Research Centre., 2017)
Five	Dairy	Five naturally ventilated housing units, 1 manure pile, 1 yard, 1 slurry lagoon and 1 grazing area.	One measured naturally ventilated housing unit. Remaining sources used SCAIL.	Grazing Extend grazing period from 4 to 9 months (SMT). No % reduction applied to pollutants, lower housing emissions achieved extending duration livestock are in pastures.

305 Detailed questionnaire, interview results and pollutant (NH₃ and PM_{2.5}) measurements collected from each farm in this study were reviewed to establish ADMS' source type representation such as point, volume and area and extent of time varying profile to apply. The primary emission data used in the modelling has used the same quality assurance protocol detailed within the measurement study (Leonard and Wiltshire, 2025), with monitoring data being processed into hourly averages to reflect hourly meteorological limitations of ADMS. The measurement, questionnaire and interview results were used to establish existing emission profiles, any existing mitigation measures to lower NH₃ or PM_{2.5} were reflected in the baseline.

310 However, none of the mitigation measures recommended in this study (Jenkins and Wiltshire, 2025) were in place at farms (Leonard and Wiltshire, 2025). An order of preference for time varying emission profile development has been implemented. The most preferred to least preferred was defined as below:

- Preferred emission profile - unique calculation for every hour in year

315 An emission rate (g/s) for every hour in a year is the most detailed emission input option in ADMS 6 (CERC, 2023), as emission measurements at farms were undertaken for periods over 2022 and 2023 did not represent a full year of measured emissions from sources. As such the most detailed option available for each farm would be to develop an emission rate (g/s) for every hour in the animal cycle, then extrapolate this over a year based on reports of all the animal cycles in a year. There was only sufficient monitoring and animal cycle data for each hour to have an emission rate at farm four (poultry). As there

are only housing emission sources at farm four every source on this farm was based on an individually calculated emission rate for every hour in a year.

- 2nd emission profile preference – annual average emission rate for each hour in a day

The next level of detail available to develop time varying emission profiles at each farm was to calculate annual average hourly emission rates (g/s) for the application of a diurnal profile in local modelling. This was applied to sources on farms one (pig), two (pig), three (poultry) and five (dairy) with measurement data. At pig farms one and two, this profile was applied to housing units with measurement data, but also to housing units based on the SCAIL emission inventory as the profile was considered relevant. At farm three (poultry) a diurnal profile based on annual average hourly emission rates (g/s) was applied to all housing units. On farm five, the milking and loafing area was the only building where emission measurements were taken and the only one for which a diurnal profile was applied. These loafing areas were non-passageway, non-feeding spaces where cows can lie down and move freely, allowing them to express natural behaviours such as grooming and heat detection. Grazing areas and cattle housing were assigned two distinct emission rates to reflect seasonal differences between periods when cattle are grazing and when they are housed.

- 3rd emission profile preference – constant emission rate for all hours in a year

The lowest level of detail occurs where no measurement or activity data was available to understand how annual emissions should vary throughout the day and or year. In this situation, annual emissions were divided by the number seconds in a year, resulting in a constant (g/s) for all hours in a year. No diurnal profile was applied to slurry and manure lagoons at farms one and two. At farm five (dairy) no diurnal profile was applied to the yard, slurry lagoon or manure piles.

Information on emission sources including dimensions, fan height, diameter, exit velocity were derived from farmer data requests and interviews. Housing temperature data was derived from either farm owned temperature sensors if available, or from project monitoring equipment. Hourly emission rates of NH₃ and PM_{2.5} were calculated for each hour of the animal (flock) cycle or for the full measurement period, using equations 1 (NH₃) and 2 (PM_{2.5}) (Phillips et al., 1998). All calculations were performed on an hourly average basis. The NH₃ emission rate was calculated as:

$$ER_{NH_3} = C_{NH_3} \times Q \times R_{molecular} \times c_{mass} \quad (1)$$

Where ER_{NH₃} corresponds to the NH₃ emission rate (g/s), C_{NH₃} is the hourly average NH₃ concentration (ppb), Q is the ventilation volumetric flow rate (m³/s) and R_{molecular} is the conversion factor from parts per billion to mass concentration based on the molecular weight and molar volume of NH₃, and c_{mass} is the conversion constant (10⁶).

The PM_{2.5} emission rate was calculated as:

$$ER_{PM_{2.5}} = C_{PM_{2.5}} \times Q \times c_{mass} \quad (2)$$

With ER_{PM_{2.5}} being the PM_{2.5} emission rate (g/s), C_{PM_{2.5}} the hourly average PM_{2.5} concentration (µg/m³), Q the ventilation volumetric flow rate (m³/s) and c_{mass} the unit conversion factor from micrograms to grams (10⁶).

For instances where emission rate values could not be calculated, the SCAIL emission inventory was used. SCAIL emission rates are provided as kg/m² or kg per animal place per year, as such the area of sources and number of livestock were used in this equation to derive NH₃ and PM₁₀ kg/year. SCAIL emission rates are in PM₁₀ and this was converted into PM_{2.5} by

looking at the ratio between PM_{2.5} and PM₁₀ at Defra's Automatic Urban and Rural Network (AURN) rural background monitoring stations available at the UK AIR platform (DEFRA, 2024a) to derive a factor of 0.58. As the farms are located at different locations across the UK, an average value derived from multiple AURN stations was used for simplification, and, because the analysis considers annual concentrations, a fixed, non-time-dependent conversion factor was applied. The measured emission rates were adjusted using Equation 3 for comparison with SCAIL annual emission (kg/year). A livestock type dependent emission rate was applied to each fan of the corresponding farm buildings, to get the total emission from the farm buildings, and therefore can be scaled up using the building volume.

$$EF = ER \times V_{\text{building}} \times c_{\text{mass}} \times c_{\text{time}} \quad (3)$$

With EF the emission factor (kg/yr), ER the hourly average emission rate ($\mu\text{g}/(\text{m}^3\cdot\text{h})$), c_{mass} the conversion constant (10^9) and c_{time} the time conversion constant (24×365).

360 - Mitigation scenario emission calculations

In the mitigation scenario, each emission source and associated percentage reduction from mitigation detailed in Table 2 were applied to emission rates (g/s). For example, acid scrubbers are applicable treatment of ventilated air at farm one animal housing and the emission rate (g/s) is multiplied by 0.2 and 0.4 to reflect the proposed 80% and 60% reduction in NH₃ and PM_{2.5}, respectively.

365 3 Change in PM_{2.5} concentrations

3.1 Regional Scale

3.1.1 Evaluation of the historical simulation

The modelled concentrations have been evaluated in using the historical simulation in 2019. Only PM_{2.5} measurement data for rural background sites with at least 75% data capture in the year are used to avoid bias. The observations were downloaded from the UK AIR platform. This represents a total of 48 stations. The CMAQ annual map and the comparison with the observations at the measurement sites are shown in Figure 4. The statistics used in this evaluation are described in Appendix C.

While the comparison shows a fair agreement in the correlation ($r \sim 0.6$), a clear underestimation in the modelled concentrations is calculated (mean bias (MB) $\sim -5 \mu\text{g}/\text{m}^3$; normalized mean bias (NMB) $\sim -51\%$, mean relative error (MRE) ~ -0.5). This approximate 50% underestimation in the modelled PM_{2.5} concentrations mirrors the uniform 50% increase in NH₃ emissions (and 60% decrease in SO₂ emissions) applied by Kelly et al. (2023) and Marais et al. (2023) in using a similar emissions inventory (NAEI for the year 2019) in their simulations to obtain a reasonable agreement in their calculated PM_{2.5} concentrations with their global CTM ($r=0.66$, NMB=-11%). However, it is worth noting a sensitivity simulation, by increasing our UK NH₃ emissions by 50% was also tested. Despite this large change in the 2019 NH₃ emission, no real improvement in the comparison with the observations was found (Fig. S2). This confirms the finding in Pommier et al.

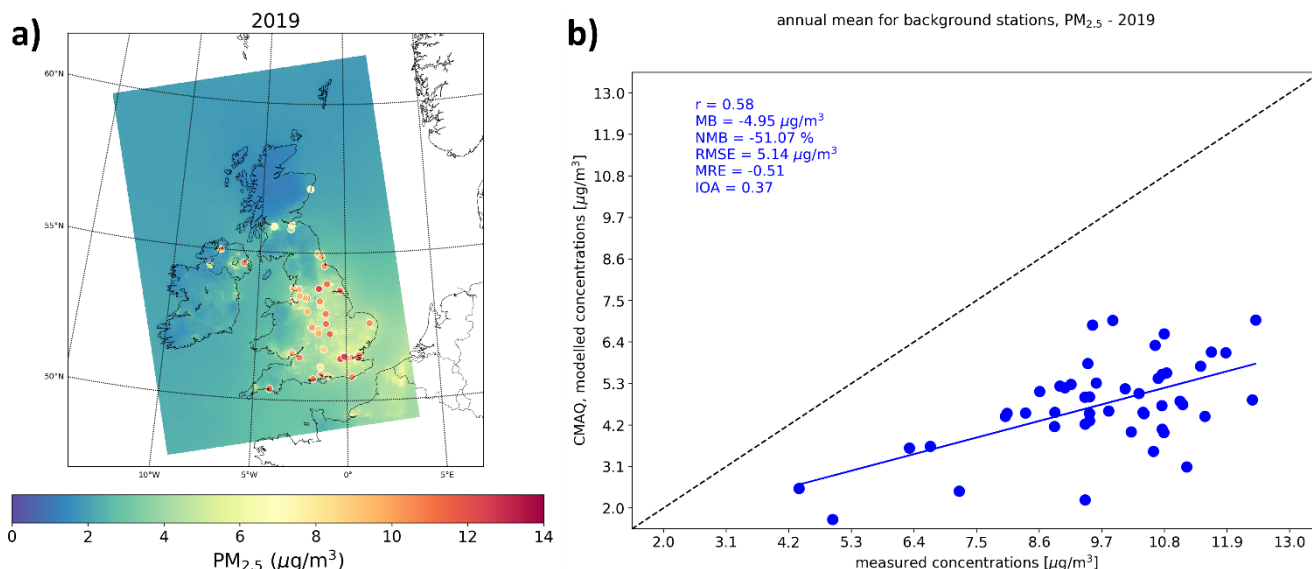
(2025) showing NH_3 is not 'limiting', thus NH_3 emissions changes will have a negligible on mitigating secondary inorganic aerosols (SIA) formation at regional scale. Kelly et al. (2023) also explained with NH_3 being in excess, the emissions scaling applied to NH_3 to resolve differences between top-down and bottom-up emissions estimates has only a limited effect on NH_4 and $\text{PM}_{2.5}$.

385 This might also suggest unrepresented atmospheric processes in the model between NH_3 and the $\text{PM}_{2.5}$ formation since this 50% increase in NH_3 emission leads to an overestimation of the modelled NH_3 concentrations (Pommier et al., 2025). For example, this could be a result of combined missing processes since the bi-directional NH_3 flux representation has not been implemented in this CMAQ simulation and this bidirectional treatment of NH_3 fluxes should improve the prediction of NH_3 (e.g. Pleim et al., 2019). It has been noted that assimilating satellite NH_3 observations help to improve the models' performance to calculate the surface SIA concentrations (e.g. Momeni et al., 2024). Overall, research consistently highlights the difficulties in accurately modelling SIA concentrations, which are frequently underestimated in the UK (e.g. AQEG, 2012, Kelly et al., 2023) while Norman et al. (2025) found very large NMB in Europe (up to 71% for SO_4 and 376% in NO_3). In addition, dry $\text{PM}_{2.5}$ concentrations has been used in the comparison and, without being the major contributor of these differences with the observations, the effect of aerosol water on the mass closure of $\text{PM}_{2.5}$ can influence the value in the total $\text{PM}_{2.5}$ concentrations (AQEG, 2012; Kelly et al., 2023; Tsyro, 2005).

390 This bias in $\text{PM}_{2.5}$ concentrations is however in agreement with the literature since Appel et al. (2012) found a NMB between -24.2% and -55% in Europe depending on seasons with the CMAQ model. A NMB of -44.39% in $\text{PM}_{2.5}$ concentrations in comparison with rural stations, and of -53.39% with urban stations were found using WRF-CMAQ in the UK (Im et al., 2015). Despite improvement in CMAQ introduced from version 5.1 shown in Appel et al. (2017), persistent underestimation in $\text{PM}_{2.5}$ (in the US) remained, with lower correlation (from ~ 0.32 to 0.47) and higher RMSE (from 5.8 to 9 $\mu\text{g}/\text{m}^3$) than our results. These biases could remain important in few stations and with a low correlation coefficient in a more recent version (5.3.1 – Appel et al. 2021). Tao et al. (2020) found a NMB near -30% in China despite using a finer scale modelling (1 km^2) compared to our spatial resolution (10 $\text{km} \times 10 \text{ km}$). A modelling study in Ireland with a similar finer scale modelling (1 km^2) with the EMEP model has also shown a bias of $\sim -30\%$, while the coupling with the urban version of ADMS had allowed to reduce the bias to $\sim -20\%$ (Stocker et al., 2023). Zhang et al. (2020) applied a postprocessing correction based a Kalman filter to improve the $\text{PM}_{2.5}$ concentrations in the US but still found important NMB with different models. They found, with monthly averages, NMB values of -24%, -48%, and -20% for GEOS-Chem, WRF-Chem, and CMAQ, respectively.

405 It is worth noting the main $\text{PM}_{2.5}$ components calculated by CMAQ for these stations are NO_3 and SO_4 (Tab. S1) and their composition spatially varies as shown on the maps (Fig. S3).

410 In the baseline 2019 simulation, the calculated Root-Mean-Square Error (RMSE $\sim 5 \mu\text{g}/\text{m}^3$) and IOA (~ 0.4) are not fully satisfactory. In addition, the analysis on NO_2 concentrations highlights a good estimate in NO_x emissions since a reasonable underestimation is found ($\sim -25.3\%$, $-4.3 \mu\text{g}/\text{m}^3$), with a good correlation (0.71) and IOA (0.78) (Figure S4).



415 **Figure 4: a) Spatial distribution of annual mean $PM_{2.5}$ concentrations in $\mu g/m^3$ calculated by CMAQ at 10 km resolution in 2019. The measured concentrations at the monitoring stations are shown with the coloured circles. b) Comparison between these annual measured concentrations with the modelled values in 2019. Only the background stations with a data capture higher than 75% are used. Insert values are the Pearson correlation coefficient (R), the mean bias (MB), the normalized mean bias (NMB), the mean relative error (MRE), the root-mean-square error (RMSE), and the index of agreement (IOA). The blue line represents the linear fit and dashed black line is the 1:1 slope.**

420 3.1.2 Future changes

Reductions in NH_3 emissions are effective at reducing NH_3 concentrations and its deposition at a regional scale ($10\text{ km} \times 10\text{ km}$) as shown in Pommier et al. (2025) (e.g. up to 22% reduction in the high2030 scenario) but considerably less effective at reducing ammonium (NH_4) since the UK is characterized by an NH_3 -rich chemical domain. This confirms the finding that the decrease in NH_3 emissions only has limited effects on mitigating SIA formation found by Ge et al. (2022) and that rural areas are less sensitive to changes in NH_3 (Pan et al., 2024). Consequently, the $PM_{2.5}$ concentrations are only slightly impacted by the mitigation on agricultural activities implemented in our scenarios, as shown in Figure 5. Indeed, the reduction in the annual mean $PM_{2.5}$ concentrations is marginal for the three scenarios, since the largest calculated reduction is around 1.2%, 1.3% and 1.5% for the low2030, medium2030 and high2030 scenario, respectively; and the mean reduction is nearly null.

430 At the opposite, Ge et al. (2023) showed an important impact of the NH_3 emission reduction in $PM_{2.5}$ concentrations in the UK. The results in Ge et al. (2023) are not comparable with our study, since their analysis was based on a large decrease in the emissions, 4 times larger than our more ambitious mitigation (high2030) scenario. This difference in the assumption of the emissions' reduction, has a crucial impact on the atmospheric chemical regime and so changing the influence of NH_3 in the SIA formation.

435 Moreover, the scenarios have focused on mitigating NH_3 emissions, while targeting other secondary $\text{PM}_{2.5}$ precursors (NO_x
 and SO_x) can be needed to effectively curb the $\text{PM}_{2.5}$ exposure (Marais et al., 2023; Pastorino et al., 2024). It is also worth
 noting that the impact of the mitigation measures, even limited, varies by months, showing a larger relative change in May-
 July (only up to -3.4%) in the example of the high2030 scenario in Figure S5. These months do not correspond to the
 maximum in the emitted NH_3 in the modelling as shown in Figure S1. This suggests also an impact of the atmospheric
 440 chemistry in the change in $\text{PM}_{2.5}$ concentrations.

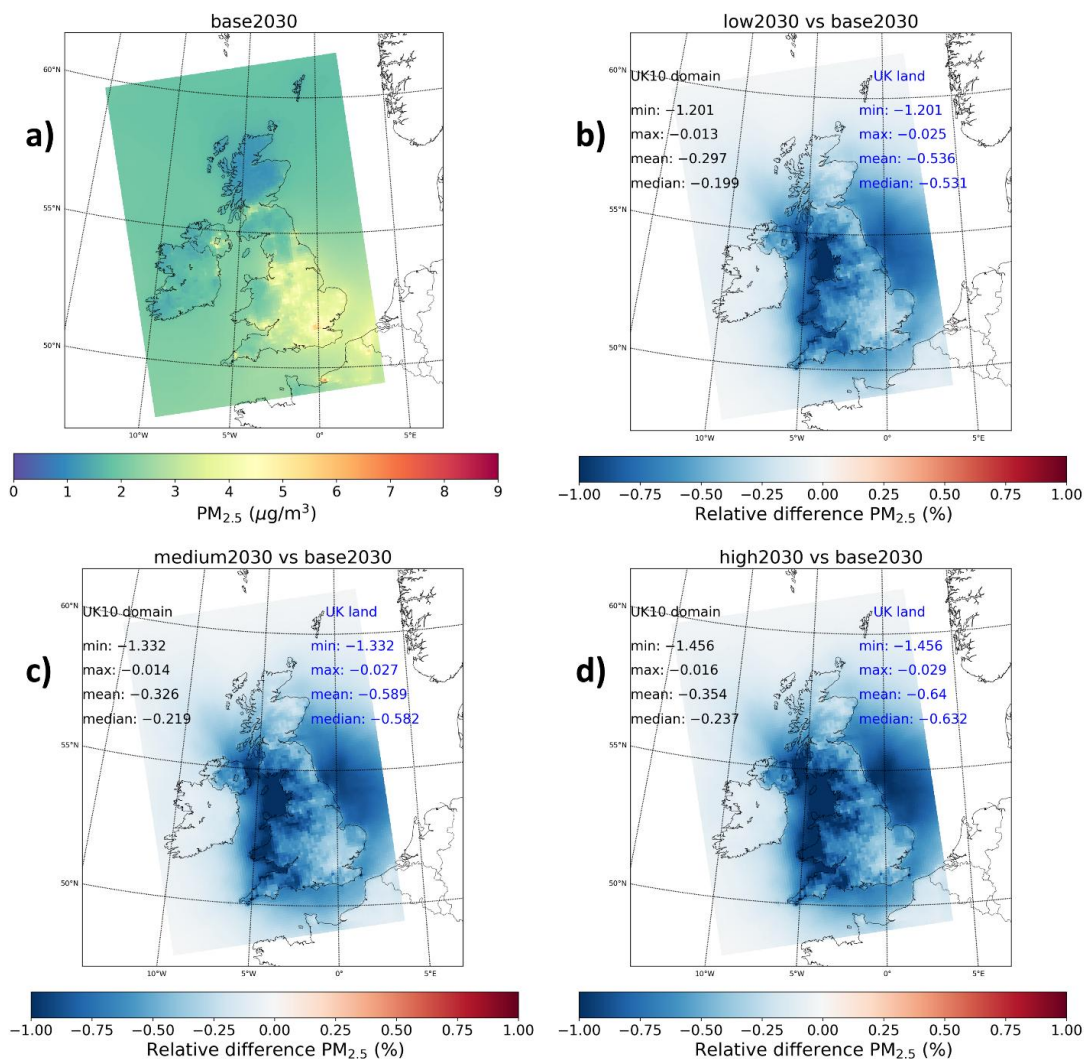


Figure 5: a) Spatial distribution of annual mean $\text{PM}_{2.5}$ concentrations in $\mu\text{g}/\text{m}^3$ calculated by CMAQ at 10 km resolution for the base2030 scenario. Relative difference of the same distribution with the low2030 (b), medium2030 (c) and high2030 (d) scenarios. The minimum, maximum, mean, and median relative difference values in the whole UK10 domain (in black) and for the UK land grid cells (blue) are provided. The relative difference is calculated as follow: $((\text{scenario-base})/\text{base}) \times 100\%$.

445 3.2 Local scale: dispersion near the farms

Regional modelling has been used to estimate the contribution of agricultural NH₃ to the formation of secondary PM_{2.5} at a regional scale, whereas local scale modelling has been used to investigate dispersion of NH₃ and PM_{2.5} closer to farms (within 10km). This modelling approach differs from regional modelling, which incorporate atmospheric chemistry to estimate PM_{2.5} from both primary emissions and secondary formation. While the local modelling considered a non-steady state (reactive chemistry) option, secondary formation contributed less than 1% of total PM_{2.5} in the 10 km study area and was ultimately excluded from the analysis. However, both modelling approaches are linked since the regional modelled concentrations have been used to define the background concentrations.

As detailed in Section 2.1, low to high mitigation refers to mitigation uptake by number of farms, but local modelling focuses on five specific farms and variable uptake values are not relevant. Instead, consistent NH₃ impact values (percentage reduction) were adopted between regional and local modelling, with PM_{2.5} impact values (percentage reductions) derived separately through best practice agricultural guidance (European Commission. Joint Research Centre., 2017). Mitigation measures were assessed in the local modelling scenario to gauge the maximum potential benefit on pollutant concentrations in local vicinity of farms.

Figure 6 represents study farm's contributions of NH₃ and primary PM_{2.5} under existing farm operations (base2030), and the differences between the mitigation scenario and this reference. These farms were in different parts of the UK as shown in Figure 2. In the local modelling, the mitigation scenario incorporates all measures from the low2030, medium2030 and high2030 scenarios. While the regional modelling assumed progressively higher national uptake from low to high scenarios, the local modelling applied only those mitigation measures relevant to each specific farm. As reminder, the mitigation measures for each farm are described in Table 2.

Across the existing and mitigation scenarios the greatest distance for concentrations of NH₃ and PM_{2.5} to reach 10% of the maximum is 700 metres (Figs. 6a & 6b). The distance at which concentrations reach 10% of the maximum varies depending on many local scale dispersion parameters at the farm and meteorology, such as air flow release rate (m/s), temperature (°C), wind speed (m/s) and direction (°) and impact of building downwash.

50% of air pollutant concentrations from farm two are dispersed at a closer distance (100m) than other farms due to an air flow rate of 5.1 m/s, whereas farms one, four and five have a flow rate ranging between 7 and 11.5 m/s which contributes to the plume grounding at a closer distance to farm two.

It is worth noting that the mitigation scenario solely impacts the distance of spread of the pollutants for the farm three, while the distances where the 50% of NH₃ and primary PM_{2.5} concentrations are dispersed; and the distances where 10% of their maximum concentrations are found are identical for the other farms (Fig. 6b). However, as illustrated in Figure S6, farm three did not contribute to PM_{2.5}, and the NH₃ concentration remained highly localized around the farm.

The highest NH₃ concentrations occur in the vicinity of the emission sources as shown in Figure S6 for the farm three. This is driven by the low release heights (< 6m) typical of agricultural emissions and, in several cases, by the enhancement of

near-field concentrations due to building-induced flow effects. Concentrations decline rapidly with distance, and beyond very short distances the influence of farm-level emissions diminishes sharply.

480

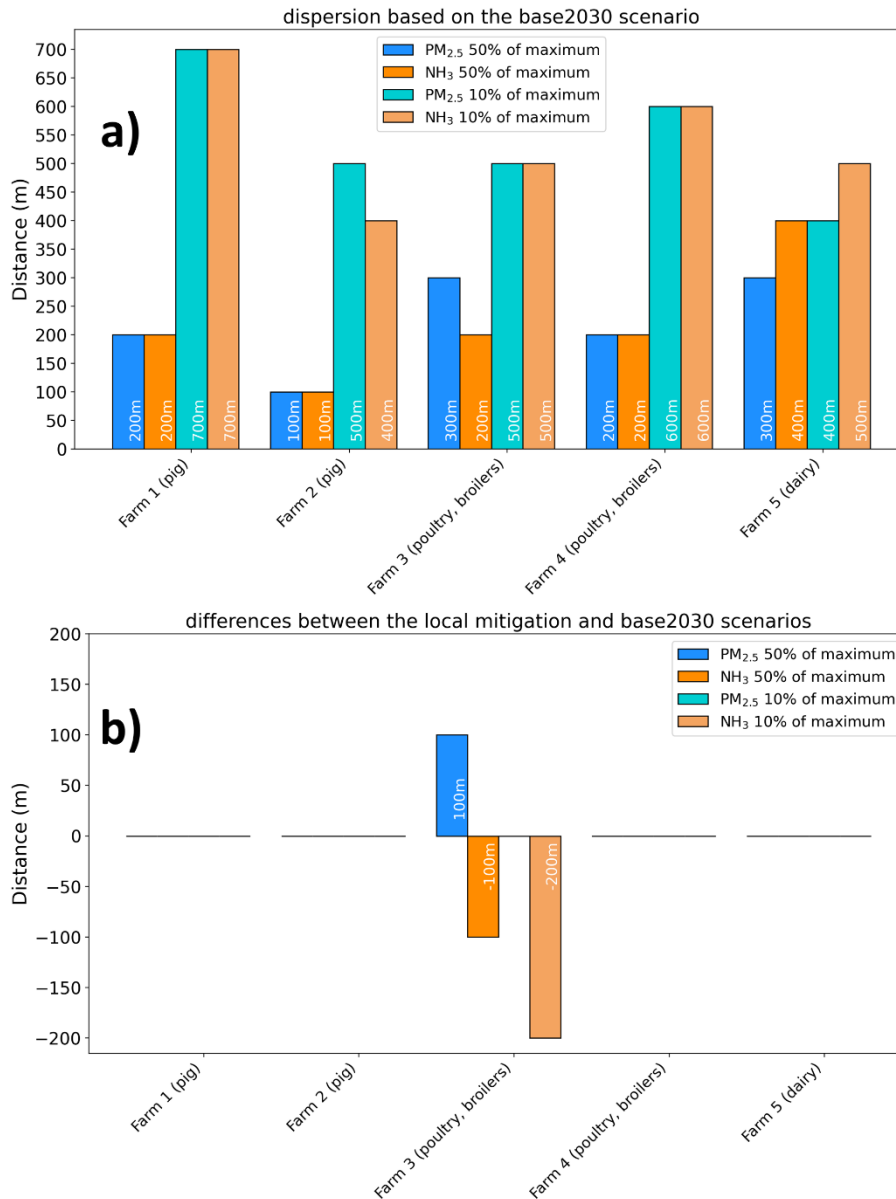


Figure 6: a) Farm’s contributions of NH₃ and primary PM_{2.5} given as a distance in meters where the concentration is 50% or 10% of maximum for the base2030 scenario (a) and the difference between the local mitigation scenario and the base2030 scenario (b).

The difference in concentrations between the mitigation and base2030 scenarios are presented in Table 3 in terms of maximum concentration in a 10km² area, and maximum concentration for sensitive receptors. Table 3 shows that within 1km

485 of farms included in this study there can be reductions between 25 and 80% of total NH₃ concentrations and 4 and 60%
reductions of PM_{2.5}.

The biggest reductions in pollutant concentrations occur at farm one and two, which are pig farms and the abatement
measure with the biggest benefit is an acid scrubber used to reduce emissions from housing and as shown in Table 2 is
estimated to achieve an 80% reduction in NH₃ and 60% reduction in PM_{2.5} emissions.

490 The only other relevant mitigation measure included at farms one and two would be to provide a cover over open manure
and or slurry lagoons, however this has a smaller 60% reduction of only NH₃ emissions and will have a smaller impact on
NH₃ concentrations than the acid scrubber. While acid scrubbers and manure/slurry covers are included in modelling of
estimated concentration the biggest will come from acid scrubbers.

495 **Table 3: Percent difference in concentrations between base2030 and mitigation scenarios.**

Farm	Reduction in max concentration in 10km ² study area (µg/m ³)		Reduction in max concentration for sensitive receptors (µg/m ³)	
	PM _{2.5}	NH ₃	PM _{2.5}	NH ₃
Farm one (pig)	-60%	-79%	-60%	-80%
Farm two (pig)	-60%	-63%	-60%	-64%
Farm three (poultry, broilers)	-13%	-25%	-31%	-71%
Farm four (poultry, broilers)	-35%	-80%	-34%	-80%
Farm five (dairy)	-4%	-43%	-7%	-33%

4 Discussion

The design of the emission scenarios was based on the views of farmers, advisers, academics, and representatives from
relevant sectors, capturing diverse perspectives and making the uptake scenarios grounded in real-world practices and
500 challenges. This approach also considered the actual barriers and incentives that farmers experience, leading to realistic
projections of mitigation measure uptake. Using multiple engagement tools (online surveys, focus groups, and one-on-one
interviews) also enabled the gathering of in-depth, well-rounded data, providing a nuanced understanding of the factors
influencing uptake. However, it is worth noting that the future uptake projections did not account for potential changes in
legislation, which could significantly impact the adoption of mitigation measures. This limits the ability to predict uptake
505 under different regulatory environments. Moreover, the method has not differentiated uptake scenarios between different
parts of the UK due to a lack of data, potentially overlooking regional variations in farming practices, environmental
conditions, or economic incentives. The study has also relied on subjective feedback, i.e. participants' perception and
understanding, which can vary widely between individuals or groups. This can introduce bias in determining which measures
are positively or negatively received, potentially affecting the estimated uptake rates.

510 Although CMAQ is state of the art and widely used in scientific research and policy development, the model also has uncertainties. The analysis presented in this study rely on the accuracy of the simulation which is subject to any uncertainties in the model's specific parameterization of atmospheric processes, as well as uncertainties in the emission inventory and meteorology input. It has been shown that CMAQ does not perfectly model the interactions between NH₃ emissions and the PM_{2.5} formation which can be explained by the local processes causing the majority of NH₃ to be dispersed near the studied
515 farms as highlighted by ADMS results showing a 90% decrease in concentrations within 700 metres of farms. This study confirms the findings from Pan et al. (2024) arguing for more collocated aerosol and precursor observations for better characterization of SIA formation.

The limited impact of the mitigation measures at a regional scale, which mainly target the NH₃ emissions, on PM_{2.5} concentrations can be due to an NH₃-rich atmosphere in the UK and highlights that other precursor of these PM_{2.5} and the
520 primary PM_{2.5} emissions need to be tackled. This also highlights that exposure on secondary PM_{2.5} near the farms needs also to be investigated while most air quality studies focus on total PM_{2.5} concentrations. ADMS has showed that the majority (90%) of secondary PM_{2.5} precursor NH₃ emissions and primary PM_{2.5} is dispersed within 700 metres of farms. This supports conclusions from CMAQ of little impact on a regional scale as most relevant exposure is beyond 700 metres of farms. Further work is recommended to assess how mitigation measures can affect primary and secondary PM_{2.5} at relevant
525 human exposure locations within 1–10 km of farms, given that national exposure weighting emphasises locations where most primary pollution has already dispersed.

Limitations of the local modelling include uncertainties related to the emission measurement data and the associated farm activity data. The project measurement study (Leonard and Wiltshire, 2025) should be referenced for the full suite of limitations associated with project measurement data, however the main aspects that affect emission rates developed for
530 local modelling includes representativeness of measurement location for entire housing unit, that measurements did not span an entire animal cycle at farms one, two and five. Regarding representativeness of measurements, at farms three and five housing air was sampled with a multiplexer, a device that samples air from multiple locations, whereas measurements at other farms only sampled air from one location. As such a limitation of emission rates used in modelling is the assumption emission rates are representative for the entire animal housing unit. Measurement data did not span entire animal lifecycles
535 at farms one, two and five and as such the project measurement data and housing emissions rates are limited in how representative they are of each animal lifecycle. Further to this, farms one, two and five did not record animals in each housing unit for each day of the measurement period and over the animal lifecycle, instead assumptions were made on the total number of animals apportioned to each housing unit. Consequently, there is uncertainty regarding animal numbers in each housing unit and extrapolations made for the annual animal places at farms one, two and five. Whilst farms two and
540 three had measurements for the entire animal cycle, like farms one and two measured fan flow rates were not available during the measurement period and ventilation manufacturer's records were used to develop air flow rates. Whilst there are limitations in data used, replacing emission and flow rate assumptions is unlikely to alter that the majority of pollution is

grounded in the nearfield (< several kilometres) of farms (e.g., AFBI, 2025), since agricultural sources are emitted from lower heights (< 6m) and have low air flow rates relative to other sources such as engine exhausts.

545 5 Conclusions and Perspectives

This study highlights the complex interactions between NH₃ emissions from farming activities and PM_{2.5} formation in the UK, with a focus on dairy, pig, and poultry sectors. Using both CMAQ model for regional-scale analysis and ADMS for local-scale dispersion, this work has evaluated the impact of mitigation measures under various uptake scenarios on reducing emissions, especially on NH₃. Although emission reductions, particularly in NH₃, were predicted under high uptake scenario, 550 these changes did not translate into significant reductions in regional-scale PM_{2.5} concentrations, with a maximum decrease of only 1.5%. This outcome is attributed to the NH₃-rich atmosphere, which diminishes the effect of NH₃ reductions on PM_{2.5} mitigation.

The findings also reveal discrepancies between CMAQ model concentrations and ground-based measurements. Although this bias aligns with findings in the literature, particularly when no emission corrections or post-processing adjustments to 555 modelled concentrations are applied, this suggests that key atmospheric processes influencing PM_{2.5} formation may not be fully represented in the model, leading to an underestimation of PM_{2.5} concentrations by approximately 50%. ADMS results further show that NH₃ is rapidly dispersed near the farms, indicating a limited role of these emissions in the formation of PM_{2.5} locally. The study has emphasized the need for integrated modelling approaches and better characterization of SIA formation, as well as the importance of addressing the primary PM_{2.5} and other PM_{2.5} precursors beyond NH₃ to achieve 560 effective air quality improvements.

Overall, this suggested limited impact on potential NH₃-focused mitigation strategies on PM_{2.5} concentrations underscores the necessity of exploring additional emission control measures targeting other precursors and primary PM_{2.5} emissions from the farming sector. Indeed, further work is recommended to review the national benefit of mitigation on primary PM_{2.5} emissions, however benefits of mitigation are likely to be localised on PM_{2.5} as demonstrated by ADMS modelling. Future 565 research should also focus on primary and secondary PM_{2.5} exposure separately near farms, as current air quality studies predominantly assess total PM_{2.5} concentrations, and further work is required to understand the impact of secondary PM_{2.5} on health. This work advocates for a more holistic approach to modelling and mitigation to better inform policies aimed at improving air quality in agricultural regions.

The study has looked at regional exposure to PM_{2.5} from agricultural sources in CMAQ, whereas ADMS has shown that the 570 majority (90%) of emission are dispersed within 700m of farms. As the UK population is concentrated in urban areas a substantial distance from farms, further work could explore the health benefit of mitigation on communities in the local vicinity of farms (from 1 to 10km). To evaluate the potential impact of these emissions on rural populations, one approach would be to map population distribution around agricultural holdings. This would help estimate the number of individuals likely to be exposed to such emissions. Although the study primarily addresses annual estimates, further investigations at

575 finer temporal resolutions (e.g., daily, monthly) could yield deeper insights into exposure impacts. To strengthen understanding of near-field NH₃ impacts, future work would benefit from expanded measurement campaigns across a wider range of farm types—not only increasing the number of monitoring sites, but also ensuring balanced representation across key sectors such as poultry, pig, and dairy systems.

Appendix -A

580 Table A1 summarises the measures and the uptake rates for each of the three scenarios for the regional modelling. These values are additional to uptake of measures already included in emissions from NAEI.

The uptake scenarios were developed through stakeholder engagement with farmers and stakeholders (i.e. farm advisers, academics and farmer representatives). Each scenario includes all 20 mitigation measures, however with varying percentages of uptake.

585 The uptake rates were unique to each mitigation measure in each sector and were reflective of feedback received through engagement activities. The engagement activities included an online survey, focus groups and one-to-one interviews with participants from the dairy, pig and poultry sectors and those in other sectors which utilise manure or slurry. A total of 161 people took part in the activities. Full results and methodology are detailed in Jenkins and Wiltshire (2025).

Discussions in these activities were centred around understanding the current level of uptake and the benefits and barriers associated with the mitigation measures to determine a potential future uptake. If a mitigation measure was received positively, it was estimated to have a higher uptake compared to measures that were received negatively by participants. This was determined in the final level of uptake for each scenario. The future uptake did not take account of any potential changes to legislation that may have an impact as this information is not known, additionally there were no different uptakes for each part of the UK due to a lack of data.

595 **Table A1. A summary of the measures and uptake rates used in each of the three scenarios modelled for this study.**

Sector	Measure	Uptake (%)		
		Low	Medium	High
Poultry	Planting tree shelter belts near livestock housing	75	80	85
Poultry	Installing air scrubbers to filter pollutants	0	1.5	3
Poultry	Covering a manure heap on permeable ground	80	85	90
Poultry	Amending diet to better match the nitrogen content to livestock need	97	98	99
Poultry	In-house poultry manure drying	10	12.5	15
Poultry	Increased litter removal (e.g. by belt removal)	50	52.5	55
Pig	Planting tree shelter belts near livestock housing	42	47.5	53

Pig	Trailing shoe	19	22.5	26
Pig	Trailing hose	10	13	16
Pig	Using slurry bags	2	3	4
Pig	Acidification of slurry in underfloor storage tanks in housing units	1	2	3
Pig	Installing air scrubbers to filter pollutants	0	1.5	3
Pig	Shallow injection - open slot	19	21.5	24
Pig	Permeable floating cover (e.g. chopped straw) on slurry store	8	13	13
Pig	Amending diet to better match the nitrogen content to livestock need	97	98	99
Pig	Increasing bedding in housing (e.g. straw)	31	36	37
Pig	Vacuum/flushing system for slurry removal from pits under slatted flooring	12	14	16
Pig	Impermeable floating sheet on slurry store	5	10	18
Pig	Using a fixed solid cover on slurry stores	15	17.5	20
Pig	Improving pen design to keep solid parts of the floor as clean as possible	20	25	27
Pig	Covering a manure heap on permeable ground	5	7.5	10
Pig	Using automatic or robotic scrapers	30	35	36
Dairy	Covering a manure heap on permeable ground	5	7.5	10
Dairy	Planting tree shelter belts near livestock housing	42	47.5	53
Dairy	Using trailing shoe	18	24	30
Dairy	Using trailing hose	35	40	45
Dairy	Acidification of slurry in underfloor storage tanks in housing units	0	1.5	3
Dairy	Shallow Injection	13	15.5	18
Dairy	Using robotic scrapers (e.g. Lely Sphere)	7.5	10	12.5
Dairy	Permeable floating cover (e.g. chopped straw) on slurry store	8	13	18
Dairy	Amending diet to better match the nitrogen content to livestock need	95	97	99
Dairy	Increasing washing in yards/parlours from once to twice a day	10	15	20
Dairy	Increasing scraping in yards/parlours from once to twice a day	40	41	43
Dairy	Increasing bedding in housing units (e.g. straw)	17	18	20
Dairy	Impermeable floating sheet on slurry store	5	10	15
Dairy	Using a fixed solid cover on slurry stores	41	43.5	46
Dairy	Extending the grazing season	74	79.5	85
Dairy	Using automatic scrapers	25	27.5	30

Appendix - B

600 Table B1 presents the practices that reduce ammonia emissions that were modelled in this study, along with a brief description on how it reduces ammonia.

Table B1. Practices that reduce ammonia emissions, with a short description of how they reduce emissions.

	Practices that reduce ammonia emissions	How does it reduce ammonia emissions?
Housing	Extending the grazing season	Grazing animals urinate directly on the grass. The urine then infiltrates, reducing the exposure to air.
	Increasing bedding material (e.g. straw, sand)	Increasing the amount of bedding helps to absorb more urine, reducing exposure to air.
	Increasing washing in yards/parlours from once to twice a day	Scraping urine, slurry and manure into a covered store reduces the exposure to the air and the reaction to produce ammonia.
	Increasing cleaning by using automatic or robotic scrapers	As above, more frequent cleaning reducing the exposure to air.
	Acidification of slurry in underfloor storage tanks in housing units	Lowering the pH, by adding an acid such as sulphuric acid, decreases emission.
	Amending diet to better match the nitrogen content to livestock need	Matching feed to the required amount for growth reduces the excretion of excess N, some of which will be emitted as ammonia.
	Planting tree shelter belts near livestock housing	Emissions are dispersed and/or taken up by the tree foliage.
	Installing air scrubbers to filter pollutants	Fitted to housing units to remove ammonia.
	Increased litter removal (e.g. by belt removal)	For layers, collecting and removing manure to a covered store, reducing exposure to air.
	Vacuum/flushing system for slurry removal from pits under slatted flooring	Removal of slurry from slatted floor storage pits to a covered store using a vacuum removal system, at least twice per week.
	Improving pen design to keep solid parts of the floor as clean as possible	For example, designing with part-slatted flooring, with a domed solid floor area and with sloping sided below slatted-floor slurry storage. Doing so reduces the floor area and therefore the residual excretion which will react to cause ammonia emissions.
	In-house poultry manure drying	Installing ventilation/drying systems to reduce the moisture content of

		laying hen manure, slowing the release of ammonia.
Storage/spreading	Using slurry bags	Creates a physical barrier between the manure/slurry and the air.
	Covering stores with a fixed solid cover	
	Covering stores with an impermeable floating sheet	
	Permeable floating cover (chopped straw)	
	Covering a manure heap on permeable ground	
	Trailing hose	Applies slurry in narrow bands at grass level, reducing the surface area, helping quicker infiltration and reducing exposure to air.
	Trailing shoe	Applies slurry in narrow bands at soil level, reducing the surface area, helping quicker infiltration, reducing the exposure to air.
	Shallow injection	Injecting slurry into the ground, helping quicker infiltration and reducing exposure to air.

605

610

615

Appendix - C

Statistics used for the evaluation of the air quality simulation with CMAQ. In the following notations, M and O refer, respectively, to the model and the observations data. N is the number of the observation data set.

620

Pearson relation coefficient (r): The ideal score of these parameters is 1. It is an unitless variable.

Mean bias (MB): The ideal score of this parameter is 0. The unit of this variable is the as the pollutant concentration ($\mu\text{g}/\text{m}^3$). The MB provides information about the absolute bias of the model, with negative values indicating underestimation and positive values indicating overestimation by the model.

625

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

Normalised mean bias (NMB): The ideal score of this parameter is 0 and the unit of the variable is in percent. The NMB represents the model bias relative to the reference.

$$\text{NMB} = \frac{\sum_{i=1}^N (M_i - O_i)}{\sum_{i=1}^N O_i} \times 100\%$$

Root-mean-square error (RMSE): The ideal score of this parameter is 0. The unit of this variable is the as the pollutant concentration ($\mu\text{g}/\text{m}^3$). The RMSE considers error compensation due to opposite sign differences and encapsulates the average error produced by the model.

630

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (M_i - O_i)^2}{N}}$$

Mean Relative Error (MRE): The ideal score of this parameter is 0. The MRE is the mean ratio of difference between the model values and the observations, on the observations. This variable is unitless.

635

$$\text{MRE} = \frac{1}{N} \sum_{i=1}^N \frac{M_i - O_i}{O_i}$$

Index of Agreement (IOA): The agreement value of 1 indicates a perfect match, and 0 indicates no agreement at all. It is an unitless variable.

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

640

Code availability:

645 The CMAQ model is freely provided by the US EPA: <https://zenodo.org/record/7218076>. The WRF model is freely available thanks to NCAR on <https://github.com/wrf-model/WRF/tree/release-v4.5>. The ADMS model is distributed under license by CERC: <https://www.cerc.co.uk/environmental-software/ADMS-model.html>.

Data availability:

650 Primary data from the regional, local modelling and emission measurements has been used in-combination with secondary data in this assessment. All data requests should be submitted to the corresponding author for consideration. Access to anonymised data may be granted following review.

Author contribution:

655 **MP:** Conceptualisation (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Project Administration (equal), Resources (lead) validation (equal), visualisation (lead), Writing – Original draft (lead), Supervision (lead). **RB:** Conceptualisation (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Project Administration (supporting), validation (equal), visualisation (supporting), Writing – Original draft (supporting). **JB:** Data curation (supporting), Investigation (supporting), Methodology (supporting). **BJ:** Methodology (supporting), Writing – Original draft (supporting). **JR:** Data curation (supporting), Formal analysis (supporting). **LR:** 660 Methodology (supporting), Writing – Original draft (supporting). **OB:** Data curation (supporting), Formal analysis (supporting), Investigation (supporting), Methodology (supporting), Writing – Original draft (supporting). **OM:** Data curation (supporting), Formal analysis (supporting), Investigation (supporting), Methodology (supporting). **AS:** Data curation (supporting), Formal analysis (supporting), Investigation (supporting), Methodology (supporting).

665 **Competing interests:**

All authors were employed by the company Ricardo Energy & Environment. All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

670 **Acknowledgements:**

The authors would like to thank the AURN measurements which are freely available on <https://uk-air.defra.gov.uk/networks/network-info?view=aurm> (last access on 01 August 2025) and David Carslaw (Department of Chemistry, University of York & Ricardo Energy and Environment) for his useful comments on the manuscript.

675

Financial support:

This project was funded by the National Institute for Health and Care Research (NIHR) AIM-HEALTH programme under award number NIHR 129449.

680 6 References

- AFBI, Agri Food and Biosciences Institute. Typical ammonia concentrations in agricultural landscapes, <https://www.afbini.gov.uk/page/typical-ammonia-concentrations-agricultural-landscapes> (last access: 02 January 2026), 2025.
- 685 Appel K. W., Chemel C., Roselle, S. J., Francis, X.V., Hu, R.-M., Sokhi, R. S., Rao, S.T., Galmarini, S., Examination of the Community Multiscale Air Quality (CMAQ) model performance over the North American and European domains, *Atmos. Env.*, 53, 142-155, <https://doi.org/10.1016/j.atmosenv.2011.11.016>, 2012
- 690 Appel, K. W., Napelenok, S. L., Foley, K. M., Pye, H. O. T., Hogrefe, C., Luecken, D. J., Bash, J. O., Roselle, S. J., Pleim, J. E., Foroutan, H., Hutzell, W. T., Pouliot, G. A., Sarwar, G., Fahey, K. M., Gantt, B., Gilliam, R. C., Heath, N. K., Kang, D., Mathur, R., Schwede, D. B., Spero, T. L., Wong, D. C., and Young, J. O.: Description and evaluation of the Community Multiscale Air Quality (CMAQ) modeling system version 5.1, *Geosci. Model Dev.*, 10, 1703–1732, <https://doi.org/10.5194/gmd-10-1703-2017>, 2017.
- 695 Appel, K. W., Bash, J. O., Fahey, K. M., Foley, K. M., Gilliam, R. C., Hogrefe, C., Hutzell, W. T., Kang, D., Mathur, R., Murphy, B. N., Napelenok, S. L., Nolte, C. G., Pleim, J. E., Pouliot, G. A., Pye, H. O. T., Ran, L., Roselle, S. J., Sarwar, G., Schwede, D. B., Sidi, F. I., Spero, T. L., and Wong, D. C.: The Community Multiscale Air Quality (CMAQ) model versions 5.3 and 5.3.1: system updates and evaluation, *Geosci. Model Dev.*, 14, 2867–2897, <https://doi.org/10.5194/gmd-14-2867-2021>, 2021.
- AQEG: Fine Particulate Matter in the United Kingdom. Department for Environment, Food and Rural Affairs; Scottish Government, Welsh Government, Department of the Environment in Northern Ireland., https://uk-air.defra.gov.uk/reports/cat11/1212141150_AQEG_Fine_Part particulate_Matter_in_the_UK.pdf, 2012.
- 700 Bessagnet, B., Beauchamp, M., Guerreiro, C., De Leeuw, F., Tsyro, S., Colette, A., Meleux, F., Rouil, L., Ruysenaars, P., Sauter, F., Velders, G. J. M., Foltescu, V. L., and Van Aardenne, J.: Can further mitigation of ammonia emissions reduce exceedances of particulate matter air quality standards?, *Environmental Science & Policy*, 44, 149–163, <https://doi.org/10.1016/j.envsci.2014.07.011>, 2014.
- 705 Bittman, S., Dedina, M., Howard, C. M. (Clare), Oenema, O., and Sutton, M. A.: Options for ammonia mitigation: guidance from the UNECE Task Force on Reactive Nitrogen, Centre for Ecology & Hydrology, on behalf of Task Force on Reactive Nitrogen, of the UNECE Convention on Long Range transboundary Air Pollution, Edinburgh, 2014.
- 710 Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., Lim, C. C., Turner, M. C., Jerrett, M., Krewski, D., Gapstur, S. M., Diver, W. R., Ostro, B., Goldberg, D., Crouse, D. L., Martin, R. V., Peters, P., Pinault, L., Tjepkema, M., Van Donkelaar, A., Villeneuve, P. J., Miller, A. B., Yin, P., Zhou, M., Wang, L., Janssen, N. A. H., Marra, M., Atkinson, R. W., Tsang, H., Quoc Thach, T., Cannon, J. B., Allen, R. T., Hart, J. E., Laden, F., Cesaroni, G., Forastiere, F., Weinmayr, G., Jaensch, A., Nagel, G., Concini, H., and Spadaro, J. V.: Global estimates of

- mortality associated with long-term exposure to outdoor fine particulate matter, *Proc. Natl. Acad. Sci. U.S.A.*, 115, 9592–9597, <https://doi.org/10.1073/pnas.1803222115>, 2018.
- 715 Carruthers, D. J., Holroyd, R. J., Hunt, J. C. R., Weng, W. S., Robins, A. G., Apsley, D. D., Thompson, D. J., and Smith, F. B.: UK-ADMS: A new approach to modelling dispersion in the earth's atmospheric boundary layer, *Journal of Wind Engineering and Industrial Aerodynamics*, 52, 139–153, [https://doi.org/10.1016/0167-6105\(94\)90044-2](https://doi.org/10.1016/0167-6105(94)90044-2), 1994.
- CEIP: EMEP gridded-emissions, <https://www.ceip.at/the-emep-grid/gridded-emissions> (last access: 08 August 2025) 2022.
- CERC: ADMS 6, Atmospheric Dispersion Modelling System, User Guide, https://www.cerc.co.uk/environmental-software/assets/data/doc_userguides/CERC_ADMS_6_User_Guide.pdf (last access: 02 January 2026), 2023.
- 720 CERC: ADMS, <https://www.cerc.co.uk/environmental-software/ADMS-model.html> (last access: 08 August 2025) 2024.
- Churchill, S., Misra, A., Brown, P., Del Vento, S., Karagianni, E., Murrells, T., Passant, N., Richardson, J., Richmond, B., Smith, H., Stewart, R., Tsagatakis, I., Thistlethwaite, G., Wakeling, D., Walker, C., Wiltshire, J., Hobson, M., Gibbs, M., Misselbrook, T., Dragosits, U., and Tomlinson, S.: UK Informative Inventory Report (1990 to 2019), 2021.
- 725 De Visscher, A.: Air dispersion modeling: foundations and applications, 1. ed., Wiley, Hoboken, NJ, 634 pp., 2014.
- DEFRA: Local Air Quality Management Technical Guidance (TG22), <https://laqm.defra.gov.uk/wp-content/uploads/2022/08/LAQM-TG22-August-22-v1.0.pdf>, 2022.
- DEFRA: LIDAR Composite Digital Terrain Model (DTM) - 1m, <https://doi.org/13787b9a-26a4-4775-8523-806d13af58fc>, 2023.
- 730 DEFRA: Automatic Urban and Rural Network (AURN), <https://uk-air.defra.gov.uk/networks/network-info?view=aur>, 2024a.
- DEFRA: Code of Good Agricultural Practice (COGAP) for Reducing Ammonia Emissions, Department for Environment Food & Rural Affairs, <https://www.gov.uk/government/publications/code-of-good-agricultural-practice-for-reducing-ammonia-emissions/code-of-good-agricultural-practice-cogap-for-reducing-ammonia-emissions#contents>, 2024b.
- 735 Dudhia, J.: Numerical Study of Convection Observed during the Winter Monsoon Experiment Using a Mesoscale Two-Dimensional Model, *J. Atmos. Sci.*, 46, 3077–3107, [https://doi.org/10.1175/1520-0469\(1989\)046<3077:NSOCOD>2.0.CO;2](https://doi.org/10.1175/1520-0469(1989)046<3077:NSOCOD>2.0.CO;2), 1989.
- Environmental Protection Ireland Agency: Air Dispersion Modelling from Industrial Installations Guidance Note (AG4), 2020.
- 740 European Commission. Joint Research Centre.: Best Available Techniques (BAT) reference document for the intensive rearing of poultry or pigs: Industrial Emissions Directive 2010/75/EU (Integrated Pollution Prevention and Control)., Publications Office, LU, 2017.
- European Environment Agency: CORINE Land Cover 2018 (raster 100 m), Europe, 6-yearly - version 2020_20u1, May 2020 (20.01), <https://doi.org/10.2909/960998C1-1870-4E82-8051-6485205EBBAC>, 2019.
- 745 Foroutan, H., Young, J., Napelenok, S., Ran, L., Appel, K. W., Gilliam, R. C., and Pleim, J. E.: Development and evaluation of a physics-based windblown dust emission scheme implemented in the C MAQ modeling system, *J Adv Model Earth Syst*, 9, 585–608, <https://doi.org/10.1002/2016MS000823>, 2017.

- 750 Friedl, M. A., McIver, D. K., Hodges, J. C. F., Zhang, X. Y., Muchoney, D., Strahler, A. H., Woodcock, C. E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., and Schaaf, C.: Global land cover mapping from MODIS: algorithms and early results, *Remote Sensing of Environment*, 83, 287–302, [https://doi.org/10.1016/S0034-4257\(02\)00078-0](https://doi.org/10.1016/S0034-4257(02)00078-0), 2002.
- Gantt, B., Kelly, J. T., and Bash, J. O.: Updating sea spray aerosol emissions in the Community Multiscale Air Quality (CMAQ) model version 5.0.2, *Geosci. Model Dev.*, 8, 3733–3746, <https://doi.org/10.5194/gmd-8-3733-2015>, 2015.
- 755 Ge, Y., Vieno, M., Stevenson, D. S., Wind, P., and Heal, M. R.: A new assessment of global and regional budgets, fluxes, and lifetimes of atmospheric reactive N and S gases and aerosols, *Atmos. Chem. Phys.*, 22, 8343–8368, <https://doi.org/10.5194/acp-22-8343-2022>, 2022.
- Ge, Y., Vieno, M., Stevenson, D. S., Wind, P., and Heal, M. R.: Global sensitivities of reactive N and S gas and particle concentrations and deposition to precursor emissions reductions, *Atmos. Chem. Phys.*, 23, 6083–6112, <https://doi.org/10.5194/acp-23-6083-2023>, 2023.
- 760 Gu, B., Zhang, L., Van Dingenen, R., Vieno, M., Van Grinsven, H. J., Zhang, X., Zhang, S., Chen, Y., Wang, S., Ren, C., Rao, S., Holland, M., Winiwarter, W., Chen, D., Xu, J., and Sutton, M. A.: Abating ammonia is more cost-effective than nitrogen oxides for mitigating PM_{2.5} air pollution, *Science*, 374, 758–762, <https://doi.org/10.1126/science.abf8623>, 2021.
- 765 Guenther, A., Jiang, X., Shah, T., Huang, L., Kemball-Cook, S., and Yarwood, G.: Model of Emissions of Gases and Aerosol from Nature Version 3 (MEGAN3) for Estimating Biogenic Emissions, in: *Air Pollution Modeling and its Application XXVI*, edited by: Mensink, C., Gong, W., and Hakami, A., Springer International Publishing, Cham, 187–192, https://doi.org/10.1007/978-3-030-22055-6_29, 2020.
- Hellsten, S., Dragosits, U., Place, C.J. et al. Modelling Seasonal Dynamics from Temporal Variation in Agricultural Practices in the UK Ammonia Emission Inventory. *Water Air Soil Pollut: Focus* 7, 3–13, <https://doi.org/10.1007/s11267-006-9087-5>, 2007.
- 770 Hill, R., Bealey, B., Johnson, C., Ball, A., Simpson, K., Smith, A., Theobald, M., Braban, C., Magaz, I., and Curran, T.: SCAIL-Agriculture update, 2014.
- Hogrefe, C., Bash, J. O., Pleim, J. E., Schwede, D. B., Gilliam, R. C., Foley, K. M., Appel, K. W., and Mathur, R.: An analysis of CMAQ gas-phase dry deposition over North America through grid-scale and land-use-specific diagnostics in the context of AQMEII4, *Atmos. Chem. Phys.*, 23, 8119–8147, <https://doi.org/10.5194/acp-23-8119-2023>, 2023.
- 775 Hood, C., MacKenzie, I., Stocker, J., Johnson, K., Carruthers, D., Vieno, M., and Doherty, R.: Air quality simulations for London using a coupled regional-to-local modelling system, *Atmos. Chem. Phys.*, 18, 11221–11245, <https://doi.org/10.5194/acp-18-11221-2018>, 2018.
- Iacono, M. J., Delamere, J. S., Mlawer, E. J., Shephard, M. W., Clough, S. A., and Collins, W. D.: Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models, *J. Geophys. Res.*, 113, 2008JD009944, <https://doi.org/10.1029/2008JD009944>, 2008.
- 780 IIASA: ECLIPSE V6b; Global emission fields of air pollutants and GHGs, <https://iiasa.ac.at/models-tools-data/global-emission-fields-of-air-pollutants-and-ghgs>, 2019.
- Im, U., Bianconi, R., Solazzo, E., Kioutsioukis, I., Badia, A., Balzarini, A., Baró, R., Bellasio, R., Brunner, D., Chemel, C., Curci, G., Denier Van Der Gon, H., Flemming, J., Forkel, R., Giordano, L., Jiménez-Guerrero, P., Hirtl, M., Hodzic, A.,

- Honzak, L., Jorba, O., Knote, C., Makar, P. A., Manders-Groot, A., Neal, L., Pérez, J. L., Pirovano, G., Pouliot, G., San Jose, R., Savage, N., Schroder, W., Sokhi, R. S., Syrakov, D., Torian, A., Tuccella, P., Wang, K., Werhahn, J., Wolke, R., Zabkar, R., Zhang, Y., Zhang, J., Hogrefe, C., and Galmarini, S.: Evaluation of operational online-coupled regional air quality models over Europe and North America in the context of AQMEII phase 2. Part II: Particulate matter, *Atmospheric Environment*, 115, 421–441, <https://doi.org/10.1016/j.atmosenv.2014.08.072>, 2015.
- 785
- Jenkins, B.; Wiltshire, J. Farmer perceptions of the benefits and barriers to ammonia mitigation measures. *Preprints 2025*, 2025082071. <https://doi.org/10.20944/preprints202508.2071.v1>
- 790
- Kain, J. S.: The Kain–Fritsch Convective Parameterization: An Update, *J. Appl. Meteor.*, 43, 170–181, [https://doi.org/10.1175/1520-0450\(2004\)043<0170:TKCPAU>2.0.CO;2](https://doi.org/10.1175/1520-0450(2004)043<0170:TKCPAU>2.0.CO;2), 2004.
- Kelly, J. M., Marais, E. A., Lu, G., Obszynska, J., Mace, M., White, J., and Leigh, R. J.: Diagnosing domestic and transboundary sources of fine particulate matter (PM_{2.5}) in UK cities using GEOS-Chem, *City and Environment Interactions*, 18, 100100, <https://doi.org/10.1016/j.cacint.2023.100100>, 2023.
- 795
- Kelly, J. T., Bhawe, P. V., Nolte, C. G., Shankar, U., and Foley, K. M.: Simulating emission and chemical evolution of coarse sea-salt particles in the Community Multiscale Air Quality (CMAQ) model, *Geosci. Model Dev.*, 3, 257–273, <https://doi.org/10.5194/gmd-3-257-2010>, 2010.
- 800
- Kiesewetter, G., Schoepp, W., Heyes, C., and Amann, M.: Modelling PM_{2.5} impact indicators in Europe: Health effects and legal compliance, *Environmental Modelling & Software*, 74, 201–211, <https://doi.org/10.1016/j.envsoft.2015.02.022>, 2015.
- Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., and Pozzer, A.: The contribution of outdoor air pollution sources to premature mortality on a global scale, *Nature*, 525, 367–371, <https://doi.org/10.1038/nature15371>, 2015.
- Leonard, A.; Wiltshire, J. Agricultural Emissions Measurements from Five English Farms. *Preprints 2025*, 2025082187. <https://doi.org/10.20944/preprints202508.2187.v1>
- 805
- Luecken, D. J., Yarwood, G., and Hutzell, W. T.: Multipollutant modeling of ozone, reactive nitrogen and HAPs across the continental US with CMAQ-CB6, *Atmospheric Environment*, 201, 62–72, <https://doi.org/10.1016/j.atmosenv.2018.11.060>, 2019.
- Marais, E. A., Pandey, A. K., Van Damme, M., Clarisse, L., Coheur, P.-F., Shephard, M. W., UK ammonia emissions estimated with satellite observations and GEOS-Chem, *Journal of Geophysical Research: Atmospheres*, 126, e2021JD035237. <https://doi.org/10.1029/2021JD035237>, 2021.
- 810
- Marais, E. A., Kelly, J. M., Vohra, K., Li, Y., Lu, G., Hina, N., and Rowe, E. C.: Impact of Legislated and Best Available Emission Control Measures on UK Particulate Matter Pollution, Premature Mortality, and Nitrogen-Sensitive Habitats, *GeoHealth*, 7, e2023GH000910, <https://doi.org/10.1029/2023GH000910>, 2023.
- 815
- Misselbrook, T. H., Gilhespy, S. L., Carswell, A. M., and Cardenas, L. M.: Inventory of Ammonia Emissions from UK Agriculture 2021, 2023.
- Momeni, M., Choi, Y., Kashfi Yeganeh, A., Pouyaei, A., Jung, J., Park, J., Shephard, M. W., Dammers, E., and Cady-Pereira, K. E.: Constraining East Asia ammonia emissions through satellite observations and iterative Finite Difference Mass

- Balance (iFDMB) and investigating its impact on inorganic fine particulate matter, *Environment International*, 184, 108473, 820 <https://doi.org/10.1016/j.envint.2024.108473>, 2024.
- NAEI: <https://naei.energysecurity.gov.uk/air-pollutants/ammonia> (last access: 22 October 2025) 2025.
- Natural Resources Wales: Modelling the concentration and deposition of ammonia emitted from intensive farming - Guidance note, <https://cdn.cyfoethnaturiol.cymru/media/691876/gn36-checked-3.pdf>, 2021.
- NCAR: Official repository for the Weather Research and Forecasting (WRF) model, <https://github.com/wrf-model/WRF/tree/release-v4.5>, 2022. 825
- Norman, O. G., Heald, C. L., Bililign, S., Campuzano-Jost, P., Coe, H., Fiddler, M. N., Green, J. R., Jimenez, J. L., Kaiser, K., Liao, J., Middlebrook, A. M., Nault, B. A., Nowak, J. B., Schneider, J., and Welti, A.: Exploring the processes controlling secondary inorganic aerosol: evaluating the global GEOS-Chem simulation using a suite of aircraft campaigns, *Atmos. Chem. Phys.*, 25, 771–795, <https://doi.org/10.5194/acp-25-771-2025>, 2025.
- 830 Pan, D., Mauzerall, D. L., Wang, R., Guo, X., Puchalski, M., Guo, Y., Song, S., Tong, D., Sullivan, A. P., Schichtel, B. A., Collett, J. L., and Zondlo, M. A.: Regime shift in secondary inorganic aerosol formation and nitrogen deposition in the rural United States, *Nat. Geosci.*, 17, 617–623, <https://doi.org/10.1038/s41561-024-01455-9>, 2024.
- Pastorino, S., Milojevic, A., Green, R., Beck, R., Carnell, E., Colombo, P. E., Misselbrook, T., Miller, M., Reis, S., Tomlinson, S., Vieno, M., and Milner, J.: Health impact of policies to reduce agriculture-related air pollutants in the UK: 835 The relative contribution of change in PM_{2.5} exposure and diets to morbidity and mortality, *Environmental Research*, 262, 119923, <https://doi.org/10.1016/j.envres.2024.119923>, 2024.
- Pay, M. T., Jiménez-Guerrero, P., and Baldasano, J. M.: Assessing sensitivity regimes of secondary inorganic aerosol formation in Europe with the CALIOPE-EU modeling system, *Atmospheric Environment*, 51, 146–164, <https://doi.org/10.1016/j.atmosenv.2012.01.027>, 2012.
- 840 Phillips, V. R., Holden, M. R., Sneath, R. W., Short, J. L., White, R. P., Hartung, J., Seedorf, J., Schröder, M., Linkert, K. H., Pedersen, S., Takai, H., Johnsen, J. O., Groot Koerkamp, P. W. G., Uenk, G. H., Scholtens, R., Wathes, C. M.: The development of robust methods for measuring concentrations and emission rates of gaseous and particulate air pollutants in livestock buildings. *Journal of Agricultural Engineering Research*, 70(1), 11–24. <https://doi.org/10.1006/jaer.1997.0283>, 1998.
- 845 Pleim, J. E.: A Simple, Efficient Solution of Flux–Profile Relationships in the Atmospheric Surface Layer, *Journal of Applied Meteorology and Climatology*, 45, 341–347, <https://doi.org/10.1175/JAM2339.1>, 2006.
- Pleim, J. E.: A Combined Local and Nonlocal Closure Model for the Atmospheric Boundary Layer. Part II: Application and Evaluation in a Mesoscale Meteorological Model, *Journal of Applied Meteorology and Climatology*, 46, 1396–1409, <https://doi.org/10.1175/JAM2534.1>, 2007.
- 850 Pleim, J. E., Ran, L., Appel, W., Shephard, M. W., and Cady-Pereira, K.: New Bidirectional Ammonia Flux Model in an Air Quality Model Coupled With an Agricultural Model, *J Adv Model Earth Syst*, 11, 2934–2957, <https://doi.org/10.1029/2019MS001728>, 2019.
- Pommier, M., Bost, J., Lewin, A., and Richardson, J.: The Impact of Farming Mitigation Measures on Ammonia Concentrations and Nitrogen Deposition in the UK, *Atmosphere*, 16, 353, <https://doi.org/10.3390/atmos16040353>, 2025.

- 855 Pope, C. A. and Dockery, D. W.: Health Effects of Fine Particulate Air Pollution: Lines that Connect, *Journal of the Air & Waste Management Association*, 56, 709–742, <https://doi.org/10.1080/10473289.2006.10464485>, 2006.
- Porwisiak, P., Werner, M., Kryza, M., ApSimon, H., Woodward, H., Mehlig, D., Gawuc, L., Szymankiewicz, K., and Sawiński, T.: Application of ADMS-Urban for an area with a high contribution of residential heating emissions - model verification and sensitivity study for PM_{2.5}, *Science of The Total Environment*, 907, 168011, <https://doi.org/10.1016/j.scitotenv.2023.168011>, 2024.
- 860 Pye, H. O. T., Murphy, B. N., Xu, L., Ng, N. L., Carlton, A. G., Guo, H., Weber, R., Vasilakos, P., Appel, K. W., Budisulistiorini, S. H., Surratt, J. D., Nenes, A., Hu, W., Jimenez, J. L., Isaacman-VanWertz, G., Misztal, P. K., and Goldstein, A. H.: On the implications of aerosol liquid water and phase separation for organic aerosol mass, *Atmos. Chem. Phys.*, 17, 343–369, <https://doi.org/10.5194/acp-17-343-2017>, 2017.
- 865 Ricardo EE: SMT: Designing a scenario-modelling tool to inform policy on air pollutant emissions, <https://www.ricardo.com/en/case-studies/designing-a-scenario-modelling-tool-to-inform-policy-on-air-pollutant-emissions> (last access 08 August 2025), 2021.
- Seinfeld, J. H. and Pandis, S. N.: *Atmospheric chemistry and physics: from air pollution to climate change*, Third edition., Wiley, Hoboken, New Jersey, 1120 pp., 2016.
- 870 Smirnova, T. G., Brown, J. M., Benjamin, S. G., and Kenyon, J. S.: Modifications to the Rapid Update Cycle Land Surface Model (RUC LSM) Available in the Weather Research and Forecasting (WRF) Model, *Mon. Wea. Rev.*, 144, 1851–1865, <https://doi.org/10.1175/MWR-D-15-0198.1>, 2016.
- Stocker, J., Jonhson, K., Hood, C., Bien, B., Hamilton, V., Aves, C., Jackson, R.: Regional-to-local scale air quality modelling of the Republic of Ireland, CERC report for EPA, FM1297/T5.3, <https://www.epa.ie/publications/monitoring--assessment/air/20230710-CERC-EPA-Eire-AQ-modelling---Final.pdf> (last access on 23.01.2026), 2023
- 875 Tsyro, S. G.: To what extent can aerosol water explain the discrepancy between model calculated and gravimetric PM₁₀ and PM_{2.5}?, *Atmos. Chem. Phys.*, 5, 515–532, <https://doi.org/10.5194/acp-5-515-2005>, 2005.
- US EPA Office of Research and Development; <https://zenodo.org/records/7218076>: CMAQ, 2022a.
- US EPA Office Of Research And Development: CMAQ - BCON, <https://github.com/USEPA/CMAQ/tree/main/PREP/bcon>,
- 880 2022b.
- U.S Environmental Protection Agency, Guideline for Determination of Good Engineering Practice Stack Height (Technical Support Document For the Stack Height Regulations), <https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=2000MXYW.txt> (last access on 09.12.2025), 1985.
- 885 Support Center for Regulatory Atmospheric Modeling, 2017 Appendix W Final Rule: <https://www.epa.gov/scram/2017-appendix-w-final-rule> (last access: 08 August 2025).
- Tao, H., Xing, J., Zhou, H., Pleim, J., Ran, L., Chang, X., Wang, S., Chen, F., Zheng, H., and Li, J.: Impacts of improved modeling resolution on the simulation of meteorology, air quality, and human exposure to PM_{2.5}, O₃ in Beijing, China, *Journal of Cleaner Production*, 243, 118574, <https://doi.org/10.1016/j.jclepro.2019.118574>, 2020.

- 890 Vieno, M., Heal, M. R., Hallsworth, S., Famulari, D., Doherty, R. M., Dore, A. J., Tang, Y. S., Braban, C. F., Leaver, D., Sutton, M. A., and Reis, S.: The role of long-range transport and domestic emissions in determining atmospheric secondary inorganic particle concentrations across the UK, *Atmos. Chem. Phys.*, 14, 8435–8447, <https://doi.org/10.5194/acp-14-8435-2014>, 2014.
- Webb, J. and Misselbrook, T. H.: A mass-flow model of ammonia emissions from UK livestock production, *Atmospheric Environment*, 38, 2163–2176, <https://doi.org/10.1016/j.atmosenv.2004.01.023>, 2004.
- Webb, J., Ryan, M., Anthony, S., Brewer, A., Laws, J., Aller, M., and Misselbrook, T.: Cost-effective means of reducing ammonia emissions from UK agriculture using the NARSES model, *Atmospheric Environment*, 40, 7222–7233, <https://doi.org/10.1016/j.atmosenv.2006.06.029>, 2006.
- 900 Wyer, K. E., Kelleghan, D. B., Blanes-Vidal, V., Schaubberger, G., and Curran, T. P.: Ammonia emissions from agriculture and their contribution to fine particulate matter: A review of implications for human health, *Journal of Environmental Management*, 323, 116285, <https://doi.org/10.1016/j.jenvman.2022.116285>, 2022.
- Zhang, Y., Gautam, R., Pandey, S., Omara, M., Maasackers, J. D., Sadavarte, P., Lyon, D., Nesser, H., Sulprizio, M. P., Varon, D. J., Zhang, R., Houweling, S., Zavala-Araiza, D., Alvarez, R. A., Lorente, A., Hamburg, S. P., Aben, I., and Jacob, D. J.: Quantifying methane emissions from the largest oil-producing basin in the United States from space, *Science Advances*, 6, eaaz5120, <https://doi.org/10.1126/sciadv.aaz5120>, 2020.
- Zhong, J., Harrison, R. M., James Bloss, W., Visschedijk, A., and Denier Van Der Gon, H.: Modelling the dispersion of particle number concentrations in the West Midlands, UK using the ADMS-Urban model, *Environment International*, 181, 108273, <https://doi.org/10.1016/j.envint.2023.108273>, 2023.

910