

# Impact of agricultural interventions on ammonia emissions and on PM<sub>2.5</sub> concentrations in the UK: a local and regional modelling study

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**Abstract.** The contribution of agricultural emissions of fine particulate matter (PM<sub>2.5</sub>) 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<sub>2.5</sub> formed through chemical reactions from precursors such as ammonia (NH<sub>3</sub>). 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 NH<sub>3</sub> emissions. Under the high uptake scenario, NH<sub>3</sub> 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 NH<sub>3</sub> to secondary PM<sub>2.5</sub> 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<sub>2.5</sub> concentrations since the maximum modelled decrease was around 1-1.5%. This finding is explained by an NH<sub>3</sub>-rich atmosphere reducing the impact of these reductions in NH<sub>3</sub> emissions on mitigating PM<sub>2.5</sub> concentrations. Results from ADMS show that the NH<sub>3</sub> and PM<sub>2.5</sub> concentrations are quickly dispersed near the farms, highlighting the usefulness of local modelling in addressing impact studies on PM<sub>2.5</sub> formation near these sources. Indeed, for the five studied livestock farms, it has been found that 50% of maximum NH<sub>3</sub> and PM<sub>2.5</sub> 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<sub>2.5</sub> dispersion near agricultural areas. The comparison with ground-based measurements might suggest a non-representation of atmospheric processes in the PM<sub>2.5</sub> formation by CMAQ (with an underestimation of PM<sub>2.5</sub> concentrations by approximately 50%). It underscores the need for integrated modelling approaches to guide mitigation strategies for both primary and secondary PM<sub>2.5</sub>, as well as to improve understanding of the chemical atmospheric processes involved in the secondary inorganic aerosols.

## 35 1 Introduction

Air pollution from PM<sub>2.5</sub> (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<sub>2.5</sub> 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<sub>2.5</sub> 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<sub>2.5</sub> concentrations, ammonia (NH<sub>3</sub>) has an important role in secondary particulate formation. In the atmosphere, NH<sub>3</sub> reacts with acidic compounds such as sulfuric acid (H<sub>2</sub>SO<sub>4</sub>) and nitric acid (HNO<sub>3</sub>), forming ammonium sulphate ((NH<sub>4</sub>)<sub>2</sub>SO<sub>4</sub>) and ammonium nitrate (NH<sub>4</sub>NO<sub>3</sub>), which are significant constituents of 45 PM<sub>2.5</sub> (Seinfeld and Pandis, 2016; Wyer et al., 2022).

The UK presents a significant case for examining the influence of NH<sub>3</sub> on PM<sub>2.5</sub> levels due to its varied agricultural practices, transport-related emissions, and industrial activities. NH<sub>3</sub> 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 NH<sub>3</sub> 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<sub>2.5</sub> concentrations (e.g. Wyer et al. 2022). Various mitigation measures (i.e. farm practices) have been developed to mitigate emissions of NH<sub>3</sub>, 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 NH<sub>3</sub> and PM<sub>2.5</sub> to inform regulatory measures and mitigate adverse health effects. For instance, the work by Vieno et al. (2014) demonstrated that reductions in NH<sub>3</sub> emissions could lead to significant decreases in PM<sub>2.5</sub> levels, especially in areas with large nitrogen oxides (NO<sub>x</sub>) concentrations, suggesting that targeted strategies in NH<sub>3</sub> 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 NH<sub>3</sub> 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<sub>2.5</sub> concentrations. The impact of NH<sub>3</sub> emissions reduction is significantly more efficient with large emission reduction measures (Bessagnet et al., 2014) and abating NH<sub>3</sub> emissions can even be more cost-effective than NO<sub>x</sub> for mitigating PM<sub>2.5</sub> air pollution (Gu et al., 2021). Conversely, other work such as Ge et al. (2022) and Pay et al. (2012), suggested NH<sub>3</sub> 65 emissions reduction may only lead to minor improvements in airborne PM<sub>2.5</sub> concentrations, especially in the UK since the UK is characterized by a NH<sub>3</sub>-rich atmosphere. A study in the United States also showed controlling NH<sub>3</sub> became significantly less effective for mitigating PM<sub>2.5</sub> 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<sub>2.5</sub> 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<sub>2.5</sub> 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 NH<sub>3</sub> concentrations and nitrogen deposition at a regional scale (Pommier et al., 2025). This study primarily focussed on

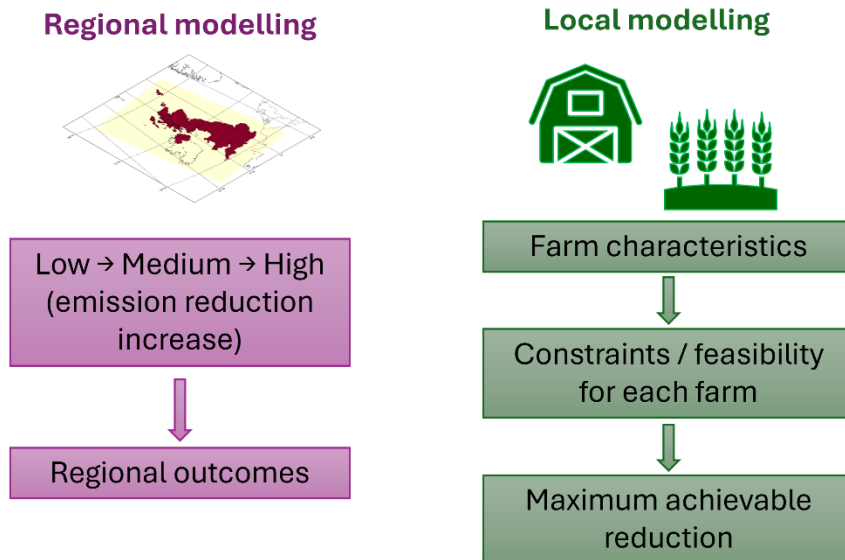
90 measures to reduce emissions from housed dairy, pigs and poultry, while emissions from other sources such as manufactured fertilisers were not within its scope. Three intervention scenarios were developed to model the impact on PM<sub>2.5</sub> concentrations nationally based on differing uptake levels of the mitigation measures across the UK, ranging from low, medium and high. Additionally, local modelling was done to show how primary emissions of NH<sub>3</sub> and PM<sub>2.5</sub> 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<sub>2.5</sub> 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.**

110 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 (NO<sub>2</sub>), ozone (O<sub>3</sub>) and PM<sub>2.5</sub>. 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 NH<sub>3</sub> emissions and not on  
125 mitigating the primary PM<sub>2.5</sub> 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 diverse sources in the UK, including agricultural sources. 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

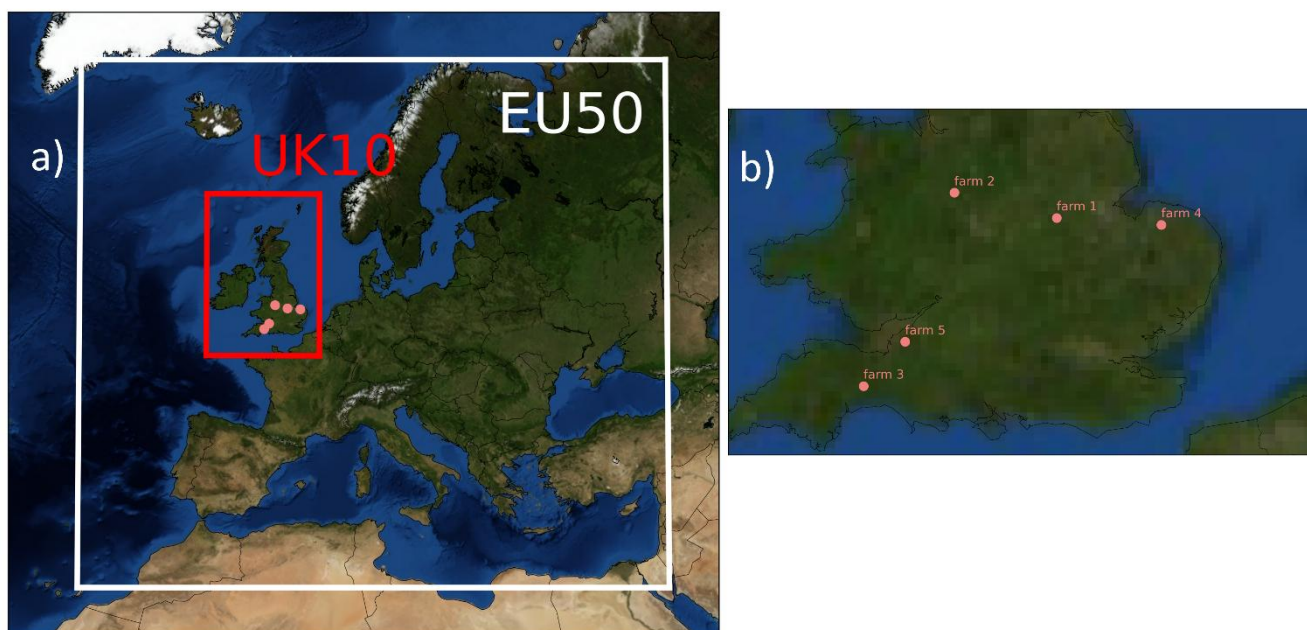
### 2.2.1 Model set-up

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 use of a single year meteorology is a common approach in emission-driven scenario assessments. Nevertheless, interannual meteorological variability can influence secondary  $PM_{2.5}$  formation and dispersion, meaning that results based on one year may not capture the full range of possible outcomes. As the study is designed to evaluate relative differences between emission scenarios under consistent meteorological conditions, the scenario-to-baseline contrasts are expected to be less sensitive to this limitation.

210 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  
215 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  $50 \times 50$  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  
220 (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.

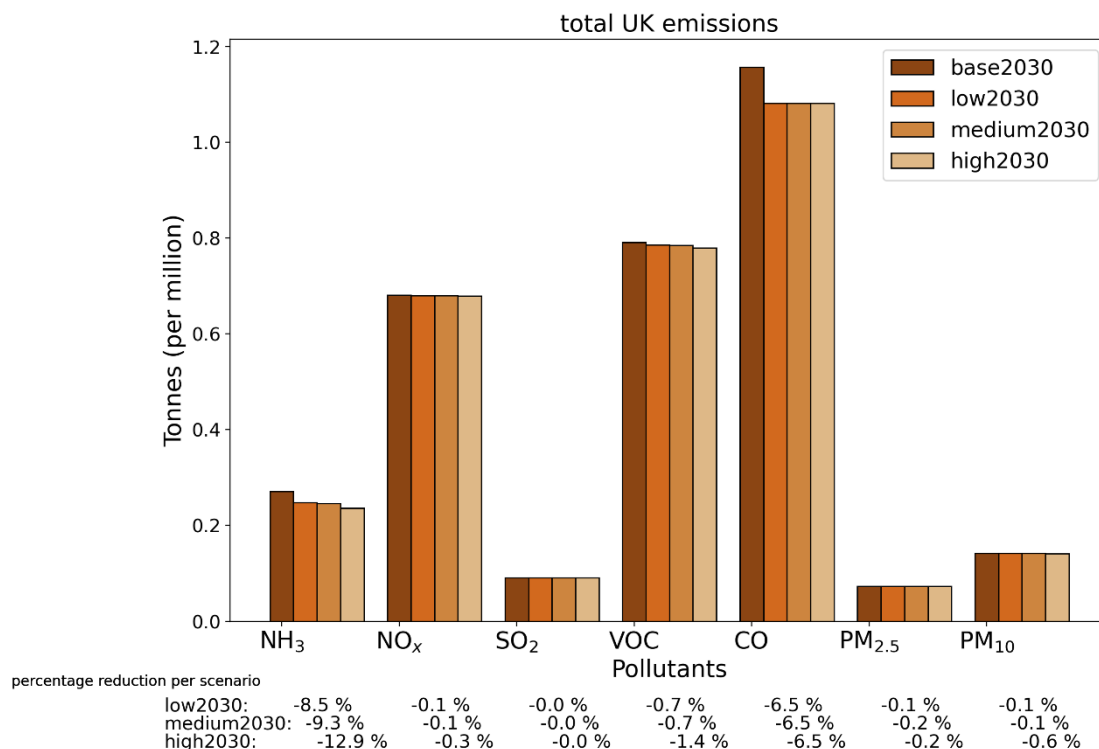
The baseline 2030 future scenario for the EU50 domain was based on the EMEP gridded emissions for 2019 and scaled with  
the factors provided by the GAINS ECLIPSE (Greenhouse Gas and Air Pollution INteractions and Synergies - Evaluating  
225 the Climate and Air Quality Impacts of Short-Lived Pollutants) 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  
230 for the different scenarios. Since the mitigation measures mainly tackle the  $\text{NH}_3$  emissions, this explains the large decrease  
calculated for this pollutant. As explained in Pommier et al. (2025), the reduction in  $\text{NH}_3$  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  $\text{NH}_3$  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  
235 satellite observations, alongside the spring peak. In contrast, the Emissions Database for Global Atmospheric Research  
(EDGAR) applies a uniform temporal profile for agricultural  $\text{NH}_3$  emissions in the UK in its latest inventory version  
(EDGARv8.1: [https://edgar.jrc.ec.europa.eu/dataset\\_ap81#p1m](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  
240 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 ( $\text{PM}_{10}$ , PM with an aerodynamic diameter lower than  $10 \mu\text{m}$ ), while  
the changes in  $\text{NO}_x$  and  $\text{PM}_{2.5}$  remain limited, and null for sulphur dioxide ( $\text{SO}_2$ ).

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  
245 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 NH<sub>3</sub>, NO<sub>x</sub>, SO<sub>2</sub>, VOC, CO, PM<sub>2.5</sub>, and PM<sub>10</sub>. The relative difference for the low2030, medium2030 and high2030 scenarios compared to the base2030 are given below each corresponding bar.**

## 250 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 Aermod (Support Center for Regulatory Atmospheric Modeling, 2017 Appendix W Final Rule). NH<sub>3</sub>

deposition was considered by using deposition velocities that vary depending on the surface. The deposition velocity values  
265 used for NH<sub>3</sub> 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  
NH<sub>3</sub> and PM<sub>2.5</sub> 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  
270 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  
275 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 NH<sub>3</sub> and PM<sub>2.5</sub>. Indeed, the concentrations calculated by CMAQ or other CTMs with a somewhat-coarse  
resolution are mostly representative of the background conditions.

### 280 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.

285 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).  
290 However, overall, at a national level, the reductions are on average more modest, even if these farms are located were larger  
reduction in national NH<sub>3</sub> 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  
295 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.	<b>Housing - ventilation scrubber</b> 80% NH <sub>3</sub> reduction (SMT) 60% PM <sub>2.5</sub> reduction (European Commission. Joint Research Centre., 2017) <b>Slurry lagoon</b> Floating cover 60% NH <sub>3</sub> (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.	<b>Housing - ventilation scrubber</b> 80% NH <sub>3</sub> reduction (SMT) 60% PM <sub>2.5</sub> reduction (European Commission. Joint Research Centre., 2017) <b>Manure piles</b> Manure cover 60% NH <sub>3</sub> (SMT)
Three	Poultry, broilers	Eight mechanically ventilated housing units	Measured at 8 mechanically ventilated housing units	<b>Housing - ventilation scrubber</b>

				80% NH <sub>3</sub> reduction (SMT) 35% PM <sub>2.5</sub> reduction (European Commission. Joint Research Centre., 2017)
Four	Poultry, broilers	Three mechanically ventilated housing units	Measured at 3 mechanically ventilated housing units	<b>Housing-ventilation scrubber</b> 80% NH <sub>3</sub> reduction (SMT) 35% PM <sub>2.5</sub> 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.	<b>Grazing</b> Extend grazing period from 4 to 9 months (SMT). No % reduction applied to pollutants, lower housing emissions achieved extending duration livestock are in pastures.

310 Detailed questionnaire, interview results and pollutant (NH<sub>3</sub> and PM<sub>2.5</sub>) 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 NH<sub>3</sub> or PM<sub>2.5</sub> were reflected in the baseline. 315 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

320 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 NH<sub>3</sub> and PM<sub>2.5</sub> were calculated for each hour of the animal (flock) cycle or for the full measurement period, using equations 1 (NH<sub>3</sub>) and 2 (PM<sub>2.5</sub>) (Phillips et al., 1998). All calculations were performed on an hourly average basis. The NH<sub>3</sub> emission rate was calculated as:

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

Where ER<sub>NH<sub>3</sub></sub> corresponds to the NH<sub>3</sub> emission rate (g/s), C<sub>NH<sub>3</sub></sub> is the hourly average NH<sub>3</sub> concentration (ppb), Q is the ventilation volumetric flow rate (m<sup>3</sup>/s) and R<sub>molecular</sub> is the conversion factor from parts per billion to mass concentration based on the molecular weight and molar volume of NH<sub>3</sub>, and c<sub>mass</sub> is the conversion constant (10<sup>6</sup>).

The PM<sub>2.5</sub> emission rate was calculated as:

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

With ER<sub>PM<sub>2.5</sub></sub> being the PM<sub>2.5</sub> emission rate (g/s), C<sub>PM<sub>2.5</sub></sub> the hourly average PM<sub>2.5</sub> concentration (µg/m<sup>3</sup>), Q the ventilation volumetric flow rate (m<sup>3</sup>/s) and c<sub>mass</sub> the unit conversion factor from micrograms to grams (10<sup>6</sup>).

For instances where emission rate values could not be calculated, the SCAIL emission inventory was used. SCAIL emission rates are provided as kg/m<sup>2</sup> or kg per animal place per year, as such the area of sources and number of livestock were used in this equation to derive NH<sub>3</sub> and PM<sub>10</sub> kg/year. SCAIL emission rates are in PM<sub>10</sub> and this was converted into PM<sub>2.5</sub> by

looking at the ratio between PM<sub>2.5</sub> and PM<sub>10</sub> 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. This assumed ratio (0.58), derived from background AURN observations, lies within the range typically reported for agricultural sources (Gladding et al. 2020), even if lower values were found by Demmers et al. (2010) (0.16 for broilers, 0.26 free-range layers, and 0.41 for caged layers). A high variability in PM<sub>2.5</sub>/PM<sub>10</sub> emission factors for UK poultry farms was also highlighted in a review study (DEFRA, 2012).

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 ( $\mu\text{g}/(\text{m}^3 \cdot \text{h})$ ),  $c_{\text{mass}}$  the conversion constant ( $10^9$ ) and  $c_{\text{time}}$  the time conversion constant ( $24 \times 365$ ).

- 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 NH<sub>3</sub> and PM<sub>2.5</sub>, respectively.

In summary, emission inputs from different data sources were harmonized before their use in ADMS by converting all source terms to a consistent pollutant-specific emission format. Farm-specific measurements were used preferentially and combined with hourly ventilation rates to derive hourly NH<sub>3</sub> and PM<sub>2.5</sub> emission rates. Where measurements were unavailable, SCAIL emission factors were converted to source-specific annual emissions using source area or livestock numbers; SCAIL PM<sub>10</sub> emissions were converted to PM<sub>2.5</sub> using a fixed factor.

Temporal allocation was harmonized separately from emission magnitude: where appropriate, SCAIL-derived housing emissions were assigned a measured diurnal profile from a comparable farm source, while sources lacking supporting activity or measurement data were assigned constant annual-average emissions. This hierarchy also reflects relative confidence in the inputs, with fully measured hourly emissions considered most robust and fully inventory-based annual-average emissions the most uncertain.

### 3 Change in PM<sub>2.5</sub> concentrations

#### 385 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<sub>2.5</sub> 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)  $\sim -0.5$ ). This approximate 50% underestimation in the modelled PM<sub>2.5</sub> concentrations mirrors the uniform 50% increase in NH<sub>3</sub> emissions (and 60% decrease in SO<sub>2</sub> 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<sub>2.5</sub> concentrations with their global CTM ( $r=0.66$ , NMB=-11%). However, it is worth noting a sensitivity simulation, by increasing our UK NH<sub>3</sub> emissions by 50% was also tested. Despite this large change in the 2019 NH<sub>3</sub> 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<sub>3</sub> is not 'limiting', thus NH<sub>3</sub> emissions changes will have a negligible on mitigating secondary inorganic aerosols (SIA) formation at regional scale. Kelly et al. (2023) also explained with NH<sub>3</sub> being in excess, the emissions scaling applied to NH<sub>3</sub> to resolve differences between top-down and bottom-up emissions estimates has only a limited effect on NH<sub>4</sub> and PM<sub>2.5</sub>.

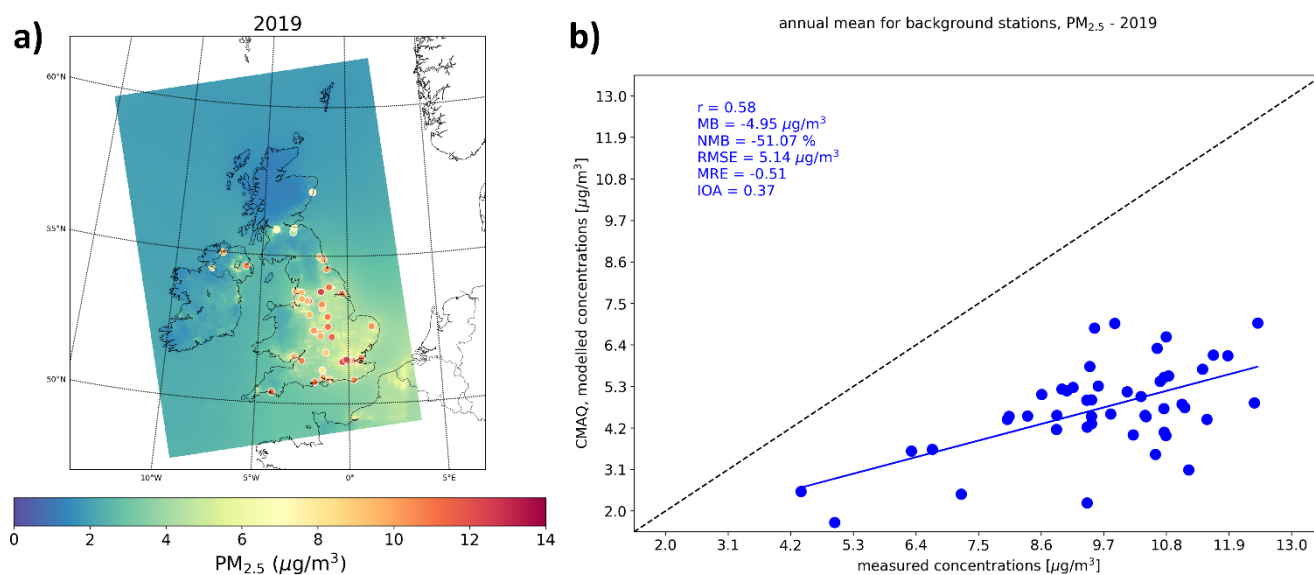
This might also suggest unrepresented atmospheric processes in the model between NH<sub>3</sub> and the PM<sub>2.5</sub> formation since this 50% increase in NH<sub>3</sub> emission leads to an overestimation of the modelled NH<sub>3</sub> concentrations (Pommier et al., 2025). For example, this could be a result of combined missing processes since the bi-directional NH<sub>3</sub> flux representation has not been implemented in this CMAQ simulation and this bidirectional treatment of NH<sub>3</sub> fluxes should improve the prediction of NH<sub>3</sub> (e.g. Pleim et al., 2019). It has been noted that assimilating satellite NH<sub>3</sub> 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<sub>4</sub> and 376% in NO<sub>3</sub>). In addition, dry PM<sub>2.5</sub> 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 PM<sub>2.5</sub> can influence the value in the total PM<sub>2.5</sub> concentrations (AQEG, 2012; Kelly et al., 2023; Tsyro, 2005).

This bias in PM<sub>2.5</sub> 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 PM<sub>2.5</sub> 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  $PM_{2.5}$  (in the US) remained, with lower correlation (from  $\sim 0.32$  to  $0.47$ ) and higher RMSE (from  $5.8$  to  $9 \mu\text{g}/\text{m}^3$ ) than our 420 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 ( $1 \text{ km}^2$ ) compared to our spatial resolution ( $10 \text{ km} \times 10 \text{ km}$ ). A modelling study in Ireland with a similar finer scale modelling ( $1 \text{ km}^2$ ) 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 425 Kalman filter to improve the  $PM_{2.5}$  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.

It is worth noting the main  $PM_{2.5}$  components calculated by CMAQ for these stations are  $\text{NO}_3$  and  $\text{SO}_4$  (Tab. S1) and their composition spatially varies as shown on the maps (Fig. S3).

430 In the baseline 2019 simulation, the calculated Root-Mean-Square Error (RMSE  $\sim 5 \mu\text{g}/\text{m}^3$ ) and IOA ( $\sim 0.4$ ) are not fully satisfactory. In addition, the analysis on  $\text{NO}_2$  concentrations highlights a good estimate in  $\text{NO}_x$  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).



435 **Figure 4: a) Spatial distribution of annual mean  $PM_{2.5}$  concentrations in  $\mu\text{g}/\text{m}^3$  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.**

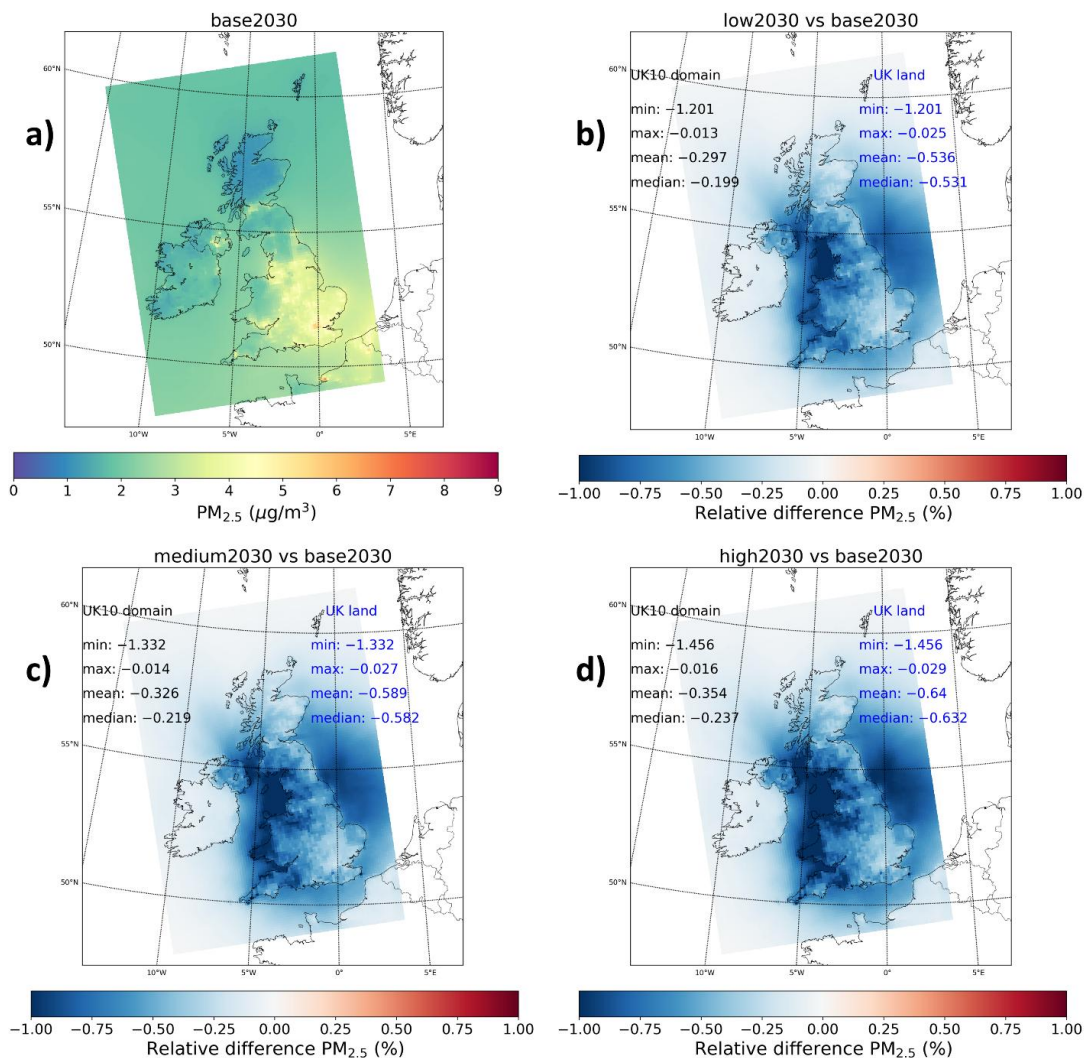
### 3.1.2 Future changes

440 Reductions in NH<sub>3</sub> emissions are effective at reducing NH<sub>3</sub> concentrations and its deposition at a regional scale (10 km × 10 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<sub>4</sub>) since the UK is characterized by an NH<sub>3</sub>-rich chemical domain. This confirms the finding that the decrease in NH<sub>3</sub> 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<sub>3</sub> (Pan et al., 2024). Consequently, the PM<sub>2.5</sub> concentrations are only slightly  
445 impacted by the mitigation on agricultural activities implemented in our scenarios, as shown in Figure 5. Indeed, the reduction in the annual mean PM<sub>2.5</sub> 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.

At the opposite, Ge et al. (2023) showed an important impact of the NH<sub>3</sub> emission reduction in PM<sub>2.5</sub> concentrations in the  
450 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<sub>3</sub> in the SIA formation.

Moreover, the scenarios have focused on mitigating NH<sub>3</sub> emissions, while targeting other secondary PM<sub>2.5</sub> precursors (NO<sub>x</sub>  
455 and SO<sub>x</sub>) can be needed to effectively curb the PM<sub>2.5</sub> 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<sub>3</sub> in the modelling as shown in Figure S1. This suggests also an impact of the atmospheric chemistry in the change in PM<sub>2.5</sub> concentrations.

460 The evaluation of CMAQ has shown a substantial negative bias in simulated PM<sub>2.5</sub> concentrations affecting confidence in the absolute concentration levels. This also requires caution when interpreting the mitigation scenarios, because the simulated PM<sub>2.5</sub> responses are small. Since the baseline and scenarios simulations use the same modelling framework, some systematic errors may partially cancel when scenario differences are calculated. These scenarios results should therefore be interpreted as indicative of the direction and likely limited regional influence of NH<sub>3</sub>-focused mitigation on PM<sub>2.5</sub>, rather than as precise  
465 quantitative estimates of change.



470 **Figure 5: a) Spatial distribution of annual mean PM<sub>2.5</sub> concentrations in µg/m<sup>3</sup> 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: ((scenario-base)/base) × 100%.**

### 3.2 Local scale: dispersion near the farms

475 Regional modelling has been used to estimate the contribution of agricultural NH<sub>3</sub> to the formation of secondary PM<sub>2.5</sub> at a regional scale, whereas local scale modelling has been used to investigate dispersion of NH<sub>3</sub> and PM<sub>2.5</sub> closer to farms (within 10km). This modelling approach differs from regional modelling, which incorporate atmospheric chemistry to estimate PM<sub>2.5</sub> 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<sub>2.5</sub> 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.

480 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 NH<sub>3</sub> impact values (percentage reduction) were adopted between regional and local modelling, with PM<sub>2.5</sub> 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.

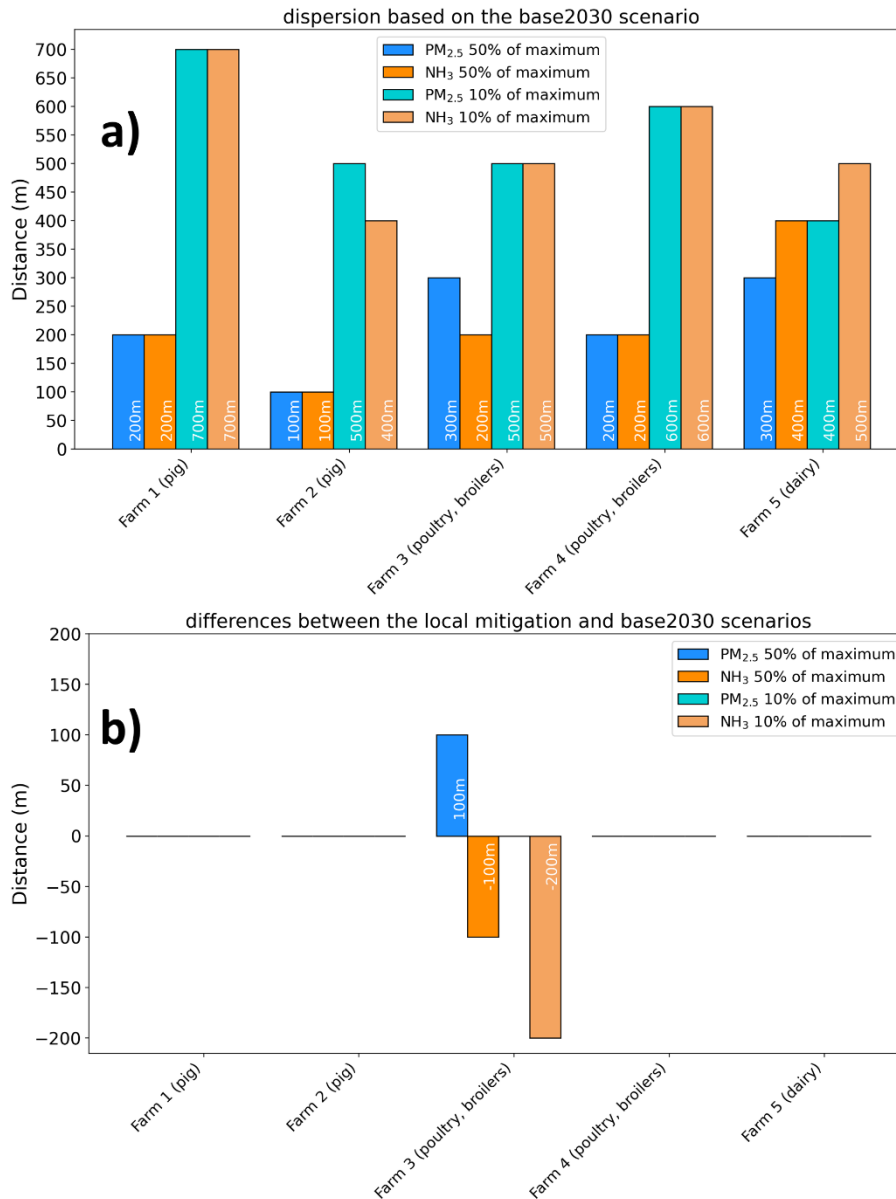
485 Figure 6 represents study farm's contributions of NH<sub>3</sub> and primary PM<sub>2.5</sub> under existing farm operations (base2030), and the differences between the mitigation scenario and this reference. These farms were in different parts of the UK as shown in Figure 2. In the local modelling, 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  
490 measures for each farm are described in Table 2.

Across the existing and mitigation scenarios the greatest distance for concentrations of NH<sub>3</sub> and PM<sub>2.5</sub> 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. Indeed, such near-source concentrations in local  
495 modelling are highly sensitive to source geometry, release height, buoyancy, and initial momentum. Predictions beyond ~100 m are less sensitive to source dimensions but can still depend strongly on efflux conditions and building effects (Stocker et al., 2015).

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  
500 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 NH<sub>3</sub> and primary PM<sub>2.5</sub> 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<sub>2.5</sub>, and the NH<sub>3</sub> concentration remained highly localized around the farm.

505 The highest NH<sub>3</sub> 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.



510 **Figure 6: a) Farm's contributions of NH<sub>3</sub> and primary PM<sub>2.5</sub> 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 10km<sup>2</sup> area, and maximum concentration for sensitive receptors. Table 3 shows that within 1km of farms included in this study there can be reductions between 25 and 80% of total NH<sub>3</sub> concentrations and 4 and 60% reductions of PM<sub>2.5</sub>.

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 NH<sub>3</sub> and 60% reduction in PM<sub>2.5</sub> emissions.

520 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 NH<sub>3</sub> emissions and will have a smaller impact on NH<sub>3</sub> 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.

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

Farm	Reduction in max concentration in 10km <sup>2</sup> study area (µg/m <sup>3</sup> )		Reduction in max concentration for sensitive receptors (µg/m <sup>3</sup> )	
	PM <sub>2.5</sub>	NH <sub>3</sub>	PM <sub>2.5</sub>	NH <sub>3</sub>
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%

525

#### 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 challenges. This approach also considered the actual barriers and incentives that farmers experience, leading to realistic  
530 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 under different regulatory environments. Moreover, the method has not differentiated uptake scenarios between different  
535 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.

Although CMAQ is state of the art and widely used in scientific research and policy development, the model also has  
540 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 NH<sub>3</sub> emissions. In addition, the local processes cause the majority of NH<sub>3</sub> to be dispersed near the studied farms as highlighted by ADMS results. The ADMS results showed a steep decline in farm-scale NH<sub>3</sub> and primary PM<sub>2.5</sub> concentrations, with concentrations decreasing by around 90% within 700 metres of the studied farms. This indicates strong near-source concentration gradients and highlights the importance of local exposure close to farms.

The limited impact of the mitigation measures at a regional scale, which mainly target the NH<sub>3</sub> emissions, on PM<sub>2.5</sub> concentrations can be due to an NH<sub>3</sub>-rich atmosphere in the UK and highlights that other precursor of these PM<sub>2.5</sub> and the primary PM<sub>2.5</sub> emissions need to be tackled. This confirms the findings from Pan et al. (2024) arguing for more collocated aerosol and precursor observations for better characterization of SIA formation. This also highlights that exposure on secondary PM<sub>2.5</sub> near the farms needs also to be investigated while most air quality studies focus on total PM<sub>2.5</sub> concentrations.

Further work is recommended to assess how mitigation measures can affect primary and secondary PM<sub>2.5</sub> at relevant 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 model parametrisation, emission measurement data and the associated farm activity data. A targeted local-scale modelling study can be developed to evaluate how variations in parameters such as emission factors, turbulence, and deposition velocities influence pollutant dispersion in the vicinity of the farms. 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 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 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 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.

## 5 Conclusions and Perspectives

This study highlights the complex interactions between NH<sub>3</sub> emissions from farming activities and PM<sub>2.5</sub> 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 NH<sub>3</sub>. Although emission reductions, particularly in NH<sub>3</sub>, were predicted under high uptake scenario, these changes did not translate into significant reductions in regional-scale PM<sub>2.5</sub> concentrations, with a maximum decrease of only 1.5%. This outcome is attributed to the NH<sub>3</sub>-rich atmosphere, which diminishes the effect of NH<sub>3</sub> reductions on PM<sub>2.5</sub> 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 modelled concentrations are applied, this suggests that key atmospheric processes influencing PM<sub>2.5</sub> formation may not be fully represented in the model, leading to an underestimation of PM<sub>2.5</sub> concentrations by approximately 50%. ADMS results further show that NH<sub>3</sub> is rapidly dispersed near the farms, indicating a limited role of these emissions in the formation of PM<sub>2.5</sub> 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<sub>2.5</sub> and other PM<sub>2.5</sub> precursors beyond NH<sub>3</sub> to achieve effective air quality improvements.

Overall, this suggested limited impact on potential NH<sub>3</sub>-focused mitigation strategies on PM<sub>2.5</sub> concentrations underscores the necessity of exploring additional emission control measures targeting other precursors and primary PM<sub>2.5</sub> emissions from the farming sector. Indeed, further work is recommended to review the national benefit of mitigation on primary PM<sub>2.5</sub> emissions, however benefits of mitigation are likely to be localised on PM<sub>2.5</sub> as demonstrated by ADMS modelling. Future research should also focus on primary and secondary PM<sub>2.5</sub> exposure separately near farms, as current air quality studies predominantly assess total PM<sub>2.5</sub> concentrations, and further work is required to understand the impact of secondary PM<sub>2.5</sub> 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<sub>2.5</sub> from agricultural sources in CMAQ, whereas ADMS has shown that the 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

finer temporal resolutions (e.g., daily, monthly) could yield deeper insights into exposure impacts. To strengthen understanding of near-field NH<sub>3</sub> 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.

610 Finally, the simulations were performed using meteorological fields from a single year (2019) and future work could incorporate multi-year or climate-perturbed meteorological datasets to better characterise the influence of meteorological variability on agricultural PM<sub>2.5</sub> formation.

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## Appendix -A

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.

640 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.

645 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).

650 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.

**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

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.**

	<b>Practices that reduce ammonia emissions</b>	<b>How does it reduce ammonia emissions?</b>
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.

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675 **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.

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

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**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.

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

685 **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.

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

690 **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.

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

**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.

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

695 **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.

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

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**Code availability:**

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>.

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**Data availability:**

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.

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**Author contribution:**

**MP:** Conceptualisation (equal), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Project Administration (lead), 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:** 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).

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**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.

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