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Integrating concepts of population exposure into atmospheric dispersion models at different spatial scales, taking into account individual mobility

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Abstract: The traditional approach of using static maps of residential population and annual average concentrations to determine population exposure levels is not capable of taking into account the spatial heterogeneity and the temporal variability of both ambient air pollutant concentrations, and the fact that populations are highly mobile. People spend substantial amounts of time at work places, schools, universities, often far away from their residence. In the United Kingdom, the 2011 census revealed that for some local authorities in the city of London, the population during a working day was tens of times larger than outside of working hours. This is, to a varying degree, the case in all urban areas. As pollution levels vary due to the temporal profile of emissions (driven by human activities), meteorology, physical transport and chemical transformation as well, applying state-of-the-art atmospheric chemistry transport models (ACTMs), integrated with the latest information on population distribution, offer the capability of quantifying human exposure in a dynamic fashion and with high spatial resolution. However, spatial and temporal resolution are related to at times substantial costs, in computing time, in the amount and degree of detail of input data required, and output data generated. For this reason, applying a nested approach with urban scale dispersion models (e.g. ADMS-Urban) within regional ACTMs (e.g. EMEP4UK) provides a suitable balance by providing the necessary resolution where it matters, while being efficient with regard to computing time and data needs overall.

In this paper, we focus on two aspects, first, we introduce the state of work on integrating data from the 2011 census to generate a consistent, detailed population data product for ingestion in our air pollution models. Secondly, we demonstrate the approach taken for a one-way nesting of the ADMS-Urban model within EMEP4UK. Finally, we illustrate the direct relevance and application of this approach for the development of national air pollution control policies on the example of identifying options for reducing population exposure to fine particulate matter ($PM_{2.5}$) in the United Kingdom.

The research described here is work in progress, as the census 2011 data have only recently been made available. Data processing is currently being completed with the results being computed in time for both the submission of the final version of this paper, as well as for presentation at iEMSs in San Diego. This paper will be revised accordingly for final submission to include these results.

Keywords: air pollution, health effects, spatial analysis, atmospheric modeling, population exposure.

1. INTRODUCTION

1.1. Rationale

Traditionally, environmental exposure of populations for instance to ambient air pollution is quantified by relating the location of residence to average pollutant concentrations derived from few air quality monitoring sites. This approach, while being relatively straightforward and not requiring detailed data on populations at risk, is subject to a range of potential errors and bias. One source of error is the implied representativeness of monitoring sites for a relatively large population catchment, while site locations are - in most cases - not selected to be representative for population exposure, but rather for specific urban or rural concentration patterns (e.g. kerbside, hotspot, urban or rural background). Secondly, a static approach does not account for the spatial and temporal variability of both the population at risk, and ambient pollutant concentrations. This introduces potentially substantial errors which may result in an overestimation (e.g. by allocating high urban exposure levels to population groups who do not spend time in that location during peak times) or underestimation of exposure (e.g. when episodic pollution levels are affecting specific population groups, which are not resident where the events occur).
More sophisticated approaches have been developed based on Geographical Information Systems (GIS) and Land-use Regression (LUR) models (e.g. Briggs, 2005; Gulliver and Briggs, 2011), using statistical representations of air pollution dispersion, primarily due to the rather high computing time required for full chemistry transport calculations. Yet, atmospheric chemistry transport models (ACTMs) today are well capable of modelling ambient air pollution levels with high spatial and temporal resolution. By combining space and time resolved model output with different detail levels of population mobility, we will demonstrate how different exposure assessments are compared to traditional, static approaches, and what the implications for the design of air quality policies are at different scales.

1.2. Aims and objectives

In this paper, we will demonstrate the approach taken to conceptually integrated data and nest models at different spatial scales to improve the resolution for the assessment of exposure of the population in the United Kingdom to ambient air pollution. This is particularly timely, as recent research has confirmed the long-standing theory that existing national air pollution monitoring networks are not adequate (in terms of their spatial representativeness) to relate exposure to air pollution to resulting respiratory or cardio-vascular health effects in the population (e.g. Willocks et al., 2012). However, epidemiologists still mainly rely on observations, to some extent motivated by the notion that model results are less accurate and reliable than monitoring data, when trying to quantify exposure and human health effects or ambient air pollution. To overcome this, we aim here to demonstrate that (a) atmospheric chemistry transport models are capable of representing real-world concentrations of key air pollutants with sufficient accuracy, (b) the capabilities of nested modelling systems are able to resolve specific urban and local hotspot conditions with a level of detail that is superior to any geo-statistical approaches to derive spatial maps of pollutant concentrations based on sparse monitoring network sites, and (c) the ability of models to enable assessments of future scenarios, as well as pollutant mixtures, provides unique advantages for the design of air pollution control strategies.
In this paper, we will focus on the methodological development of linking regional scale atmospheric dispersion models (in this case, the EMEP4UK model, Vieno et al., 2009, 2010) with a urban/street scale model (ADMS-Urban, Stocker et al., 2012) to assess, in a first step, how different scales affect the spatiotemporal distribution of priority air pollutants (Particulate Matter, Ozone) at each scale. This will include the effect of resolution on meteorological parameters, physical transport and chemical transformation from emissions to ambient concentrations. Furthermore, this paper will describe the process to link and integrated the two different models, establishing a model framework for the assessment of the main drivers of concentration changes and how they will affect population exposure to air pollution at each spatial scale. Finally, we will demonstrate how this model framework can be applied to assess the effect of air quality policy measures, as well as the impact of population mobility (commuting for work, school, spending time indoors and outdoors etc. based on Steinle et al., 2013) on population exposure assessment. This will provide robust evidence for future modelling and monitoring strategies, as current air quality monitoring networks are likely to present an inaccurate picture of population exposure.

Here, we describe here first and foremost results on (a) and (b), while work on (c) is still ongoing. A full paper is planned for publication in peer-reviewed literature later in 2014.

2. INPUT DATA

2.1. Population data

High resolution population data is a key requirement to assess exposure to air pollution in a spatially explicit fashion. For the United Kingdom, the 2011 Census provides the most up-to-date dataset available. As Fig. 1 illustrates, the changes in population levels and distribution over the ten years since the last census have been profound in many regions of the country, with some areas experiencing changes of more than 15%.

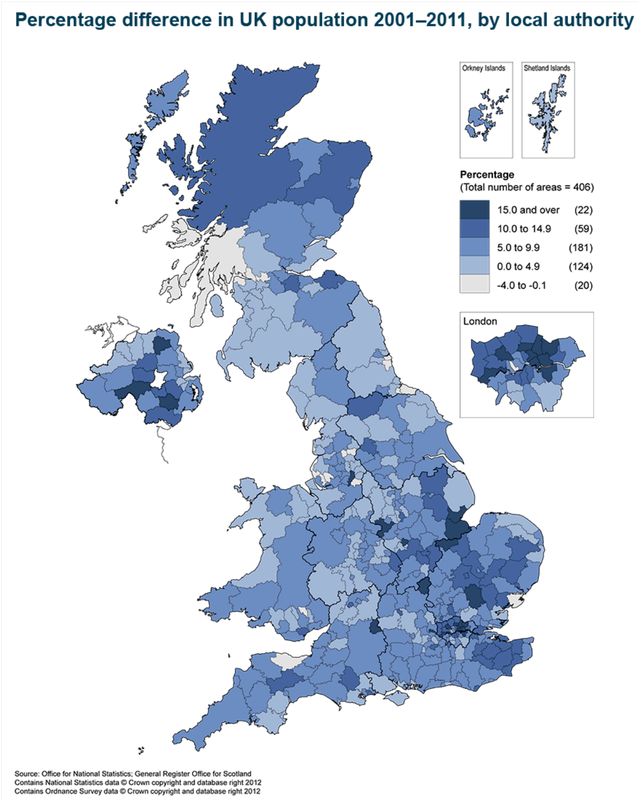

Figure 1. Illustration of the difference in UK population between the census in 2001 and 2011, by local authority

Census data is accumulated on so-called Output Areas[1] (OA), with a minimum OA size at 40 resident households and 100 resident people, while the recommended size being rather larger at 125 households. There are substantial differences in the area covered by individual OAs due to the large variation of population density between urban and rural areas. And as the OAs are based on administrative boundaries and thus polygon-based, they need to be processed and transformed into a format that can more readily be integrated with grid-based atmospheric model results.

2.2 Data processing

In a first instance, the geospatial data products (ESRI Shapefiles) provided by the Office for National Statistics (ONS) of the UK, in separate datasets for the four devolved administrations England, Wales, Northern Ireland and Scotland have been combined and quality checked and corrected for spatial integrity. Secondly, the resulting UK-wide dataset was overlaid with land-use data from the UK Landcover Map[2] 2007, which was released in July 2011 and presents the most up-to-date land-use information available. The two sub-classes "Urban" and "Suburban" were extracted and mapped in

[1] http://www.ons.gov.uk/ons/guide-method/geography/beginner-s-guide/census/output-area--oas-/index.html
[2] http://www.ceh.ac.uk/landcovermap2007.html

the same format as the Census population data. The data processing is conducted using the SAFE Software Feature Manipulation Engine (FME) and ESRI ARC Map 10.

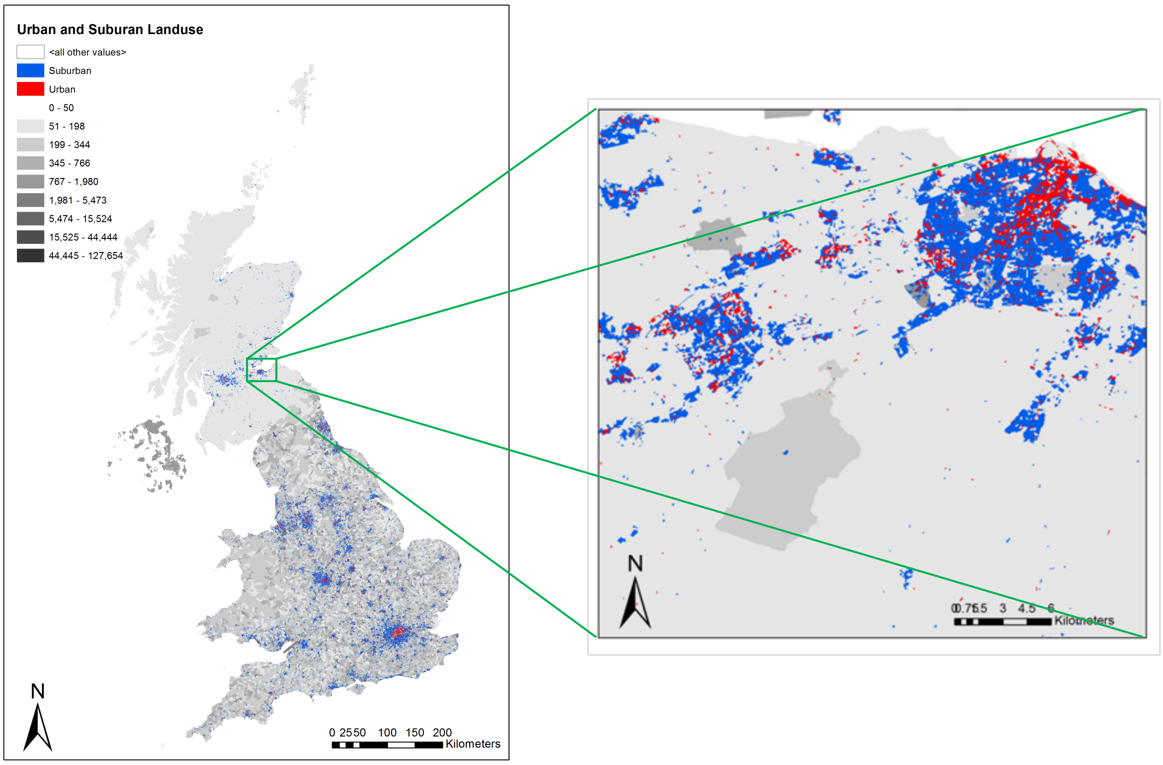

Figure 2. Combination of Census 2011 population data on Output Areas (Source: Office of National Statistics, UK, 2014) and Landcover Map 2007 (Source: Centre for Ecology & Hydrology, 2011) subclasses 'Urban' and 'Suburban' land-use for the whole of the UK (left) and the greater Edinburgh area (right).

2.3 Preliminary results

The integration of these two datasets is currently underway and will be completed in time for the final submission of this paper, providing a UK population map for 2011 at 1 km^2, 5 km^2 and 50 km^2 spatial resolution, which is consistent with the output resolution of the EMEP4UK atmospheric chemistry transport model (see Section 3.1). For the urban scale, higher resolution maps will be generated to match, as far as possible, the horizontal resolution from 25 - 100 m as required by the ADMS-Urban model, but this will likely require higher resolution data from local authorities, as the OA-based approach may be too coarse.

3. NESTED ATMOSPHERIC MODELLING APPROACH

3.1 The models

EMEP4UK

The EMEP4UK model, which is derived from the *European Monitoring and Evaluation Programme* (EMEP)[3] open source model version rv4.3. The model uses two domains, European at 50 km × 50 km, within which the domain covering the British Isles is nested at a resolution of 5 km × 5 km (Figure 2). The meteorological fields are computed with the Weather Research Forecast (WRF) model version 3.1. This model has been used to calculate hourly surface concentrations key pollutants for the year 2008 in a first approach to nest a regional model with an urban model for the greater London area. The emissions are derived from the EMEP inventory (for the European domain),

[3] http://www.emep.int

the UK National Atmospheric Emission Inventory (NAEI) (for the UK) and, for shipping, a separate inventory generated by AMEC[4]. The EMEP4UK model uses meteorological data from the Weather Research Forecast (WRF) model version 3.1. The horizontal resolution of the model over London used for testing the nesting approach is 5 km x 5 km, with the depth of the lowest vertical grid layer is 90 m. Meanwhile, 1 km x 1 km horizontal resolution runs with EMEP4UK have been tested for the UK and are available for selected regions. Concentrations were extracted from each EMEP4UK grid cell of interest for comparison with monitored data and for input to the nesting system.

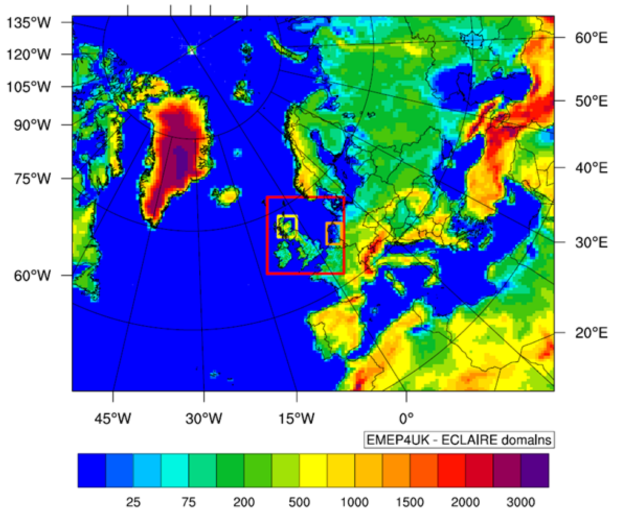

Figure 3. EMEP4UK model domains, including the outer domain covering Europe and the North Atlantic at 50 km x 50 km horizontal resolution and the British Isles at 5 x 5 km resolution (red box). The yellow and orange rectangles show domains for which 1 km x 1 km resolution has been successfully tested, with further high resolution areas currently being added.

ADMS-Urban

A standard ADMS-Urban[5] model run with meteorology from the Heathrow airport meteorological station and measured upwind rural background concentrations was carried out by Cambridge Environmental Research Consultants (CERC). Emissions for ADMS-Urban were taken from the LAEI for 2008. Major roads and large point sources are modelled explicitly, with other emissions such as minor roads and domestic combustion modelled on a grid at 1 km resolution. The results from this run are labelled as 'ADMS only' in the graphs and tables which follow.

ADMS-Urban nested in EMEP4UK

A map of the EMEP4UK nesting domains is given in Fig. 4 (left). Note that this figure uses the EMEP4UK coordinate system, which is rotated relative to Ordnance Survey Great Britain National Grid (OSGB) coordinates. The nesting domain covers a 10 km x 10 km area including the congestion charging zone in central London. Each of the four EMEP4UK cells covered by the nesting domain was modelled as a separate sub-domain. Meteorology for each sub-domain was extracted from the data used in the corresponding EMEP4UK grid cell. Emissions for ADMS-Urban were taken from the London Authority Emission Inventory (LAEI) for 2008. Time-varying profiles for nesting background concentrations were taken from EMEP4UK, while the gridded and explicit nested runs used standard profiles for London. Background concentrations were extracted from EMEP4UK, and a nesting background calculated to represent the concentration in the relevant EMEP4UK cell during the period $0 < t < t_m$.

3.2 Results of the nested modelling approach

Fig. 4 illustrates both the area covered by the nested modelling approach (left) and exemplary results for concentrations of Nitrogen Dioxide (NO_2). The figure confirms the relevance of and need for high resolution modelling, if population exposure in densely populated urban areas is to be assessed with a sufficient degree of detail. The spatial features reproduced in the ADMS-Urban model results are not visible in the 5 km x 5 km or even the 1 km x 1 km EMEP4UK grid cells. On the other hand, however, both the requirements for high resolution input data (emissions, road networks, traffic flows, populations) and computing time make running models at a resolution of 25-100 meters on a country scale infeasible. The nesting approach combines the best of two worlds, in that it provides spatial

[4] http://www.amec-ukenvironment.com/downloads/Concawe_Final_Report_170407_v1_WEB_LOWRES.pdf
[5] http://www.cerc.co.uk/environmental-software/ADMS-Urban-model.html

detail where it is most needed, i.e. where high population density as well as spatial heterogeneity will affect population exposure most profoundly. At the same time, the regional model enables the assessment and evaluation of national to regional policy scenarios more efficiently, while providing vital boundary and initial conditions for the local scale models nested within their domain.

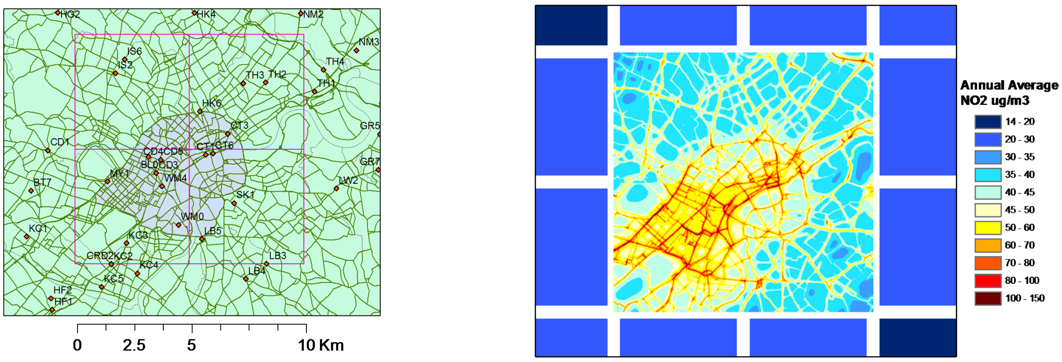

Figure 4. *Left:* Map of nesting domains. Air quality monitor locations are shown as red diamonds, and each pink square is the limit of a nesting sub-domain. The blue shading indicates the London congestion charging area. *Right:* Contour plots of annual average NO_2 concentrations, showing nested output within the nesting domain and EMEP4UK output outside.

4. FURTHER DEVELOPMENTS

The steps described in the previous sections illustrate the processing of input data, as well as the approach taken for nesting atmospheric chemistry transport models. In the case of population data, there are surprisingly no detailed data products readily available for the UK, for instance gridded population data, hence making the processing steps necessary. However, the UK Census 2011 has, for the first time, collected data on aspects of population movements, which we will describe in the following.

4.1 Workday population

One of the main concerns with using place-of-residence based population data and annual mean concentration data for the assessment of population exposure is that the majority of the residential population does spend substantial amounts of their time not at their residence. This includes children spending most of weekday daytime hours at nurseries or schools and people of working age about 25% of their time at the work place, which can be subject to very different air pollution levels. Research in Australia (Walsh et al., 2011; Cope et al., 2011) have found a general underestimation of population exposure in the greater Melbourne area using a residence-based approach in a modelling study for the year 2006.

For our study, the new product in the UK 2011 Census of *'workday population'* includes people who are usually resident and in employment (aged 16 and over) with a fixed place of work (part-time or full-time); when there is no fixed place of work, or work is mostly done from home, then the home address of the person is used for the workday population. The workday population includes shift and night workers such as hospital staff and security guards. Those not working (including those under 16) are counted at their usual residence.

The evaluation of this dataset is still ongoing, as it has only been recently released for all devolved administrations, but initial assessments indicate the potential for profound variations of exposure assessments. For the England and Wales, the workday population in 2011 was 56 million people, with the largest workday population gains for the age group from 16-74 being observed for the Inner London Boroughs, which experience more than 50% greater workday than usually resident populations. For example, the City of London Borough has a 56 times greater, the Westminster Borough 3 times and the Tower Hamlets 58% greater workday populations.

Further variability in age and gender distribution, which will be of interest for exposure and effects modelling, are available as well, but have not been assessed yet.

4.2 Episodes vs. annual average concentrations

Related to the aspect of people moving within their domain is the relevance of air pollution episodes and peak concentrations, which are not always well captured by monitoring networks. While individual sites may pick up peak concentrations, local conditions and the location of the site means that any interpolated products based on the few available monitoring stations are unlikely to represent the true spatial heterogeneity of pollution events.
On the other hand, the real meteorology drivers for state-of-the-art atmospheric chemistry transport models make it possible to reproduce pollution events, such as the 2003 ozone episodes over the UK (Vieno et al., 2010) or the high concentrations of secondary inorganic aerosols contributing to high levels of fine particulate matter (PM2.5) due to long-range transport (Vieno et al., 2014). This means, that a combination of spatio-temporally detailed population data and effectively modelling full 4D concentration fields can provide substantial added value to air pollution exposure assessment.

5. SUMMARY AND OUTLOOK

In this paper, we have described the approach and methodology for improving the use of - in a first instance - static high resolution population data based on the most recent UK census to improve the modelling of population exposure to air pollution. We have described as well the state of play for the development of a more dynamic approach under development.
While this comprises work in progress, we are well on track to demonstrate the first results of our assessments of different exposure scenarios based on these new datasets in time for the submission of the final, revised version of this paper.

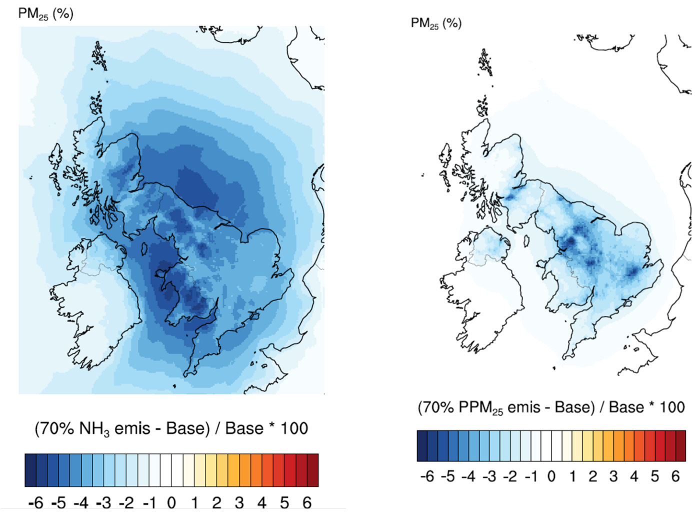

Figure 5. Percentage change in $PM_{2.5}$ concentrations simulated by the EMEP4UK model for a 30% emissions reduction of UK ammonia (NH_3) emissions (left) and the same for primary $PM_{2.5}$ emissions (right).

The relevance of this work can be demonstrated best by highlighting two recent modelling activities in support for the development of UK national air pollution control strategies. Fig. 5 illustrates the result of modelling a 30% reduction of UK emissions in either ammonia or fine particulate matter with the key question being on which emission control would be most effective in reducing population exposure (similar model calculations for sulphur dioxide, nitrogen oxides and volatile organic compounds conducted for this study are not shown here). These 30% reductions in NH_3 and primary $PM_{2.5}$ yield the greatest percentage reductions in $PM_{2.5}$ concentrations (up to ~6%, Fig. 5) but the key observation is the inverse relationship in the geographic patterns of the resulting $PM_{2.5}$ concentration sensitivity to these two components. The reductions in NH_3 emissions lead to the largest $PM_{2.5}$ concentration decrease in rural areas, whereas the reductions in primary $PM_{2.5}$ yield the largest decrease in areas of high population density. This reflects the geographical pattern of the sources and that, through the short atmospheric lifetime of NH_3, UK ammonia emissions primarily have short range impacts. Even though specific calculations for population-weighted concentrations have to be conducted (planned for April 2014), these simulations already give a clear indication that if the focus is on policies for the reduction of simple spatially-averaged $PM_{2.5}$ concentrations (e.g. ecosystem focus) then the most effective UK control is via NH_3, but that if the focus is on reduction of population-weighted $PM_{2.5}$ (i.e. a human health focus) the most effective UK control is via UK primary $PM_{2.5}$ emissions.

The method for integrating high resolution population data based on the latest Census and land-use information will substantially enhance the quantitative evaluation of this kind of policy scenario assessment and thus provide more robust policy evidence for the development of strategies. Ultimately, however, the introduction of a more dynamic approach, taking into account of population movement from rural into urban areas during workdays, may at the same time moderate the effect of control strategies focused on urban emissions. Due to several factors contributing to the overall outcome (time and location of emissions and concentrations, population movement, meteorology and land-use, respectively urban topography), the use of models in general, and nested regional and urban-scale models in particular, can without doubt be seen as the most promising way forward.

6. ACKNOWLEDGMENTS

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