Sub-grid variability and its impact on air quality exposure assessment

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Abstract: Long term exposure estimates over large areas can be made using a combination of air quality models and population density data. However, the grid resolution of such models is often limited to 25 – 50 km and there may be a significant level of unresolved variability within the grids that will impact on the exposure estimates. In this paper the sub-grid variability is assessed using air quality monitoring (AirBase) and population data, concentrating on the covariance of concentration and population, which is the defining term in estimating sub-grid population exposure. The error that occurs when calculating the urban background exposure is assessed. The assessment shows that the error made in the exposure calculation for all of Europe is small for typical CTM resolutions of 50 km. The error is largest for NO_2, where the average European urban background exposure is underestimated by 16%. Particulate matter is also underestimated, but only by 6%. Conversely, estimates of ozone exposure (SOMO35) are overestimated by a factor of 15%.

Introduction

The health impacts of air pollution have been investigated in a number of studies. Many of these studies make use of gridded air quality data either directly from models, e.g. CAFÉ (IIASA, 2005), or using a combination of models and monitoring, e.g. Fiala et al. (2009), to estimate the static population exposure for all of Europe. When finite grid resolutions are used the question arises:

"What is the error in the exposure calculation when using finite gridded concentration data and can a correction be implemented to account for this?"

Though grid resolution may have an impact on the physical and chemical descriptions of the models themselves, the subject of this study is the effect of grid resolution on the exposure estimates. Since regional scale chemical transport models (CTMs) do not capture the same spatial variability as the population, sub-grid variability (SGV) will also contribute to the exposure estimate. To deal with this question various schemes have been employed, e.g. CityDelta (Amann et al., 2007), that parameterize the 'urban increment'. This represents the concentration difference between urban and regional areas and is employed to improve the population exposure estimates in urban areas. An alternative to implementing an 'urban increment' is to simply increase the model resolution to better represent the population variability, though this is highly impractical on continental scales for long term assessments.

In actual fact, it is not necessary to increase the model resolution to resolve the concentration and population *variability* in an urban area. It is sufficient to resolve the *covariance* of the population and concentration fields. In other words, it is not necessary to increase a models resolution to improve the population exposure estimate if the population or concentration fields are uncorrelated since enhancing the model resolution will not improve the population exposure estimate.

To address this, a study has been carried out to quantify SGV, including parameterisations that can be used to estimate it. In this paper however we present just one aspect of the study, quantifying the total error when estimating European wide population weighted concentrations. This is achieved using air quality monitoring and population density data then calculating their covariance at varying spatial resolutions, to show how the total exposure estimate is dependent on resolution.

Method

The discretised population exposure (or population weighted concentration) $C_{pw,j}$ over any defined area A_j (index j) for a given period of time is defined as:

$$C_{pw,j} = \frac{\sum_i^n c_i p_i}{\sum_i^n p_i} \tag{1}$$

where c_i is the spatially distributed concentration within a specified sub-area i, p_i is the total population within that sub-area and there are n discrete sub-areas within the area A_j. $C_{pw,j}$ is used in exposure studies since it represents the average concentration that members of a population are exposed to. Since most epidemiological studies are carried out based on ambient air concentrations representative of larger urban areas we consider the sub-areas i to be some kilometers in size. In this study 3x3 km^2 is the smallest resolution assessed. The area A_j over which $C_{pw,j}$ is calculated can be representative of a typical grid square in a regional or global CTM, usually in the range of 25 - 200 km.

Eq. 1 can be rewritten in terms of the mean concentration C_j and the mean population P_j in the area A_j as follows:

$$C_{pw,j} = C_j \left(1 + \frac{\mathrm{cov}_j(c,p)}{C_j P_j} \right) = C_j \left(1 + COV_{CP,j} \right) \qquad (2)$$

Here we have substituted the discretised covariance function (cov_j) into Eq. 1. Eq. 2 written in this form implies a 'covariance correction factor' ($COV_{CP,j}$) for each of the j grid cells based on the covariance of population and concentration. Knowledge of this correction factor will indicate the 'increment' needed to the mean concentration (C_j) for each grid square j. If there is no covariance between population and concentration then this factor is 0. However, some degree of covariance is expected as many of the emission sources are directly related to population density.

COV_{CP} can be directly assessed using available monitoring (AirBase) and population data with the application of spatial statistical methods. This involves determination of the accumulated cross-variogram, which provides the covariance of two spatially distributed data fields, for a range of effective grid resolutions.

Monitoring data for NO_2, PM_{10} and the ozone indicator SOMO35 have been extracted from AirBase (AirBase, 2010) for use in the assessment. Only regional and (sub)urban background stations have been used in the study and population data at a resolution of 3x3 km^2 is used as representative for these background stations.

Results

In Fig. 1 the total covariance correction factor, as function of grid resolution, are shown for NO_2, PM_{10} and SOMO35. The curves provide the empirical relationship between the total covariance correction factor (as in Eq. 2 but additionally assessed over the whole domain) and the grid resolution. This factor represents the error made in calculating the total population weighted concentration for any given grid resolution. For example, at 50 km the correction factor for NO_2 is 16%, for PM_{10} this is just 6%. For SOMO35 the correction factor is negative at -15%.

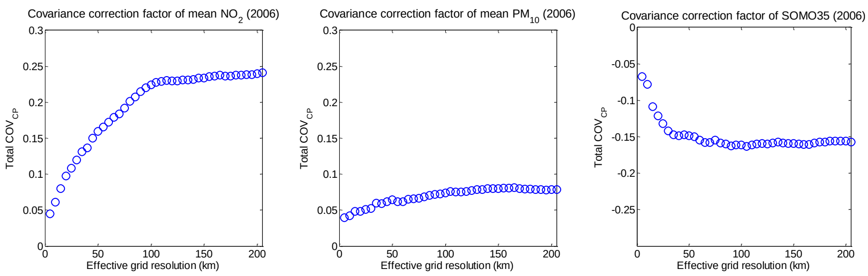

Fig. 1. Total covariance correction factor (COV_{CP}) for NO_2, PM_{10} and SOMO35 as a function of effective grid resolution (km). Scales are the same in all cases but note that the values are negative for SOMO35.

Conclusion

In this paper, the first part of a study assessing sub-grid variability and its impact on European wide exposure estimates is shown. These results indicate that a small but significant error in the population weighted concentrations can result due to the use of finite grid sizes. It is shown that the sub-grid covariance is the defining factor in determining this error and an assessment of this has been made using monitoring and population data for NO_2, PM_{10} and the ozone indicator SOMO35. The following conclusions can be made:

- The NO_2 covariance correction factor (16% at 50 km; 23% at 100 km) is more strongly dependent on grid resolution than is the PM_{10} factor. This is due to the relatively high correlation between NO_2 concentrations (NO_x emissions) and population density.
- The PM_{10} covariance correction factor (6% at 50 km; 8% at 100 km) shows a weak dependence on grid resolution. This is due to the spatial homogeneity of PM_{10} concentrations.
- SOMO35 shows a negative correlation, likely due to NO_x titration in urban areas, and as such ozone exposure estimates will be overestimated by 15% when finite grids of 50 km or more are used.
- Significant variability in the covariance correction factors will occur from grid to grid, but most 'gridded' covariance correction factors were found to be < |0.5| for all compounds.

The results presented in this paper are the first part of a wider study. In addition to the results presented here a simple paramaterisation for the sub-grid covariance has been developed that is based on the covariance of population density with emission and altitude data at 3 – 5 km resolution. This parameterisation has been applied to 50 km resolution model data (Unified EMEP model) for the entire EMEP domain to determine the total impact of SGV on exposure estimates. The results from this further work have shown that the impact of SGV may be more significant than is indicated by the assessment presented here, which is based on monitoring with a limited spatial coverage. This further assessment implies that the total error made in exposure estimates may be twice that presented here.

References

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