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Model and observation uncertainty analysis towards data assimilation on the urban scale

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1. Executive Summary

In this case study a model and observation uncertainty analysis towards the ultimate aim of combining an urban grid model with urban background observations in Oslo using methods and techniques of data assimilation has been performed. The model considered is the 22 x 18 km^2 urban grid model AirQUIS-EPISODE, which is a well-established air pollution dispersion model for the city of Oslo. The urban background observations consist of hourly and daily mean concentrations of NO_2, PM10 and PM2.5 at the three urban background stations Aker Hospital, Sofienberg Park and Skøyen. A model evaluation has been performed for the period 1 February – 31 March 2004, which shows a reasonable good agreement between observed and modelled values for the three compounds. The agreement is relatively poor for PM10 however, during dry periods in the spring each year, because of traffic-induced suspension and re-suspension of road dust mainly due to the use of cars with studded tyres.

Comparing observed and model calculated values, special emphasis have been put on analysing representativeness errors, since such errors become much more important than pure observation (or instrument) errors when comparing and combining point-like urban background observations with spatially averaged urban grid model concentrations using different methods and techniques of data assimilation. A theoretical relationship between model error and representativeness error standard deviations has been developed as part of this case study, based on estimated averages of ratios of observed and model calculated values at the urban background stations. Even though the derived relationships (and associated graphical curves) cannot be used to directly estimate model and observation uncertainties, using the derived relationships are nevertheless important if we are to be consistent in the apportionment of these uncertainties as input to data assimilation. The presently small number of available urban background stations (only 1-2 depending on compound) however, makes it difficult to use data assimilation as a technique for improving the urban grid model in Oslo at the present stage, except perhaps in areas close to the monitoring stations. Ideally we believe that at least 5-8 monitoring stations should be available as urban background stations in order to perform such data assimilation in a proper way.

Estimated model uncertainties have nevertheless been used to calculate probability of exceedance (POE) of national target values for 1 March 2004, which was a day during the winter/spring season of 2003/2004 with particularly high levels of air pollution in Oslo. Calculation of such values represents in our view a more robust approach for checking compliance with limit values, rather than simply checking whether a given model calculated value is above or below a certain limit value, since the former is generally less sensitive to errors in the model.

2. Case study description

This chapter contains a short background and situation overview of the air pollution situation in Oslo, with aim and description of the case study and relevance to recommendations in Air4EU.

2.1 Background

The city of Oslo is situated at about 60°N and 11°E in a basin at the end of a 100 km long fjord, surrounded by hills up to 500 m above sea level (see Fig. 1). The normal average monthly temperature is −5°C in January and 17°C in July.

Air pollution concentrations of nitrogen dioxide (NO_2) and coarse and fine particles (PM10 and PM2.5) in Oslo are mainly due to emissions from traffic and domestic heating (oil and wood burning) (Larssen et al., 2006; Laupsa et al., 2006, 2005, 2003; Oftedal et al., 2006; Lützenkirchen et al., 2004). The main source of PM2.5 are wood burning and emission of diesel exhaust from traffic, while road dust is the main source of PM10, mainly due to the use of cars with studded tyres. Large increases in the levels of PM10 typically occur during dry periods in the spring every year, due to re-suspension of road dust from traffic. During wintertime, periods with low wind speeds and strong atmospheric inversions typically lead to episodes with high levels of air pollution.

Fig. 1 shows the city of Oslo with the monitoring stations for the year 2004 (the year selected for this case study).

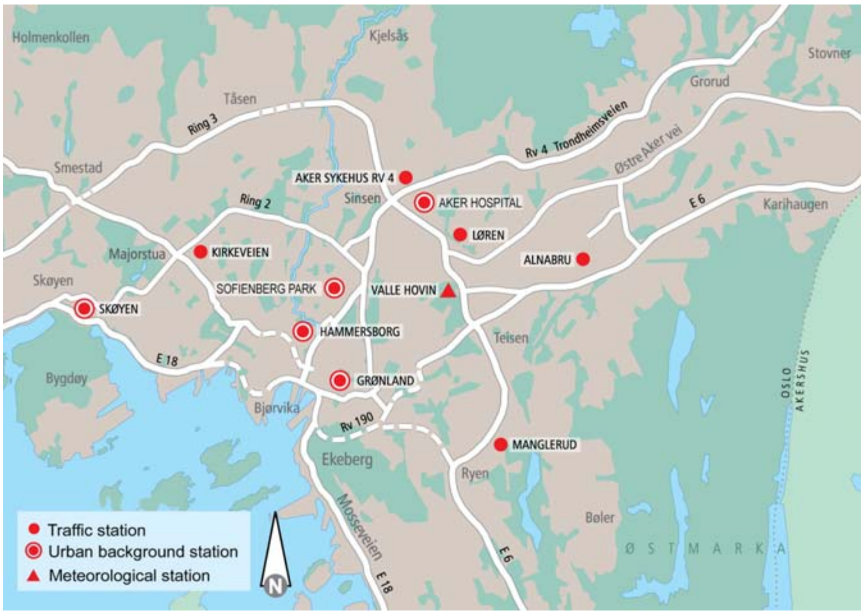

Figure 1: City of Oslo with the monitoring stations for 2004.

2.2 Aim and description

The main aim of this case study is to perform model and observation uncertainty analysis, towards the ultimate goal of combining concentrations calculated by an urban grid model with available observed urban background concentrations in Oslo, using methods and techniques of data assimilation (Swinbank, 2003; Kalnay, 2003). A thorough description of the concept of using data assimilation for combining air quality models with observations is given in the Air4EU milestone report M.5. The main motivation is to obtain a more accurate assessment of air pollution levels in Oslo, and to check compliance with any limit values.

The model considered here is the 22 x 18 km^2 urban grid model AirQUIS-EPISODE, which is a well-established air pollution dispersion model for the city of Oslo (Ødegaard et al., 2005; AirQUIS, 2003; Slørdal et al., 2003). The AirQUIS-EPISODE model is used on a regular basis in this city for calculating ambient hourly and daily mean concentrations of NO_2, PM10 and PM2.5 with a resolution of 1 x 1 km^2, which can be compared with observations from urban background stations (see Fig. 1). Since the focus of this case study will be on analysing such urban background concentrations, rather than local or hotspot concentrations close to busy streets or roads with traffic, we have put special emphasis on analysing so-called representativeness errors, which inevitably arises when comparing point-like observations with gridded (1 x 1 km^2) model values.

The calculation period selected is February-March 2004, which was the period during the winter/spring of 2003/2004 with the highest air pollution levels of NO_2, PM2.5 and PM10 in Oslo (Lützenkirchen et al., 2004), and hourly mean values of NO_2 and daily mean values of PM10 and PM2.5 are considered since these averaging periods are directly related to the limit values. Probabilities of exceedance of limit values (POE) are calculated based on estimated model uncertainties.

2.3 Relevance to recommendations in Air4EU

The main recommendations addressed in this case study are:

- Use of monitoring to evaluate and validate urban grid models
- Evaluation of model and observation uncertainties as necessary input for combining urban grid model concentrations with urban background observations using different methods and techniques of data assimilation
- Evaluation of urban grid model uncertainties as necessary input to calculate gridded fields of probabilities of exceedance (POE) of limit values

3. Methodology

This chapter contains the methodology used to derive the results in Chapter 4.

3.1 The AirQUIS-EPISODE model system

3.1.1 The AirQUIS-EPISODE model

The AirQUIS-EPISODE model has been used in several studies already for Oslo (Larssen et al., 2006; Oftedal et al., 2006; Kukkonen et al., 2005; Laupsa et al., 2006, 2005, 2003; Ødegaard et al., 2005). The model is a combined three-dimensional Eulerian/Lagrangian air pollution dispersion model for urban and local-to-regional scale applications, and calculates hourly average ground level concentrations both in grids and in irregularly placed receptor points. A detailed technical description of the AirQUIS-EPISODE model is given in Slørdal et al. (2003). The model is also described in the Model Documentation System (MDS) of the European Topic Centre on Air and Climate Change (http://air-climate.eionet.europa.eu/). The version of the model used in this case study was recently updated regarding emissions of PM2.5 from wood burning (Larssen et al., 2006).

The Eulerian part of the model consists of a numerical solution of the atmospheric (mass) conservation equation of pollutant species in a three-dimensional Eulerian grid. For Oslo, the grid consists of 22 x 18 km^2 grid cells in the horizontal E-W and N-S directions and 10 layers in the vertical. The height of the layers are 14 m closest to the ground and then increasing upwards, being approximately 1000 meter for the layer furthest from the ground. The advection and diffusion equations of the model are formulated using a sigma coordinate transform, where the grid cells follows the terrain close to the ground and being more independent of the terrain higher up (stretched vertical coordinate). The Lagrangian part of the model consists of separate subgrid-models for line- and point sources, but this part of the model is, however, not used here.

3.1.2 Emission data

The emission data used in the AirQUIS-EPISODE model for Oslo consists of hourly emissions from the following four source categories:

- Road traffic (line and area sources)
- Domestic heating (area sources)
- Industry (point sources)
- Other sources (area sources)

About 70% of the emissions of nitrogen oxides (NO_x and NO_2) in Oslo are due to traffic sources, while the emissions of PM2.5 are distributed evenly between traffic sources and domestic heating (mainly wood burning) during the winter season (Haakonsen, 2001, 2000). The main source of PM10 is traffic, in particular as suspended and re-suspended road dust due to the use of cars with studded tyres. High levels of PM10 typically occur during dry periods in the spring every year, due to the re-suspension of road dust from traffic.

The calculation of emissions from traffic use emission factors which take into account characteristics of each road and street such as speed limit, elevation, type of vehicles, year of emission, technical vehicle improvements etc. Estimated annual average daily traffic flow for each road and street is thus converted to estimated traffic emissions in tons per year, for each road and for each emitted pollutant. Time variations in the traffic is then used to calculate emissions according to weekday and hour of the day, capturing typical variations during working days and weekends, but without seasonal adjustment. In this case study, emissions from all line sources (roads) are distributed as area sources for each grid cell, uniformly within the lowest layer. For PM10, re-suspension of road dust induced by car turbulence has also been taken into account in the estimation of traffic emissions.

Calculation of emissions from domestic heating is based on consumption data for fuel oil and wood burning, together with specific emission factors for each pollutant (Haakonsen, 2001, 2000). In addition weekly and hourly factors, reflecting seasonal and daily variations, are used to calculate hourly emissions, which are distributed horizontally in proportion to the population size within each grid cell, and evenly in the two vertical grid layers closest to the ground.

Emissions from other sources such as primary industry, public services, motorized instruments, ship and railway traffic etc. have also been included in the model emissions. These sources are, however, of minor importance in Oslo compared to car traffic and domestic heating.

3.1.3 Meteorological data

Meteorological data for Oslo is obtained from the meteorological station Valle Hovin (see Fig. 1). The data consists of hourly measured values of wind speed and direction at 10 m (above ground), temperature at 2 m, temperature difference between 25 m and 8 m (stability), and relative humidity.

Hourly wind fields are calculated using the diagnostic wind field model MATHEW (Slørdal, 2002), which takes into account both topography and stability in the construction of the wind fields. A separate meteorological preprocessor (MEPDIM) is used to calculate other meteorological data, such as horizontal and vertical turbulence intensity, friction velocity, Monin-Obukhov length, Lagrangian time scale, mixing height etc., based on standard boundary layer (Monin-Obukhov) similarity theory (Slørdal et al., 2003).

3.1.4 Regional background and photochemistry

Maximum of hourly average concentrations of observed ozone (O_3) at the three rural stations Birkenes, Prestebakke and Hurdal in southern Norway are used as spatially constant hourly average regional background ozone concentrations for Oslo. Daily mean concentrations of NO_2, PM10 and PM2.5 observed at Birkenes are used as spatially constant hourly average regional background concentrations of these compounds for Oslo for each day. Regional background concentrations of NO are considered to be negligible and have not been included in the calculations.

NO_2 is calculated in the AirQUIS-EPISODE model based on a standard photochemical equilibrium model between NO, NO_2 and O_3 (Slørdal et al., 2003).

3.2 Urban background air quality observations

During the period February-March 2004, which is the period considered in this case study, between 5 and 7 air quality monitoring stations were available in Oslo depending on compound (see Fig. 1) (Helse og velferdsetaten, 2004a,b). The stations are either classified as traffic stations, or urban background stations, depending on the distance to the closest road or street with busy traffic. Urban background stations are defined as those stations where nearby roads (closer than 50 m) have an annual average daily traffic of less than 3000 vehicles.

The stations Grønland and Hammersborg, however, although being classified as urban background stations, have not been used in this case study since the observed concentrations at these stations (DOAS) represent averages over longer distances, and much higher above ground, than the observed concentrations at the other urban background stations.

The resulting set of urban background stations used in this case study is shown in Table 1.

Table 1: Urban background air quality stations in Oslo in February-March 2004

Name of station	Compounds measured
Aker Hospital	NO_2, PM10, PM2.5
Sofienberg Park	NO_2
Skøyen	PM10

The distance to the nearest road varied from 15 to 160 m at these urban background stations, and the instrument equipment used to measure the compounds were Monitor Labs Nitrogen Oxides Analyser Model 8840 for NO_2, and TEOM Series 1400 Ambient Particle Monitor for PM2.5 and PM10.

3.3 Model evaluation

Before combining observed and model calculated values using methods of data assimilation it is important that the model has been thoroughly evaluated. Table 2 show model evaluation parameters used to evaluate the AirQUIS-EPISODE model in this case study.

Ideally, the model should show little or no bias as compared to the observations, i.e., the model should not underestimate or overestimate concentrations systematically as compared to the observations. This means e.g., that the normalized mean difference parameter (NMD) defined in Table 2 should be zero or close to zero. Also the root mean square error parameter (RMSE) should be small. In particular, the systematic root mean square error (RMSEs) should be small compared to RMSE. Furthermore, there should be a reasonable good time correlation (perhaps 0.5 or higher) between the model and observed values before attempting to apply data assimilation.

For a more comprehensive overview and interpretation of these evaluation parameters and others see Chang & Hanna (2005; 2004). This is also described in the Air4EU milestone report M.2.

Table 2: Definition of model evaluation parameters

Parameter	Formula
Average	$\overline{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$
Standard deviation	$\sigma_C = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(C_i - \overline{C})^2}$
Maximum	$C_{max} = \max C_i \text{ for } i = 1,...,n$
Normalized mean difference	$NMD = (\overline{M} - \overline{O})/\overline{O}$
RMSE (Root Mean Square Error)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - M_i)^2}$

RMSE Systematic part	$\mathrm{RMSE_s} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - M'_i)^2}$
Linear regression equation with coefficients a and b	$M'_i = a + b \cdot O_i$
Normalized RMSE	$\mathrm{NRMSE} = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(O_i - M_i)^2}{\bar{O} \cdot \bar{M}}}$
Correlation	$\rho = \frac{\frac{1}{n-1}\sum_{i=1}^{n}(O_i - \bar{O}) \cdot (M_i - \bar{M})}{\sigma_O \cdot \sigma_M}$

In addition to using the above defined evaluation parameters, a good evaluation also includes using different graphical techniques to study the relationship between the model and the observed values, such as e.g., time series plots, scatter plots etc.

3.4 Model and observation uncertainty analysis

Here we define model, observation and representativeness errors and we will describe how averages of ratios of modelled and observed concentrations at the urban background stations can be used to estimate first and second order moments, i.e., mean and standard deviation of these errors. This can be used to check consistency of model and observation uncertainty as input to data assimilation, and in the calculation of probability of exceedance (POE).

For more on the issue of model and observation uncertainty, see the Air4EU milestone report M.2.

3.4.1 Model errors

Estimating errors and uncertainties in model calculated concentrations constitutes an essential part of combining model and observations using data assimilation, since this determines subsequently how much weight will be put on the model versus the observed values (Air4EU M.5; Swinbank et al., 2003; Kalnay, 2003). The total model error reflects the types of errors involved in the modelling of concentrations in an area, such as e.g., errors in emissions, errors in meteorology, errors associated with the description of physical or chemical processes, numerical errors etc.

If M_{ij} is a modelled grid cell concentration value in grid cell ij, and T_{ij} is the corresponding true grid cell concentration, we may write:

$$M_{ij} = T_{ij}(1 + \rho_{ij}) \qquad (1)$$

where ρ_{ij} denotes the relative error or accuracy of the modelled value. We may view the model error ρ_{ij} as a stochastic variable realized in the same moment as the model calculated value M_{ij} is produced by the model, given the true (but unknown) value T_{ij}.

For a good model, model errors ρ_{ij} should be close to zero, and if the model does not systematically overestimate or underestimate concentrations, the relative model errors ρ_{ij} should, on average, also be close to zero. Statistically this can be described by stating that the expectance value of ρ_{ij}, $E(\rho_{ij})$, should be zero, or close to zero.

If grid model concentrations, which represents spatial averages over the grid cells, are to be compared with observations from a set of irregularly placed urban background stations, which are assumed here to be point-like in nature, grid values will typically be interpolated to receptor points using different interpolation procedures, such as e.g., most typically bilinear interpolation. If e.g., M_1, M_2, M_3 and M_4 are four model grid cell concentration values closest to an observation point, a general interpolation procedure may be described as follows:

$$M_0 = w_1M_1 + w_2M_2 + w_3M_3 + w_4M_4 \qquad (2)$$

where w_i for i = 1,…,4, are four weights associated with the interpolation procedure, and M_0 is the resulting interpolated grid model value. The four weights are typically nonnegative and determined by the position of the observation point relative to the neighbouring grid cells. Usually they also sum to 1.

If we let T_i denote the true grid cell concentration, and ρ_i the relative model error, in each of the four grid cells i = 1,…,4, the interpolated grid model value M_0 can be written:

$$\begin{aligned} M_0 &= w_1T_1(1+\rho_1) + w_2T_2(1+\rho_2) + w_3T_3(1+\rho_3) + w_4T_4(1+\rho_4) \\ &= (w_1T_1 + w_2T_2 + w_3T_3 + w_4T_4)(1+\overline{\rho}_0) \\ &= T_0(1+\overline{\rho}_0) \end{aligned} \qquad (3)$$

where T_0 is the corresponding true interpolated concentration, and $\overline{\rho}_0$ is the resulting interpolated model error at the observation point. The interpolated model error can be viewed as the relative model error incurred at the observation point, compared to a perfect grid model having true concentrations as grid values, and T_0 as the corresponding true interpolated value.

Using Eq. 3 it also follows that the interpolated model error $\overline{\rho}_0$ can be expressed as follows:

$$\overline{\rho}_0 = \theta_1\rho_1 + \theta_2\rho_2 + \theta_3\rho_3 + \theta_4\rho_4 \qquad (4)$$

where the weights θ_i for i = 1,…,4 are defined as:

$$\theta_i = \frac{w_iT_i}{\sum_{j=1}^{4} w_jT_j} \qquad (5)$$

The interpolated model error $\overline{\rho}_0$ thus represents a nonnegative weighted average, with weights that sum to 1, of the relative model errors associated with the four neighbouring grid cells closest to the given observation point. From Eqs. 4 and 5 it follows that $\min(\rho_i, i = 1,\ldots,4) \le \overline{\rho}_0 \le \max(\rho_i, i = 1,\ldots,4)$.

It is, however, not possible to calculate the weights θ_i for i = 1,…,4, since they are all partly determined by the true grid cell concentrations, which are generally unknown.

3.4.2 Observation errors

Observation or measurement errors reflect the quality (precision and accuracy) of the instrument or instruments involved in the measurement process itself, and in the further processing of the measured values (Air4EU M.5; Swinbank, 2003; Kalnay, 2003).

If O is an observed concentration value at a given air quality station, and T_O is the corresponding true concentration at the same observation site, we may write:

$$O = T_O(1 + \rho_O) \tag{6}$$

where ρ_O denotes the relative observation error or accuracy of the measurement. This relative observation error ρ_O may also be viewed as a stochastic variable, being realized as part of the measurement process of obtaining the observed value O, given the true (but unknown) value T_O.

For a well-calibrated (unbiased) instrument, observation errors ρ_O should all be close to zero, also as an average. Statistically this can be described by stating that the expectance value of ρ_O, $E(\rho_O)$, should be zero, or close to zero. Observation errors are typically much smaller than model errors.

3.4.3 Representativeness errors

In addition to the above-defined model and observation errors, extra uncertainties may arise when comparing model-calculated and observed concentration values due to so-called representativeness errors (Air4EU M.5; Swinbank, 2003; Kalnay, 2003).

Representativeness errors are deviances or differences that occur between modelled and observed values due to different spatial or temporal averaging. For example, if we compare a modelled 1 x 1 km^2 hourly average concentration with an observed hourly averaged value measured at a single point within the same km^2, the two values may still differ because of their different spatial averaging.

If T_{ij} denotes the true grid cell concentration in grid cell ij, and T_O denotes the true concentration at an observation point within this grid cell, we may write:

$$T_{ij} = T_O(1 + \rho_R) \tag{7}$$

where ρ_R denotes the direct (non-interpolated) relative representativeness error at this observation point.

Furthermore, if T_i, for i = 1,…,4, denotes the true grid cell concentrations in the grid cells closest to the observation point, an interpolated representativeness error ρ_R can be defined as follows:

$$w_1T_1 + w_2T_2 + w_3T_3 + w_4T_4 = T_O(1 + \rho_R) \tag{8}$$

where w_i, for i = 1,…,4, denotes four weights involved in a linear interpolation of grid values to the observation point as defined in Chapter 3.4.1 above.

Either way, we may view the representativeness errors ρ_R as stochastic variables being realized by the real physical and chemical processes in the real atmosphere. Thus, they are clearly independent of both the model errors and the observation (measurement) errors.

If the measurement stations are representative as urban background stations, and the observed concentration values are close to the true gridded values, the representativeness errors ρ_R, or their expected value(s) $E(\rho_R)$, should be zero or close to zero.

For data assimilation purposes, especially when combining a given grid model with a set of point-like observations, it is important to take such representativeness errors properly into account, since they are usually much larger than pure observation or instrument errors. If they are not properly taken into account, too much weight will be put on observations as compared to the model-calculated values, and the assimilated values will appear with too small associated uncertainty (e.g., standard deviation).

For more on the general issue of representativeness of monitoring stations, see the Air4EU milestone report M.3.

3.4.4 Combining the errors together

We will now derive an expression linking the above three types of errors.

To this end consider the ratio between a given model calculated concentration value M and an observed concentration value O for a given observation point. The model value M can either be a direct grid value M_{ij} given by Eq. 1, or an interpolated value M_0 given by Eq. 3. The ratio of M divided by O can in either case be written:

$$\begin{aligned} \frac{M}{O} &= \frac{T\,(1+\rho_M)}{T_O(1+\rho_O)} \\ &= \frac{T_O(1+\rho_R)(1+\rho_M)}{T_O(1+\rho_O)} \\ &= \frac{(1+\rho_M)(1+\rho_R)}{(1+\rho_O)} \end{aligned} \qquad (9)$$

where T represents the true grid cell concentration T_{ij} given by Eq. 1, with model error $\rho_M = \rho_{ij}$, or the interpolated true value T_0 given by Eq. 3, with model error $\rho_M = \overline{\rho}_0$, and where we have used Eqs. 6-8 to define observation and representativeness errors ρ_O and ρ_R respectively.

The ratio M/O given by Eq. 9 thus represents a link between the above three types of error. It is nonnegative and dimensionless and independent of any of the underlying true (but unknown) concentrations, and also independent of any unit used for defining the concentrations. The ratio is equal to 1, and we have a perfect fit between modelled and observed concentration, if all the involved errors are zero.

Eq. 9 cannot be used though to uniquely identify the errors since it represents only one equation, but with three unknowns. If two of the errors are known, however, it be can be used to calculate the third.

The ratio M/O is related to the normalized (mean) difference NMD given in Table 2 simply by:

$$NMD = \frac{M - O}{O} = \frac{M}{O} - 1 \qquad (10)$$

Thus the ratio M/O is essentially the same as the NMD quantity, and the NMD quantity can therefore be expressed using the same involved errors as follows:

$$\mathrm{NMD} = \frac{(1+\rho_M)(1+\rho_R)}{(1+\rho_O)} - 1 \\ = \frac{\rho_M + \rho_R + \rho_M \cdot \rho_R - \rho_O}{(1+\rho_O)} \tag{11}$$

In the following we will, however, prefer to use Eq. 9 rather than 11, to relate the errors, since Eq. 9 is simpler and more symmetric.

The observation error is usually the smallest of the three errors, and can be included in a new (total) representativeness error $\rho_R = \rho_{O+R}$ by replacing $1/(1+\rho_O)$ in Eq. 9 with $1-\rho_O$ and neglecting higher order terms.

The ratio M/O may then be written:

$$\frac{M}{O} = (1+\rho_M)\cdot(1+\rho_R) \tag{12}$$

Further, if the (total) representativeness error $\rho_R = \rho_{O+R}$ is small compared to the model error, the ratio M/O can tentatively be expressed using the model error alone:

$$\frac{M}{O} = 1+\rho_M \tag{13}$$

3.4.5 Mean and standard deviation of errors

We will next derive expressions for the first and second order moment, i.e. the mean (expectation) and variance (or standard deviation) of the stochastic variables $1+\rho_M$ and $1+\rho_R$ given by Eq. 12.

If we let E(·) denote expectation, the following expression links the expected value of M/O to the model and representativeness error related expected values $\mu_M = E(1+\rho_M)$ and $\mu_R = E(1+\rho_R)$:

$$E(\frac{M}{O}) = E((1+\rho_M)\cdot(1+\rho_R)) \\ = E(1+\rho_M)\cdot E(1+\rho_R) \\ = \mu_M \cdot \mu_R \approx \overline{\left(\frac{M}{O}\right)} \tag{14}$$

In deriving the expressions in Eq. 14 we have used the assumption that the model and (total) representativeness errors are statistically independent, which is a reasonable assumption in the view of the definition of these errors in Chapters 4.3.1-3. The last part of Eq. 14 states that the expectation value may be estimated using averages of different M/O values.

Furthermore, if we let var(·) denote variance, the following expression links the expected value of $(M/O)^2$ to the model and representativeness error variances $\sigma_M^2 = \mathrm{var}(1+\rho_M)$ and $\sigma_R^2 = \mathrm{var}(1+\rho_R)$:

$$
\begin{aligned}
E\left(\left(\frac{M}{O}\right)^2\right) &= E\left(\left((1+\rho_M)\cdot(1+\rho_R)\right)^2\right) \\
&= E\left((1+\rho_M)^2\cdot(1+\rho_R)^2\right) \\
&= E(1+\rho_M)^2\cdot E(1+\rho_R)^2) \\
&= \left(\mathrm{var}(1+\rho_M) + (E(1+\rho_M))^2\right)\cdot\left(\mathrm{var}(1+\rho_R) + (E(1+\rho_R))^2\right) \\
&= (\sigma_M^2 + \mu_M^2)\cdot(\sigma_R^2 + \mu_R^2) \approx \overline{\left(\frac{M}{O}\right)^2}
\end{aligned}
\qquad (15)
$$

In deriving the expressions in Eq. 15 we have used the same assumption as in Eq. 14, namely that the model and (total) representativeness errors are statistically independent. The last part of Eq. 15 again states that the expectation value may be estimated using averages of different $(M/O)^2$ values.

Eqs. 14-15 represents two equations with four unknowns, the unknowns being the model and (total) representativeness error expectance or mean values μ_M and μ_R, and their variances σ_M^2 and σ_R^2 (or equivalently standard deviations σ_M and σ_R).

If we further assume that monitoring station(s) are representative as urban background stations, i.e., that the representativeness errors are approximately unbiased, then $\mu_R \approx 1$, and $\mu_M \approx \overline{(M/O)}$ from Eq. 14, and we have the following single expression linking model and representativeness error variances (or standard deviations):

$$
\overline{\left(\frac{M}{O}\right)^2} = \left(\sigma_M^2 + \overline{\left(\frac{M}{O}\right)}^2\right)\cdot(\sigma_R^2 + 1) \qquad (16)
$$

based on averages of ratios (linear and squared) of model and observed concentrations.

Eq. 16 can then be used to define consistent corresponding levels of model and representativeness error variances (or standard deviations) given average ratios of modelled and observed concentrations at different urban background stations. One should, however, bear in mind that the relationship given by Eq. 16 is only an approximation based on averages of ratios M/O and $(M/O)^2$, and furthermore that we have also assumed that the sample average bias $\overline{(M/O)} - 1$ is all due to the model.

3.4.6 Mean and standard deviation of Bayesian prior PDFs

Finally we want to find expressions for the first and second order moments, i.e., the mean (expectance) value and variance (or standard deviation) of a Bayesian statistical prior probability density function (PDF) of the true concentration T given the model-calculated concentration M. An overview of the relationship between Bayesian statistics and data assimilation is given in the Air4EU milestone report M.5, and also in Swinbank (2003) or Kalnay (2003). See also Box and Tiao (1992) or Berger (1985) for a more general and comprehensive description of Bayesian statistics.

Using Eq. 9 we may express the true concentration T in terms of the model calculated concentration M and the relative model error ρ_M as follows:

$$T = \frac{M}{(1+\rho_M)} \tag{17}$$

Given M, T can also be viewed as a stochastic variable, in a Bayesian subjective sense, given by the inverse of the relative model error stochastic variable $1+\rho_{iM}$. The mean and variance of T can then be written:

$$\begin{aligned} E(T) &= M \cdot E\left(\frac{1}{(1+\rho_M)}\right) \\ var(T) &= M^2 \cdot var\left(\frac{1}{(1+\rho_M)}\right) \end{aligned} \tag{18}$$

using the mean and variance of the inverse of the relative model error stochastic variable $1+\rho_M$. Based on the same derivation of expressions as in Eqs. 1–15, but using the inverse of the model and representativeness errors, one can easily show that the following expressions hold based on the inverse ratios O/M rather than M/O:

$$\begin{aligned} E\left(\frac{O}{M}\right) &= E\left(\frac{1}{(1+\rho_M)}\right) \cdot E\left(\frac{1}{(1+\rho_R)}\right) \\ &\approx \overline{\left(\frac{O}{M}\right)} \end{aligned} \tag{19}$$

for the expectance value, and the following expression for the variance:

$$\begin{aligned} E\left(\left(\frac{O}{M}\right)^2\right) &= \left(var\left(\frac{1}{(1+\rho_M)}\right) + \left(E\left(\frac{1}{(1+\rho_M)}\right)\right)^2\right) \cdot \left(var\left(\frac{1}{(1+\rho_R)}\right) + \left(E\left(\frac{1}{(1+\rho_R)}\right)\right)^2\right) \\ &\approx \overline{\left(\frac{O}{M}\right)^2} \end{aligned} \tag{20}$$

Deriving Eqs. 19-20 we have used the same assumption as before, namely that the inverse of the model and representativeness errors can be viewed as independent stochastic variables.

Furthermore, if we also assume that the observation point is representative as an urban background station, i.e., that the inverse of the representativeness error has expectance value 1, or close to 1, we may use Eqs. 19-20 to express a link between the inverse model and representativeness error variances:

$$\overline{\left(\frac{O}{M}\right)^2} = (\mathrm{var}(\frac{1}{(1+\rho_M)}) + \overline{\left(\frac{O}{M}\right)}^2) \cdot (\mathrm{var}(\frac{1}{(1+\rho_R)}) + 1) \qquad (21)$$

given averages of the inverse ratios (linear and squared) of the model and observed concentration values at the observation point.

Eq. 21 can be used to estimate the variance (or standard deviation) of the Bayesian statistical prior PDF given the representativeness error variance (or standard deviation), or vice versa. Like the previous expression given by Eq. 16, one should, however, bear in mind that the relationship given by Eq. (21) is also an approximation, now based on averages of ratios O/M and $(O/M)^2$, and that we have assumed that the average bias $\overline{(O/M)} - 1$ is all due to the model.

3.5 Probability of exceedance of limit values

Given a Bayesian statistical probability density function (PDF) p(c) one may calculate the probability that the true concentration exceeds a given concentration limit value c_{lim}. The probability, which is denoted by POE (Probability Of Exceedance), is calculated directly from the PDF p(c) by the following integral:

$$\mathrm{POE} = \int_{c_{lim}}^{\infty} p(c)\, dc \qquad (22)$$

POE values are typically given as percentage (%) values between 0 and 100%. If POE = 0%, the true concentration is below the given limit value with certainty. If POE = 100%, the true concentration is above the given limit value with certainty.

4. Results

This chapter contains the results based on the methodology described in Chapter 3.

4.1 Model evaluation

The AirQUIS-EPISODE model has previously been evaluated for Oslo in several studies (Oftedal et al., 2006; Kukkonen et al., 2005; Larssen et al. 2006; Laupsa et al., 2005, 2003; Ødegaard et al., 2005). These evaluations generally show that the model agrees reasonably well with hourly and daily observations of NO_2, PM10 and PM2.5. Best agreement is generally found for NO_2 and PM2.5. The agreement is somewhat poorer for PM10 during dry periods in the spring each year (March and April) mainly due to traffic-induced re-suspension of road dust. It is generally difficult to estimate the actual emission levels and dispersion of PM10 during these episodes.

In this case study we have evaluated the model for a 2-months period, 1 February – 31 March 2004, comparing the interpolated model grid concentrations with air quality observations taken from the urban background stations Aker Hospital, Sofienberg Park and Skøyen, for the three compounds NO_2, PM10 and PM2.5. The results of the evaluation is shown in Tables 3-5. For a description of the evaluation parameters used, see Chapter 3.3. The evaluation has been performed using hourly values of NO_2, and daily mean values of PM10 and PM2.5. Figs. 2-4 shows scatter plots of the same observed and modelled concentrations for the same stations and compounds.

Table 3: Model evaluation for NO_2 at stations Aker Hospital and Sofienberg Park. Period: 1 February – 31 March 2004. Unit: µg/m^3.

	Aker Hospital NO_2		**Sofienberg Park NO_2**	
Parameter	**Observed**	**Modelled**	**Observed**	**Modelled**
Average	32.6	28.9	56.2	38.8
Standard deviation	23.7	26.5	26.1	29.1
Maximum	129.6	115.2	145.7	125.6
Number of values	1427		1409	
Correlation	0.64		0.57	
RMSE	21.8		31.0	
RMSE systematic	7.7		19.8	
NRMSE (%)	51		66	

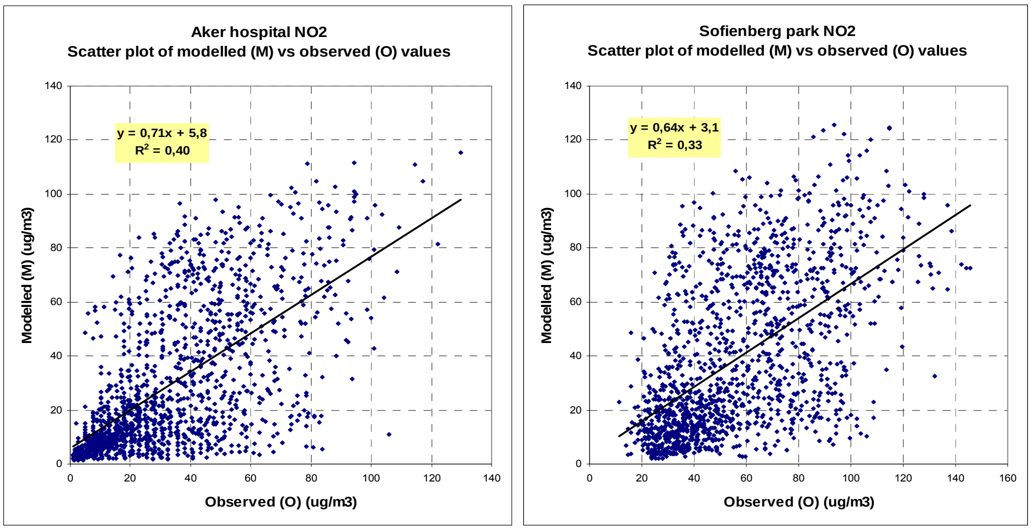

Figure 2: Scatter plot of observed (O) versus modelled (M) hourly mean values of NO_2 at stations Aker Hospital (left) and Sofienberg Park (right). Period: 1 February – 31 March 2004. Unit: µg/m^3.

As can be seen from Table 3, the evaluation shows a reasonable agreement between observed and modelled hourly average concentrations of NO_2 at the two stations Aker Hospital and Sofienberg Park, with somewhat better results at the former station compared to the latter, where there seems to be a slight underprediction of modelled NO_2 values. The scatter plots shown in Fig. 2 shows relatively large scatter around the regression lines at both stations. So there is clearly room for improvement in the modelling of NO_2 in Oslo during this period.

For PM10 and PM2.5 there are fewer values used in the evaluation since daily mean values are used instead of hourly average concentrations. The evaluation for PM10 (Table 4) based on daily mean values shows reasonable agreement between observed and modelled values at the two stations Aker Hospital and Skøyen, but this time with some overprediction of modelled values instead, especially regarding the maximum values. Correlation coefficients are found to be somewhat lower than for NO_2, while RMSE values are similar. Note however the very low systematic RMSE for PM10 at Skøyen, which is quite good. The scatter plot in Fig. 3 shows, as for NO_2, quite a bit of scatter around the regression line, so there is clearly room for improvement in the modelling of PM10 as well.

Table 4: Model evaluation for PM10 at stations Aker Hospital and Skøyen. Period: 1 February – 31 March 2004. Unit: µg/m^3.

	Aker Hospital PM10		**Skøyen PM10**	
Parameter	**Observed**	**Modelled**	**Observed**	**Modelled**
Average	20.8	30.6	41.1	41.2
Standard deviation	11.2	24.4	17.2	30.6
Maximum	63.5	103.8	100.8	185.2
Number of values	60		44	
Correlation	0.46		0.57	
RMSE	23.7		25.1	
RMSE systematic	9.8		0.2	
NRMSE (%)	94		61	

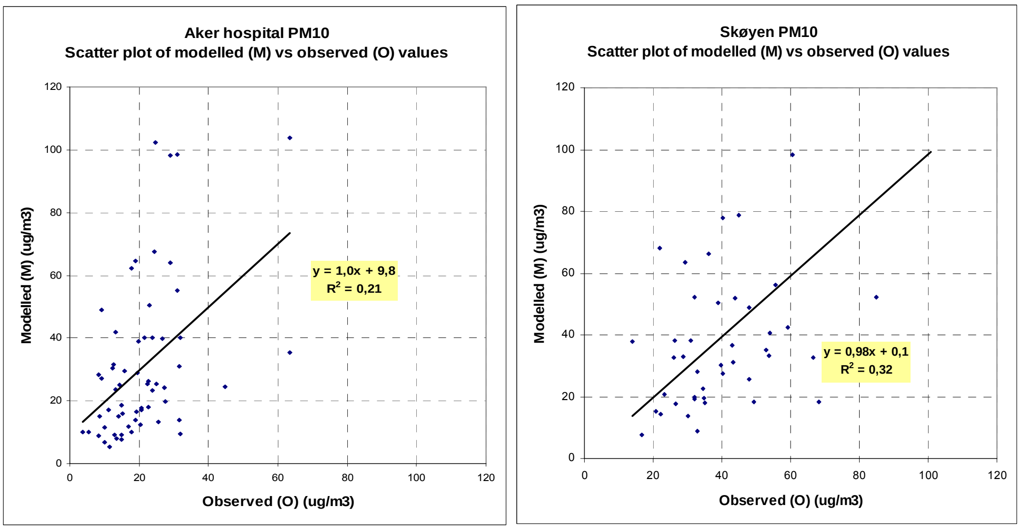

Figure 3: Scatter plot of observed (O) versus modelled (M) daily mean values of PM10 at stations Aker Hospital (left) and Skøyen (right). Period: 1 February – 31 March 2004. Unit: µg/m³.

The results of the evaluation of PM2.5 at station Aker Hospital (only) is shown in Table 5. Again some model overprediction is found, especially regarding the maximum concentration. The correlation coefficient is however quite good, and much better than for the other two compounds. This is also reflected in the much lower RMSE, which is quite good. The scatter plot (Fig. 4) also shows less scatter around the regression line for PM2.5 than for PM10 and NO_2. So all in all, the model seems to work quite well for PM2.5.

Table 5: Model evaluation for PM2.5 at station Aker Hospital. Period: 1 February – 31 March 2004. Unit: µg/m³.

	Aker Hospital PM2.5	
Parameter	**Observed**	**Modelled**
Average	10.2	12.1
Standard deviation	4.4	11.1
Maximum	23.6	55.9
Number of values	60	
Correlation	0.76	
RMSE	8.5	
RMSE systematic	4.4	
NRMSE (%)	76	

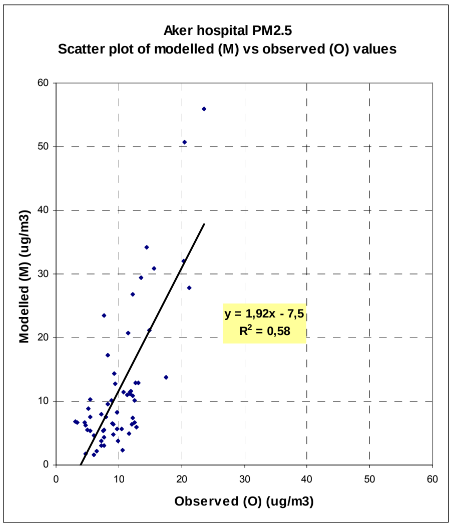

Figure 4: Scatter plot of observed (O) versus modelled (M) daily mean values of PM2.5 at station Aker Hospital. Period: 1 February – 31 March 2004. Unit: µg/m^3.

4.2 Analysis of model and representativeness errors

We want to estimate model and representativeness errors and their statistical properties (mainly mean and standard deviations), at each station and for each compound, based on Eqs. 12 and 14-16 given in Chapters 3.4.4 and 3.4.5.

To this end, ratios of M/O values have been calculated at each of the urban background stations Aker Hospital, Sofienberg Park and Skøyen and for each of the compounds NO_2, PM10 and PM2.5 during the period 1 February – 31 March 2004. The modelled concentrations M considered here are the interpolated model grid cell concentration values at each station (given by Eq. 2), based on a bilinear interpolation procedure. The calculations for NO_2 is based on hourly average values, while the results for PM10 and PM2.5 are based on daily mean values (only). The results are shown as time series in Figs. 5-7. Each value in the time series is then (approximately) the product of the involved relative model errors $1+\rho_M$ and $1+\rho_R$ according to Eq. 12.

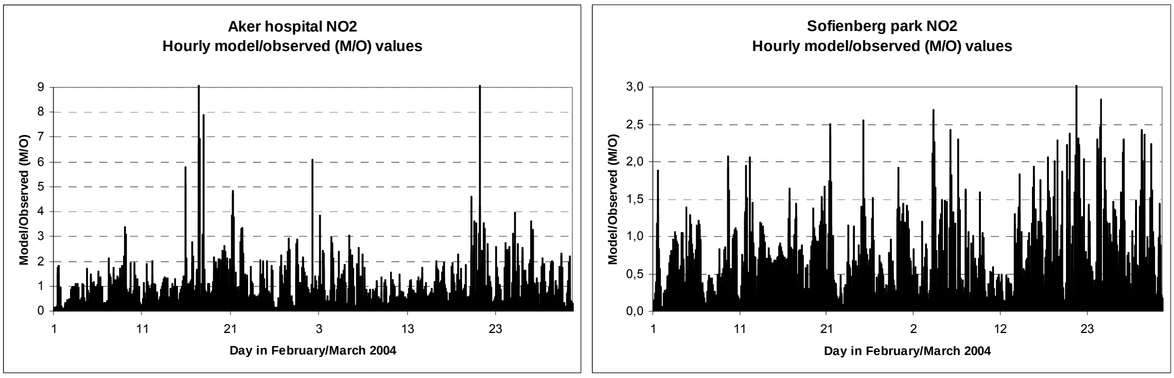

Figure 5: Hourly modelled/observed (M/O) values for NO_2 at station Aker Hospital (left) and Sofienberg Park (right). Period: 1 February 2004 – 31 March 2004. Unit: -.

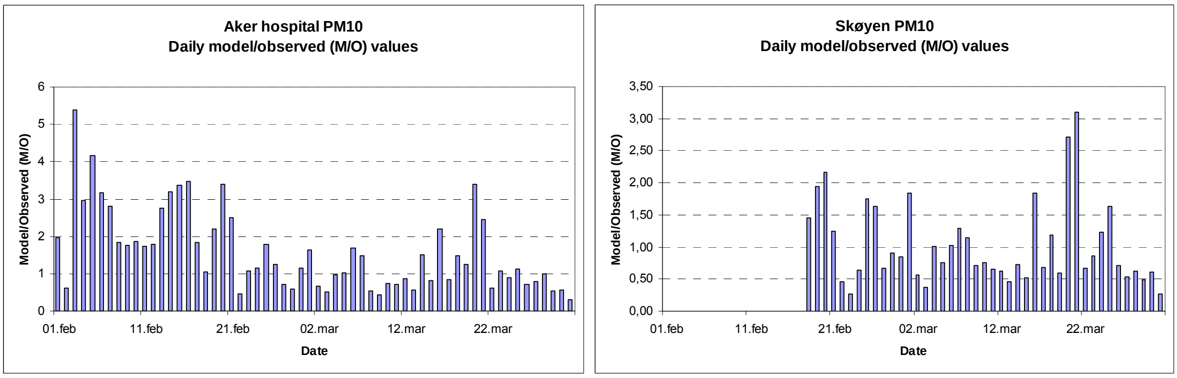

Figure 6: Daily modelled/observed (M/O) values for PM10 at station Aker Hospital (left) and Skøyen (right). Period: 1 February 2004 – 31 March 2004. Unit: -.

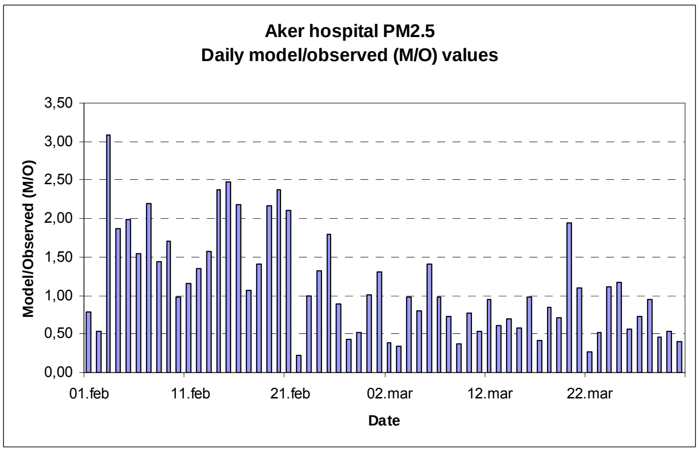

Figure 7: Daily modelled/observed (M/O) values for PM2.5 at station Aker Hospital. Period: 1 February 2004 – 31 March 2004. Unit: -.

Histograms showing the empirical distributions of the ratios M/O are shown in Figs. 8-10.

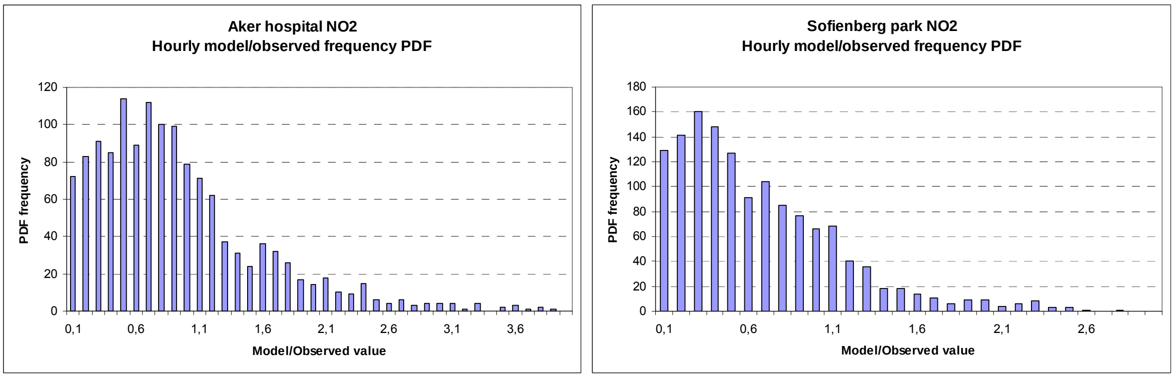

Figure 8: Frequencies (PDF) of modelled/observed (M/O) values for NO_2 at station Aker Hospital (left) and Sofienberg Park (right) from 1 February 2004 – 31 March 2004.

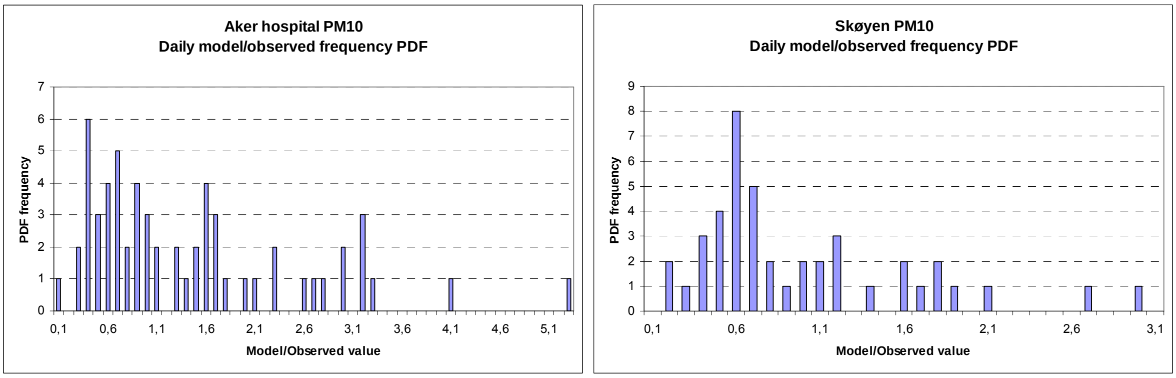

Figure 9: Frequencies (PDF) of modelled/observed (M/O) values for PM10 at station Aker Hospital (left) and Skøyen (right). Period: 1 February 2004 – 31 March 2004.

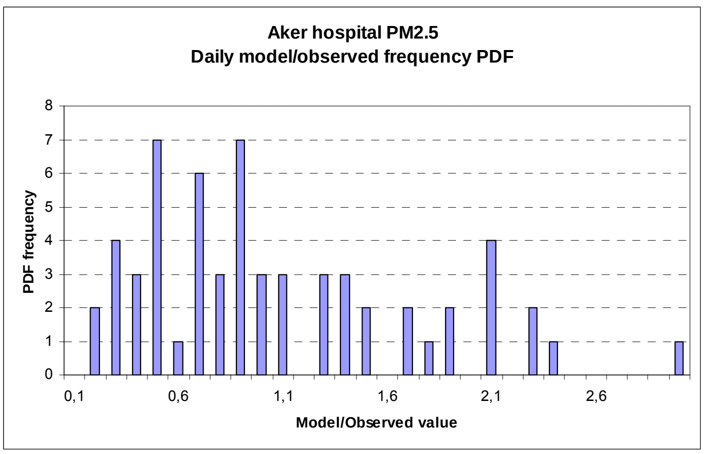

Figure 10: Frequencies (PDF) of modelled/observed (M/O) values of PM2.5 at station Aker Hospital. Period: 1 February 2004 – 31 March 2004.

Estimated means of M/O and $(M/O)^2$ values are shown in Table 6 for each compound and station.

Table 6: Estimated means of M/O and $(M/O)^2$ at urban background stations in Oslo. Period: 1 February 2004 – 31 March 2004. Unit: -.

Compound	**Station**	**Resolution**	**Number of values**	**M/O mean**	**$(M/O)^2$ mean**
NO_2	Aker Hospital	Hour	1408	1.01	1.72
NO_2	Sofienberg Park	Hour	1409	0.70	0.72
PM10	Aker Hospital	Day	60	1.59	3.67
PM10	Skøyen	Day	43	1.03	1.46
PM2.5	Aker Hospital	Day	60	1.13	1.70

Corresponding values of model (M) and representativeness (O+R) standard deviation values based on the data given in Table 6 and Eq. 16 are shown in Figs. 11-13. We have here assumed that the representativeness errors $1+\rho_R$ have a mean value of 1 for each station and compound. In addition to results for M being the interpolated model value at the station, we also show results (right figure) for M being the direct model concentration in the grid cell containing the station.

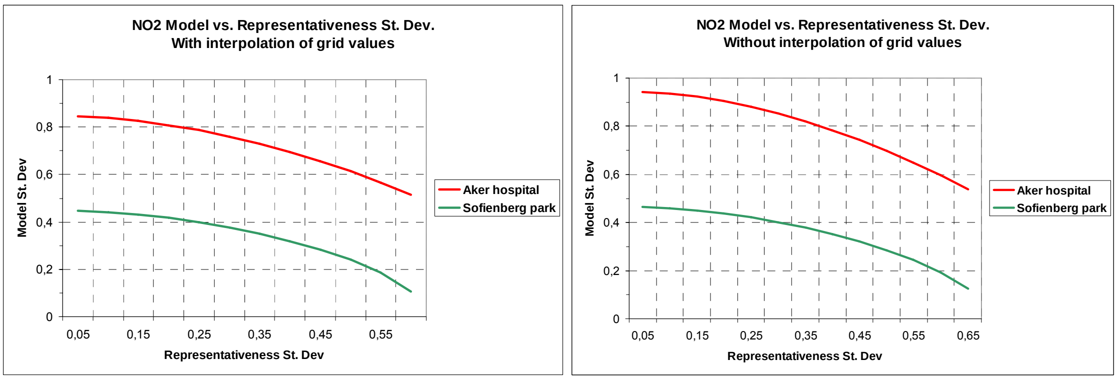

Figure 11: Corresponding values of model (M) and representativeness (O+R) standard deviations for NO_2 based on time series of M/O and $(M/O)^2$ values at Aker Hospital (red curve) and Sofienberg Park (green curve). Left figure is based on interpolation of model grid values, right figure is without. Unit: -.

As can be seen from Fig. 11, the estimated model error standard deviation $SDev(1+\rho_M)$ for NO_2 at station Aker Hospital is about 0.8 (or 0.9 for the right figure) or lower depending on the amount of representativeness error standard deviation $SDev(1+\rho_R)$ at the station. Similarly for station Sofienberg Park the estimated model error standard deviation is 0.4 or lower.

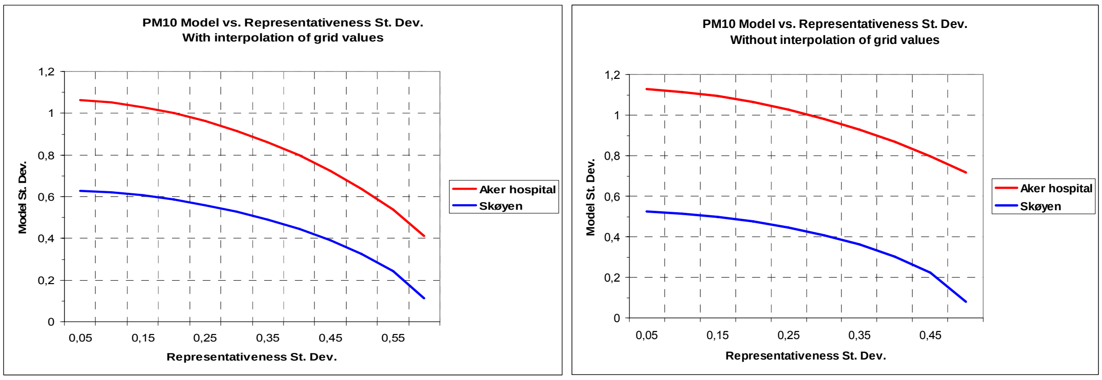

Figure 12: Corresponding values of model (M) and representativeness (O+R) standard deviations for PM10 based on time series of M/O and $(M/O)^2$ values at Aker Hospital (red curve) and Skøyen (blue curve). Left figure is based on interpolation of model grid values, right figure is without. Unit: -.

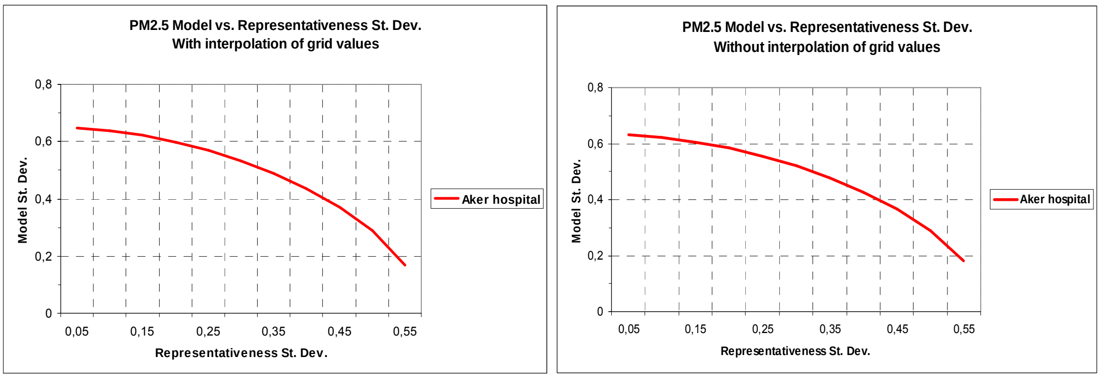

Figure 13: Corresponding values of model (M) and representativeness (O+R) standard deviations for PM2.5 based on time series of M/O and $(M/O)^2$ values at Aker Hospital (red curve). Left figure is based on interpolation of model grid values, right figure is without. Unit: -.

For PM10 (Fig. 12) we see that the model error standard deviation is around 1 or lower at station Aker Hospital, and 0.6 or lower at station Skøyen. For PM2.5 (Fig. 13) the corresponding value is around 0.6 or lower at station Aker Hospital.

The curves in Figs. 11-13 represents consistent estimates of model and representativeness error standard deviation for the different stations and compounds. It is not possible, however, to deduce the right amount of model and representativeness error standard deviation values based on these curves alone. We only know that the standard deviation values must lie somewhere along these curves, in order to be consistent with the observed M/O and $(M/O)^2$ ratios. This is also further based on the assumption that the representativeness errors are unbiased (i.e., $E(1+\rho_R) = 1$), or in other words, that the stations involved are representative as urban background stations.

4.3 Mean and standard deviation of Bayesian prior PDFs

In addition to consistent estimates of model and representativeness error mean and standard deviation, for each station and compound, as given in Chapter 4.2, we also want to estimate mean and standard deviation of Bayesian prior PDFs of true concentrations, for each station and compound, based on Eqs. 18, 19 and 21 derived in Chapter 3.4.6.

The focus will be on 1 March 2004 (only), which was a day during the winter and spring of 2003/2004 with very high concentrations of NO_2, PM10 and PM2.5 (Helse og Velferdsetaten, 2004a, 2004b; Lützenkirchen et al., 2004). Highest levels of air pollution were recorded at the traffic stations (see Fig. 1), with 246 μg/m^3 as peak hourly average concentration of NO_2 at station Alnabru, and 209 μg/m^3 and 36 μg/m^3 as daily mean values of PM10 and PM2.5 respectively at station Løren. High levels were also being recorded at the urban background stations with 145.7 μg/m^3 as peak hourly average concentration of NO_2 at station Skøyen, and 100.8 μg/m^3 and 21.2 μg/m^3, as daily mean values of PM10 and PM2.5 at stations Skøyen and Aker Hospital respectively. This build-up of pollution was predominantly due to local urban conditions in Oslo, since low concentrations were being recorded at the regional background station Birkenes in South Norway, with e.g., daily mean values of PM10 and PM2.5 < 2 μg/m^3.

The high levels of PM10 recorded at the traffic stations were caused by traffic re-suspension of road dust due to dry conditions on the roads, and available deposits of road dust (Helse og Velferdsetaten, 2004a, 2004b). In addition, low wind speed and stable atmospheric conditions prevailed most of the day. At the meteorological station Valle Hovin (see Fig. 1), the average wind speed at 10 m above ground was 0.8 m/s, and the average temperature difference between 25 and 8 m was +0.5°C. The average temperature and relative humidity were 0,2 °C and 75,1% respectively,

Estimated mean values of O/M and (O/M)^2 using the data at the urban background stations Aker Hospital, Sofienberg Park and Skøyen for 1 March 2004 are shown in Table 7. The M values here denotes the direct (non-interpolated) grid model values M_{ij} associated with each station.

Table 7: Estimated mean values of O/M and (O/M)^2 at urban background stations in Oslo for 1 March 2004. Ratios of NO_2 are based on a 24-hour average, while ratios of PM10 and PM2.5 are based on 3-day (moving) averages centred at 1 March 2004. Unit: -.

Compound	Station	Resolution	Number of values	O/M mean	(O/M)^2 mean
NO_2	Aker Hospital	Hour	24	1.03	1.28
NO_2	Sofienberg Park	Hour	24	1.06	1.22
PM10	Aker Hospital	Day	3	1.00	1.15
PM10	Skøyen	Day	3	1.05	1.28
PM2.5	Aker Hospital	Day	3	1.50	2.87

The mean values for NO_2 are based on averaging the hourly ratios of O/M and (O/M)^2 for 1 March 2004, while the mean values for PM10 and PM2.5 are based on averaging the daily ratios of (O/M) and (O/M)^2 for the three days 29 February, 1 March and 2 March 2004.

The data in Table 7 then gives us an estimate of the “error of the day” for 1 March 2004 by calculating corresponding values of model (M) and representativeness (O+R) error standard deviation values using Eq. 21. The result of this is shown in Figs. 14-16.

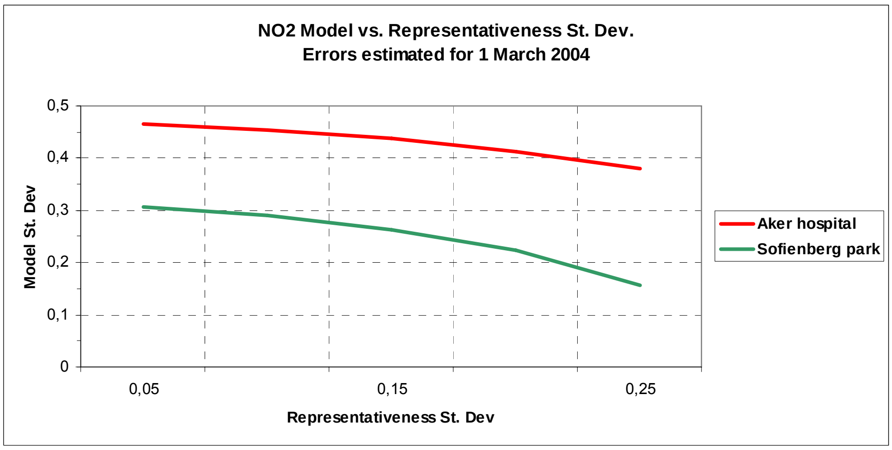

Figure 14: Corresponding values of model (M) and representativeness (O+R) error standard deviations for NO_2 based on 24-h average values of O/M and $(O/M)^2$ for 1 March 2004 at Aker Hospital (red curve) and Sofienberg Park (green curve). Unit: -.

For NO_2 (Fig. 14) and at station Aker Hospital, the relative model error standard deviation ranges from slightly above 0.45 to slightly below 0.4 depending on the amount of relative representativeness error standard deviation, and from around 0.3 to around 0.15 for station Sofienberg Park.

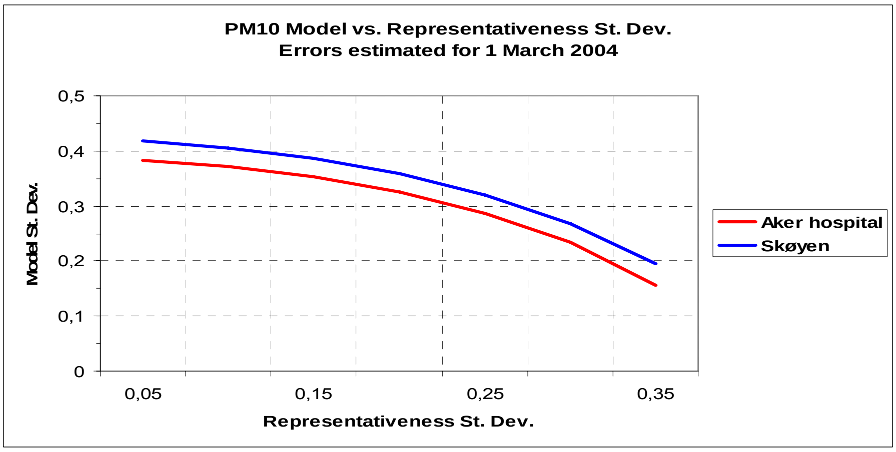

Figure 15: Corresponding values of model (M) and representativeness (O+R) error standard deviations for PM10 based on 3-day moving averages of O/M and $(O/M)^2$ for 1 March 2004 at Aker Hospital (red curve) and Skøyen (blue curve). Unit: -.

For PM10 (Fig. 15) somewhat similar results are obtained, but in this case the two curves lies much closer together. The relative model error standard deviations ranges in this case from about 0.4 to about 0.2 at both stations (Aker Hospital and Skøyen) depending on the amount of relative representativeness error standard deviation.

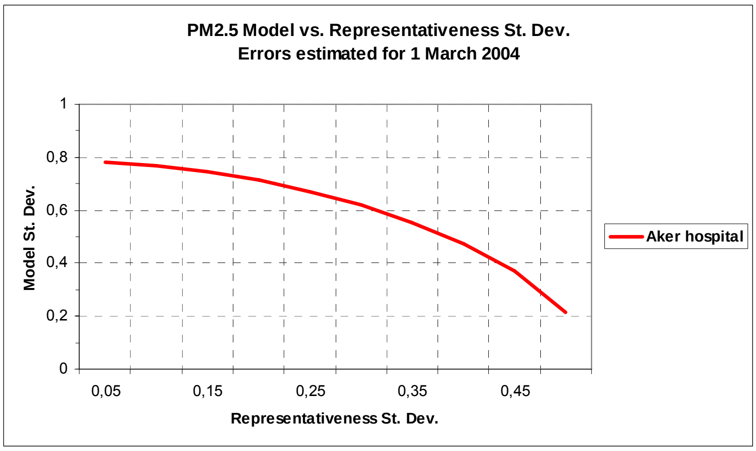

Figure 16: Corresponding values of model (M) and representativeness (O+R) error standard deviations for PM2.5 based on 3-day moving averages of O/M and $(O/M)^2$ for 1 March 2004 at Aker Hospital (red curve). Unit: -.

For PM2.5 (Fig. 16) there is only one curve (for Aker Hospital). In this case the relative model error standard deviation ranges from slightly below 0.8 to slightly above 0.2.

Next we want to estimate mean and standard deviations of Bayesian prior PDFs for 1 March 2004 based on the above results given in Table 7 and Figs. 14-16. The result is shown in Table 8.

Table 8: Mean and standard deviations of Gaussian PDFs used in the POE calculations. M_{ij} denotes model calculated concentration in grid cell ij, i = 1,..,18, j = 1,…,22. Unit: µg/m^3.

	PDF mean	**PDF st. dev.**
NO_2	$M_{ij} \cdot 1.0$	$M_{ij} \cdot 0.30$
PM10	$M_{ij} \cdot 1.0$	$M_{ij} \cdot 0.35$
PM2.5	$M_{ij} \cdot 1.5$	$M_{ij} \cdot 0.70$

The mean values in Table 8 are calculated from the O/M mean values given in Table 7 by taking the average over the stations for each compound, and rounding off the result using one decimal only. The standard deviation values given in Table 8 are estimated using the curves given in Figs. 14-16, assuming that the combined observation and representativeness relative errors are on the order of (at least) 20% for each of the three compounds and stations. Remember that observation errors are on the order of 5% for each compound and station. Averages are again taken (over the stations) and the result is rounded off, this time using two decimals. The values are finally multiplied with the actual model calculated grid cell concentrations for 1 March 2004 for each compound, in order to give the mean and standard deviations of true grid cell concentrations as subjective Bayesian stochastic variables according to Eq. 18. For NO_2, the model field at 16h this day is used, while for PM10 and PM2.5, the daily mean value is used.

Maps of main grid concentration standard deviation values for 1 March 2004 based on the above given “error of the day” (1 March 2004) are shown in Figs. 17-19.

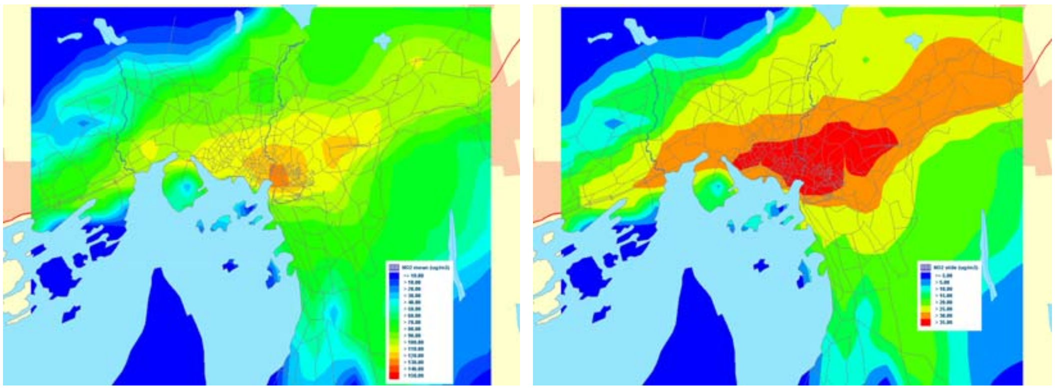

Figure 17: Model concentration map (left) together with a map of estimated model error standard deviations (right) for NO_2 at 1 March 2004 16h. Unit: µg/m^3.

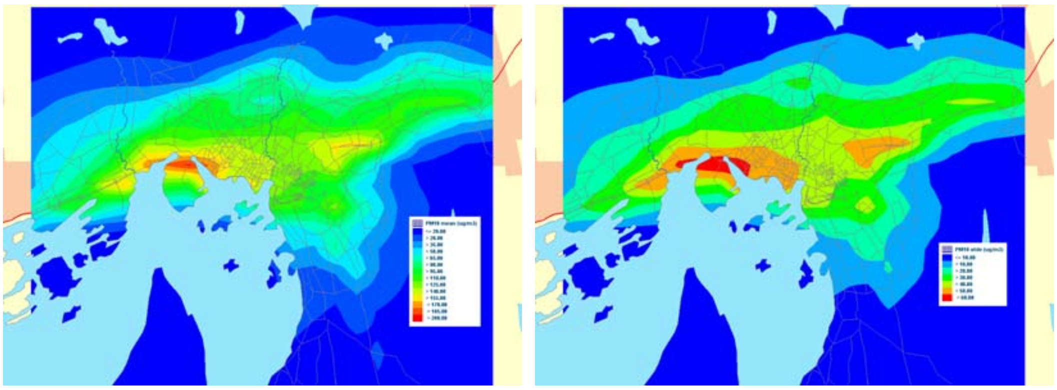

Figure 18: Model concentration map (left) together with a map of estimated model error standard deviations (right) for PM10 at 1 March 2004. Unit: µg/m^3.

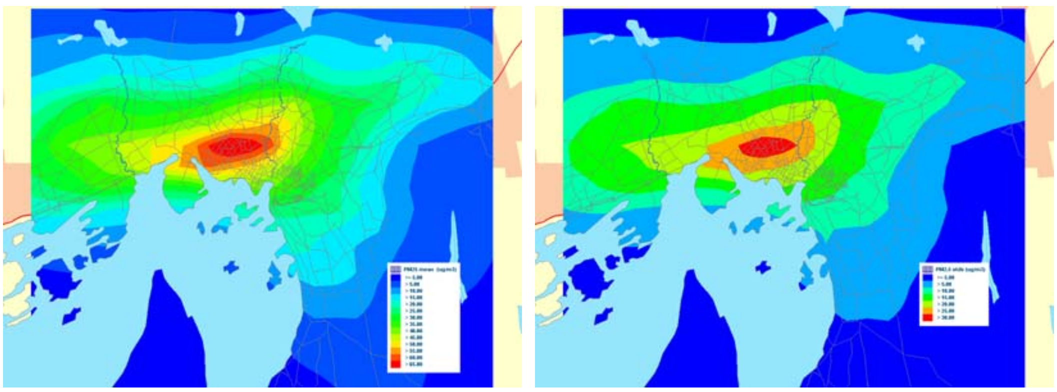

Figure 19: Model concentration map (left) together with a map of estimated model error standard deviations (right) for PM2.5 at 1 March 2004. Unit: µg/m^3.

4.4 Probability of exceedance of limit values

Probabilities of exceedance (POE) of limit values have been calculated for 1 March 2004 based on the uncertainty analysis presented in Chapter 4.3. The results are presented in Figs. 17-19 below. We have here assumed that the Bayesian prior PDF is defined as a (multi-dimensional) Gaussian probability distribution function. Other function types for these PDFs could also be selected, see e.g., (Walker, 2006) for other Bayesian prior PDF function types that could be used.

The mean and standard deviation of the Gaussian PDFs defined for each grid cell is given in Table 8.

Three sets of limit values exists for the city of Oslo as shown in Table 9, namely recommended air quality criteria, national targets and judicially binding limit values. For NO_2, the limit values are based on hourly average values, while for PM10 and PM2.5, daily average values are used.

Table 9: Limit values for air quality in Oslo. Unit: µg/m^3.

	Averaging period	**Recommended air quality criteria**	**National target**	**Judicially binding limit**
NO_2	Hour	100	150	200
PM10	Day	35	50	50
PM2.5	Day	20	35	-

For the calculation of probability of exceedance (POE) values shown here, we have selected to use the national target values for air quality. Calculated maps of POE for 1 March 2004 based on these limit values are shown in Figs. 20-22 below for NO_2 (at 16h), PM10 and PM2.5 respectively.

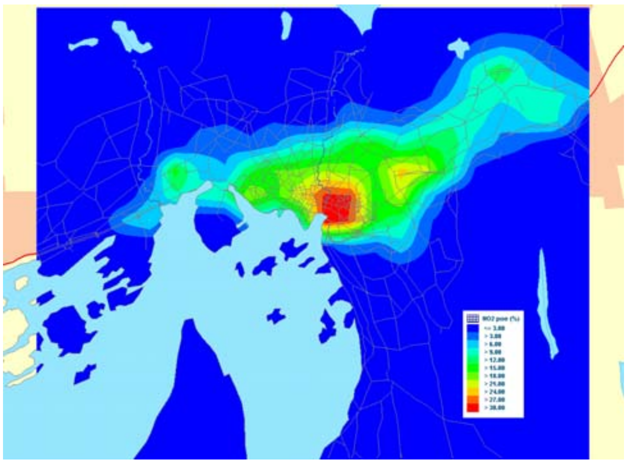

Figure 20: Probability of exceedance (POE) map for NO_2 at 1 March 2004 16h based on the national target value 150 µg/m^3 as hourly mean value. Unit: %.

For NO_2 (Fig. 20) the highest POE value is 33.1%, which is associated with a (maximum) modelled grid cell concentration value of 133 µg/m^3 in the same grid cell. The national target value to compare with in this case is 150 µg/m^3.

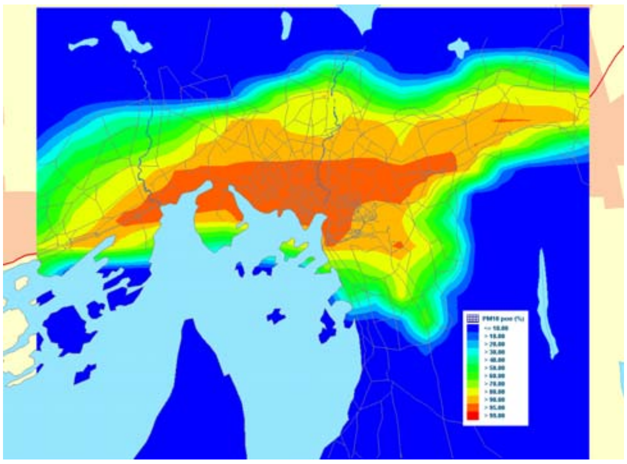

Figure 21: Probability of exceedance (POE) map for PM10 for 1 March 2004 based on the national target value 50 µg/m^3 as daily mean value. Unit: %.

For PM10 (Fig. 21), the highest POE value is 98.3%, associated with a (maximum) modelled value of 203 µg/m^3. The national target value in this case is 50 µg/m^3.

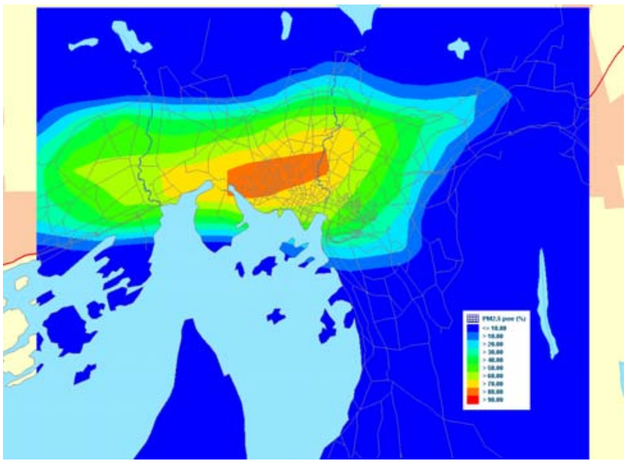

Figure 22: Probability of exceedance (POE) map for PM2.5 for 1 March 2004 based on the national target value 35 µg/m^3 as daily mean value. Unit: %.

For PM2.5 (Fig. 22), the highest POE value is 86.8%, corresponding to a (maximum) modelled value of 74 µg/m^3, where the national target value in this case being 35 µg/m^3. Thus for both PM10 and PM2.5, it is highly likely that the national target values are exceeded in Oslo at 1 March 2004, while for NO_2 (at 16h), this is much less likely.

5. Conclusions and discussion

5.1 Assessment of the case study

A model evaluation, comparing the AirQUIS-EPISODE urban grid model results of NO_2, PM10 and PM2.5, with hourly and daily mean urban background observations of the same species at the three stations Aker Hospital, Sofienberg Park and Skøyen in Oslo, shows a reasonable good agreement between model calculated and observed concentrations during the period February-March 2004. However, the Air4EU Oslo III case study, dealing with source apportionment of PM (Laupsa et al., 2006), has revealed some weaknesses in the estimated emissions of PM10 and PM2.5 during the period, which it is important to correct for before applying data assimilation.

When combining urban grid model concentrations with urban background observations, it is important to take representativeness errors properly into account, since they are usually much larger than pure observation (instrument) errors. Theoretical relationships between model and representativeness error standard deviations, based on averages of ratios of observed and model calculated values at urban background stations have been developed as part of this case study. Even though the derived relationships (and associated graphical curves) cannot be used to directly estimate model and observation uncertainties, the derived relationships are nevertheless important to use if we are to be consistent in the apportionment of these uncertainties as input to data assimilation.

The case study also shows the usefulness of using estimated model uncertainties to calculate probabilities of exceedance (POE) values in connection with checking compliance with limit values, rather than merely checking whether a given model calculated value is above or below a given limit, since the former is generally less sensitive to errors in the model.

5.2 Improvements in assessment derived from the case study

Averages of ratios of observed and modelled concentration values at urban background stations in Oslo have been used to derive relationships between model and representativeness error standard deviations at the same stations. Estimating proper and consistent levels of model and observation uncertainties are necessary for any successful application of data assimilation, combining the urban grid model AirQUIS-EPISODE with urban background observations in Oslo.

However, the presently small number of available urban background stations (only 1-2 depending on the compound) makes it in general difficult to use data assimilation as a technique for improving the urban grid model in Oslo at the present stage, except perhaps in areas close to the monitoring stations. Ideally we believe that at least 5-8 such stations should be available in order to perform data assimilation in a proper way.

Estimated model uncertainties have nevertheless been used to calculate probability of exceedance (POE) of national target values for 1 March 2004, which was a day during the winter/spring season of 2003/2004 with particularly high levels of air pollution in Oslo.

5.3 Recommendations resulting from the case study

The main recommendations resulting from this case study are:

- It is recommended to take representativeness errors properly into account when comparing urban grid model concentrations with urban background observations, since they are usually much larger than pure observation (instrument) errors

- It is recommended to calculate consistent levels of model and representativeness error standard deviations, using the derived relationships based on averages of ratios of observed and modelled concentrations at the urban background stations, when combining urban grid model values with urban background observations, using methods and techniques of data assimilation
- It is recommended that at least 5-8 urban background stations are available in order to estimate model errors properly, and to perform data assimilation
- It is recommended to also calculate probability of exceedance (POE) values in order to check compliance with limit values, rather than merely checking whether a model calculated value is above or below a given limit, since the former is less sensitive to errors in the model

5.4 Suitability for implementation in other cities

The findings in this case study should be applicable to other cities, provided that a thoroughly evaluated urban grid model and a sufficient number of urban background stations are available.

References

Air4EU – CS D7.1.5 (2006) Source apportionment of PM using dispersion and receptor modelling. http://www.air4eu.nl.

Air4EU – M.2 (2006) Uncertainty of models and monitoring. http://www.air4eu.nl.

Air4EU – M.3 (2006) Representativeness of model outputs and monitoring data. http://www.air4eu.nl.

Air4EU – M.5 (2006) Data assimilation. http://www.air4eu.nl.

AirQUIS (2003) Models Module - User's Guide. Kjeller, Norwegian Institute of Air Research (NILU 2003).

Berger, J.O. (1985) Statistical Decision Theory and Bayesian Analysis, *Springer Verlag*.

Box, G.E.P and G.C. Tiao (1992) Bayesian Inference in Statistical Analysis, *Wiley Classics Library Ed., New York*.

Chang, J.C., S.R. Hanna (2005) Technical Descriptions and User's Guide for the BOOT Statistical Model Evaluation Software Package, Version 2.0.

Chang, J.C., S.R. Hanna (2004) AQ model performance evaluation, *Meteorol. and Atmos. Phys*., 87, 167-196.

Haakonsen, G., Kvingedal E. (2001) Utslipp til luft fra vedfyring i Norge. Utslippsfaktorer, ildstedsbestand og fyringsvaner. Report 2001/36, Statistics Norway, Kongsvinger (in Norwegian)

Haakonsen, G. (2000) Utslipp til luft i Oslo, Bergen, Drammen og Lillehammer 1991–1997 Report 2000/2023, Statistics Norway, Oslo (in Norwegian).

Helse og Velferdsetaten (OPHA), Oslo kommune (2004a) Månedsrapport luftforurensninger: mars 2004, (in Norwegian).

Helse og Velferdsetaten (OPHA), Oslo kommune (2004b) Ekstrarapport luftforurensninger: 1. mars 2004, (in Norwegian).

Kalnay, E. (2003) Atmospheric Modeling, Data Assimilation and Predictability, *Cambridge University Press, Cambridge UK*.

Kukkonen, J., Pohjola, M., Sokhi, S., Luhana, L., Kitwiroon, N., Fragkou, L., Rantamäki, M., Berge, E., Ødegaard, V., Slørdal, L.H., Denby, B. and Finardi, S. (2005) ‘Analysis and evaluation of selected local-scale PM10 air pollution episodes in four European cities: Helsinki, London, Milan and Oslo’, *Atmospheric Environment*, Vol. 39, pp.2759–2773.

Larssen, S., Laupsa, H., Slørdal, L.H., Tønnesen, D., Hagen, L.O. (2006) Spredningsberegninger av PM2,5 for Oslo vinteren 2003-2004. Kjeller, Norwegian Institute for Air Research (NILU OR 28/2006) (in Norwegian).

Laupsa, H., Denby, B., Slørdal, L.H. and Tønnesen, D. (2005) Model calculations to estimate urban levels of particulate matter in Oslo, with respect to the requirements of the EU directives. Accepted for publication in: Proceedings of 5th International Conference on Urban Air Quality. March 29-31, 2005, Valencia, Spain.

Laupsa, H. and Slørdal, L.H. (2003) Applying model calculations to estimate urban air quality with respect to the requirements of the EU directives on NO2, PM10 and C6H6. Internat. J. Environ. Pollut., vol. 20, no.1-6 (2003).

Lützenkirchen, S., Lutnæs G. (2004) Luftkvaliteten i Oslo, Status 2004, Helse og Velferdsetaten (OPHA), Oslo kommune (in Norwegian).

Oftedal, B., Walker, S.E., Gram, F., McInnes, H., Nafstad, P. (2006) Modelling long-term averages of local ambient air pollution in Oslo, Norway: evaluation of nitrogen dioxide, PM10 and PM2.5, submitted to Int. J. of Environment and Pollution.

Slørdal, L.H., Walker, S.E., Solberg, S. (2003) The urban air dispersion model EPISODE applied in AirQUIS2003. Technical description. Kjeller, Norwegian Institute for Air Research (NILU TR 12/2003).

Slørdal, L.H. (2002) MATHEW as applied in the AirQUIS system. Model description. Kjeller, Norwegian Institute for Air Research (NILU TR 09/2002).

Swinbank R., V. Shutyaev, and W.A., Lahoz (eds.) (2003) Data Assimilation for the Earth System, *Nato Science Series, IV. Earth and Environmental Sciences*, Vol. 26.

Walker, S.-E., (2006) Air4EU program tool SAM version 1.0, User’s Guide. http://www.air4eu.nl.

Ødegaard, V., Gjerstad, K.I., Bjergene, N. (2005) Better City Air – Evaluation of prognosis models of meteorology and air quality, winter 2004/2005, met.no report no. 14/2005 (in Norwegian).