

SOURCE APPORTIONMENT OF PM_{2.5} IN URBAN AREAS USING MULTIPLE LINEAR REGRESSION AS AN INVERSE MODELLING TECHNIQUE

Bruce Denby and Herdis Laupsa bde@nilu.no

Norwegian Institute for Air Research (NILU), Norway



Overview



- Sources of PM_{2.5} in Oslo
- Observations
- Modelling (AirQUIS)
- Multiple linear regression
- Uncertainty assessment
- Results
 - All data
 - Filter days at RV4 (validation)
- Conclusions



Contributions to PM_{2.5} in Oslo



Modelled source contributions at a traffic station in Oslo based on the current emissions inventory



Observations of PM_{2.5} in Oslo



PM_{2.5} observational network during winter 2004

Traffic stations

- RV4
- Kirkeveien
- Løren

Urban background

Aker Hospital

Filter samples

- RV4
- 38 twelve hour samples



Modelling of PM_{2.5} in Oslo



PM_{2.5} emissions

•Wood burning based on questionnaires and emission factors (climatological temperature dependence)

Traffic exhaust is a bottom up inventory

•Resuspension related to exhaust emissions, studded tyre percentage and surface conditions (precipitation and temperature)

•Number of other combustion sources, e.g. shipping.

Dispersion modelling (AirQUIS-Area sources, e.g. wood burning, use Traffic sources use Gaussian line sour Industrial sources use a Gaussian poir Meteorology using meteorological mas field model (MATHEW)



Figur 14: Årsmiddelverdier for PM₂₅ for 2003.

Inverse modelling



- The aim is to provide an assessment of the average contributions from the different source sectors to the total observed PM_{2.5} mass concentration
- Consider the total concentration (C) to be the sum of the individual source contributions (C_i)

$$C(x, y, t) = \sum_{i=1}^{n} c_i(x, y, t)$$

The observed concentration is the weighted sum of the model source contributions (*c_{mod i}*) plus an error (ε) where the scaling factor (*a_i*) is the weight

$$C_{obs}(x, y, t) = \sum_{i=1}^{n} a_i c_{\text{mod}\,i}(x, y, t) + \varepsilon_i(x, y, t)$$

Multiple linear regression



- We wish to minimise the error (ε)
- In this case we minimise the mean square error (MSE)
- This is equivalent to multiple linear regression when forcing the intercept to pass through 0.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_i (x, y, t)^2$$



When can MLR be applied?

1. When the different source contributions are not well correlated

2. When two more more sources are of a similar order of magnitude

3. There are no significant missing sources

4.Linearity is applicable

Uncertainty in the factors (a_i)



Boot strapping methods are applied

The random selection, with replacement, of the data

- 10 000 realisations are made and the standard deviation of the source correction factors (*a_i*) are determined
- Provides an uncertainty in the scaling factors based on the limitted sample representation



Results



Two sets of data used:

•All data: 103 daily mean modelled and observed PM_{2.5} concentrations from 4 stations

•Filter days RV4: 38 twelve hourly mean modelled and observed PM_{2.5} concentrations corresponding to the filter samples at the RV4 site (for validation)



All data: 103 days at RV4 site

Results: all data (1)



Model source contributions and correlation (r²) matrix

Model source	(%)	1.	2.	3.	4.	5.	6.
1. Background	32	1	0	0	0.01	0.01	0.01
2. Exhaust	18	0	1	0.86	0.17	0.38	0.35
3. Suspension	4	0	0.86	1	0.06	0.33	0.24
4. Wood burning	40	0.01	0.17	0.06	1	0.25	0.22
5. Area sources	6	0.01	0.38	0.33	0.25	1	0.79
6. Industrial	0	0.01	0.35	0.24	0.22	0.79	1

Modelled source contribution to total PM_{2.5} mass

Four sources used in the multiple linear regression

Results: all data (2)



NILU

	Model source	Scaling factor (a_i)	
	1. Regional background	1.22 ± 0.07	
Iultiple	3. Traffic induced suspension	7.6 ± 1.0	
legression	4. Wood burning	0.30 ± 0.06	
Corcoroli	5. Other area sources	0.75 ± 0.42	-

HARMO12, 2008,

60

Modelled concentration (ug/m³)

10

Results: all data (3)



- Correlation (r²) increases from 0.36 to 0.50 •
- RMSE decreases from 7.9 μ g/m³ to 5.7 μ g/m³ •



PM2.5 mean concentrations for 4 stations and 103 days

Results: validation at RV4 (1)





Results: validation at RV4 (2)



Comparison of regression model with receptor modelling for the filter days at RV4



Conclusions



- The inverse modelling indicates a significant discrepancy in the dispersion model source contribution for wood burning and traffic suspension
- This deviation has been quantitatively confirmed by comparison with independent source apportionment studies using receptor modelling
- For wood burning this deviation could be due to either emissions or to model formulation. The dispersion model is sensitive to emission height and wind speed.
- For traffic induced suspension this deviation is due to emissions
- Combination with receptor modelling results is important for interpretation