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SIMULATING BUILDING DOWNWASH OF HEAVY METALS BY USING VIRTUAL SOURCES: METHODOLOGY AND RESULTS

W. Lefebvre[1], G. Cosemans[1], K. Van de Vel[1], S. Janssen[1], C. Mensink[1], D. Celis[2], F. Sleeuwaert[1], H. Van Rompaey[1], F. Blommaert[2]

[1] Flemish Institute for Technological Research (VITO), Department of Environmental Modelling, Boeretang 200, 2400 Mol, Belgium
[2] Vlaamse Milieumaatschappij, Afdeling Lucht, Milieu en Communicatie, Kronenburgstraat 45, B-2000 Antwerpen

Abstract: There is a discrepancy in data quality between the highly detailed concentration measurements in the surroundings of industrial plants emitting heavy metals and the registered emission data at these sites. When simulating the concentration fields in the direct vicinity of the emitting plants by using the bi-gaussian model IFDM and the reported emissions, the simulated concentrations were much lower than the measured concentrations.
Originally, this was thought to be due to diffuse, wind-fugitive emissions not reported in the official inventories. Therefore, inverse modeling was performed to get the emission data and wind dependency of these emissions. It was expected that the emissions coming out of the inverse modeling would follow a power law of the wind speed except for very low and very high wind speeds. In the latter case, a constant emission was expected, while in the former case, no emissions were expected to be found. However, this lower threshold did not seem to exist in the modeled emissions. Furthermore, these emissions seemed to have their source in spots not used for storage of heavy metals such as parking lots. Detailed analysis of these results showed that another effect, known as building downwash, is responsible for this behavior. Thereafter, it was shown that it is possible for a bi-gaussian model that lacks a building downwash module, to simulate correct concentration levels by putting in virtual sources just behind the buildings causing the building downwash phenomenon.
By using half of the available concentration data for the inverse modeling and half for the validation, it was shown that this technique can be used to produce detailed and validated concentration maps of the surroundings of the industrial site. Finally, it was shown that in this case studying building downwash has an important effect on local concentrations and that a better representation of building downwash is needed in bi-gaussian models to describe the complex dispersion patterns in the wake of industrial sites.

Key words: *Building downwash, inverse modelling, heavy metals*

INTRODUCTION

There is a discrepancy in data quality between the highly detailed concentration measurements in the surroundings of industrial plants emitting heavy metals and the registered emission data at these sites. When simulating the concentration fields in the direct vicinity of the emitting plants by using the bi-gaussian model IFDM and the reported emissions, the simulated concentrations were much lower than the measured concentrations. This discrepancy was thought to be originated from diffuse, wind-driven emissions not reported in the official inventories. This study describes the methodology and the results of a study which tries to determine these sources.

MODEL

The model used in this study is IFDM. IFDM is a bi-Gaussian air pollution model, designed to simulate non-reactive pollutant dispersion on a local scale. The dispersion parameters are dependent on the stability of the atmosphere and the wind speed following the Bultynck and Malet formulation (Bultynck and Malet, 1972). The meteorological input for this model is taken from measurements made in Antwerp (Luchtbal) or in Mol. More information on the IFDM model can be found in the European Model Database (http://air-climate.eionet.europa.eu/databases/MDS/index_html).

In order to determine the unknown sources, which were supposed here to come from diffuse emissions, the following procedure is developed. The measurement dataset is split up in two, with half of it used for the determination of the sources and half for the validation of the results. The measurements contained in the former half are noted by $M_{i,t}$ with i the location of the measurement and t the time step. In order to determine the unknown sources, it is necessary to eliminate the effect of the known sources. Therefore, a corrected measurement series $M'_{i,t}$ is created as follows:

$M'_{i,t} = M_{i,t} - B - \mu_{i,t}$, (1)

with B the known background of the pollutant and $\mu_{i,t}$ the modelled value of the concentration at the measurement location i and at time step t, by taking into account the known sources. However, it was shown that the $M'_{i,t}$ was close to $M_{i,t}$, showing that the known sources are less important than the unknown. Therefore, a list of possible sources s_j is compiled. This is done as follows:

- At places where one would expect diffuse emissions, several sources s_j are placed. These sources differ for instance in their treatment of the emission dependence on the wind speed (see below).
- To incorporate for unexpected sources, several grids of sources (for different wind dependences) are placed on the company terrain.

This leads to a list of possible sources s_j which can contain up to 200 possible sources.

The wind dependence is treated by determining four parameters: the basic emission strength of the source s_j: Q_j, a minimum wind value u_{min}, a maximum wind value u_{max} and a factor describing the form of the wind dependence p. The emission at a time t for this source is then determined by the following equations:

- If $u < u_{min}$: $Q_{j,t}=0$
- If $u_{min} < u < u_{max}$: $Q_{j,t} = Q_j(u-u_{min})^p$
- If $u > u_{max}$: $Q_{j,t} = Q_j(u_{max}-u_{min})^p$.

For each of the possible sources s_j, their effect, assuming a unit value U for the emission, is calculated on the measurement locations i at every time step t. We call these values $\sigma_{i,j,t}$. Then, for every measurement location and time step (which can amount easily to values over 20.000) an equation is composed:

$M'_{i,t}=\Sigma_j Q_j \sigma_{i,j,t}$ (2)

This set of equations is then solved for Q_j using the Gram-Schmidt algorithm (Wampler, 1979). In the results, all the sources with negative values of Q_j are eliminated. The remaining set of equations is then solved again. This is reiterated until only positive emission values remain.

The Gram-Schmidt algorithm determines not only the value of Q_j, but also the standard deviation on this value. The following procedure is now reiterated:

- The set of equations for the remaining sources is solved using the Gram-Schmidt algorithm.
- The source for which the standard deviation divided by Q_j is the largest is eliminated.

This procedure continues until all emission strengths are at least three times their standard deviation. The final set of sources is composed by combining the known sources with the remaining unknowns, assigning them a source strength of UQ_j. In general, less than 10 sources are needed to describe most of the variability of the measurement data.

Finally, the results calculated using these final sources are checked for having the same pollution roses, cumulative frequency distributions, … as the measurements.

RESULTS

When applying the procedure described above on data for three industrial sites in Belgium, the results showed that the found sources could not be due to fugitive emissions. On the one hand, with fugitive emissions, one would expect to get a threshold value u_{min} different from 0, as for very low winds, no fugitive emissions are expected. On the other hand, one would expect the emissions to be found at locations with storage of heavy metals. However, here, we got emissions located for instance at parking spots.

Detailed analysis of the data then led to the conclusion that it was not the fugitive emissions that played an important role, but building downwash. The plume of the known sources plummets to the ground behind some of the buildings. In our model, this leads to the placement of a source just behind the building. This source is wind dependent with a lower threshold u_{min} of 0.

Using now the data that was kept out of the calculations for validation, we can show that the major measurement characteristics can easily be reproduced by the model. For instance, in Figure 1, the validation plot for one pollutant (Nickel) near a copper-lead recycling plant in the Northern part of Belgium is shown. It is seen that the model captures very well the yearly mean concentration values. In Figure 2, for one station, a time series plot is shown. In this plot, it can be seen that the model is correct not only for the yearly mean values, but also for the time dependency of the measurements. This is not only true for the periods used in the inverse modelling but also for the periods which were deliberately left out for validation. Finally, in Figure 3, the geographical distribution of the yearly mean model values is shown. By connecting these results to a satellite image, the exposure of the population can be assessed.

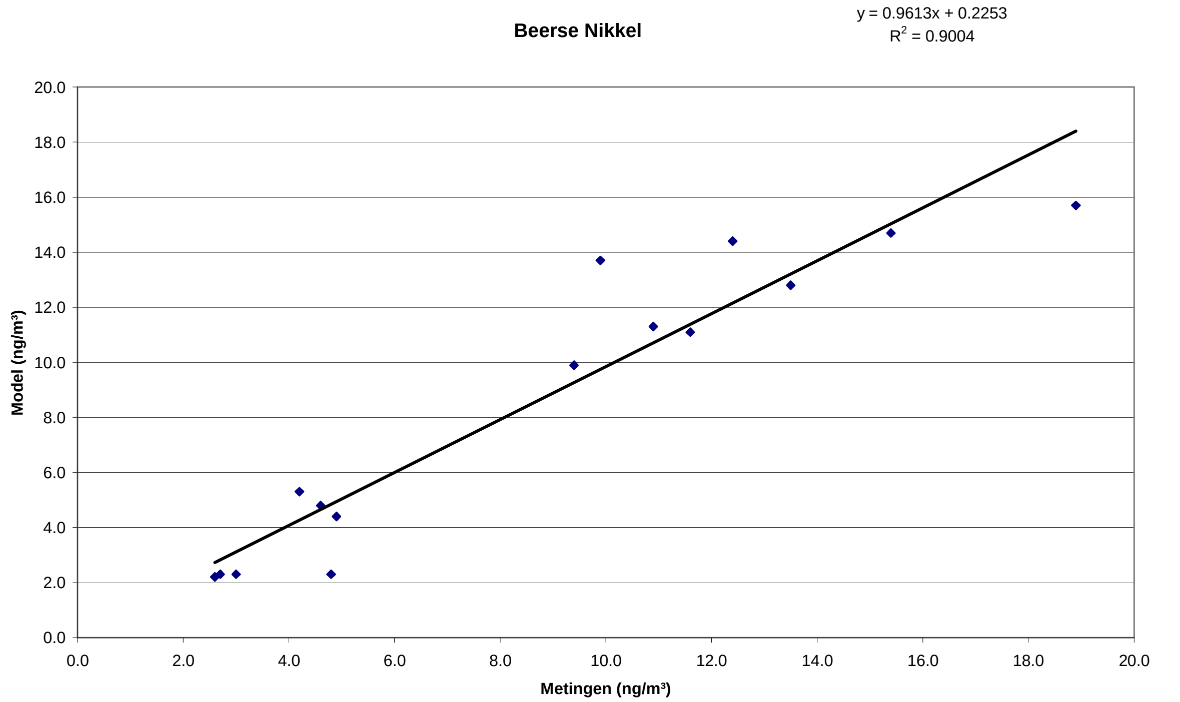

Figure 1: The validation plot for the Nickel concentration at the village of Beerse. On the x-axis: the yearly mean measurements of Nickel are shown (in ng/m³). On the Y-axis: the yearly mean model values of Nickel are shown (in ng/m³). Every dot represents a yearly mean value at one measurement location (4 years for 3 stations, 3 year for 1 station, both determination and validation data) in the vicinity of the company.

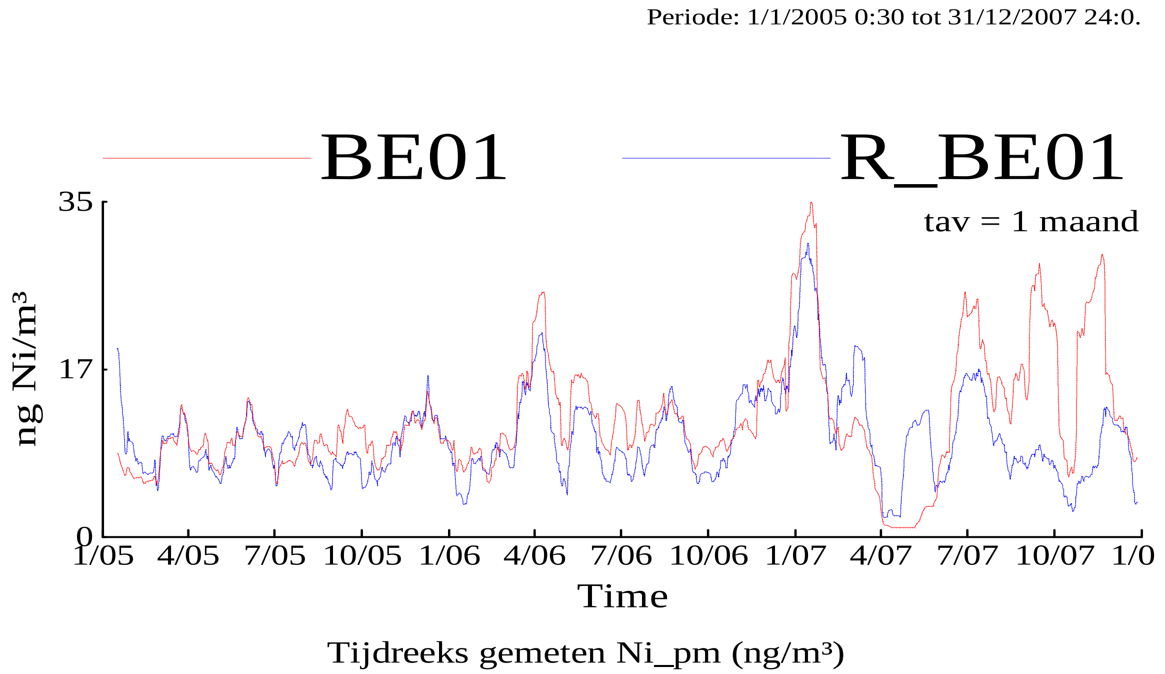

Figure 2: The running mean (over one month) measurement and model values at the location BE01, covering three years. In red: the measured concentrations. In blue: the modelled concentrations using the four remaining sources. On the x-axis: the time denoted in format month/year. On the y-axis: the concentration values in ng/m³. The period on which the sources are determined extends from the 31st of May 2006 up to the 19th of October 2007. The rest of the period is used for validation.

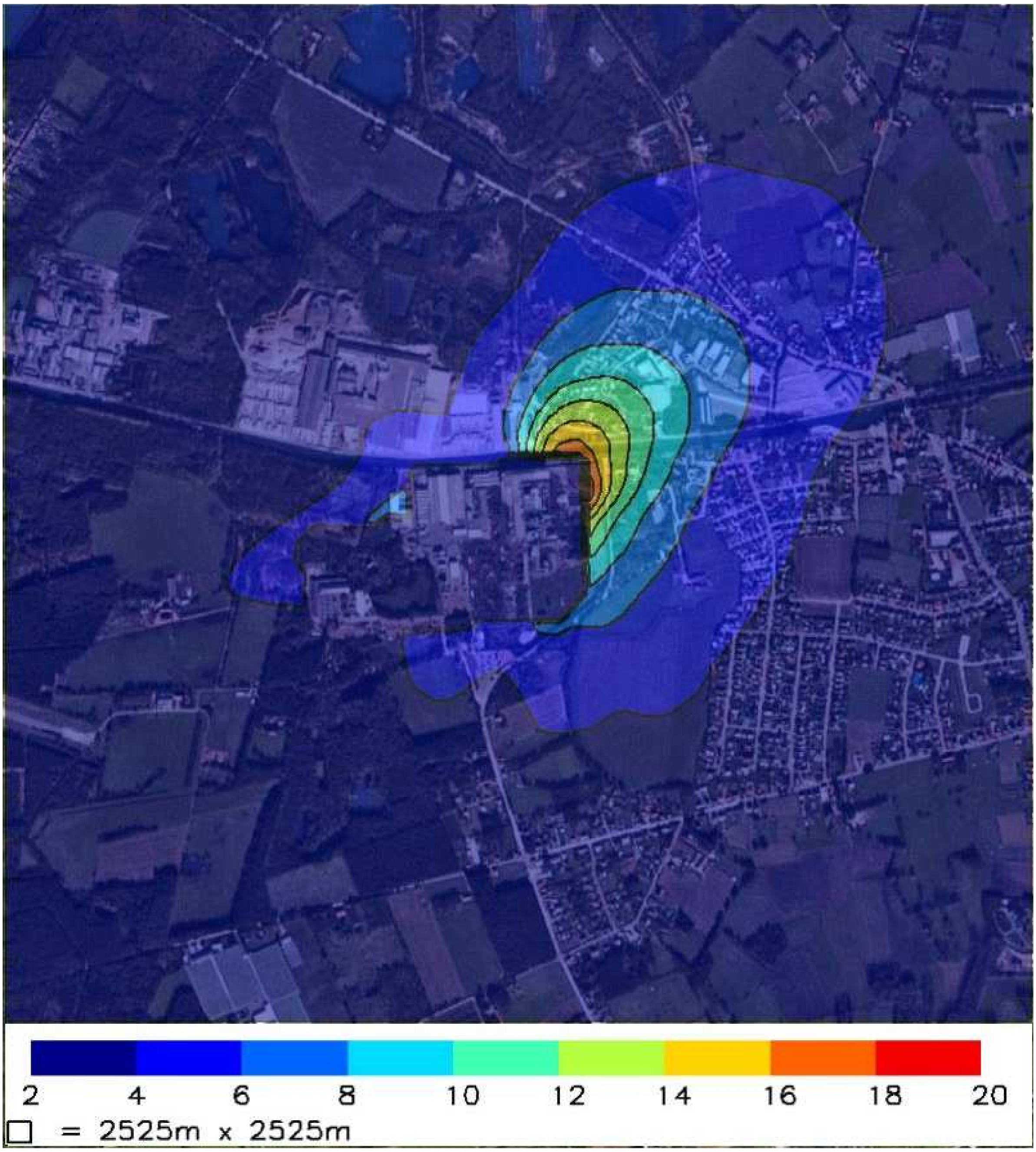

Figure 3 : The final yearly mean Nickel concentration map for 2007 near a heavy-metal plant in ng/m³. Background image: Google Earth.

RESULTS

In this study, it is shown that building downwash plays an important role in the measured occurrence of high pollutant concentrations near some heavy metals plants. Furthermore, it is shown that using virtual sources can lead to an accurate model re-creation of the measurement data. However, an improved building downwash algorithm for bi-gaussian plume models would be welcome in order to better study these cases.

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