Air Quality Forecasting Using Neural Network Approaches

Steve Dorling

School of Environmental Sciences, UEA

Gavin Cawley

School of Information Systems, UEA

Jaakko Kukkonen, Ari Karppinen

Finnish Meteorological Institute, Helsinki

Air Quality Forecasting Meeting, Culham, 15th April 2003

UEA ENV

Neural Networks

Keywords

Data Driven, Site-Specific, Black Box, Expert Knowledge, Input/Output/Hidden Layers, Cost Function, Interaction Between Input Variables, Over-training (Noise), Training/Testing/Validation datasets, MLP, Transfer Functions, Cross Validation ….

Early Work

Gardner, M.W. & Dorling, S.R. (1998) Artificial Neural Networks (The Multilayer Perceptron) - a Review of Applications in the Atmospheric Sciences. *Atmospheric Environment* **32** (14/15), 2627-2636.

Gardner, M.W. & Dorling, S.R. (1999) Neural network modelling and prediction of hourly NO_X and NO_2 concentrations in urban air in London. *Atmospheric Environment* **33**(5), 709-719.

Gardner, M.W. & Dorling, S.R. (1999) Statistical Surface Ozone Models: An improved methodology to account for non-linear behaviour. *Atmospheric Environment* **34** (1), 21-34.

Gardner, M.W. & Dorling, S.R. (1999) Meteorologically adjusted trends in UK daily maximum ozone concentrations. *Atmospheric Environment* **34** (2), 171-176.

Gardner, M.W. & Dorling, S.R. (2001) Artificial Neural Network Derived Trends in Surface Ozone Concentrations. *Journal of the Air & Waste Management Association* 51, 1202-1210.

Recent Work

European Commission IST FP 5 Programme

APPETISE project

APPETISE

http://www.uea.ac.uk/env/appetise

Air Pollution Episodes: Modelling Tools for Improved Smog Management (2000-2002)

Project objectives:

- To quantitatively inter-compare the performance of Deterministic and Statistical Air Quality models

- To produce recommendations on the suitability of various models or various classes of models for specific applications

APPETISE Pollutants and Case Studies

$\mathbf{NO_X}$, $\mathbf{NO_2}$, $PM_{\mathbf{10}}$ - Helsinki

$\mathbf{SO_2}$ - Siracusa, Belfast

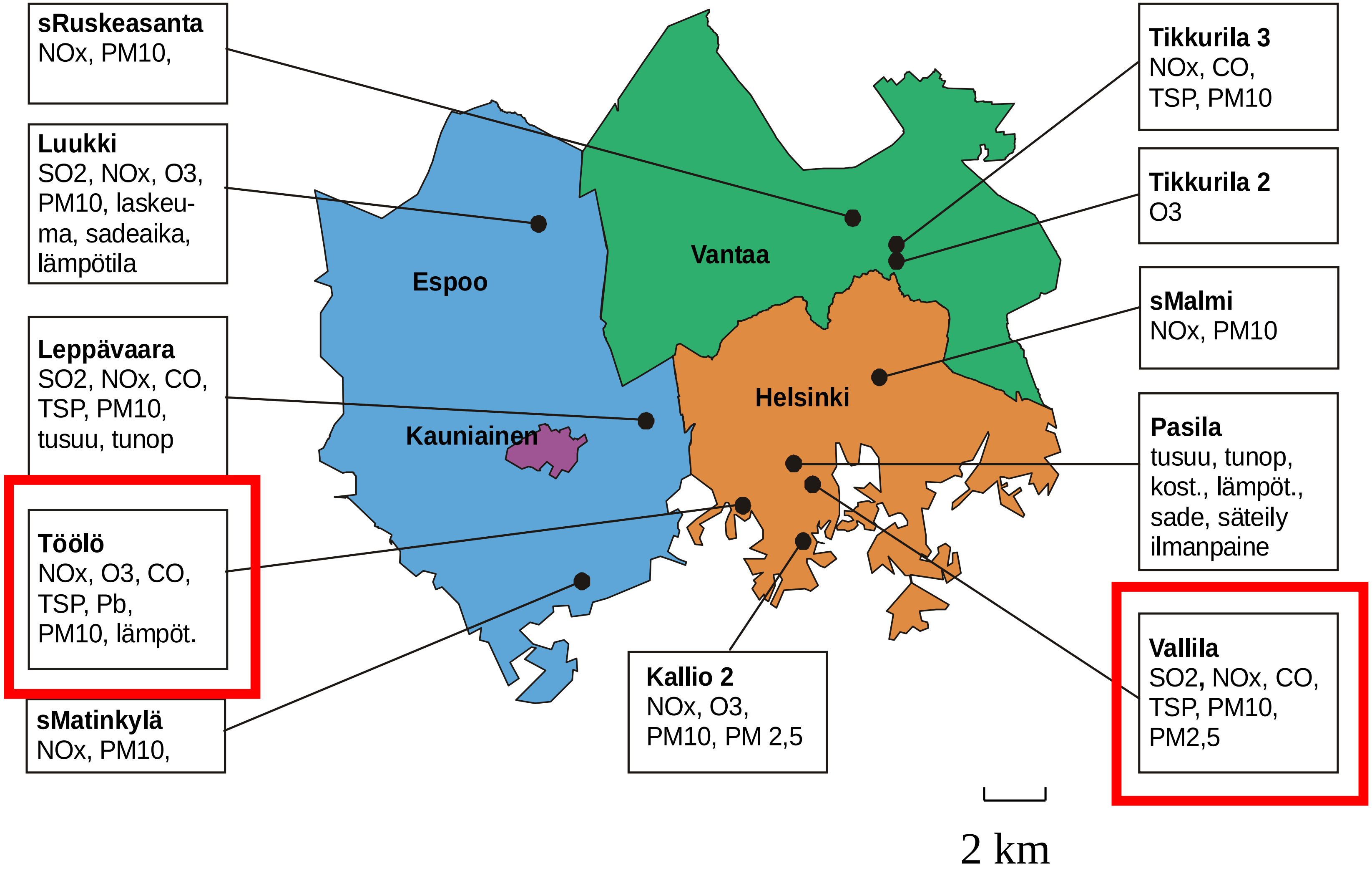
$\mathbf{O_3}$ - Rural Stations in the UK,

Germany and the Czech Republic

YTV

Environmental Office

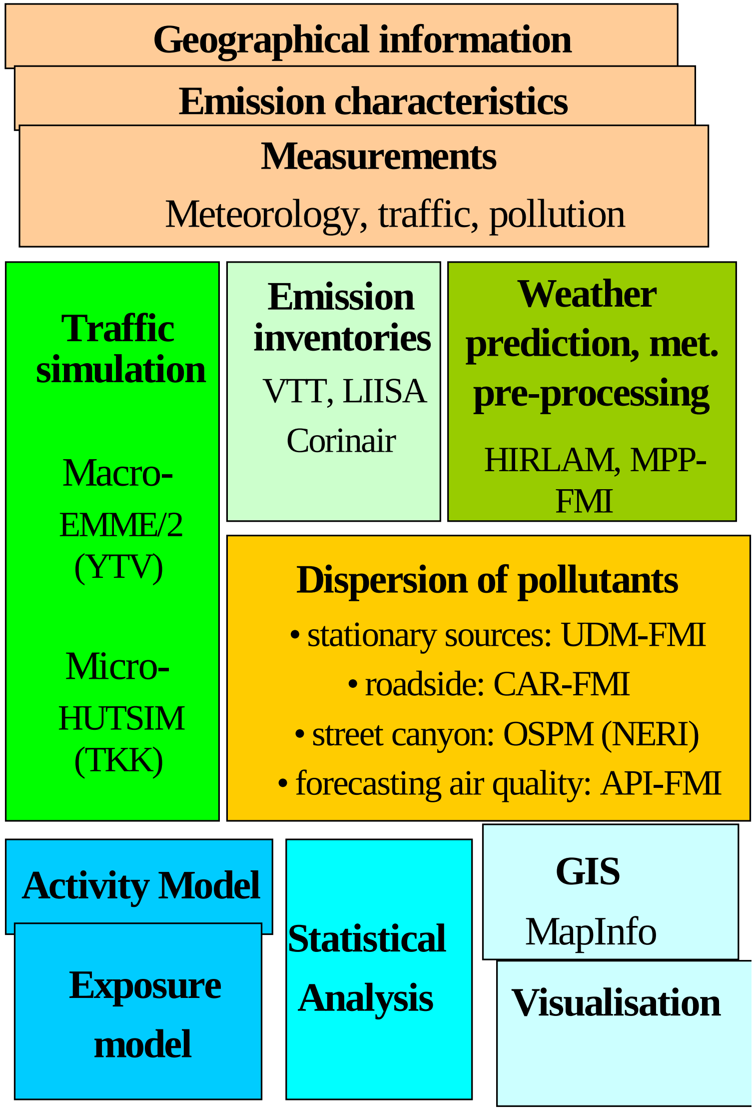
Air Quality Stations in Helsinki Metropolitan Area 2002



Finnish Meteorological Institute

Deterministic urban scale modelling system

Kukkonen, J. et al (2003)
Proccedings of the 4th International Conference on Urban Air Quality.
Prague, Czech Republic.



Neural Network (NN) models

Feed-forward back-propagation

Multilayer Perceptron

Five MLP ‘types’:

1) NNS-L assuming homoscedastic Gaussian noise
2) NNG-L assuming heteroscedastic Gaussian noise
3) NNL-L assuming Laplacian noise
4) NN2-L assuming two component mixture heteroscedastic Gaussian noise
5) NN3-L assuming three component mixture heteroscedastic Gaussian noise

One linear model:

6) LIN assuming homoscedastic Gaussian noise

Experimental data, Helsinki, 1996 - 1999

Concentration data

- PM_{10}, NO_X and NO_2
- Urban, traffic stations of Töölö and Vallila

Traffic flow data

- Hourly traffic volumes and average driving speeds for various vehicle categories

Replacement of missing concentration values:

- In order to obtain a harmonised and uniform database
- Linear interpolation and a self-organising map, developed at UKU

Experimental data, Helsinki, 1996 - 1999

Meteorological data

- Observed meteorological data - synoptic stations at Helsinki-Vantaa and Helsinki-Isosaari

- Observed meteorological data - an urban station at Kaisaniemi in Helsinki

- Pre-processed meteorological data -based on measured data from the synoptic stations

Outputs

- The concentration time series of PM_{10} and NO_2 at the stations of Töölö and Vallila
- Four sequential testing periods, each with a duration of one year

Statistical evaluation of model performance

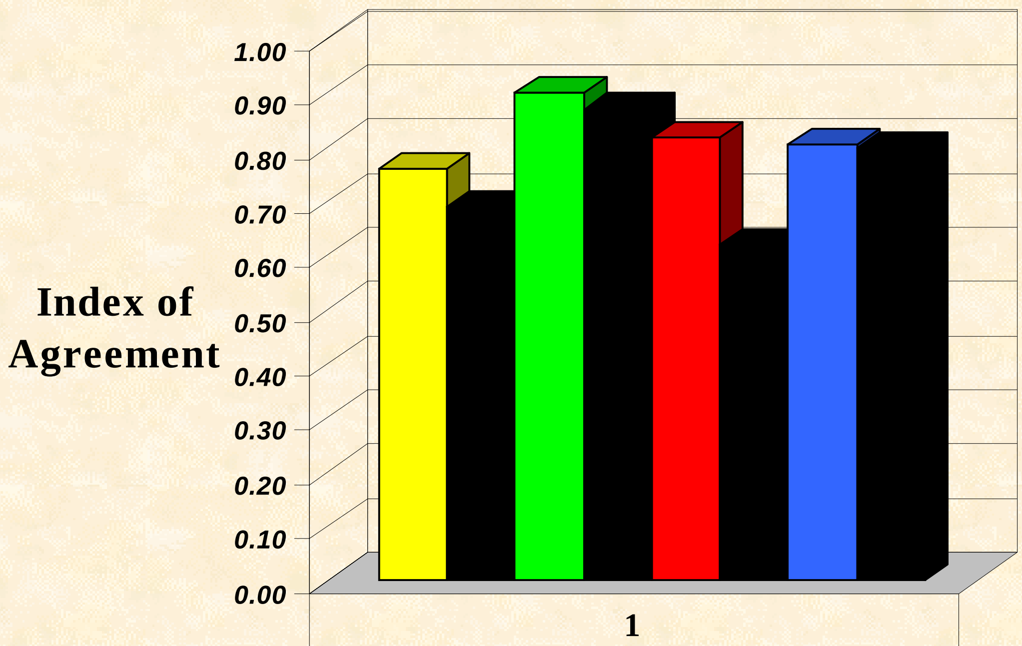
Various statistical parameters, e.g.,
Index of Agreement:

$$IA = 1 - \frac{\overline{(C_P - C_O)^2}}{\overline{\left[\left|C_P - \overline{C_O}\right| + \left|C_O - \overline{C_O}\right|\right]^2}}$$

Where
C_p = Predicted Concentrations

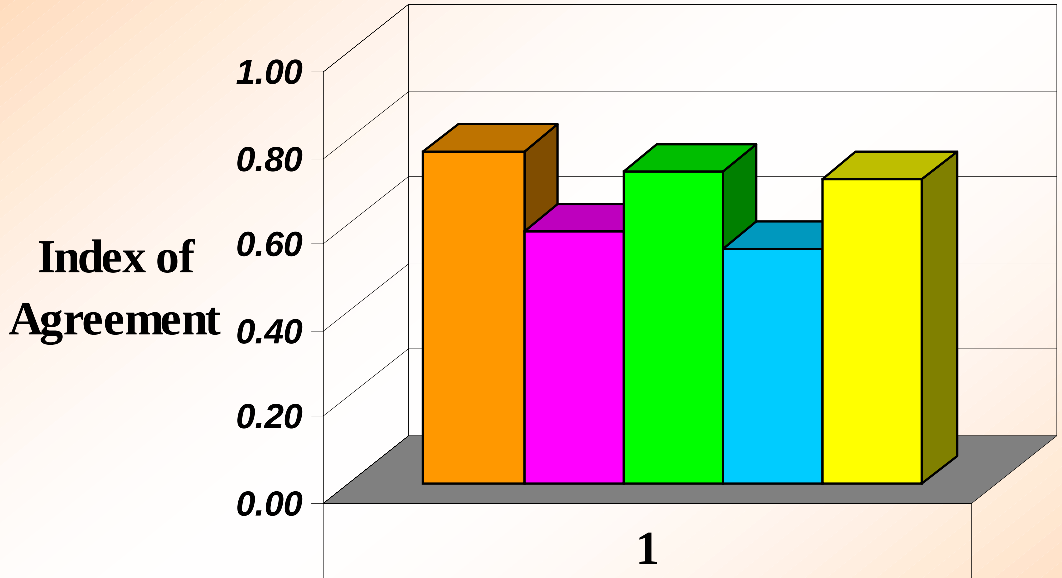
C_o = Observed Concentrations

Averages 1996-1999, Töölö and Vallila, NO2



	1
DET (Töölö)	0.76
DET (Vallila)	0.69
NNG-L (Töölö)	0.90
NNG-L (Vallila)	0.87
LIN (Töölö)	0.82
LIN (Vallila)	0.62
MLP (Töölö)	0.81
MLP (Vallila)	0.80

Averages 1996-1999
Töölö, PM10



	1
NNG-L (Imputed)	0.77
LIN (Imputed)	0.59
NNS-L (Imputed)	0.73
MLP (Imp., No met.)	0.54
MLP (Imputed)	0.71

Summary (1/2)

The performance of the neural network (NN) models (against measured data)

The non-linear NN models perform better than the linear models (clearly, the processes are not linear …)

The NN model performance is better for NO_2, compared with that for PM_{10} (many source categories for PM_{10})

Summary (2/2)

The performance of NN models compared with deterministic (DET) models

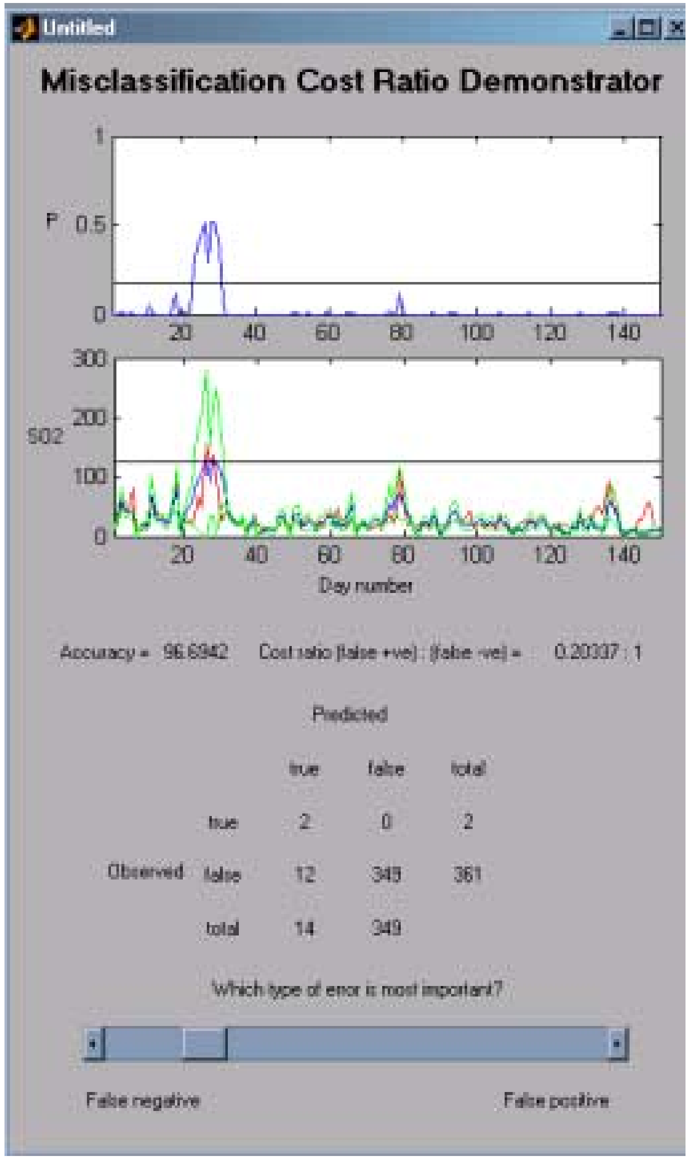
For predictions at a specific spatial location: The performance of both the neural network models and the deterministic models was fairly good and of the same order.

For predictions of spatial concentration distributions: The neural network models are not applicable

NN models (once trained) are computationally more effective

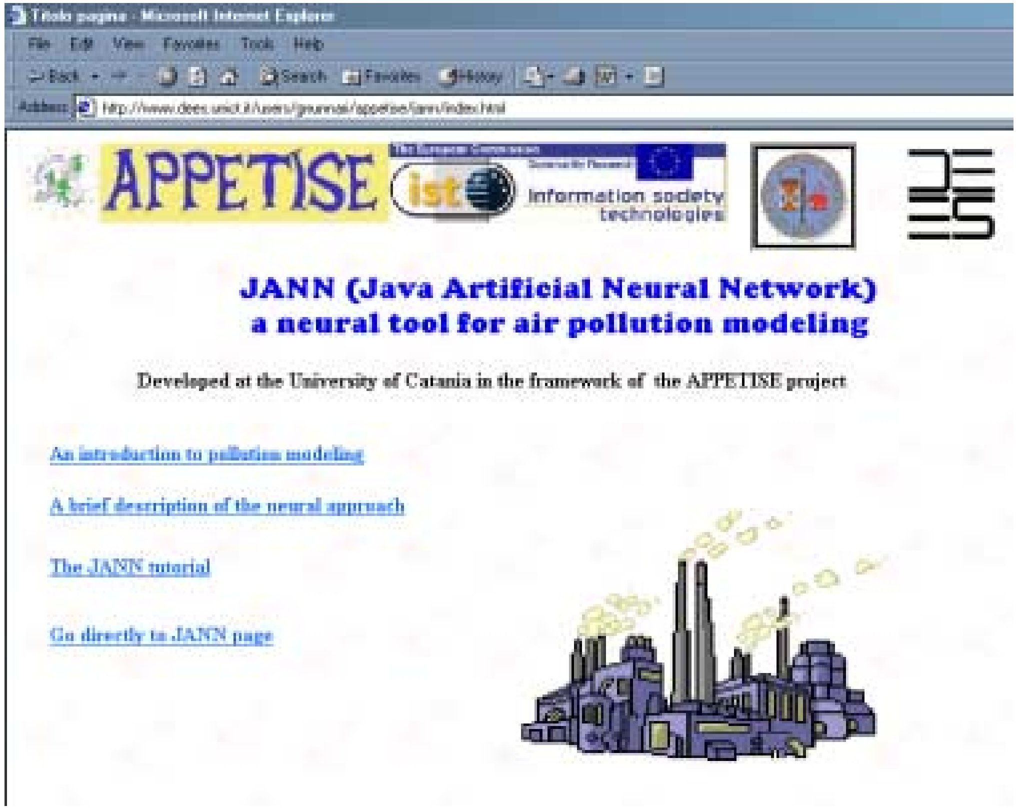
DET models can be more easily extended to other locations and time periods (e.g., analysis of scenarios for the future)

http://theoval.sys.uea.ac.uk/~gcc/projects/appetise/demonstrator/Berlin_SO2.html



JANN (Java Artificial Neural Network), tool for air pollution modelling by using Multi-layer Perceptron Neural Networks

http://www.dees.unict.it/users/gnunnari/appetise/jann/index.html



Future work (1)

FORECAST

Forecasting Air Quality using HIRLAM NWP Model Output

Funding: Academy of Sciences, Finland

Participants: FMI, Kuopio, UEA

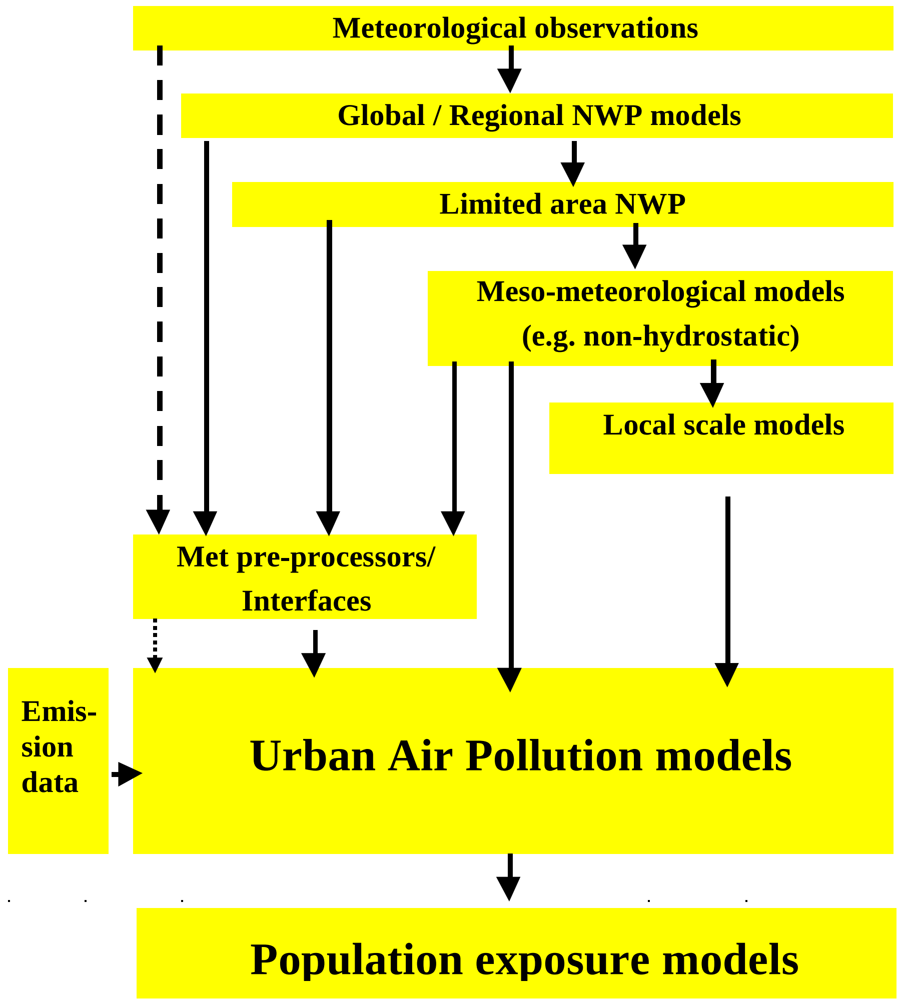
Future work (2)

FUMAPEX

"Integrated Systems for Forecasting Urban Meteorology, Air Pollution and Population Exposure"

Coordinated by DMI

EC FP5



Conclusions

- Neural Network models are useful for simulating air quality at a point
- Expert Knowledge can be used in selection of input variables
- Neural Network models can regularly be updated to reflect the effects of emission changes

Acknowledgements

European Commission IST FP5 Programme