

Supplement of Atmos. Meas. Tech., 13, 4601–4617, 2020  
<https://doi.org/10.5194/amt-13-4601-2020-supplement>  
© Author(s) 2020. This work is distributed under  
the Creative Commons Attribution 4.0 License.



*Supplement of*

## **High-resolution mapping of urban air quality with heterogeneous observations: a new methodology and its application to Amsterdam**

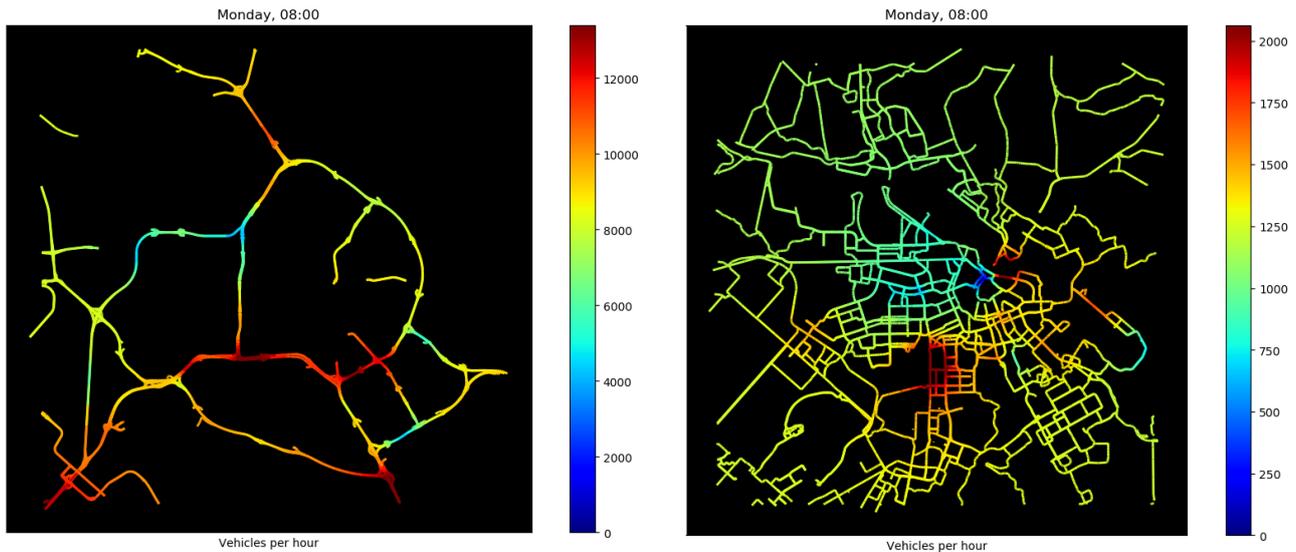
**Bas Mijling**

*Correspondence to:* Bas Mijling (mijling@knmi.nl)

The copyright of individual parts of the supplement might differ from the CC BY 4.0 License.

## 1 Interpolating traffic flow

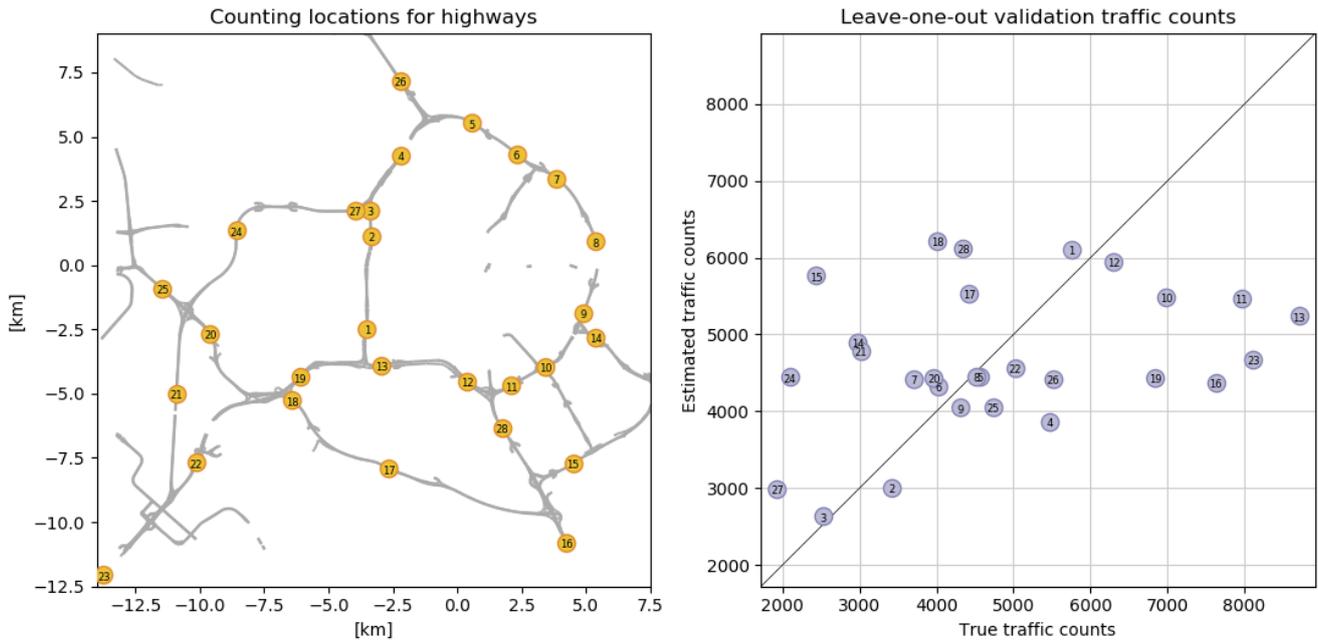
The local traffic flow at a given hour of day remains a large unknown. For Amsterdam we dispose of hourly data for 24 locations on the primary (urban) roads, and 29 representative locations on the surrounding highways. Traffic flow at other locations are derived by interpolating the traffic flow using inverse distance weighting (IDW). By doing this separately for the two different road types, blending in of the large differences in traffic volume is prevented. Figure S1 shows an example of interpolated traffic flow.



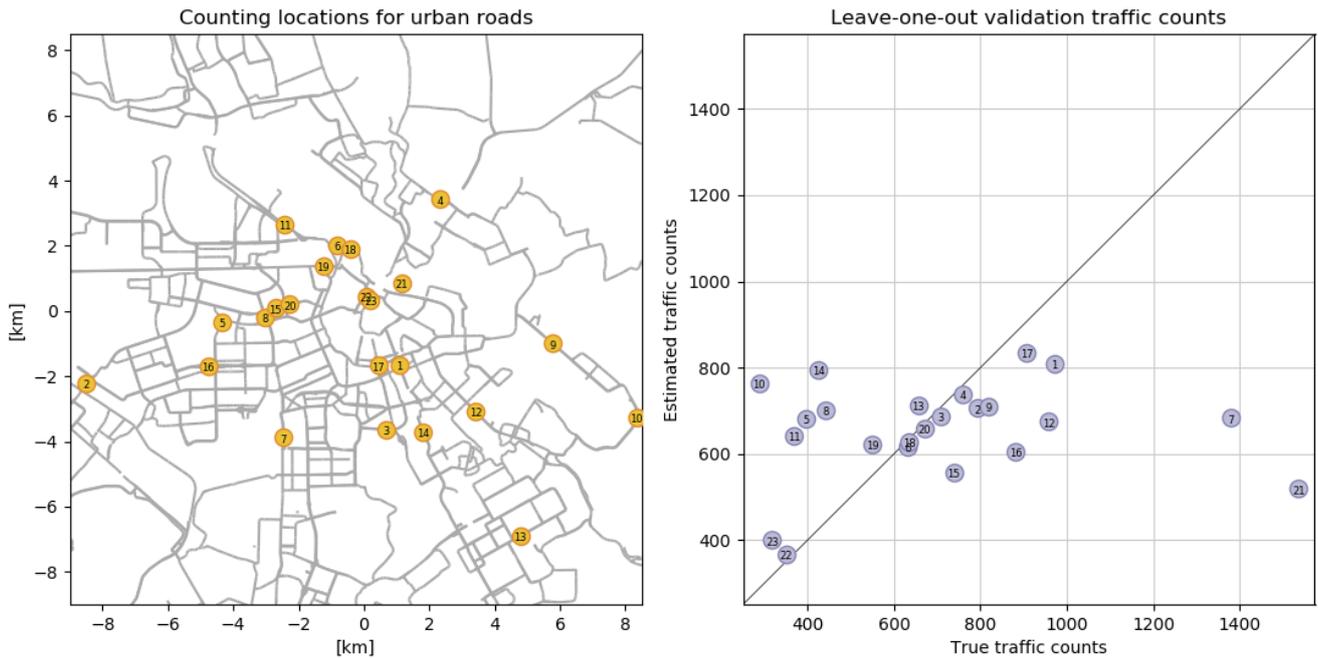
**Figure S1: Example of interpolated traffic flow for Monday at 8:00, for highways (left) and the primary road network (right). The colours indicate the number of vehicles per hour.**

### 10 1.1 Leave-one out validation for traffic counting locations

The question remains how well this IDW interpolation describes the traffic flow differences found for nearby roads of the same road type. This is assessed by a leave-one-out validation. Estimations for the highway network are shown in Figure S2. Strong biases are found at 15,16, 23 and 24, due to wrong extrapolation towards the borders of the counting network. Strong underestimations are also found at 11 and 13, the busiest parts of the southern ring road. Interpolations for locations between major highway exits go well when counting data at those exits are defined, such as at 2 and 8.



**Figure S2: (left) Counting locations at the highway network. (right) Comparison between the true vehicle count and the estimated count by IDW.**



**20 Figure S3: (left) Counting locations at the urban road network. (right) Comparison between the true vehicle count and the estimated count by IDW.**

Figure S3 shows the estimations for the urban road network. A strong underestimation is found at 21, located at a busy arterial road, for which nearby locations 22 and 23 at the low-traffic area of the city centre are not representative. Also the traffic at the busy artery at 7 is not well described by 3 and 16 alone when location 7 is omitted. The opposite effect, strong overestimation of traffic, is found at 10.

In general, estimated vehicle counts are within a 50% error range. More locations obviously will improve the accuracy of the traffic flow model. But when working with less data, the counting locations should be chosen strategically, when possible.

## 1.2 Concentration validation of different traffic emission models

Three different traffic scenarios (TS) are considered to test how inferior traffic data affects the simulated concentrations. All three describe the traffic with a weekly cycle (i.e. a diurnal cycle for 7 weekdays), distinct for highways and primary roads.

- TS1: Model simulations with a weekly traffic cycle, based on all 2016 data, where the magnitude is taken location independent.
- TS2: As in TS1, but the magnitude for each location is now interpolated from fixed counting locations by IDW. This is the default scenario used in this study.
- TS3: As in TS2, but using monthly traffic data at the counting locations, instead of yearly data.

June 2016 is selected as the test month for an intercomparison. For all reference locations the simulated time series of NO<sub>2</sub> concentrations are evaluated in terms of RMSE, bias, and correlation. Table S1 highlights for each statistical parameter the best performing scenario (i.e. lowest RMSE, smallest bias, highest correlation). Not surprisingly, at most locations the best performance is obtained using the more sophisticated traffic models TS2 and TS3. A bit counterintuitive might seem that the difference between TS1 and the other scenarios is relatively small. This can be explained from the dynamic calibration of the dispersion model and the collinearity of the emission proxies (Section 4). The calibration compensates for the lack of location-dependent traffic data in TS1 by putting more emphasis on the population density as a proxy for traffic emissions. Although the calibration is able to compensate for incorrect or incomplete traffic emissions in this way, it goes at the expense of less pronounced simulated gradients in the vicinity of roads.

55 **Table S1: Statistical analysis of simulated concentration time series under different traffic emission models. In grey the best result at a given location is highlighted.**

ID	<i>n</i>	mean obs. <sup>1)</sup>	scenario	RMSE <sup>1)</sup>	bias <sup>1)</sup>	correlation <sup>1)</sup>
NL49002	646	39.42	<b>TS1</b>	19.437	-12.344	0.564
			TS2	19.555	-12.552	0.565
			TS3	19.591	-12.787	<b>0.576</b>
NL49007	646	42.35	TS1	20.658	-7.519	0.482
			<b>TS2</b>	<b>20.380</b>	-6.431	<b>0.489</b>
			TS3	20.663	-7.388	0.477
NL49012	646	27.04	TS1	11.888	-1.663	0.634
			TS2	11.831	-1.491	0.637
			<b>TS3</b>	<b>11.740</b>	-1.680	<b>0.646</b>
NL49017	641	30.68	TS1	13.626	-0.493	0.452
			TS2	13.706	0.738	0.456
			<b>TS3</b>	<b>13.493</b>	0.243	<b>0.473</b>
NL49020	646	34.42	TS1	14.659	-5.127	0.530
			<b>TS2</b>	<b>14.530</b>	-4.980	0.534
			TS3	14.544	-5.254	<b>0.542</b>
NL49003	646	14.86	TS1	8.408	3.125	0.582
			TS2	8.616	3.465	0.573
			<b>TS3</b>	<b>8.374</b>	3.220	<b>0.591</b>
NL49014	646	18.33	TS1	13.636	7.414	0.421
			TS2	13.657	7.678	<b>0.438</b>
			<b>TS3</b>	<b>13.369</b>	7.340	<b>0.438</b>
NL49019	646	21.31	<b>TS1</b>	<b>12.198</b>	3.932	<b>0.463</b>
			TS2	12.505	4.467	0.445
			TS3	12.562	4.682	0.452
NL49021	612	14.55	<b>TS1</b>	<b>10.320</b>	5.171	<b>0.547</b>
			TS2	10.624	5.702	0.551
			TS3	10.440	5.403	0.552
NL49022	646	15.57	TS1	9.550	1.284	0.516
			<b>TS2</b>	<b>9.525</b>	1.341	<b>0.517</b>
			TS3	9.546	1.242	0.515
NL49565	628	18.27	TS1	9.965	-3.672	0.452
			<b>TS2</b>	<b>9.421</b>	-2.984	<b>0.506</b>
			TS3	9.603	-3.108	0.482
NL49703	626	13.46	TS1	8.550	1.640	0.514

			TS2	8.275	1.368	0.526
			<b>TS3</b>	8.227	1.194	0.533
			<b>TS1</b>	12.574	-5.645	0.645
NL49546	646	20.00	TS2	12.659	-5.636	0.637
			TS3	12.632	-5.728	0.645
			TS1	11.354	-5.549	0.676
NL49704	646	18.66	TS2	11.357	-5.515	0.676
			TS3	11.355	-5.569	0.678
			TS1	10.427	-4.157	0.549
NL49561	646	21.84	<b>TS2</b>	10.071	-3.525	0.567
			TS3	10.124	-3.709	0.569

<sup>1)</sup> In units  $\mu\text{g}/\text{m}^3$

## 60 2. Validation results at reference sites

Below the validation of hourly time series at all reference sites, for the period June 1 to August 31, 2016. Statistics are given for correlation ( $\rho$ ), coefficient of determination ( $R^2$ ), and the root-mean-squared error (RMSE). Note that  $R^2$  can become negative if the predicted values perform worse than just taking the average of the observed values. The right panels compare the error distributions: the observation minus forecast (OmF) and the observation minus analysis (OmA).

65

