Geoscientific
Model Development

Supplement of

DRIVE v1.0: a data-driven framework to estimate road transport emissions and temporal profiles

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S1 Implementation and Application

This supplement contains extended model and implementation descriptions tailored to the application of the DRIVE (Data-driven Road-Transport Inventory for Vehicle Emissions) framework. It complements the README documents in the code repository to serve as a user manual.

The framework is developed in Python and targets users with programming skills. For all scripts that require user interaction, Jupyter Notebooks[1] were used, which combine code, visualization, and documentation in one file. All notebooks are set up in the same way, starting with a description of the content, the import of libraries, the user-defined processing settings, data imports, dedicated notebook functions, and all downstream processing steps. These notebooks access a custom utils module that implements functions for calculating cold and hot emissions, processing the traffic counts, accessing calendar functions, and rasterizing the line source emissions.

Additionally, QGIS [2], a free and open-source geographic information system, is used for manual data curation (e.g., assigning the locations of traffic counting stations to their respective road links) and visualization.

S1.1 Workflow Overview

The framework is intended to be used according to the following workflow:

1. Data curation: Preparation of input files before automatic processing is conducted.

2. Data pre-processing: Combine data with information from different sources and clean the dataset.

3. Model setup and run: Define model parameters and run emission calculation.

4. Processing of the model output: Rasterize the line source emissions and visualize the data.

S2 Data Curation

Before automatic data processing can occur, the user needs to prepare the datasets and convert them to a machine-readable format. The required steps depend entirely on the availability of the data and its structure. This section describes the procedures that were carried out in Munich.

– Allocate traffic counting stations to the respective road links in the traffic model.
  Where and how these detectors are allocated depends on the representation of the road links in the traffic model (e.g., different driving directions could be represented as a single road link or as separate road links). Figure S1 shows how a single counting station could include several detectors (e.g., multiple lanes on a cross-section). Subsequently, the count data of multiple detectors on a single road link is aggregated. We performed this step manually for all detectors that can be assigned to road links in the traffic model. Several detectors were excluded near the trade fair (Messe München) and Munich's football stadium (Allianz Arena). They are solely used for traffic control during special events.

– Convert the traffic counting data to a standard data format for subsequent automatic processing.

– Convert the information from the traffic model to an HBEFA-compatible format (e.g., speed, gradient, road type).

– Create an Excel calendar file that lists local public holidays and vacation periods.

– Export the emission factors as tabular *.csv data from the HBEFA MS-Access application. Cold-start excess emissions and hot exhaust emission factors are available in separate tables.

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[1]https://jupyter.org/
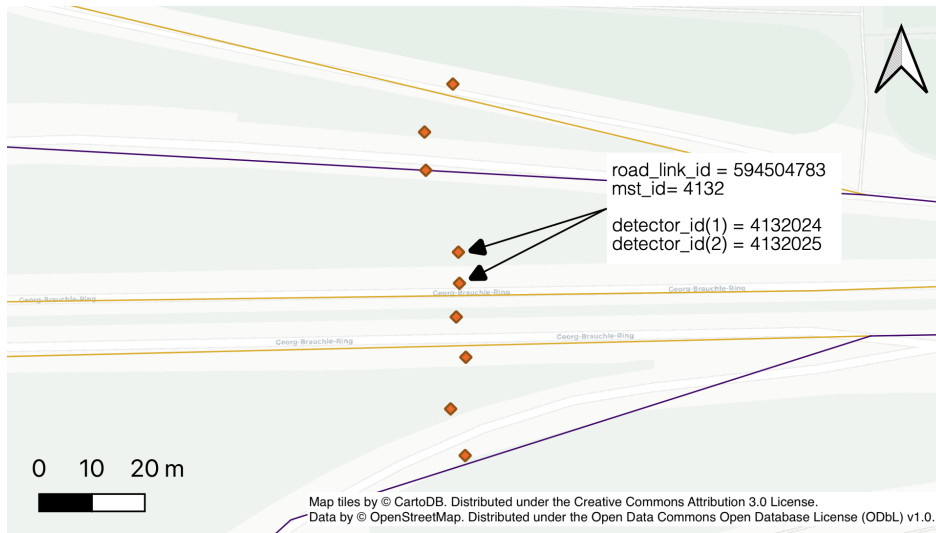[2]https://www.qgis.org/

Figure S1. Example of four two-lane roads and one single-lane road, each equipped with individual detectors identified with a detector_id that form a counting station (mst_id) together. These multiple detectors must be correctly assigned to their corresponding road links (road_link_id) in the traffic model. Counter locations provided by the City of Munich. The road link information was derived from the Munich traffic model.

S3 Optimization of the Volume-Capacity Ratio Thresholds

The volume-capacity ratio (VCR) was utilized to estimate the traffic condition on each road link. Schmaus et. al. (2023) investigated the distribution of the vehicle kilometers traveled (VKT) among different traffic conditions in Germany based on floating car data. Table S1 shows the distribution for different road types in urban areas. These shares were used as a reference for the optimization process and are suitable for urban roads in Germany.

The optimization process requires manual parameterization of the VCR thresholds. A script is provided that calculates the VKT distribution across different traffic conditions on a given road type. By iteratively changing the VCR thresholds, the target distribution is achieved.

Table S1. Share of vehicle kilometers traveled (VKT) in different HBEFA traffic conditions for different road types in German urban areas. The shares were collected from Schmaus et. al. (2023).

	Freeflow	*Heavy*	*Saturated*	*Stop&Go*	*Stop&Go 2*
Motorway	38 %	31 %	28 %	2.7 %	0.3 %
Primary-National	55 %	27 %	12 %	2.3 %	4.2 %
Primary-City	57 %	25 %	11 %	3.2 %	4.7 %
Secondary	54 %	23 %	14 %	5 %	3.6 %
Residential	55 %	23 %	13 %	4.7 %	3.4 %

S4 Cross Validation of the Traffic Model and Counting Data

The VISUM model used in Munich represents the average annual norm-weekday (Tuesday-Thursday outside the holiday sea-
45 son) traffic volume $q_{i,vc}^{model}$ for passenger cars (PC), light commercial vehicles (LCV), heavy goods vehicles (HGV). To compare
it with the counting data and evaluate the fit, we calculated the average weekday count from 2019. This allows for estimating
the modeled and observed values for multiple road links, enabling the computation of the coefficient of determination (R^2) and
the scalable quality value (SQV).

The coefficient of determination indicates how effectively the model represents the traffic volumes across the city area and dif-
50 ferent road types. It also reveals systematic model errors like an over- or underestimation of traffic volumes on particular road
types and can indicate misplaced or faulty traffic detectors. Figure S2 shows scatter plots for the total traffic volume (SUM)
and all vehicle-specific traffic volumes available in the traffic model (PC, LCV, and HGV). The LCV category shows higher
values in the model than the counting stations. Upon request, the city department responsible argued that no LCV-specific
calibration had been performed. Misclassifications between PC and LCV of the double loop traffic detectors could also play
55 an important role. The fit is particularly worse at trunk roads where only double loop detectors are installed, compared to the
motorway, where a more robust camera-based classification is in place. We are aware of the data-model mismatch, but we have
more confidence in the traffic model.

Secondly, the Scalable Quality Value (Equation S1), a quality measure used in traffic engineering, provides an additional,
magnitude-independent criterion for traffic model assessment. Proposed by Friedrich et. al. (2019), the SQV introduces a
60 scaling factor f to assess traffic volumes at different time aggregations (hourly traffic volume: $f = 10^3$, daily traffic volume:
$f = 10^4$). M is the modeled traffic volume and C the counted volume. Furthermore, he proposes SQV thresholds for perfect
matches ($SQV \geq 0.9$) to acceptable matches ($SQV \geq 0.8$). Given the extensive size of the road network and the fact that
data from these counting stations was not utilized in optimizing the traffic model, a lower threshold was justified. We use a
$SQV \geq 0.6$ to select trustworthy counting stations. Figure S3 shows a histogram of the SQV statistics of all counting stations
65 in our area of interest. 52.4% of all counting stations on different road types show a $SQV \geq 0.9$ while 90.5% of all stations
have a $SQV \geq 0.6$. Figure S4 shows the spatial allocation of valid counting stations. In total, 82 road links have valid counting
data assigned to them.

$$SQV = \frac{1}{1 + \sqrt{\frac{(M-C)^2}{f \cdot C}}} \tag{S1}$$

S4.1 Validation of modeled, vehicle-specific and κ-corrected daily traffic volumes

70 To model the traffic volume on each road link, we apply road and vehicle class-specific temporal extrapolation to the average
weekday traffic volume provided by the traffic model. In addition, vehicle-share correction factors κ were applied to account
for different modal splits on the same road type (example: higher HGV share on the ring motorway vs. on radial motorways
into the city). In Figure S5 and S6, κ-corrected, modeled vehicle count and daily counts from counting stations on the same
road link are shown. Figure S5 shows the daily traffic volume for all weekdays in 2019. A good fit for SUM, PC, and HGV
75 can be observed across all road types. LCV, MOT, and BUS have worse fit statistics and higher variance. This is related to
the small daily counts of MOT and BUS and the already worse fit of LCV in the traffic model (cp. Figure S2). The modeled
traffic volume underestimates MOT and BUS and overestimates LCV. Additionally, we observe no significant difference but
only slightly lower R^2-values for weekend days compared to weekdays. In particular for SUM, PC, and HGV, we conclude
that κ-corrected daily traffic volumes are equally valid on weekdays and weekends.
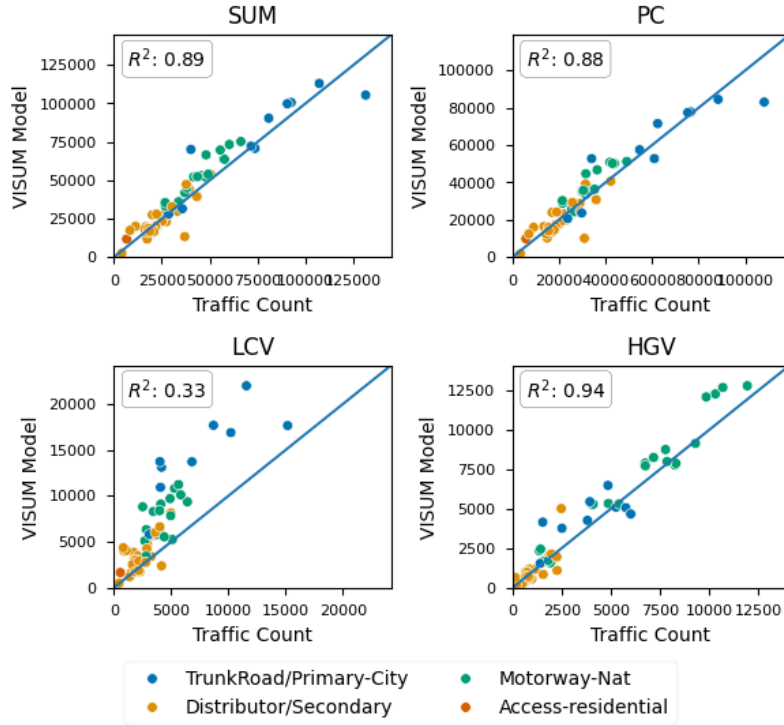
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Figure S2. Scatter plot of the average annual norm-weekday traffic volume in the traffic model and calculated from the traffic counting data. The total traffic (SUM), passenger cars (PC), and heavy goods vehicles (HGV) show a good fit for all road types. Light commercial vehicle volume (LCV) is not well calibrated in the model or shows a strong classification error in the traffic counting data.
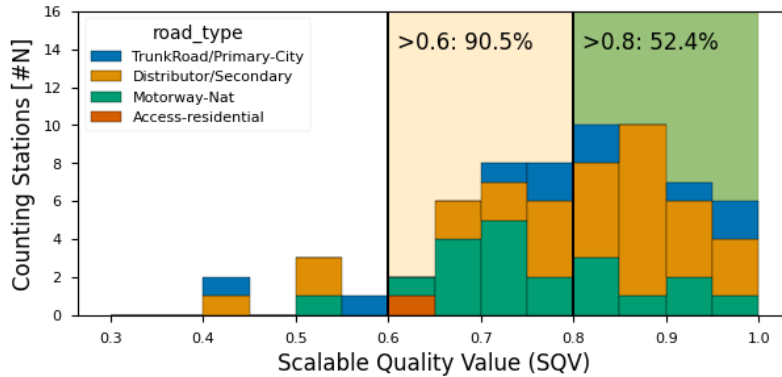

Figure S3. Histogram of the scalable quality value (SQV) of the average annual norm-weekday traffic volume in the traffic model and calculated from the traffic counting data. 52% of all counting stations have an acceptable fit according to the threshold provided by Friedrich et. al. (2019) ($SQV \geq 0.8$). We relaxed the criterion and used it to select trustful counting stations with an $SQV \geq 0.6$, which includes $> 90\%$ of all stations in our region of interest.
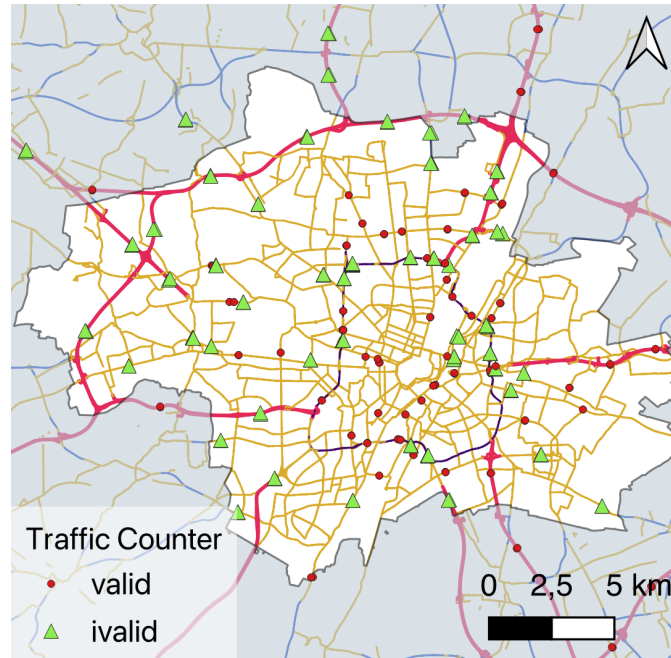
Figure S4. Classification and spatial allocation of "valid" and "invalid" flagged traffic counting stations. Valid stations provide data for 2019 and have an SQV greater than 0.6. In total, 82 road links have valid traffic counting data assigned to them. Counter locations provided by the City of Munich and BASt (2024). The road link information was derived from the Munich traffic model.
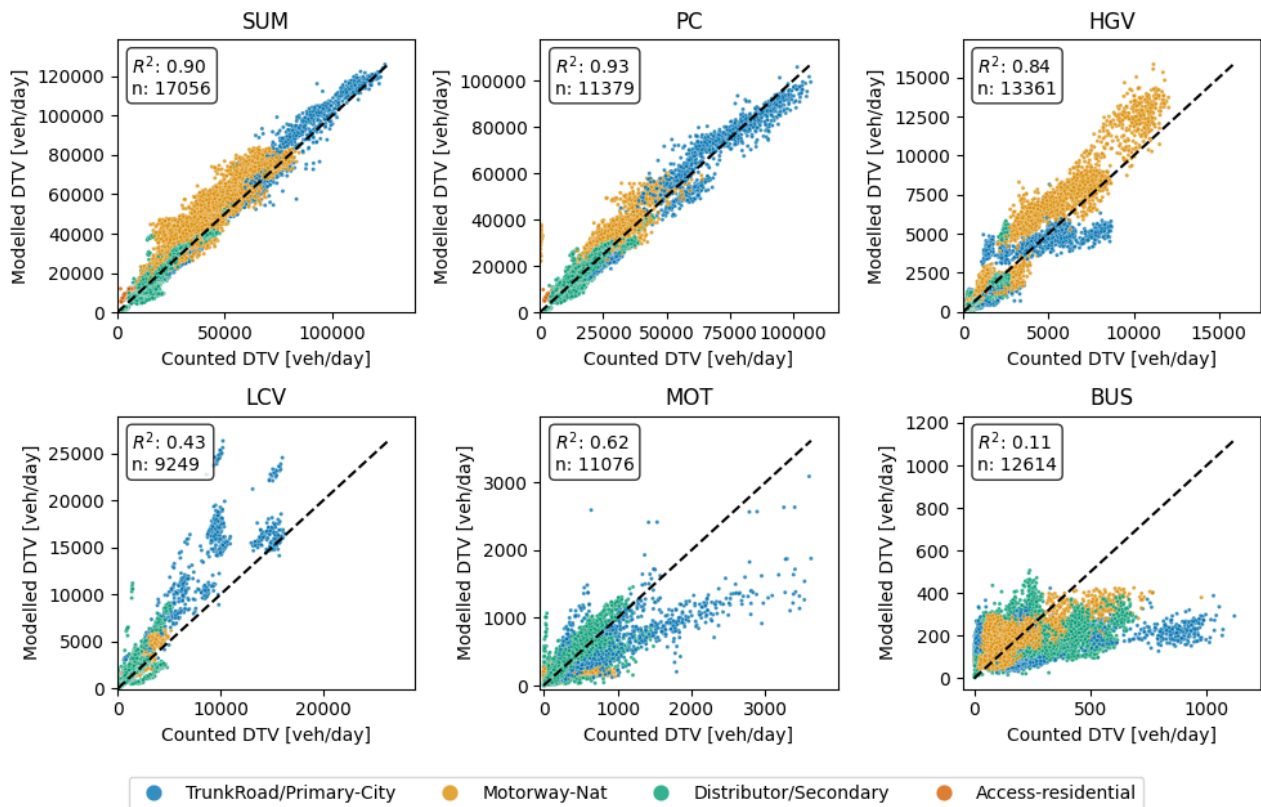
Figure S5. Comparison of κ-corrected modeled vs. counted daily traffic volume on weekdays (Monday-Friday). The daily modeled count for SUM, PC, and HGV shows a good fit and a high R^2. For MOT, bus, and LCV, the fit statistics are less satisfactory, which is attributed to lower counts and a poorer overall fit with the traffic model.
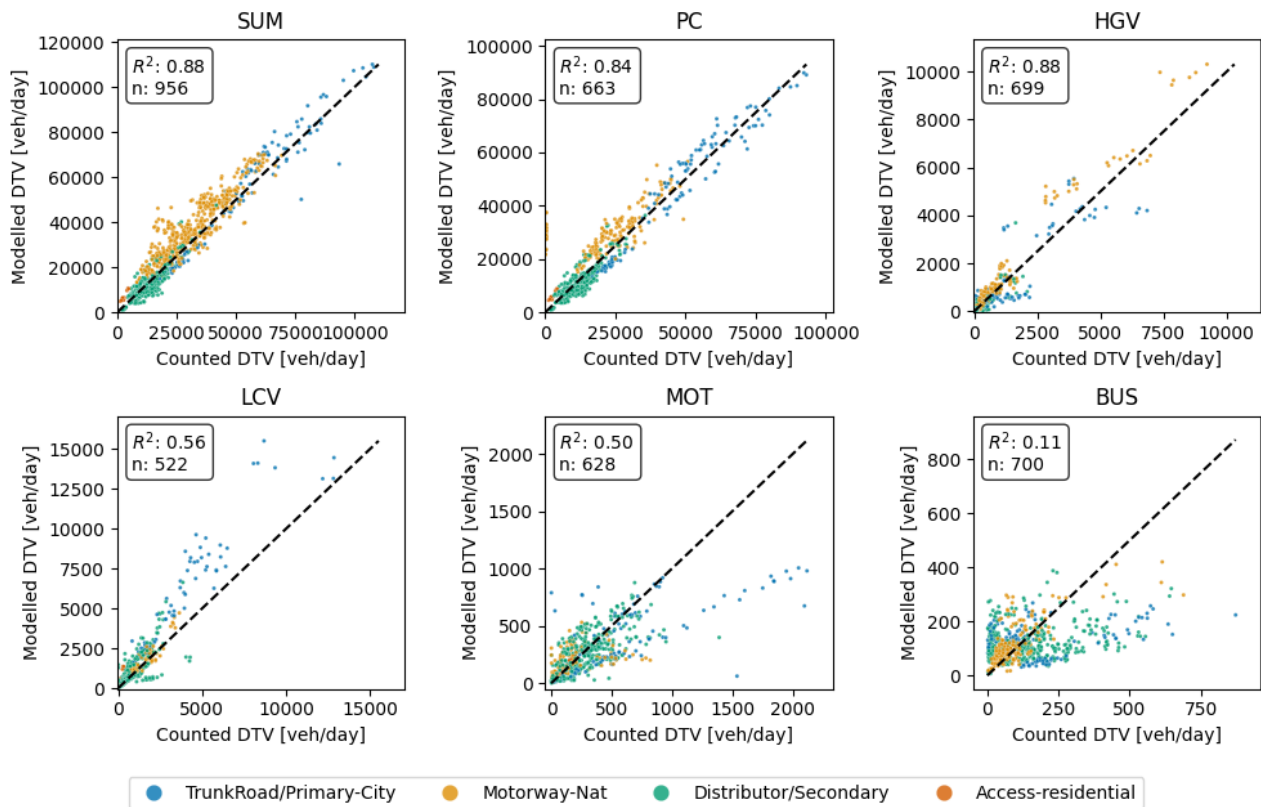
Figure S6. Comparison of κ-corrected modeled vs. counted daily traffic volume on weekend days (Saturday, Sunday). Compared to the weekday fit, we observe a similarly high agreement for SUM, PC, and HGV, and similar deviations for LCV, MOT, and BUS. We conclude that κ-corrected vehicle volumes are as valid on weekends as they are on weekdays.

References

Friedrich, M., Pestel, E., Schiller, C., and Simon, R.: Scalable GEH: a quality measure for comparing observed and modeled single values in a travel demand model validation, Transportation Research Record: Journal of the Transportation Research Board, 2673, 722-732, https://doi.org/10.1177/0361198119838849, 2019.

Schmaus, M., Bawidamann, J., Friedrich, M., Haberl, M., Trenkwalder, L., Fellendorf, M., Uhlig, J., Lohse, R., and Pestel, E.: Flüssiger Verkehr für Klimaschutz und Luftreinhaltung, Final report 14/2023, Umweltbundesamt (UBA), ISSN 1862-4804, 2023.

BASt: Automatische Dauerzählstellen auf Autobahnen und Bundesstraßen, https://www.bast.de/DE/Themen/Digitales/HF_1/Massnahmen/verkehrszaehlung/verkehrszaehlung.html (last access: 27 March 2025), 2024.