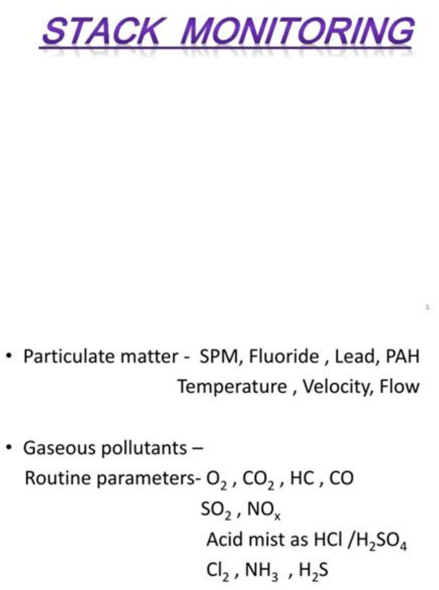

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Book Descriptions:

Caline4 manual

Widely used in Germany, AUSTAL is capable of modeling complex wind fields and transient behavior. CALRoads can model timed intersections, parking lots and account from traffic patterns. This stateofart model is extraordinarily powerful, capable of providing realistic modeling of complex three dimensional emergency releases. The SLAB model is an atmospheric dispersion model for denserthanair releases. This model is an ideal tool to predict hazardous zones and potential impacts of accidental releases. SCREEN3 is a screening version of the ISC3 model. It contains 3 models SCREEN3, PUFF, and RVD Relief Valve Discharge.CTSCREEN is a screening version of the CTDMPLUS model. AERMET AERMET is a meteorological data preprocessor for AERMOD. AERMET processes commercially available or custom onsite met data and creates two files a surface data file and a profile data file. The tool AERSURFACE can be used to estimate the surface characteristics for input to AERMET. AERMAP AERMAP is a terrain preprocessor for AERMOD. AERMAP processes commercially available Digital Elevation Data and creates a file suitable for use within an AERMOD control file. This file would contain elevation and hillheight scaling factors for each receptor in the air dispersion study.CAL3QHC is an enhanced version of CALINE3, with the additional traffic algorithm to estimate vehicular queue lengths at intersections with traffic stop lights. We recommend that you get both models. The theoretical information regarding the CALINE3 implementation in CsAL3QHC is only presented in CALINE3 Users Guide. It is based on the Gaussian diffusion equation and employs a mixing zone concept to characterize pollutant dispersion over the roadway. CALINE4 comes with a Windows user interface. Wind roses are useful to define the dominant transport direction of the winds for a location.http://agelectric-bs.com/userfiles/digital-delay-dd-7-manual.xml

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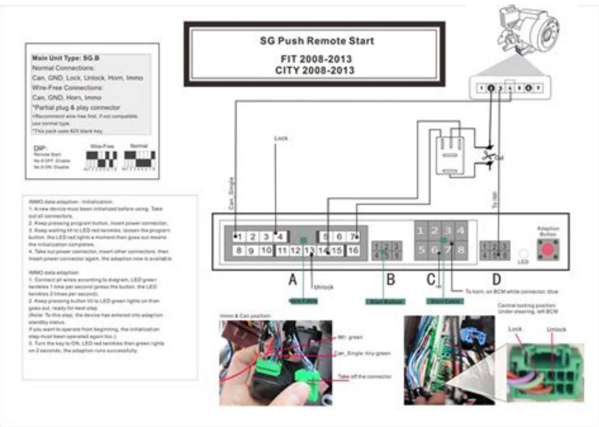
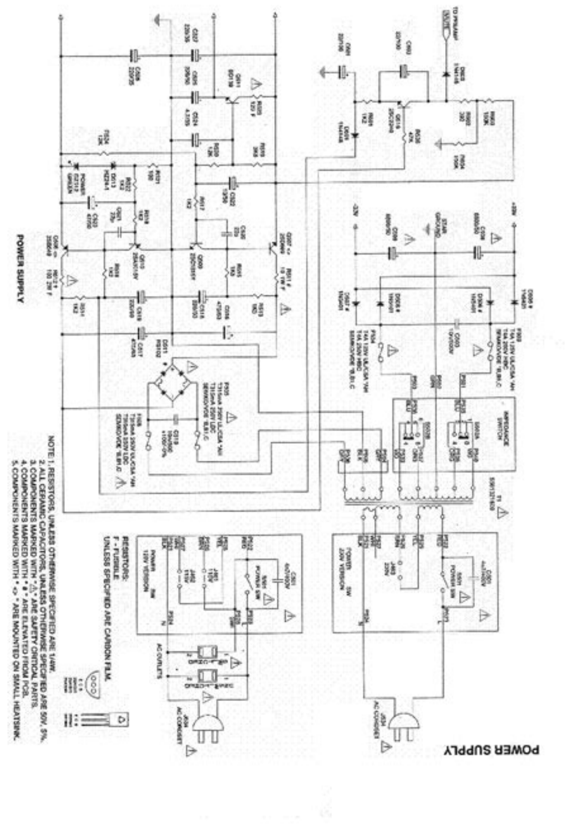


Four types of releases can be treated by the model a groundlevel evaporating pool, an elevated horizontal jet, a stack or elevated jet, and an instantaneous volume source. SPECIATE SPECIATE is EPAs repository of Total Organic Compound TOC and Particulate Matter PM speciated profiles for a variety of sources for use in source apportionment studies. TANKS LandGEM The Landfill Gas Emissions Model LandGEM is an automated estimation tool with a Microsoft Excel interface that can be used to estimate emission rates for total landfill gas, methane, carbon dioxide, nonmethane organic compounds, and individual air pollutants from municipal solid waste landfills. It is available from the EPAs Clean Air Technology Center. WATER9 WATER9, a wastewater treatment model, consists of analytical expressions for estimating air emissions of individual waste constituents in wastewater collection, storage, treatment, and disposal facilities; a database listing many of the organic compounds; and procedures for obtaining reports of constituent fates, including air emissions and treatment effectiveness. PM Calculator March 31, 2006. After receiving numerous inquiries regarding the removal of the PM Calculator, EPA has reposted the software. The software is here for your convenience, however, it is no longer supported by EPA. The model uses traffic emissions, site geometry and meteorology to predict air pollutant concentrations near roadways. Predictions can be made for carbon monoxide, nitrogen dioxide and suspended particles. Options for modeling near intersections, parking lots, evaluated or depressed freeways, and within canyons are given. A modal emissions model developed for the CALINE4 intersections link option is described. Also, an adjustment for transient emissions is developed. Computer documentation and user instructions for CALINE4 are included in the report. Sensitivity of the model to various input parameters is illustrated in a series of the model response curves.http://djarkitek.com/temp/vinney/HTML/userfiles/digital-delay-dd-5-manual.xml

The model is verified using data from five separate field studies. Two of the studies were conducted as part of this research and are described in detail. Data from one of these, a highway tracer gas release experiment, are presented in an appendix to the report. Author All Rights Reserved. Terms of Use and Privacy Statement. Three models are listed in Schedule 1 in the Annex and are referred to as Schedule 1 models. These models are currently accepted by EPD for general use in EIA. These can be used in relatively straightforward assessments and usually cover impacts from the first two tiers project induced; pollutantemitting activities in the immediate neighbourhood. The last model PATH2016 is a gridbased system and operates on a set of comprehensive emission data after generating its own meteorological data. This covers the third tier background contribution. The meteorological output from PATH2016 can be used to drive the above mentioned Tier 1 and 2 models while the concentration output from PATH2016 can be taken as Tier 3 contribution. The following guidelines supplement the standard user's guide in focusing on areas that are of common concern in an EIA in Hong Kong for these two models. PATH2016 is constituted from open source modules with documentations available in the open literature. Specific information on the configuration of the PATH2016 system and the public accessible data model output for EIA application can be found on. In cases an anemometer height is required as input to models for Tier 1 and Tier 2 assessment, it should be set at the midlayer height of the relevant PATH2016 grid cells. Typical values of range from 12 o for rural areas to 24 o for highly urbanised areas under D class stability. For semirural areas such as new development, 18 o is more appropriate under the same stability condition.

The following reference or more uptodate version can be consulted for typical ranges of standard deviation of wind direction under different stability categories and surface roughness conditions. As a first approximation, the surface roughness can be estimated as 3 to 10 percent of the average height of physical structures. Typical values used for urban and new development areas are 370 cm and 100 cm, respectively. The current recommendation is excerpted below Surface roughness length may be varied by sector to account for variations in land cover near the measurement site; however, the sector widths should be no smaller than 30 degrees. Two approaches are currently acceptable in the determination of NO 2 These ratios can be found on. Otherwise, project specific ratios can be proposed with strong supporting evidence and should be fully agreed with EPD. Conversion of modelcomputed hourly average results to 5second values is therefore necessary to enable comparison against the recommended standard. The hourly concentration is first converted to 3minute average value according to a power law relationship which is stability dependent Ref. 2 and a result of the statistical nature of atmospheric turbulence. Another conversion factor 10 for unstable conditions and 5 for neutral to stable conditions is then applied to convert the 3minute average to 5second average Ref. 3. In summary, to convert the hourly results to 5second averages, the following factors can be applied Note, however, that the combined use of such conversion factors together with the AERMOD results may not be suitable for assessing the extreme closeup impacts of odour sources. In all these situations, the AERMOD model will have to be used instead of the CALINE4 model. A receptor grid, whether Cartesian or Polar, may be used to generate results for contour outputs.



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It was determined that PATH2016’s output of RSP concentrations should be adjusted as follows before being applied for EIA to account for the limited information on pollutant emissions on a larger scale Contours of pollutant concentration are also required for indicating the general impacts of emissions over a study area. This article has been cited by other articles in PMC. Associated Data Supplementary Materials Additional file 1 Supplemental figures and tables referred to in the text. 1476069X929S1.DOC 360K GUID 1E5985959538431789F784895B50730E Abstract Background Nearroad exposures of trafficrelated air pollutants have been receiving increased attention due to evidence linking emissions from hightraffic roadways to adverse health outcomes. To date, most epidemiological and risk analyses have utilized simple but crude exposure indicators, most typically proximity measures, such as the distance between freeways and residences, to represent air quality impacts from traffic. This paper derives and analyzes a simplified microscale simulation model designed to predict short hourly to longterm annual average pollutant concentrations near roads. Sensitivity analyses and case studies are used to highlight issues in predicting nearroad exposures. Methods Processbased simulation models using a computationally efficient reducedform response surface structure and a minimum number of inputs integrate the major determinants of air pollution exposures traffic volume and vehicle emissions, meteorology, and receptor location. The first predicts carbon monoxide CO concentrations at a monitoring site near a freeway. The second predicts CO and PM 2.5 concentrations in a dense receptor grid over a 1 km 2 area around the intersection of two major roads. We analyze the spatial and temporal patterns of pollutant concentration predictions. Results Predicted CO concentrations showed reasonable agreement with annual average and 24hour measurements, e.g.

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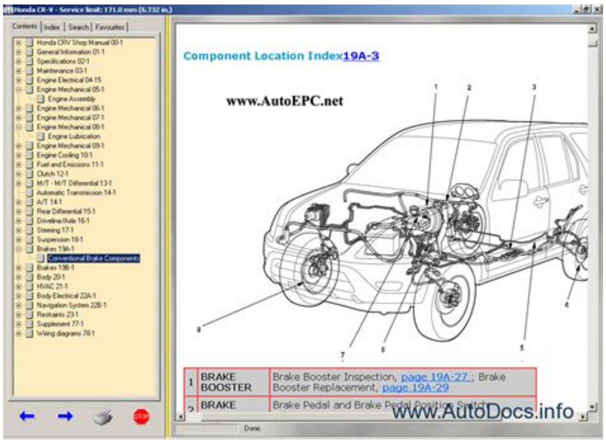

, 59% of the 24hr predictions were within a factor of two of observations in the warmer months when CO emissions are more consistent. The highest concentrations of both CO and PM 2.5 were predicted to occur near intersections and downwind of major roads during periods of unfavorable meteorology e.g., low wind speeds and high emissions e.g., weekday rush hour. Conclusions The case study findings can likely be generalized to many other locations, and they have important implications for epidemiological and other studies. The reducedform model is intended for exposure assessment, risk assessment, epidemiological, geographical information systems, and other applications. Background The use of geocoded data and geographical information systems GIS has rapidly becoming routine practice in many types of environmental analyses, including risk assessment and environmental epidemiology. Most studies have used surrogates of pollutant exposure, including proximity measures such as the distance from residences or schools to highways or Superfund sites. While easy to display and analyze within a GIS, proximity is at best a crude surrogate of exposure since it incompletely accounts for the nature of emission sources, effects of meteorology, orographic features and other factors that affect pollutant emissions, transport, fate and exposure. Relatively few studies have used emission and dispersion models to predict exposures to ambient air pollutants. Such models, which can predict spatially and temporallyresolved concentrations, have the potential to improve exposure estimates and facilitate new types of analyses. While quite easy to derive within GIS framework, a significant drawback of proximity and traffic intensity measures is the potential for biased and misclassified exposure estimates since such measures do not consider effects of meteorology, vehicle emissions, and timeactivity patterns of the study subjects, e.g., time spent away from the location considered.

These models utilize emission and dispersion components, the latter typically based on the Gaussian plume equation. Such models can be dataintensive, requiring data on pollutant emissions, emission source and roadway configurations, meteorological conditions, and land use parameters. Vehicle emissions depend on many factors, including the number, speed, type and age of vehicles, all of which can vary significantly over the course of a day. The drawbacks of dispersion models include, among others, extensive input data requirements, errors due to unmeasured variability in emissions and other parameters, the need for accurate locational information, simplified and possibly unrealistic model assumptions; the relevance of the background estimates, and a need for validation. Based on the NavierStokes equations, such models are useful for estimating shortterm dispersion of plumes, especially in areas containing obstacles like large buildings and complex terrain, and with calm or very light winds, a situation when other types of models perform poorly. However, CFD models are especially demanding in terms of data inputs and computational requirements, and they are not immune to many of the other drawbacks just discussed for dispersion models. The primary advantage of LUR models is their ability to characterize smallscale variations in urban settings without the need for detailed and accurate emission information. However, these models are areaspecific and cannot be reliably extrapolated to areas with different topography, land uses, emission types, etc. Since monitored pollutant levels are used as the dependent variable in the regression model, they also require a network of air sampling sites and historical data. LUR models have been used to estimate only longterm concentrations.

The reducedform model has several advantages over existing models, including the ability to predict concentrations for an arbitrarily large number of receptors and time periods, fast computations, and relatively limited data needs. Also, the simple form of the reducedform model permits easily incorporation into GIS and other applications. The second objective of this paper is to identify critical variables, exposure patterns and knowledge gaps that should be recognized in exposure and risk assessment applications addressing nearroad exposures. The paper is organized as follows. We first review approaches for estimating exposures from vehicles. The development of reducedform submodels to simulate emissions and dispersion is then described. This involves the use of response surface techniques for key variables, which are assembled in a modular fashion to facilitate development and verification. Sensitivity analyses identify critical variables and illustrate the models behavior. We then select key variables and derive parameterizations for the reducedform model. The assembled model is demonstrated using two case studies. The first compares predictions of CO to concentrations monitored near a major freeway. The second highlights issues in exposure assessment by predicting CO and PM 2.5 concentrations in an area surrounding a major freeway and an arterial road. These applications show several surprising and important results regarding the distribution, spatial and temporal variability of concentration predictions. We close on comments regarding implications for exposure and risk assessment, and limitations of the model. Methods Emission modeling The first of two submodels, which predicts hourly estimates of vehicle emission rates, is based on MOBILE6.2 model, a macroscopic model developed by the U.S. Environmental Protection Agency that is widely used in emission inventory and dispersion modeling applications. Our goals were to match MOBILE6.

2 predictions given the information that is typically available for mobile source modeling, to incorporate the major factors that affect vehicle emissions, and to strike a reasonable balance between simplicity and the ability to predict emissions. We were primarily concerned with exposures near large roads, i.e., freeways and arterials, and did not examine idling, cold start, and other types of emissions. After selecting critical inputs, we used a set of lookup tables for emission factors organized by year and pollutant, taken directly from MOBILE6.2 outputs, and then estimated emissions on the segment by scaling up the emission factors by the roads vehicle mix and volume. The model can also simulate formation and dispersion of NO 2, using a simple set of reactions to predict its formation from precursors NO and O 3, and PM, using algorithms to model deposition and settling processes. Required inputs include roadway geometry, hourly surface meteorology, traffic volume and emission rates. We derived a reducedform dispersion submodel using multiplicative parametric equations that are simple to implement and solve, essentially representing a response surface analysis for individual processes in the model. To guide the development of the reducedform model, we performed sensitivity analyses for key parameters that were individually varied over a wider range than analyzed previously, while other parameters were maintained at nominal values. Receptors are defined with respect to the road by distance x m measured normal from the road centerline. Open in a separate window Figure 1 Depiction of road and receptor coordinate system for arbitrary road and wind directions. Model predictions were subsequently adjusted to derive concentrations for a nominal emission rate of 1 g km 1. These can be important in special cases, but they generally represent secondary influences.

Reducedform dispersion model A reducedform dispersion model using analytical expressions was derived that obtained comparable predictions to CALINE4, guided by the results of the sensitivity analysis. A multiplicative and modular model structure using submodels for each major input parameter was selected, thus allowing easy updates. We attempted to strike a balance between reproducing CALINE4s output exactly, using readily available data, and keeping calculations fast and simple, and we maintained those inputs that changed predicted concentrations by more than 10 or 15%. This criterion applies only to the nominal conditions modeled, e.g., flat terrain, and road at grade level. Generally, input parameters making smaller differences were omitted. A variety of model structures for the submodels were evaluated, including exponential, power law and polynomial regression models, among others, and parameter coefficients were estimated using maximum likelihood estimates and nonlinear Newton gradient search procedures. Like other Gaussian dispersion models, calm winds cannot be accurately modeled. We set the minimum wind speed to 0.5 m s 1. For calms, no calculations were attempted the hours concentration was recorded as not available. Daily averages were calculated if at least half of the hourly observations were available. Model evaluation We first verified the reducedform model by examining intermodel agreement using correlations, relative errors, absolute relative error statistics, and scatter plots. The performance of the reducedform model was evaluated over the full range of input parameters. Next, we conducted a limited evaluation of the reducedform model by comparing hourly and daily average predictions to CO measurements for the year 2004 at the Allen Park, Michigan monitoring site, which is operated by the Michigan Department of Environmental Quality MDEQ.

The site was selected due to its proximity to both a major freeway and a permanent traffic recorder PTR, which records hourly traffic volume. The surrounding land use is primarily residential, although there are various commercial and industrial facilities within 5 km of the site. CO is monitored using U.S. EPA approved instrumentation DASIBI 3008 analyzer. Surface meteorological observations are also collected at this site. We obtained hourly CO, meteorological, and PTR data for 2004. After rowwise eliminations including calms, 6,046 hours, representing 263 days with most data available, were available. Due to some local features that appeared to influence wind direction, primarily a line of trees 25 m N, we used hourly wind direction data from the local airport, located 18 km to the west of the monitoring site. Detroit case study To demonstrate a more complex application, we modeled a 1 km 2 area of Detroit, Michigan around the intersection of a freeway M39, the Southfield Expressway and arterial road M5, Grand River. We set up a rectangular receptor grid consisting of 43 rows by 41 columns on 25 m centers 1935 receptors; Additional file 1 figure S1. We adjusted the hourly volumes for Saturday, Sunday and holiday periods using factors derived from the hourly yearround PTR measurements on I75 described previously since traffic volume measurements for the two roads were available for only weekday periods. Hourly meteorological data was obtained from the local airport, located 23 km SW of the study region. We then used the reducedform model to predict CO and PM 2.5 concentrations at each receptor for each hour in 2004, which were processed into daily averages. Road type influenced CO and NO x discussed below. Light duty gas vehicles LDGVs, which represented 45 48% of the total traffic volume and more on arterials emitted 59% of the CO, 20 26% of the NO x more on arterials and 56% of the HC.

Heavy duty diesel vehicles HDDVs, which represented 7 11% of the traffic more on freeways, account for 45 55% of the NO x more on freeways, and 69 75% of the PM 2.5 more on freeways. The other vehicle classes contributed the remainder of emissions, particularly light duty gas trucks. Open in a separate window Figure 2 Estimated composite vehicle emission rates as function of speed, averaged over vehicle mix in the case study on both freeways FW and arterial roads ART. Sulfur in fuel strongly affects SO 2 and PM emission rates. Other fuel parameters can also be important, e.g., Reid vapor pressure strongly affects evaporative but not tailpipe emissions of VOCs. The model is generally insensitive to relative humidity, trip length, and the number of starts per day for onroad emissions. Reducedform submodel for road segment emissions Based on the available information and sensitivity analyses, we decided to maintain information regarding vehicle speed, vehicle age distribution, vehicle type, traffic volume, ambient temperature, and fuel sulfur content in the reducedform model. We used constant and default values for other parameters, including road type and relative humidity, to which the model demonstrated very limited sensitivity. Information regarding traffic volume, vehicle speed, age distribution and vehicle mix on specific road segments is generally is limited. In the case study area, for example, available information included hourly measurements of traffic volume at multiple locations on the major roads for a few weekdays; estimates of vehicle age distributions across the Detroit area; estimates of hourly vehicle mix on arterial and freeways, also across the Detroit area; posted speed limits; and speed estimates for four periods per weekday. We predicted emissions every 5 mph from 5 to 65 mph in each season, and used a lookup table to match the predictions closest to the segments estimated speed.

Hourly estimates of V D, I, T and M D, I, K, T are available for typical weekday periods, but generally not for each hour of the year. We assume that the available pattern holds for nonholiday weekdays throughout the entire year. We developed three additional patterns to represent Saturdays, Sundays and major U.S. holidays New Years Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas. F3 D, I, K, T was estimated from the PTR data for Saturday, Sunday and holiday periods for light and heavy duty vehicles separately, and was applied to both freeway and arterial roads. Lastly, results were normalized to obtain the correct daily volume 5 The effect of these adjustments is shown in Additional file 1 figures S2 S5. As examples on weekends and holidays, volumes are reduced overall and the morning rush hour peak is eliminated; heavy dutyvehicles show different patterns than the total volume, which is dominated by LDVs; and truck volumes on nonweekday evenings are particularly low. We also compared the approach represented by eqs. 35 to the 13 classifications, mainly based on weight, given by the PTR. Predictions for the more common SCs were similar, e.g., changes from F to B ranged were within 1 to 12% for the same comparisons just discussed. We also note that the greatest differences occurred at relatively large distances when roadway impacts are not likely to be large. For these reasons, we conclude that SC has only moderate influence on CALINE4 predictions. This conclusion differs from point source modeling in which stability category is one of the most sensitive parameters. Open in a separate window Figure 3 Predicted CO concentrations showing sensitivity to A atmospheric stability category; B wind speed; C mixing height; and traffic volume. Panel A uses a wind speed of 2 m s 1. Panel C uses a constant link emission rate. Panel D plots concentrations from the two models for all conditions showing 11 line and 15% error intervals.

Higher traffic volume increases CALINE4 predictions due to its proportional relationship with emission rates. However, the effect on concentrations is less than proportional since higher volumes also increase dilution due to vehicleinduced heat fluxes that increase vertical dispersion. For the purpose of the sensitivity analysis, we held the emission rates constant when changing traffic volume. Depressed roadways are simulated by increasing the residence time in the mixing zone, which increases vertical mixing and lowers concentrations. This pattern results as CALINE4 assumes uninterrupted wind flows beneath the bridge, thus elevating the plume over nearroad receptors. The size of these effects depends on the vertical distance above or below grade level. CALINE4 defines the mixing zone width as the roadway width plus 3 m on both sides. However, this effect is more than offset by the closer proximity of the mixing zone to the receptor. Additional processes sometimes relevant in modeling PM concentrations include coagulation for the ultrafine fraction, precipitation scavenging, entrainment of roadway dust, and PM emissions from tire and brake wear. Reducedform dispersion submodel We developed a reducedmodel form of CALINE4 with variable selection and structure based on the sensitivity and additional analyses. Of the factors evaluated, we deemed that mixing height and stability category had only minor effects in most cases and did not warrant inclusion. For simplicity, because information regarding the roadway height above or below grade for complex road networks is generally unavailable in GIS shape files, and because effects were not large past about 100 m, we assumed that roads were at grade level. For similar reasons, we did not account for the mixing zone width, and assumed a width of 30 m, which suits many larger roads. We modeled the remaining parameters using multiplicative submodels.

One of the more complex submodels fits concentration profiles from the road for each wind angle and downwind distance, parameters that had large impacts on predictions. After testing a number of expressions, we found that a double exponential closely matched the concentration profile seen for distances from 15 to 300 m for each wind angle. The two exponential terms represent fast and slow decay processes. Applies to an emission rate of 1 g km 1 hr 1. A means to estimate wind angles for all possible road and receptor geometries is needed. Parameters k 7 and k 8 were estimated as 2.81 and 0.739, respectively, over the wind speeds 1 12 m s 1 and distances 15 300 m considered. This model had an average absolute error of 3.3% for wind speeds and distances from 45 to 300 m; very short distances 15 to 30 m had larger errors, e.g., predictions from 15% lower for winds of 1 m s 1 to 35% higher 12 m s 1 . These errors occurred at only the shortest distances. As mentioned, higher vehicle traffic increases vertical dispersion, and the effect on concentration depends on wind angle and downwind distance. We tried a number of model forms and parameterizations, and attempted to fit winds that were both perpendicular and parallel to the road. This is somewhat smaller than the range predicted by CALINE4, 0.88 to 1.42, since eq. 9 does not depend on wind angle. Still, this submodel performed reasonably well with an average absolute relative error of 3.4%. To reduce errors, parameters in eq. 9 could be made a function of wind angle, but this complexity did not seem warranted, especially since the largest errors 8 12% occurred at low traffic volumes 1 , which would normally yield small concentrations. Composite model and model evaluation Using eqs. 6, 8 and 9, a multiplicative model was assembled which contained 13 parameters and four input variables wind direction, wind speed, receptor distance from roadway and traffic flow.