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# An Integrative Modeling Approach for Predicting Exposures to Traffic-Related Air Pollution during Commuting

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# An integrative modeling approach for predicting exposures to traffic-related air pollution during commuting

**Extended Abstract #511**

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## INTRODUCTION

While a consistent link between ambient air pollution and cardiopulmonary effects has been demonstrated[1], the health effects of exposure to traffic-related air pollution during commuting are still poorly understood. Furthermore, little is known about how commute exposures vary with mode and route choice. Due to their proximity to roads, and their increased ventilation rate, cyclists may represent an especially vulnerable population. Therefore, a need exists to improve understanding of both the impacts of commute mode and route on exposures to traffic-related air pollution and the effects of these exposures on health.

Commuter exposures to traffic-related air pollution are difficult to capture due to the transient and spatially-varying nature of this activity. We aim to develop, apply, and evaluate a predictive commuter exposure modeling system that integrates mechanistic air pollution fate and transport simulation, path-following exposure estimation using geographical information systems (GIS), and Bayesian updating using measurement data. Model estimation helps to overcome the challenges of determining pollutant concentrations near sources by representing these processes mechanistically. Models can also be used to facilitate planning of city transportation infrastructure and for commuter decision-making on mode and route choice. Furthermore, by incorporating a Bayesian evaluation approach, uncertainties in input data, model parameters, and measurement data are inherently represented.

Here, we describe the development and application of the path-following exposure estimator. The estimator combines spatiotemporal data on travel activity with ambient concentrations to calculate exposures. Specifically, we estimate distributions of exposure to carbon monoxide during commuting for actual commuters. We compare exposure between commute modes, seasons, and times of day.

## MODEL DESIGN

Our overarching goal is to develop a system for simulating exposure to traffic-related pollution during commuting, for members of a population defined by commute mode (bicycling, driving), route type (high traffic, low traffic), and time (hour, day type, season).

To estimate commuter exposures to traffic-related pollutants, the model combines highly temporally-resolved, geo-referenced commute activity information with hourly-resolved gridded spatial concentration data for traffic-related pollutants. Our exposure estimator, implemented in the R programming platform, calculates exposure to traffic-related air pollutants by numerically integrating pollutant concentrations experienced by a commuter over the commuting time interval ($\Delta$t), as:

$$E_{m,r,h} = \int_{t_0}^{t_0+\Delta t} C_\sigma(t)dt$$

where $E$ is the cumulative exposure (concentration × time) to a pollutant by an individual commuter for a specific mode of transit ($m$, car, bike), route type ($r$), and hour of day ($h$). $t_0$ is the specific commute start time within hour, $h$, and $dt$ is the time step of the integration. $C_\sigma$ is the ambient pollutant concentration at the same location ($\sigma$) as the commuter, which varies in time due to temporal changes in ambient concentration and due to the commuter's movement in space. During estimation, concentrations are numerically extracted from hourly-resolved spatial concentration field data by matching the location and time of the commute path with that of the modeled concentrations. Because commuter ventilation rates and micro-environmental factors are expected to change by transit mode, cumulative personal intake, $I$, will also calculated as:

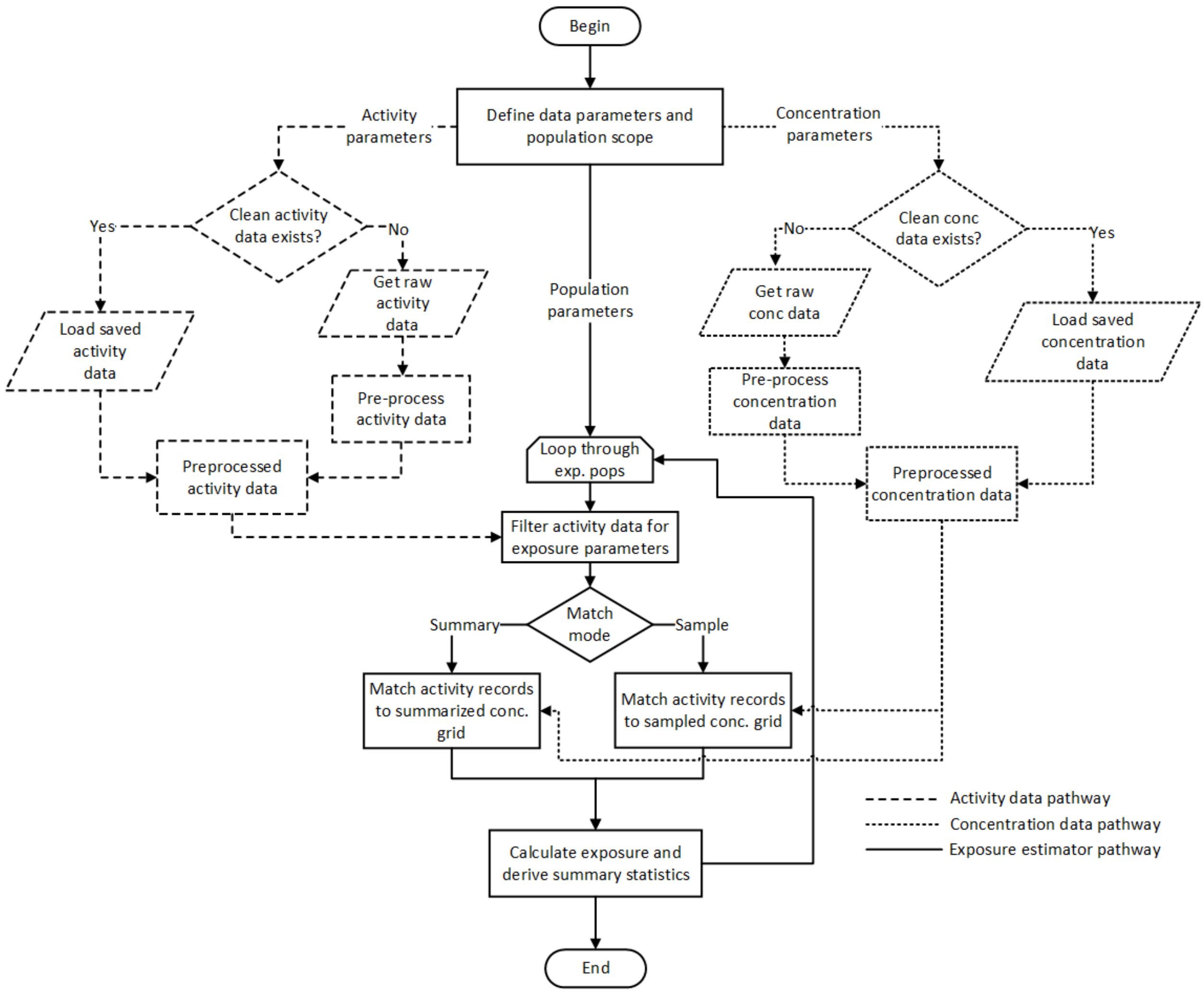
$$I_{m,r,h} = b_m \gamma_m E_{m,r,h}$$

$b_m$ is the ventilation rate, which will vary by mode of transit (biking versus driving). $\gamma$ is an adjustment factor that accounts for penetration of ambient concentrations into vehicles and the personal cloud effect. Specifically, it is the ratio of the pollutant concentration in the commuter's breathing zone to the ambient concentration. Using this approach, commute exposures and intakes are estimated as a function of route, mode of transit, and start hour.

With Figure 1, we illustrate the logic flow of our algorithm for commute exposure estimation from activity and concentration data. Structurally, our logic flow defines three interacting process pathways: activity data processing (dashed lines), concentration data processing (dotted lines), and exposure estimation (bold lines). An input file first defines the path, state (processed/unprocessed), and parameters of the activity and concentration data. It also defines the scopes of populations (combinations of commute mode, route type, and time parameters including season and day type) for which exposures will be estimated.

Two types of activity information are anticipated, actual personal monitoring data and simulated activities for hypothetical individuals. We are currently working with the first type of data. Both types include temporally-resolved sequential records of individual activities. Essential data in each record is the activity type (e.g. at home, at work, bicycling, driving), date-referenced time of activity start, and geo-referenced spatial location. Pre-processing of activity data involves appending temporal descriptors (hour of day, day type [weekday/weekend], month, season) to the activity data, rediscretizing the highly temporally-resolved records into discrete spatiotemporal intervals of consistent activity type, hour of day, and spatial movement less than 100 m, and calculating and appending discrete activity durations. Pre-processed activity data saved from previous runs can also be used.

**Figure 1. Logic flow for estimating commute exposures**




For concentrations, the model takes hourly-resolved, gridded ambient concentration fields generated by mass-balance-based air pollution dispersion modeling. Pre-processing of concentration data involves splitting, repacking, and indexing the data by grid hour. For each hourly grid, temporal identifiers are appended (hour of day, month, day, day type, season). An index table is created to facilitate fast searching and retrieval of grids satisfying any particular population scope. Pre-processed concentration data saved from previous runs can also be used.

After preprocessing both types of data, the estimator loops through the exposure population scopes of interest (combinations of commute mode, route type, and time parameters). For each iteration, the pre-processed activity data is filtered to extract those records that satisfy the temporal and activity parameters specified by the scope. Similarly, subsamples of the hourly concentration fields that match the temporal parameters of the scope are extracted from the preprocessed data. Each discrete activity record is then matched to an hourly concentration field based on the temporal data; the specific concentration extracted for the activity record is chosen by spatial matching within that field. The use of either an hourly concentration field that is randomly sampled from the available fields in the temporal scope, or a field containing a summary statistic (e.g. mean) for that scope can be specified. Along with concentration matching, exposures are calculated for each discrete activity record and cumulated over each commute. Finally, summary statistics for each exposure population scope are generated and compared.

## MODEL APPLICATION

The exposure estimator was applied to determine and compare commute exposures in Fort Collins, Colorado. The study area is a suburban community with approximately 130,000 residents living within the city limits. There is an extensive network of bike trails, including over 280 miles of on-road bike lanes and more than 30 miles of off-road bike paths. We focus on estimating exposures during automobile and bicycle commuting to air pollutants with important cardiovascular and respiratory health effects that are considered markers of traffic pollution. Specifically, for the results shown here, we used hourly-resolved carbon monoxide concentration fields from all of 2008 that were generated previously by the AERMOD Gaussian plume dispersion model for all sources in the domain. Concentration data were available for a receptor grid with spatial resolution of 500m for a 10 x10 $km^2$ area centered on Fort Collins. Data from personal monitoring of 45 individuals in the study area over the period of September 2012 to February 2014 provided geo-referenced activity information.

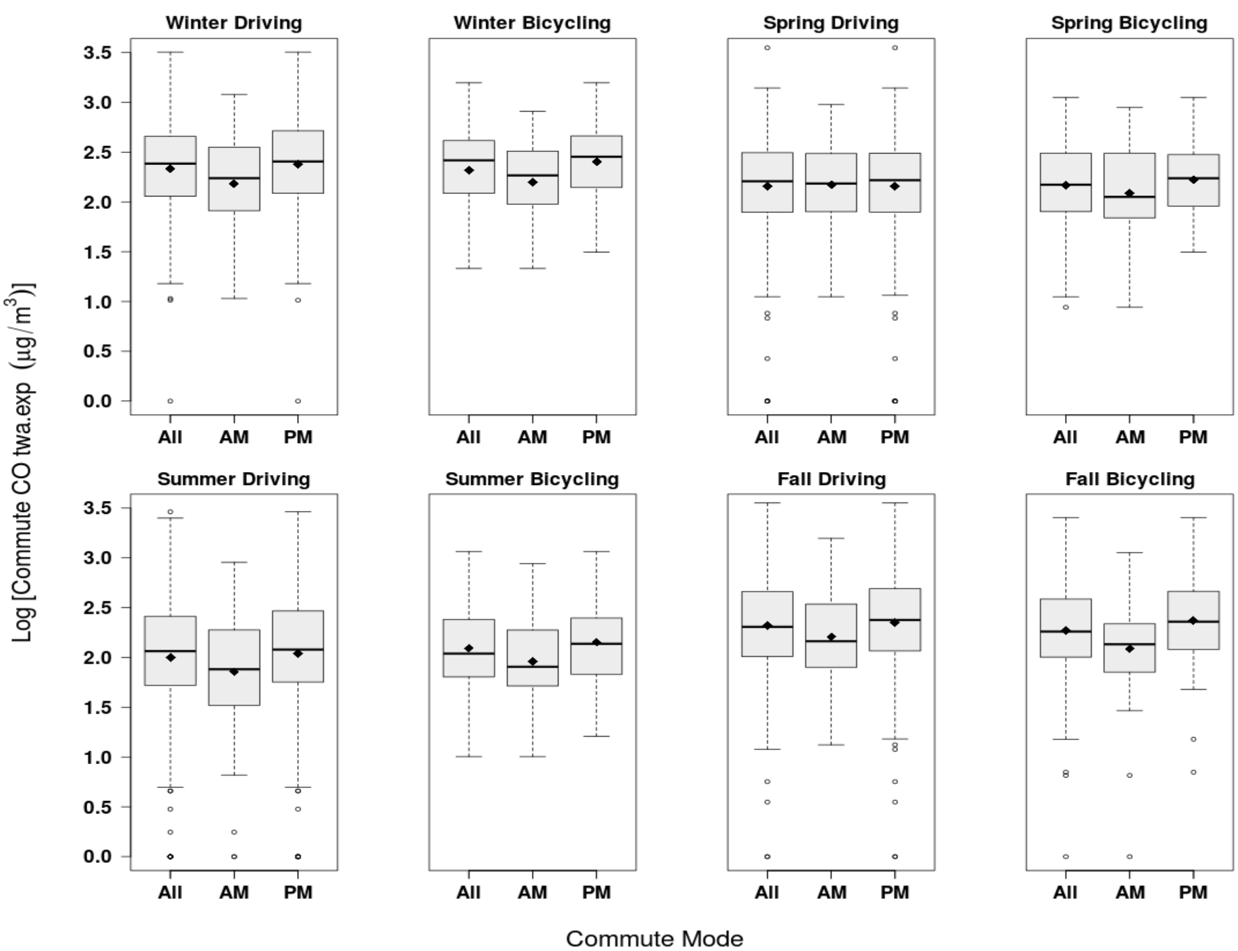
## RESULTS AND DISCUSSION

In Figure 2, we show preliminary results from application of the exposure estimator to generate distributions of carbon monoxide exposure for combinations of season, commute mode, and commute hour. We found somewhat higher average estimated commute exposures for the winter (December – February) compared with the summer (June – August). For both modes of travel, we also found higher average estimated exposures for evening commutes compared with morning commutes.

## SUMMARY

We are developing an exposure modeling system that estimates commute exposure distributions in Fort Collins, Colorado. The system combines commuter activity records with ambient concentrations generated by dispersion simulation for the study area. Here, we describe the design and application of codes to estimate commute exposures to carbon monoxide. We found estimated exposures to differ by season and time of day and by mode of travel. In ongoing work, we will apply intake factor adjustments, improve dispersion model results, and integrate Bayesian estimation.

**Figure 2. Cumulative distributions of carbon monoxide (CO) exposures by commute mode (driving and biking), commute time (morning/evening), and season.** The box shows the interquartile range, intersected by the median. The black diamond indicates the mean for each distribution. The whiskers extend to 1.5 times the interquartile range from the box. All = all commutes, AM = morning commutes, PM = evening commutes




## ACKNOWLEDGEMENTS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