MACHINE LEARNING TO SUGGEST BEST COMMUTE COMBINATIONS

Abstract: Millions of people travel around the world every year.Whenever a person goes to new city or place they might not how to reach a particular place cheaply and also efficiently.So i thought how about using ml to predict a user on how they should go about their journey what awhere to get these commute options etc

Motivation: being a traveller i know the difficulty one faces when they are in a new place.Here we take example of colarado.

METHODS

Scope. The study area of Fort Collins, Colorado(shown in Figure 1)is a mid-sized suburban citywith approximately 160,000 residents. Air quality isgenerally good, but short-term excursions in pollutant concentrations and personal exposures may adversely affect health.Automobiles emit a large portion of ambient pollution in the city, but there is also a substantial network of both on-and off-road bike trails. We focus on estimating exposures during automobile and bicycle commuting to carbon monoxide (CO) and black carbon (BC)in the fine particle ($PM_{2.5}$) size range. Both of these pollutants haveknown cardiovascular and respiratory health effects and are considered markers of traffic pollution(HEI, 2010).

Model description. To estimate exposure to traffic-pollution during commuting, we combine temporally and spatially varying pollutantconcentrations estimated via dispersion modelingwith sequential records of individual human activitycontaining detailed temporal and spatial location coordinates. Using this data, our exposure estimation modulecalculates exposure by numerically integrating pollutant concentrations experienced by a commuter over the commuting time interval.

where *E*is the cumulative exposure (concentration ×time), dtis thetime step of the integration, and*C*□is the ambient pollutant concentration at the same location (□) as the commuter, which varies in time due to temporal changes in ambient concentration and due to the commuter's movement in space. The model also calculates time-weighted-average exposure concentration (C_E) by dividing *E* by *T*. Calculation of personal intakeis currently being implementedby incorporating exposure factors that vary between commutes (including cabin infiltration fraction and breathing rate).

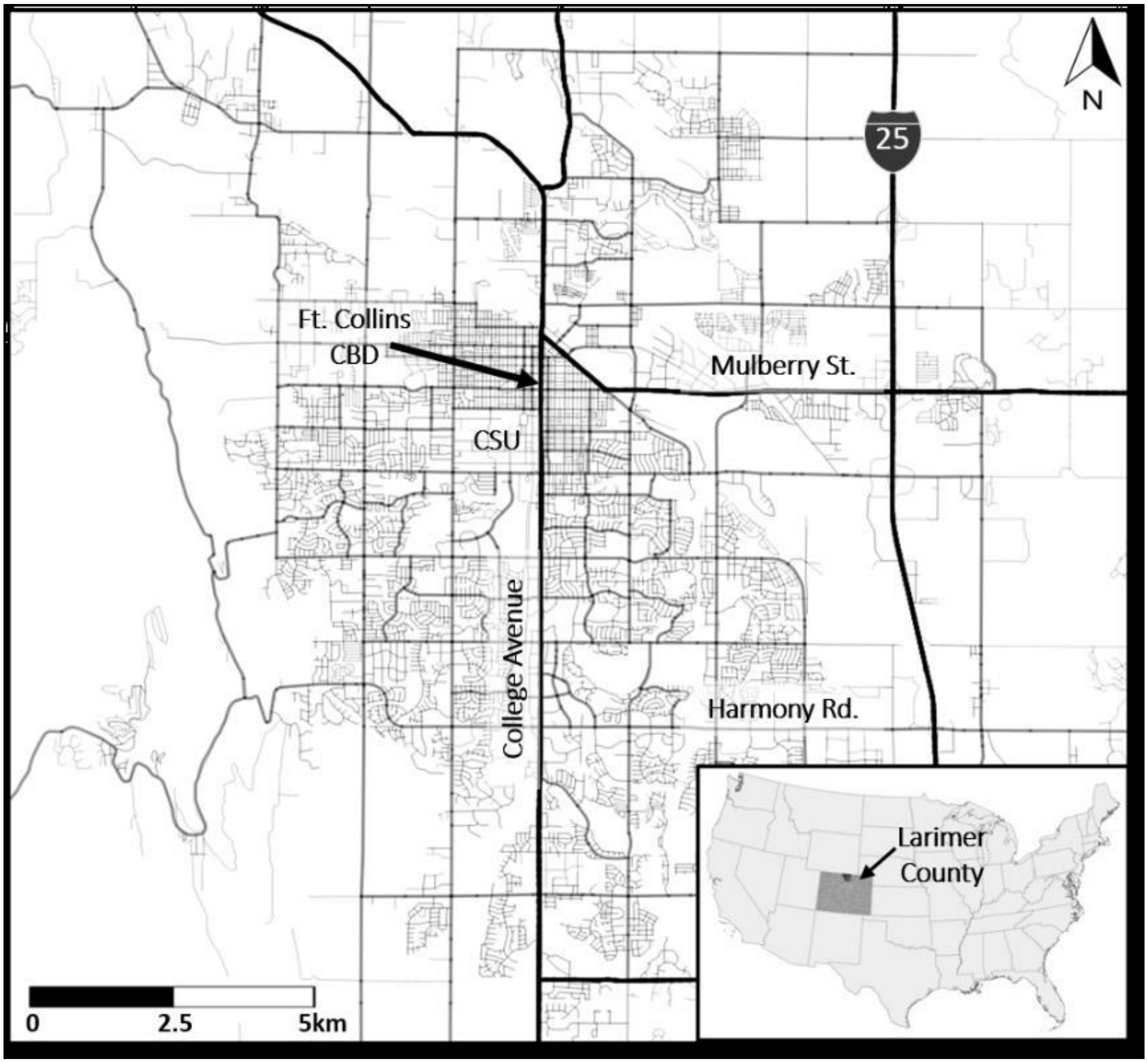

Figure 1. Map of study area(Fort Collins, Colorado), showing locations of major roadways, university area (CSU) and central business district(CBD).

Concentration estimation. To generate concentration data for this study, weusedthe AERMOD Gaussian plume model to simulate dispersion from all emissions sources in a 400km$_2$domain centered on Fort Collins.AERMOD is an established US Environmental Protection Agency (EPA) model that estimates realistic hourly-varying concentrations from multiple source types at high spatial resolution. (We chose this particular model for its simplicity –we are designing our system withina Bayesian data assimilation framework in which probabilistic estimates of concentrations and exposures are generated; this requires many repeated runs of the dispersion model to produce an adequate sample.) Emissions input to the model were calculated from the 2008 National Emissions Inventory, with spatial allocation to individual major roadway links and a regular grid of 0.25 km$_2$area sources using methods similar to those described by Yu and Stuart (2016). Hourly varying meteorological datawere obtained fromNational Weather Station (NWS) hourly surface observations (Loveland Airport, WBAN 94062), twice-daily upper air soundings (Denver/Stapleton Airport, WBAN 23062), and10-minuteonsite measurements (ColoradoState

University, WBAN 53005).AERMOD was run to produce gridded concentrationswith spatial resolution of 500m for a 100km2area centered on Fort Collinsfor each hour of the year.

Runspecifications. Using this data, we ran the exposure estimator to calculate cumulative and time-weighted average exposurefor each commute. The estimator was set to match concentrations to activity records bysampling from all thedispersion model-generated fields(for the appropriate hour of the day).

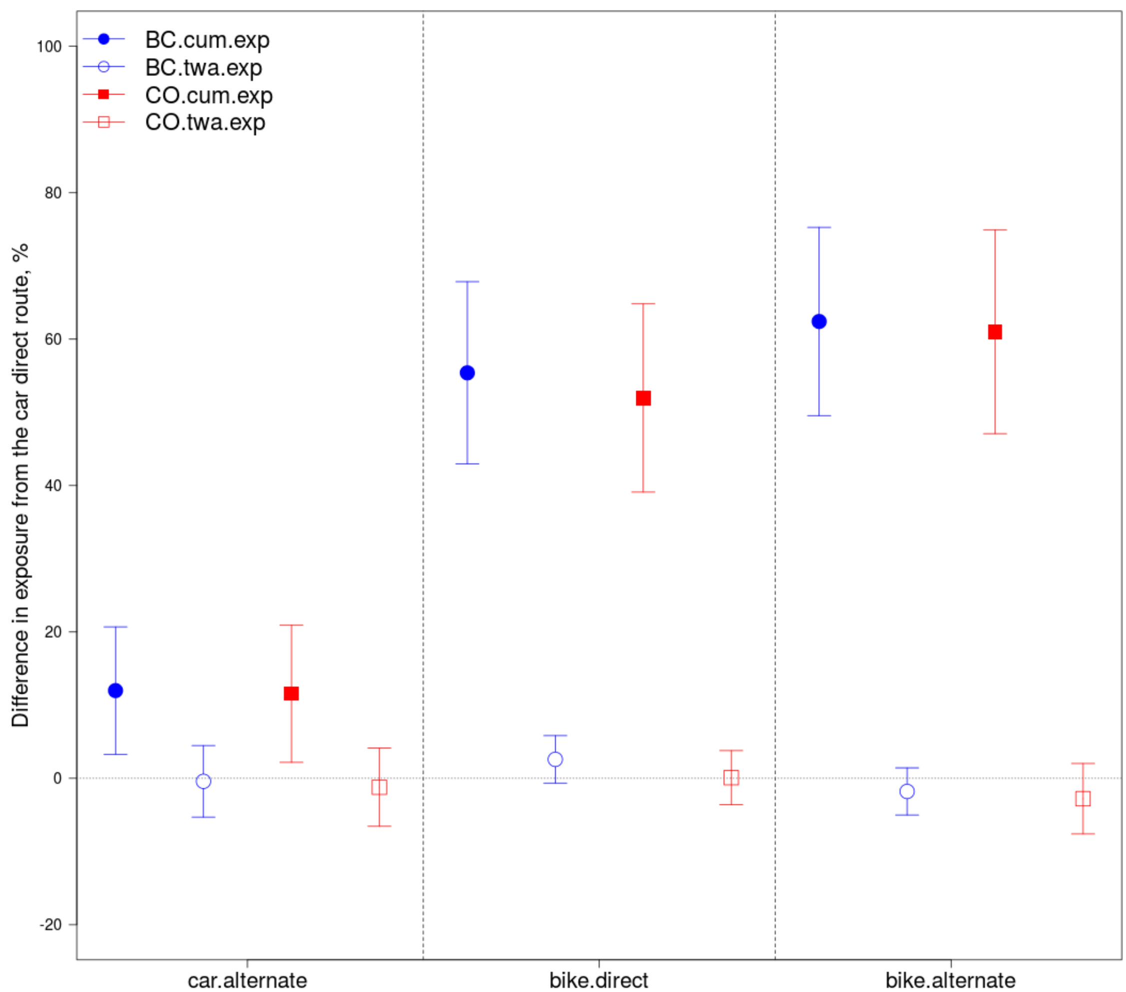

*Figure 3.*Mean (with 95% confidence intervals) of raw individual differences in cumulative and time-weighted average exposure to CO and BC for each mode/route combination compared with the direct (high traffic) car commute, including both morning and evening commutes. BC = black carbon, CO = carbon monoxide, cum.exp = cumulative exposure, twa.exp = time-weighted average exposure.

RESULTS ANDDISCUSSION

Figure 3shows the mean differences in raw individual cumulative and time-weighted average exposure for each mode/route combination compared with the direct (high traffic) car commute, as calculated by theexposure estimator. Mean cumulative exposuresto BC and CO were estimated to be substantially higher when cycling either route typecompared with the direct route, and slightly higher for driving the alternative route. This increased exposure is largely attributable to longer commute durations. Mean change in time-weighted average exposures does not appear substantiallydifferent from zero across all alternative mode/routecombinationswhen compared to driving on a direct route.Ongoing work includes incorporation of exposure and intake factors that differ bymode, microenvironment, and season(e.g. vehicle infiltration and ventilation), analysis usinglinear mixed modelingto isolatethedifferencesattributable to mode and routein the context of repeated measures,and implementation of exposure estimation within a Bayesian data assimilation framework.

Conclusion

We are developing an exposure modeling systemthat estimates probabilistic commute exposures in Fort Collins, Colorado. Theexposure estimator module, which matches predicted concentrations with personal activity records, was described here. It was also applied to explore differences in cumulative and time-weighted average exposure to CO and BC between driving and bicycling along direct and alternative routesfor a sample of 45 commuters with measured activity data. Preliminaryresults suggest that exposures to both pollutants may behigher when biking.