MADRID
inter.noise 2019
June 16 - 19
NOISE CONTROL FOR A BETTER ENVIRONMENT

An international application of the city-wide mobile noise mapping methodology: Retro-active traffic attribution on a bicycle commuters health study in New York City

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ABSTRACT
The spatial resolution of third party traffic data is not adequately describing the variation of air pollution exposure along the travelled routes of bicycle commuters. In prior work, a city-wide mobile noise mapping methodology was proposed to predict Black Carbon exposure for random bicycle trips, including meteorological variability. In a proof-of-concept pilot, funded by the National Institutes of Environmental Health Sciences (NIEHS), this method is examined in the context of a commuter study in New York City. An independent measurement campaign sampled for noise, Black Carbon and Ultrafine Particles in NYC. We focus on the spatiotemporal analysis of the preliminary data. NYC has different fleet composition compared to Ghent (ie. less diesel, more hybrids) and different geography. Additional parameters are identified to improve the model in comparison to the prior European work. The validity, feasibility and applicability of the methodology are positively evaluated. Sampling exposure across all seasons during rush hours couldn't be reached within the pilot. Adding noise levels meters to the protocol of the commuter study can supply the missing data with minimal investments. When a full year of data becomes available, the commuter study can be retro-actively attributed with meteorology independent exposure for BC and UFP.

Keywords: Noise, Air pollution, spatiotemporal models, Mobile mapping
I-INCE Classification of Subject Number: 50

1 INTRODUCTION

Traffic related exposures to noise and air pollution have a common and correlated source. This correlation and its impact on health risk evaluations are important topics in both disciplines [1, 2, 3]. The recent WHO guidelines on environmental noise encourages more multidisciplinary efforts for the benefits of both disciplines [4]. In this study, noise measurements are not used for direct health impact assessment but the mobile noise data acts as a proxy for exposure to traffic. The distinction between this method and other work is the inclusion of the spectral information in the noise exposure and adds value in the assessment of outdoor air pollution [5]. Particulate matter (PM) is a complex mixture of particles of different origin, size, chemical properties and life-time. Different measurement techniques result in the quantification of different segments of the PM exposure. PM10 and PM2.5 are better investigated than soot (Black Carbon) of diesel engines which has acquired a lot of attention in the past decade. The smallest fraction of PM, ultrafine particles (UFP, <100 nm) can pass the lung-blood and blood-brain barriers and has gained attention in more recent epidemiological efforts as it's impacts on health are still poorly understood. The newest direct-injection petrol engines have been identified as an important source for UFP. Their contribution in PM is difficult to measure with the mass-based indicators for PM2.5 and PM10. Emission control technologies developed for ~~diesel?~~ vehicles, which works mainly on larger particles, are largely ineffective on UFP. The spatiotemporal behavior of UFP also differs strongly from PM2.5 and Black Carbon. UFP is scavenged by other particles, resulting in very short life-times. The measurement technology is scarce and very expensive. As a results, the number of studies including UFP measurements are not abundant. Methods to predict the exposure to traffic related UFP are important to move forward on this issue.

In prior work, spectral noise exposure of bicyclists has been successfully used as a proxy for exposure to traffic related particulate matter exposure [6, 7]. The method is proven very efficient and effective to model the exposure of bicyclists. The method requires the inclusion of the spectral content of the noise exposure. It distinguishes the engine related noise from the rolling noise [6]. Exposure to particulate matter (Black Carbon and UFP) shows strong correlations with the engine related noise and captures the local variability in traffic density and traffic flow dynamics very accurately [7]. The noise exposure also includes an inherent distance to source component, a major driving force in the variability of the local exposure to particulate matter. The most innovative result is the possibility to disentangle the influence of meteorology and ambient background concentrations from the local variation in traffic in both space and time. This is the foundation of the 'city-wide mobile noise mapping' methodology [8]. It is possible to scan the exposure to traffic by performing mobile noise measurements only and apply a spatiotemporal model for air pollution exposure based on the results from simultaneous measurements of noise and air pollution acquired in a more limited setting. As a result, the exposure of a bicyclist can be predicted for any random trip in any specific meteorological condition if the low frequency noise exposure is assessed along the trajectory. The noise exposure can be mapped independently from the simultaneous measurement campaign but in practice the two actions are typically coordinated. The spatiotemporal models were built in the past for Ghent (2011), Belgium and for Bangalore, India (2014). This publication presents the first results of pilot application in New York City performed in 2018.

The exposure settings and the local fleet composition are very different in these three situations. Ghent is an inland European medieval structured city in a moderate climate with a fleet dominated by diesel vehicles. Bangalore, India is one of the cities in the developing countries with the highest air pollution, located on an in-continent plateau with a tropical climate. The fleet consists of diesel trucks and petrol personal cars. Motorcycles and motorized rickshaws add significantly to the emission characteristics of both noise and air pollution. In New York City, the spatial configuration is significantly different: the grid-like street network of 'avenues' and 'streets', with areas of urban canyons with uniform high-rise buildings. The fleet is dominated by petrol cars, hybrids and diesel trucks. Unlike the other locations, most vehicles use automatic transmissions.

This publication has two main aims:

(1) Present a proof of concept of the validity of the prior work for both BC and UFP in a new spatial context and an entirely different fleet composition;

(2) Illustrate the potential of the 'city-wide mobile noise mapping' methodology in an epidemiological project.

Approximately 86,000 or 2.5% of the commuters in NYC use the bicycle. An epidemiological study called the Biking and Breathing project investigates the short-term changes in cardiovascular indicators from traffic related air pollution exposure in healthy NYC bicycle commuters (NIEHS grant R33ES024734, referred to as R33 in this document). In this study, the commuters cycle for 45±15 minutes each way during commute between home and office, which are within or between four boroughs of New York City (Manhattan, Brooklyn, Queens and Bronx). The study population comprises an active and healthy segment of the population [9]. The effects due to the variation of Black Carbon exposure are evaluated for blood pressure and heartrate variability. The subjects carry a PM2.5 sampler (RTI MicroPEM) and a BC sampler (aethlabs MicroAeth AE51) and wear a biometric smart shirt to monitor their minute ventilation used to calculate potential inhaled dose (concentration x minute ventilation). Each subject measures her/his exposure while commuting within a three week window for five to six days, 24 hours each day. 129 commuters have been attempted the sampling protocol to date between 2015 and 2018, which included an initial two year validation phase. One more year of data collection is funded during 2019

The noise based instantaneous exposure models are able to adjust for the variability induced by the highly variable meteorological conditions across the sampled commutes. This publication reports on a funded supplement (referred to as "eBike") to show the potential added value of the city-wide noise methodology in the R33 grant. The aims are:

- Perform simultaneous measurements for BC and Ultrafine Particle and illustrate that noise acts as a valid traffic proxy in the new and complex context of NYC.
- Build 'noise as traffic proxy' models for BC and UFP that resolve the meteorological bias in the sampling campaigns.
- Evaluate the potential to map the mobile noise measurements and proxy models on the R33 commuting trips.

In addition, we compare the exposure to noise and air pollution of bicyclists for the different fleets in Ghent, Bangalore and New York.

2 Measurements

2.1 The measurement campaigns

An intensive campaign ("eBike")during July – November of 2018 measured noise and particulate matter simultaneously in a resolution of one second while biking along roads travelled by the commuters in the R33 study. Noise was measured in third-octave spectra, matching the requirements of the spatiotemporal modeling, sensitive to the traffic dynamics by identifying the engine and rolling noise contribution in the bicyclists' exposure.
A subset of the campaign in November included simultaneous measurements for UFP, using two DiscMini units (Testo). DiscMini measures both particle counts and particle size mode at one second resolution. A total of 397+1244=1641 km of roads were traveled, distributed over Manhattan, Bronx, Brooklyn and Queens.

2.2 Basic statistics

The noise measurements were processed as described in [6], providing the Engine Related noise exposure (OLF) and a rolling noise related component (HFmLF). The acronyms related to 1/3 **O**ctave band for **L**ow **F**requencies (energetic sum of 1/3 octave bands in dBA from 100 to 200 Hz). OHF the energetic sum of 1/3 octave bands in dBA from 1 kHz to 2kHz. 'HFmLF' relates to OHF minus OLF, the arithmetic difference between the two dBA values.
These parameters describe the form of the noise spectrum as visualized in Figure 1. The engine related noise is a traffic density and proximity indicator, the rolling noise HFmLF provides the traffic dynamics (low of high speed traffic).

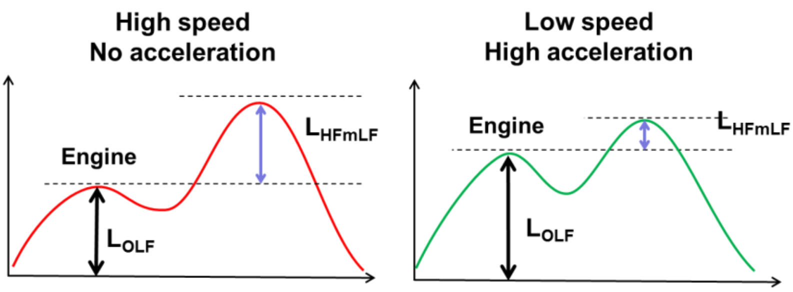

Figure 1: Visual presentation of a noise spectrum with OLF and HFmLF.

The exposure to noise and Black Carbon is sensitive to the local sampling strategy, fleet composition, road network, biking facilities, meteorology and spatial variability of the geography (buildings, etc). The fleet emission is sensitive to status of the local legislation and sensitive to the long-term changes in that legislation. This was shown in prior work for the in-vehicle micro-environment in Belgium [10].

The differences in the exposure to noise and Black Carbon in the three international campaigns are visualized (Figure 2). The exposure to measured roadside Black Carbon and ambient BC concentrations from rooftop monitors are the lowest in NYC, while the engine related noise and the wind speed are the highest. In Gent, a wider range of traffic speeds were sampled and more low exposure roads were sampled compared to NYC and Bangalore. In Bangalore, extremely low wind speeds were sampled and this represented the typical meteorological situation shortly after the end of the monsoon. In Bangalore, the ambient concentrations were measured inside the city, while in NYC and Ghent ambient BC monitors were outside of the city.

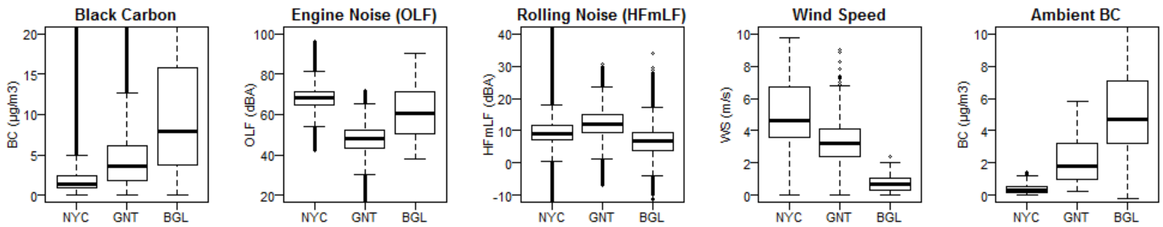

Figure 2: Distributions of Black Carbon, Engine noise, Rolling noise, Wind speed and ambient concentrations for the three locations: New York, USA (2018), Ghent, Belgium (2011) and Bangalore, India (2014). Abbreviated to NYC, GNT and BGL.

2.3 External data for the models: spatial features and meteorological data

The local variability in PM exposure is sensitive to the ambient concentrations, meteorology and local features influencing the dispersion of the air pollution. Meteorological data in NYC was retrieved from the Cornell University meteorological data portal (http://newa.cornell.edu/). The only measurement location in New York City was in Central Park. However, it did not include the wind speed from November 2018 on, the episode with the majority of the measurements. The meteorological data from JFK international airport monitoring site was the only complete dataset and is used in all models.

The dispersion of the air pollution is strongly linked to the local geography including buildings. The building configurations in New York City were retrieved from Open Street Map (www.openstreetmap.org) . This data does not include the height of the buildings. In the model for Ghent, the influence of the buildings on the local dispersion was included through the Street Canyon index [see supplemental data of 6]. The same calculation method is applied on the data in New York City. The Street Canyon index in its original format adds value to the model but the uniformity of the built-up area in New York results in poor spatial variation in the covariate. The combination of high buildings (10 floor and more) and the mostly strong inland winds result in highly unpredictable wind patterns in the city. Manhattan and the other districts are all encompassed by wide rivers and/or the ocean. The Street Canyon index has only a spatial sensitivity of 200 m but the distance to the shoreline proved relevant in this context as an additional spatial covariate. In data analysis, OLF was found to be disturbed by railway traffic. Several railways are contracted on elevated platform above the regular road network. Train passages generate high level of low frequency noise affecting the engine related L_{OLF} parameter in the models. To enable sensitivity of the model for these non-combustion related noise exposure, a spatial attribute "distance to a railway" is introduced. The ambient BC concentrations were measured at LDEO, a Columbia University campus 10 miles north of Manhattan. In contrast to Belgium, no data from government based monitoring network is available for Black Carbon in New York City.

3 Spatiotemporal models

3.1 Black Carbon

3.1.1 Generalized Additive Models: model preparation and description

The modeling process includes two variants: BC_{raw} and BC_{loc}. BC_{raw} predicts the measured exposure measurements but the prior work showed improvements in the prediction quality if the measured exposure BC_{raw} is adjusted for the ambient concentrations BC_{bg} to represented the 'local' contribution BC_{loc}.

The BC_{loc} time series is defined as:

$$BC_{loc}(t) = BC_{raw}(t) - (BC_{bg}(t) - Q1(BC_{bg}(t))) \qquad (1)$$

With Q1 the first quartile of $BC_{bg}(t)$ at LDEO, equal to 150 ng/m^3.

The OLF attribute is a logarithmic property. The generalized additive models are using the logarithm of BC as the outcome variable. This is relevant for two reasons: the log-log relation between noise and the outcome will express itself in a linear function and by using the logarithm, the highly skewed distribution of BC is transformed in a more normal distribution. High values in the tail of the BC distribution can be modeled more effectively.

In the dataset, the episodes with high OLF in the vicinity of railway disturb the model. Including the spatial attribute 'distance to railway' in the model improved the model but this approach is rejected because the inverse relation 'being in the vicinity of a railway reduces exposure' is not valid in predictions based on the model. Therefor extreme levels of OLF in combination with a short distance to a railway are removed from the data.

The temporal resolution of the models in Ghent and Bangalore was 10 seconds. In the New York City the spatial variability is even stronger due to the very dense road network. The typical distance between consecutive 'Streets' in Manhattan is 85 m. Mobile measurements by bicycle at a typical biking speed of 18 km/h results in a spatial resolution of 50 m for 10 seconds. To keep the model sensitive to this extreme spatial variability we choose to model in a temporal resolution of one second. This sets the longitudinal resolution along the bicycle trajectories to 5 m. In a later phase, when full seasonal data is gathered, other aggregation options can be reconsidered.

The summary statistics of the model covariates are shown in Table 1.

	Min.	Q1	Median	Mean	3rd Q	Max
OLF (dBA)	43.3	64.9	68.3	67.6	71.4	96.6
HFmLF (dBA)	-14.7	7.1	9.2	9.5	11.5	41.9
Wind Speed (m/s)	0.0	3.6	4.6	5.2	6.7	9.8
Streetcanyon index (%)	0%	62%	78%	68%	84%	100%
BC (ng/m3)	43	134	280	381	567	1459
log10(Coast distance)	2.00	2.63	2.88	2.80	3.06	3.58
RH (%)	40	55	66	65.81	74	96
Temp (˚C)	2	11	14	18	29	32

Table 1:Summary statistics of the model covariates.

3.1.2 Modeling the meteorological impact on BC exposure using noise as a traffic attribute

The full model on the unadjusted Black Carbon exposure ($BC_{raw,8p}$) includes eight parameters (see Figure 3 and Table 2). Gam models fit splines on the data, presented as “s(covariate)” on the y-axis of the gam plots, expressing the (multidimensional) behavior of the modeled outcome.
The strongest components are the Engine noise and the Ambient BC@LDEO. The spatial features, Street Canyon and distance to coastline are the next relevant parameters. The Wind Speed shows an exposure reduction for higher wind speeds as expected but is much less strong when compared to the model Ghent [6]. The pilot dataset does not include many data points at low wind speeds. This is identified as a potential bias in the sampling.
The full model on the adjusted Black Carbon exposure ($BC_{loc,8p}$) includes the same eight covariates for comparison (see Figure 4 and Table 2). Adjusting for the contribution of the ambient concentrations on the bicyclists Black Carbon exposure reduces the relative strength of the ambient BC as expected and the wind speed becomes a stronger covariate. The strength of the temperature covariate is increasing in strength as well. This increased sensitivity of the adjusted model to a meteorological covariate is unwanted. It is the result of a complex set of correlations between the meteorological covariates: ambient concentration and temperature (0.61), temperature and humidity (-0.40), wind speed and humidity (0.42) and wind speed and ambient concentration (-0.18).

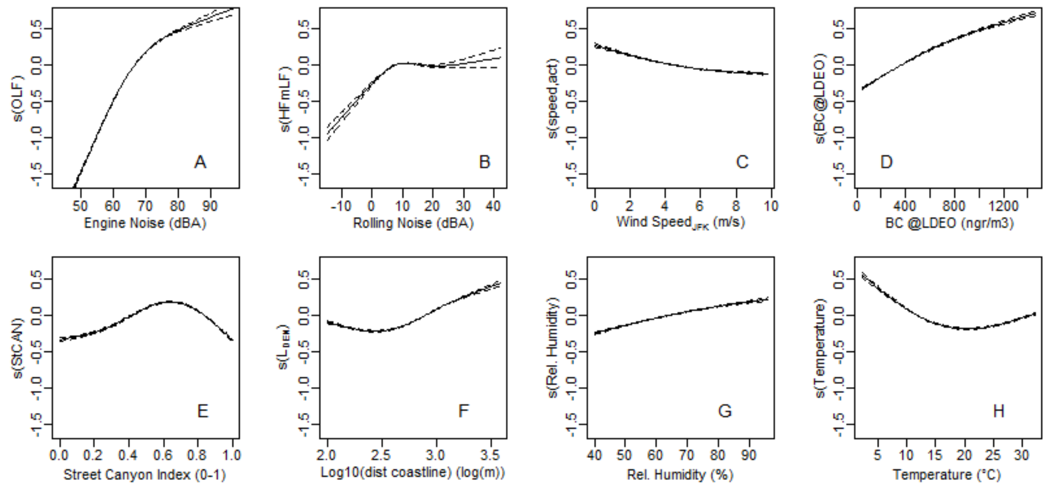

Figure 3: Splines of the BC_{raw} gam model with 8 parameters.

Covariates	$BC_{raw,8p}$	$BC_{loc,8p}$	$BC_{loc,6p}$	$BC_{loc,5p}$	UFP_{8p}	UFP_{4p}	UFP_{3p}	$UFP_{,5phum}$
Intercept (ng/m3) / (PNC)	1266	823	1124	1124	22680	22681	22681	22681
F-values of gam								
Engine Noise	9537	6737	22659	22779	2267	2163	2291	2401
Rolling Noise	168	26	285	310	295	329	236	270
Wind Speed	327	972	5128	4974	2550	2745	2922	2549
Ambient BC@LDEO	1841	811	285		1793	736		
Streetcanyon Index	920	621	1313	1275	21			
Distance to coastline	1224	797	1809	1876	133			
Rel. Humidity @JFK	552	273			1876			1675
Temperature @JFK	696	1287			2252			2157
Deviance expl. (%)	23.0	25.2	24.6	24.4				
AIC	690903	257396	619242	619811	61743	67626	69076	63805
# data points	227113	227113	227113	227113	52128	52128	52128	52128

Table 2: Intercept and F-values of the gam models for BC and UFP.

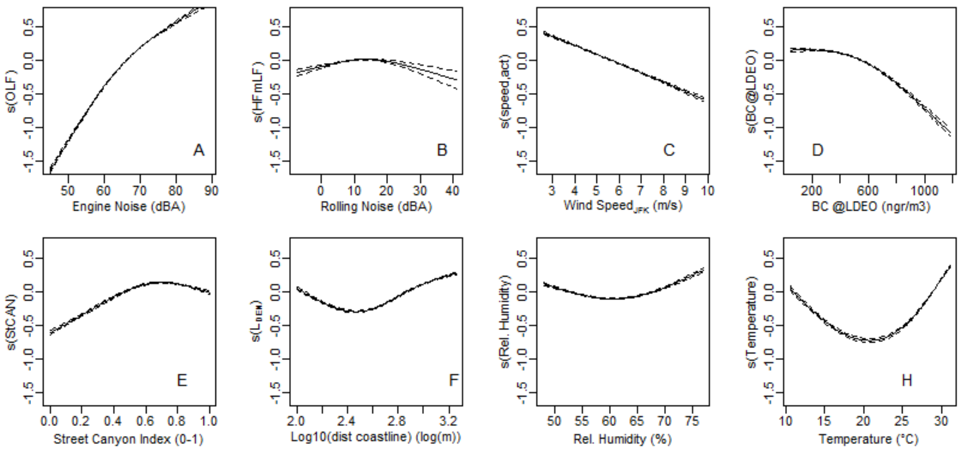

Figure 4: Splines of the BC_{loc} model with 8 parameters, including meteorology and ambient concentration at LDEO.

The $BC_{loc,8p}$ model is overfitting on the meteorological covariates as is illustrated in the $BC_{loc,6p}$ model where the temperature and relative humidity are removed. Moving from 8 to 6 covariates does not decrease the 'deviance explained' significantly (Figure 5 and Table 2).

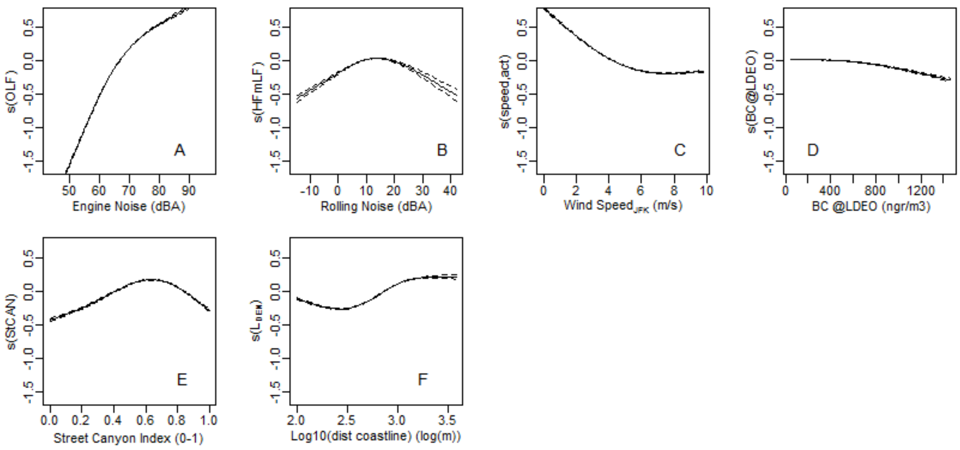

Figure 5: Splines of the BC_{loc} model with l parameters, including ambient concentration at LDEO to illustrate the impact of the correlations between ambient concentrations, temperature and humidity.

The Wind Speed covariate increases strongly and is now explaining most of the variability covered by the temperature and the relative humidity in the $BC_{loc,8p}$ model. The significance of the ambient concentration is -as expected after the background adjustment according to equation 1- irrelevant for the model (F-value drops from 1841 to 811 to 285 in the consecutive models). In the final model $BC_{loc,5p}$, the ambient concentration can be removed (see Figure 6).

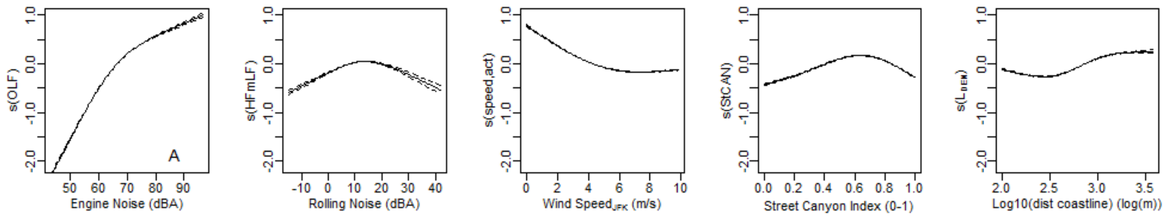

Figure 6: Splines of the BC_{loc} model with 5 parameters, excluding the ambient concentration at LDEO. Note the wider scale of the spline compared to the previous charts, necessary to present the increased strength of the Engine Noise covariate.

The modeling process fulfills every expectation regarding influence of ambient, meteorological and spatial features despite the highly biased underlying dataset (three weeks of measurements in Fall and sparse data in summer. Especially the low wind conditions are poorly sampled on the campaign.

The second observation is the strength of the background adjusted model. The $BC_{loc,5p}$ clearly outperforms the $BC_{raw,8p}$ model. The influence of the ambient concentration can be removed from the gam model.
The rolling noise has the same strength as the ambient concentration but should be included in the gam model since the spline has a high non-linear form. This illustrates why spectral noise measurements are required. The BC exposure does not correlate with the total noise level. The prediction of the instantaneous exposure of the bicyclists at the location x and at time t can be written in its simplest form as:

$$\mathrm{BC_{tot}(x,t)} = \mathrm{gamBC_{loc}(OLF\ (x), HFmLF(x), StCan(x), WS(t), DistC(x))} + \mathrm{BC_{bg}}(t) \qquad (2)$$

The traffic and spatial features can be estimated by the location only. The wind speed and the ambient concentration are temporal functions.

3.1.3 Applying the pilot model to the R33 campaign.

In Figure 8 the most relevant spatial information is presented. At the left, the poor spatial variability of the street canyon index is visible. Central Park is the eye-catcher. In the center, the BC exposure of the R33 bicycle trips are shown and at the right, the spatial extent of the Engine related Noise (OLF) sampling in the pilot campaign is shown.
The noise mapping methodology includes two sampling requirements:

- spatiotemporal coverage of all road types under all meteorological conditions
- spatial coverage of the road network used by bicyclists

The first requirement can be evaluated by comparing the distributions of BC, wind speed, temperature and relative humidity (Figure 7). The Black Carbon exposure during the eBike campaign is significantly underestimating the R33 campaign. This is in line with the biases in wind speed, temperature and humidity. The eBike campaign under sampled the low wind speeds, high temperatures and low relative humidity.

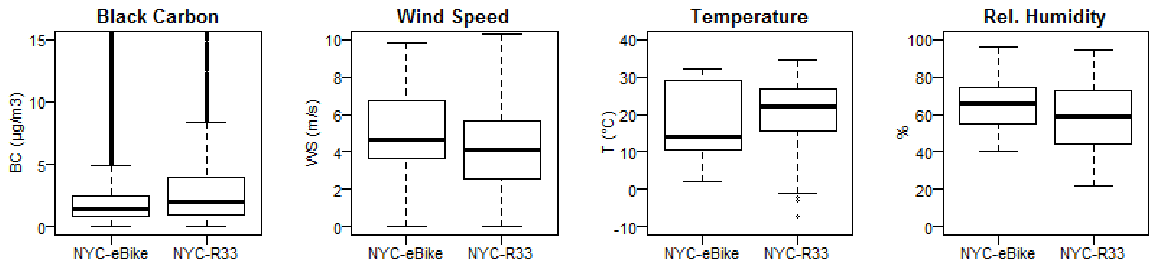

Figure 7: Comparison of the distributions of the R33 campaign and the eBike campaign.

The second requirement is the spatial and temporal mapping of the noise levels along the road network. The spatial discrepancy is visualized in Figure 8. Noise mapping has to be improved in all districts except Manhattan. It is also important to 'noise-map' the traffic during the rush hours to match the behavior of the R33 subjects. Figure 99 illustrates the diurnal bias between the R33 and eBike campaign. The eBike campaign did not sample the early morning commutes and the late evenings commutes. Especially the early morning commutes are relevant since this is also the part of the day with lower wind speeds and stable atmosphere and thus higher exposure. The pilot campaign does not reach the requirements of spatial and temporal sampling. Extending the simultaneous data capture across all meteorological conditions is necessary. Early morning sampling will be necessary to reach these requirements.

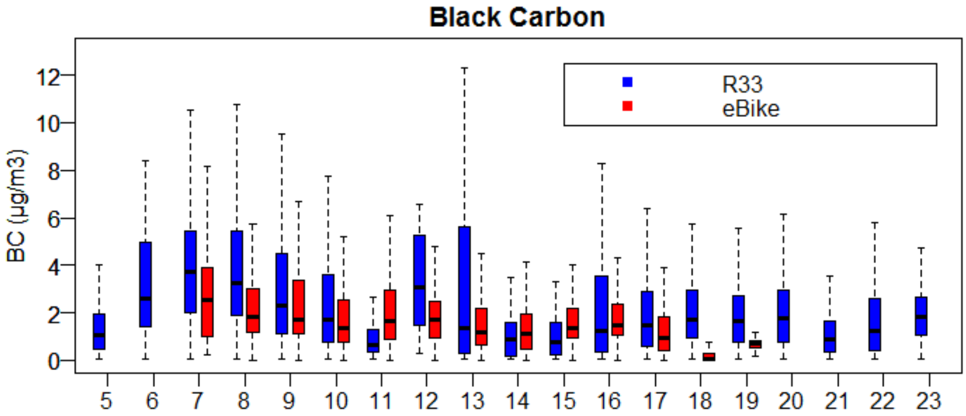

Figure 9: Comparison of the distributions of the R33 campaign and the eBike campaign by hour of the day.

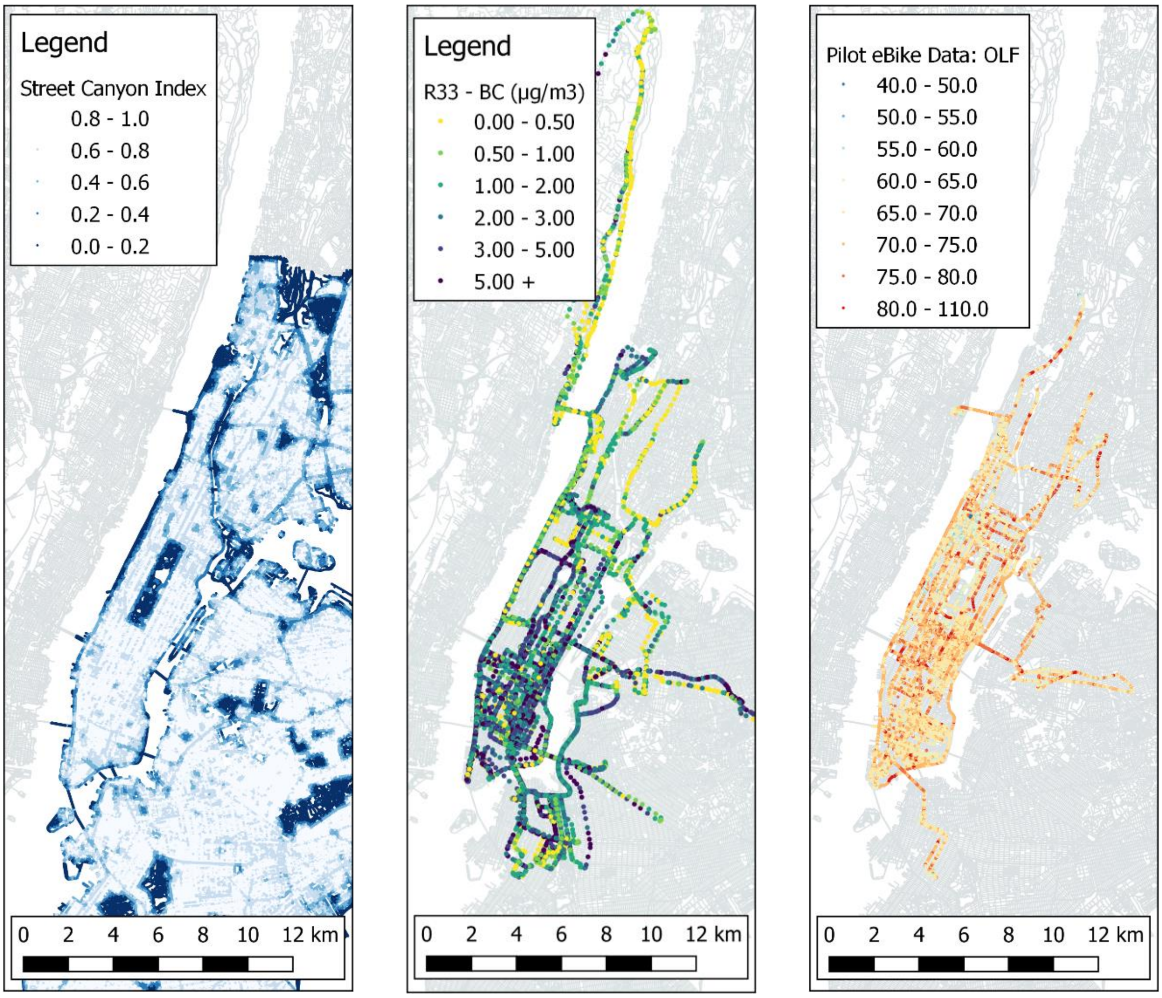

Figure 8: Street canyon Index (left), spatial extend of BC concentrations in the R33 campaign (2015-2017 data only)(mid) and the spatial extent of the OLF in the pilot campaign.

3.2 Ultrafine particles

The modeling process for UFP is more limited since no ambient concentrations are available for UFP. The gam model also predicted the logarithm (log10) of UFP, which is the standard way to present the particle number. The same benefits apply for modeling a logarithmic transformation of UFP as mentioned for the BC models (see 3.1.1). No ambient concentration for UFP are available so the ambient BC is added as a surrogate. Ambient concentrations can als act as a proxy for stability of the atmosphere.

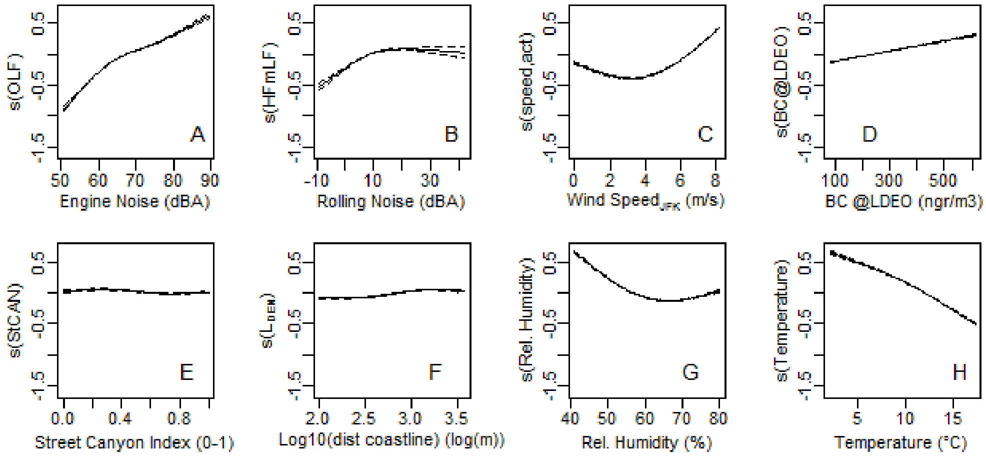

Figure 9: Splines of the UFP_{8p} gam model.

For comparison, an identical 8 parameter model, including the ambient concentration of BC, $UFP_{raw,8p}$ illustrates the differences between UFP and BC (Figure 9). The simultaneous data of UFP and BC is much more limited due to the lower availability of UFP monitor (50.000 seconds). The mean and median UFP counts are 41,871 and 26,060 particles/cm^3. Q1 and Q3 are 17,678 and 41,047 particles/ cm^3.
The most striking difference is the inversed sensitivity to relative humidity and temperature compared to Black Carbon. It has also shown from DiSCmini data that more larger particles in the air imply more scavenging of the UFP and therefore lower UFP particle counts. The spatial attributes are not statistically significant. A similar analysis as for BC results in the strongest model $UFP_{5p,hum}$, including relative humidity and temperature.

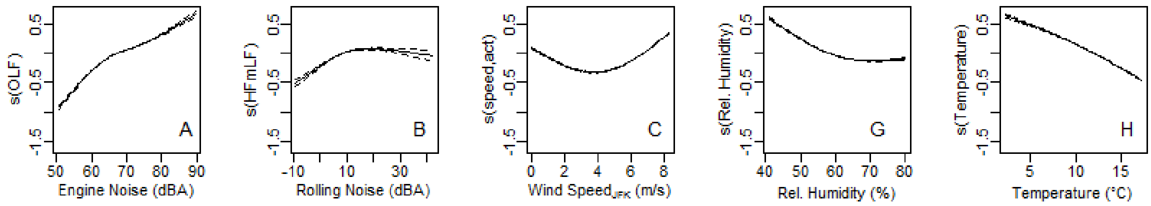

Figure 10: Pilot model with five parameters for UFP.

UFP is more event-like and the accumulation related to street canyon and low (local) wind conditions does not apply. The relative strength of the noise covariates is much lower in the UFP models compared to the Black Carbon models but the relationship exists.

4 Discussion

4.1 Mobile noise as a proxy for BC and UFP

Based on the results of the BC data, the approach can be described as 'very successful', Although additional data is necessary. The relation between noise and UFP is, in this pilot project, less strong than expected. More data is necessary before developing a more robust model. To evaluate the predictive strength of the BC and UFP models more data is required for the modeling component and a higher spatial and temporal coverage of the R33 campaign (see 3.1.3).

4.2 How to proceed to build a valid prediction model?

The short but intensive campaign showed the effectiveness for the model building. The evaluation in 3.1.3 shows the underlying datasets for the models gathered in the eBike are too biased to result in a valid prediction model for the epidemiological study. The two requirements

are not met. How can the pilot study be extended to reach both requirements at a minimal cost and additional effort?
First, we need to continue the simultaneous measurements for Noise, Black Carbon and UFP to cover all combinations of meteorology, traffic densities and bicycle facilities. Including features of the local bicycle facility in the models could potentially improve models.
Second, we need to map more of the travelled roads of the R33 study. There is also a temporal requirement to collect data better covering time ranges during a day. A significant part of the simultaneous measurements is not performed during the rush hour. The data collected outside the rush hour is valid to build the model because the noise attribute links all data points.
The fast track to fulfill both requirements is to add noise monitoring to the R33 participants for the remainder of the sampling campaign. The noise levels will be recorded on the actual long distances routes travelled by the participants at the proper time of the day from the viewpoint of using the mobile noise map to predict the exposure for the older trips (2015-2018). Furthermore, if the temporal resolution of the Black Carbon measurements is increased to one second, this data in the resolution required in the modelling process. It will not affect the R33 data quality. If one of the 10 operational equipment sets in the R33 is extended with an UFP monitor, an adequate dataset can be gathered to build a Noise-UFP or Noise-BC-UFP spatiotemporal model. In summary: add 10 noise level meters to measure 1/3 octave bands in 1 second resolution, increase the temporal resolution of the available MicroAeths to one second and find for one subject out of 10 to can carry and operate an UFP counter.

4.3 Transferability

An interesting question is the possibility of transferring models from one location to another. The transferability was evaluated between the model of Ghent and Bangalore [12]. The different ranges of the engine noise exposure resulted in valid pooled model that mainly improved the prediction for low BC exposure values in the Bangalore dataset. This improvement was the result of the inability of the sampling campaign to properly assess the lowest exposures, since the background concentrations were too high to accurately quantify the exposure at low traffic road segments. It is obvious from the basis statistics that pooling data over the three campaigns is not possible. Local calibration is a requirement for the methodology as stated in [8]. This is not a negative observation. The vehicle fleet in New York City emits much less Black Carbon compared to Ghent and Bangalore. This illustrates that the average fleet emission is very sensitive to the local situation. This also implies that local legislation has tremendous potential to remediate the exposure of the population. It is important to note that this conclusion is not limited to bicyclists. The unique feature of methodology, disentangling the local variability in traffic and meteorological disturbances, extends to other micro-environments.

5 CONCLUSIONS

The spatiotemporal models for Black carbon and UFP using noise as a traffic proxy are successful. The methodology is very robust for Black Carbon. For UFP, additional data is required to reach the same conclusion. Method the potential to understand the differences in the exposure due to the influence of fleet composition, road and bicycle infrastructure, traffic density, meteorological conditions and city design. Pooling the short-term variability in exposure to traffic by means of a simple physical measure (engine noise) adds unique information into the modeling process.
Predicting black carbon along bicycle trips will be possible as soon as the two requirements: seasonal coverage of the simultaneous measurements and rush hour assessments with mobile noise are achieved along the most frequent travelled routes for bicyclists in the R33 campaign.

6 ACKNOWLEDGEMENTS

We acknowledge the supplement funding by the NIH (grant R33ES024734). Additonal funding support came from ES009089 and S10OD016219. A group of students from Columbia University department of Earth and Environmental Engineering supported the measurement campaign.

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PROCEEDINGS INTERNOISE 2019
ISSN: 0105-175x
ISBN: 978-84-87985-31-7