Connecting Air Quality with Emotional Well-Being and Neighborhood Infrastructure in a US City

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Raj M. Lal[1], Kirti Das[2], Yingling Fan[2], Karoline K. Barkjohn[3], Nisha Botchwey[4], Anu Ramaswami[5] and Armistead G. Russell[1]

[1]School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA, USA. [2]Hubert H. Humphrey School of Public Affairs, University of Minnesota, Minneapolis, MN, USA. [3]Department of Civil and Environmental Engineering, Duke University, Durham, NC, USA. [4]School of City and Regional Planning, Georgia Institute of Technology, Atlanta, GA, USA. [5]Civil and Environmental Engineering, Princeton Institute for International and Regional Studies, Princeton Environmental Institute, Princeton University, Princeton, NJ, USA.

ABSTRACT: Cities in the United States have announced initiatives to become more sustainable, healthy, resilient, livable, and environmentally friendly. However, indicators for measuring all outcomes related to these targets and the synergies between them have not been well defined or studied. One such relationship is the linkage between air quality with emotional well-being (EWB) and neighborhood infrastructure. Here, regulatory monitoring, low-cost sensors (LCSs), and air quality modeling were combined to assess exposures to $PM_{2.5}$ and traffic-related NO_x in 6 Minneapolis, MN, neighborhoods of varying infrastructure parameters (median household income, urban vs suburban, and access to light rail). Residents of the study neighborhoods concurrently took real-time EWB assessments using a smart phone application, Daynamica, to gauge happiness, tiredness, stress, sadness, and pain. Both LCS $PM_{2.5}$ observations and mobile-source-simulated NO_x were calibrated using regulatory observations in Minneapolis. No statistically significant ($\alpha = 0.05$) $PM_{2.5}$ differences were found between urban poor and urban middle-income neighborhoods, but average mobile-source NO_x was statistically significantly ($\alpha = 0.05$) higher in the 4 urban neighborhoods than in the 2 suburban neighborhoods. Close proximity to light rail had no observable impact on average observed $PM_{2.5}$ or simulated mobile-source NO_x. Home-based exposure assessments found that $PM_{2.5}$ was negatively correlated with positive emotions such as happiness and to net affect (the sum of positive and negative emotion scores) and positively correlated (ie, a higher $PM_{2.5}$ concentration led to higher scores) for negative emotions such as tiredness, stress, sadness, and pain. Simulated mobile-source NO_x, assessed from both home-based exposures and in situ exposures, had a near-zero relationship with all EWB indicators. This was attributed to low NO_x levels throughout the study neighborhoods and at locations were the EWB-assessed activities took place, both owing to low on-road mobile-source NO_x impacts. Although none of the air quality and EWB responses were determined to be statistically significant ($\alpha = 0.05$), due in part to the relatively small sample size, the results are suggestive of linkages between air quality and a variety of EWB outcomes.

KEYWORDS: Air quality, low-cost $PM_{2.5}$ sensor, R-Line, subjective well-being, neighborhood infrastructure

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CORRESPONDING AUTHOR: Raj M. Lal, School of Civil and Environmental Engineering, Georgia Institute of Technology, 311 Ferst Dr. NW, Atlanta, GA 30332, USA.
Email: rlal6@gatech.edu

Introduction

Cities in the United States have announced initiatives to become more sustainable, healthy, resilient, livable, and environmentally friendly.[1,2] However, assessing these outcomes has been challenging, as metrics to define the outcomes and their interrelationships are limited.[3-5] This is due, in part, to the fine-scale data needed to study these factors and interactions. Studying these fine scales is challenging because of personnel limitations, data and instrumentation barriers, and high costs.[5] Nonetheless, cities are evolving, and it is helpful to understand these relationships to achieve desired goals.

A potentially important set of relationships involves local air quality, neighborhood-scale infrastructure, and subjective well-being (SWB). Air quality, typically characterized by air pollutant concentrations, has both chronic and acute health responses.[6-9] Neighborhood infrastructure is related to the services, accessibilities, and social capital provided at the neighborhood level[10] and can impact both air quality and well-being.[11,12] Subjective well-being is defined as an individual's cognitive and affective evaluation of his or her life.[13,14] Thus, relating air quality with neighborhood infrastructure parameters and person's SWB may help city planners identify strategies and infrastructure that can lead to improved public health and well-being. In addition, neighborhood-level analysis can help city planners to identify disparities across neighborhoods and identify neighborhoods at higher risks for low emotional well-being (EWB). Cognitive well-being relates to what an individual *thinks* about his or her life and is often associated with long-term well-being while affective SWB, or EWB, refers to what an individual *feels* about his or her life. Emotional well-being is more sensitive to short-term environment changes[15]; hence, this study considered EWB. Typical

studies of EWB track a range of positive and negative emotions such as happiness, anger, aggression, pleasure, fatigue, stress, and sadness.[16,17]

Emotional well-being has often been associated with health as the 2 influence each other; better health often leads to higher EWB and vice versa.[18] High EWB involves frequent pleasant emotions, infrequent unpleasant emotion, the net of which is one measure of EWB called net affect; high well-being also includes cognitive aspects, that is, high levels of life satisfaction/evaluation. Poor health, separation (encompassing widowhood, divorce, or separation), unemployment, and lack of social contact are factors of strong, negative associations to EWB.[19] Intra-personal personality traits can also influence subjective self-assessments of well-being. In addition, neighborhood-level infrastructure has also been shown to impact health and EWB.[20-22] Access to convenient and affordable transportation enables participation in activities that can improve life, including gainful employment, improved education, and social interactions.[23,24] Exposure to poor air quality, particularly $PM_{2.5}$, has been found to be one of the largest factors leading to disease burden globally, as it has both chronic and acute adverse health outcomes.[6-9] In addition, $PM_{2.5}$ affects visibility, which is an additional socioeconomic burden that influences EWB.[25]

Traditionally, air pollution has been measured using expensive, bulky, and sparsely located monitors.[26] New techniques to generate fine-scale measurements have been developed and studied in recent years, including the use of low-cost sensing technologies.[27] Low-cost sensors (LCSs) have advantages as they are cheaper and smaller, providing widespread spatial coverage that has not been viable in the past, and are easier to transport and operate than regulatory or research-grade instruments. However, evaluation of their performance is inconsistent.[27-31] City-scale modeling of air pollutants is often done using dispersion models, but the modeled concentrations do not always agree with observations, due in part to emission uncertainties, omission of complex atmospheric chemistry, and no default depositional loss mechanisms in the model. Much of the local gradients of pollution concentrations, particularly NO_x (a combustion byproduct), are driven by on-road mobile sources in cities,[32] so fine-scale dispersion simulations from on-road mobile sources can provide additional understanding of neighborhood air pollution levels and their impacts on EWB.

Historically, EWB was measured using retrospective self-reports, in which participants would reflect on certain past events and attempt to recall their feelings. The results from these studies were accordingly limited due to recall bias. Following self-reporting, the next advancement in measuring EWB was with experience sampling methods (ESMs). Experience sampling methods involve repeated sampling of subjects' behaviors in real time in natural environments.[33] Experience sampling methods assess specific events in subjects' lives or assess subjects at periodic intervals by random time sampling.[34] While ESMs allow for advancements of studying EWB, they do not offer continuous measurements of it.

The day reconstruction method (DRM) asks the respondent to reconstruct the entire sequence of daily activities and emotional experiences during each activity, which offers a more comprehensive measurement of EWB than ESMs and captures more completely the time-variant nature of EWB.[35] Recent mobile technology advancements, including smartphone applications, allow for opportunities to collect EWB data near real time (survey subjects often fill the responses throughout the day and not necessarily following each event, so their real-time EWB emotions may not be fully captured) using the DRM approach.[36,37] Smartphone-enabled DRM approaches allow for comprehensive data acquisition throughout the day as opposed to single snapshots. Using smart phones for the surveys provides additional benefits including (1) accurate location identification using the Global Positioning System (GPS),[38] (2) additional characterization of activity attributes using smartphone built-in sensors for user inputs (eg, transportation mode, companionship/event partnerships), and (3) for information on the temporal sequence of activities and experiences.[39-42]

Recent studies have addressed environmental justice and air pollution exposure based on socioeconomic status (SES) and have generally found that poor and racial minority communities are disproportionately affected with lower air quality.[43-46] And while the linkages between air pollution and health risks (mortality and morbidity) is known,[7,47] linkages to EWB are just emerging. Some studies[48-50] have noted correlations with negative emotions, such as feelings of sadness/depression, but such studies have not evaluated a full range of EWB outcomes and their variation within cities in the United States. This first-of-its-kind study explored the relationship between air quality (measured using LCS sensors and simulated with a mobile-source dispersion model) with EWB (assessed using a novel phone application) and neighborhood infrastructure (assessed from census-level data) in Minneapolis, MN, using a combination of low-cost air pollution sensors, air quality modeling, and dynamic well-being sampling using a phone-based application.

Methods

This study examined the relationship between ambient air quality with neighborhood infrastructure and individual's emotional well-being (EWB) using concurrent air quality measurements, mobile source modeling of a traffic-related air pollutant (TRAP), and individual's EWB assessments in 6 neighborhoods of varying infrastructure parameters in Minneapolis, MN.

Neighborhood selection

The study's 6 Minneapolis neighborhoods included Phillips, Near North, Brooklyn Center, St. Anthony Park, Blaine, and Prospect Park (Table 1 and SI Figure 1). Infrastructure quality

Table 1. Neighborhoods used in this study, including neighborhood infrastructure characteristics, study-average observed $PM_{2.5}$ concentrations (95% confidence interval) from low-cost sensors (LCS), and R-Line-simulated on-road mobile-source NO_x concentrations (95% confidence interval).

NEIGHBORHOOD	URBAN STATUS	LOW-INCOME STATUS	RAIL ACCESS	DISTANCE TO CENTRAL CITY (MI.)	POPULATION DENSITY (PEOPLE/ACRE)	MEDIAN HOUSEHOLD INCOME (US$/HH)	LOW-COST SENSOR $PM_{2.5}$ ($\mu G\,M^{-3}$)	R-LINE NO_X (PPB)
Prospect Park	X		X	3.5	6.0	75800	7.8 (7.5-8.2)	8.2 (7.8-8.6)
St. Anthony Park	X			4.4	5.2	79800	7.5 (7.2-7.7)	8.0 (7.7-8.4)
Phillips	X	X	X	1.8	20.8	32200	7.5 (7.2-7.9)	8.2 (7.8-8.6)
Brooklyn Center		X		7.4	6.1	56300	7.6 (7.2-7.9)	6.4 (6.1-6.7)
Near North	X	X		2.5	12.5	36200	7.5 (7.1-7.8)	7.4 (7.1-7.7)
Blaine				15.3	5.1	90400	6.4 (6.2-6.7)	3.8 (3.6-4.0)

The $PM_{2.5}$ concentrations were only considered for hours where observations existed in all 6 neighborhoods. See SI Figure 1 for a detailed spatial map of the study neighborhoods and SI Table 5 for entire sampling average concentrations.

was assumed to be correlated with median household income (with income class breaks designated from literature on income and health-based disparities),[51] access to light rail (access defined as the neighborhood either containing a light rail station or one block away from at least 2 light rail stations), and urban or suburban (urban defined as inside the city boundaries of Minneapolis and St. Paul, MN, and suburban considered outside the boundaries; Table 1 and SI Figure 1). Because the intensity of the data collected limits the size of the panel to be studied, only 6 neighborhoods were used in this study; however, these 6 neighborhoods still allowed for studying combinations of the infrastructure criteria. The study period was from October 2016 to April 2017.

Air pollution measurements and modeling

This study focuses on $PM_{2.5}$ and NO_2 air quality as these pollutants show more heterogeneity than a secondary pollutant like ozone and both are found to contribute significantly to the overall health burden.[6,52,53] There are 9 regulatory $PM_{2.5}$ monitors in the study domain and 4 are defined to capture pollutant concentrations representative of neighborhoods[54] (SI Table 1). However, the neighborhoods housed by 3 of these 4 monitors did not meet our other neighborhood criteria, so to measure suitable neighborhood $PM_{2.5}$ levels we use low-cost air quality sensors that were deployed and evaluated during a number of previous studies.[55-58] In this study, the monitors were deployed in the backyards of residents' homes. The selection criteria for the homes included no close-proximity (within 10 s of meters) sources (eg, fire pit, back alleyways for cars/parking, lawn mowing; the study was conducted from October to April, limiting lawn mowing and similar activities), no nearby construction (also limited by the choice of study period), and being at least one house away from a street intersection. Differences in $PM_{2.5}$ concentrations will exist on the neighborhood scale and within neighborhood microenvironments (eg, on the driveway vs a remote spot over the lawn) in US cities;[59-61] the location of the

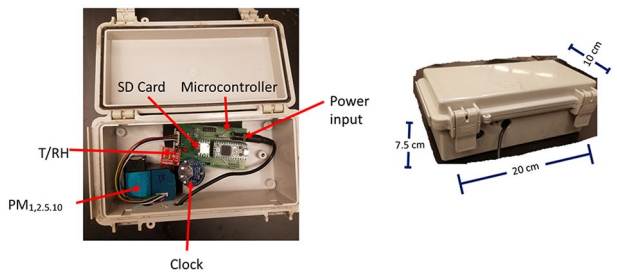

Figure 1. Air quality and meteorological sensing system.

LCSs in this analysis should be treated as representative neighborhood background levels. The monitors were zip-tied to fences or posts approximately at the inhalation height, ~1.5 m off the ground (SI Figure 2). The LCS measured PM_1/$PM_{2.5}$/PM_{10} using a Plantower PMS3003 with no upstream drier (SI Figure 3 for schematic) and relative humidity (RH) and temperature with a Sensiron SHT 15 (Figure 1).

The sensors were calibrated using a co-location approach with an EPA Near-Road (monitoring) Network (NRN) site in Minneapolis (Minneapolis—Near Road I-35/I-94). The LCS were co-located with a dry $PM_{2.5}$ measurement (Beta Attenuation Monitor [BAM]) at the NRN site. Initial $PM_{2.5}$ calibration (using the manufacturer reported $PM_{2.5}$ output) results showed a piecewise continuous response that split at ~10 $\mu g\,m^{-3}$, which has been observed in other studies.[62] A RH correction to the sensor $PM_{2.5}$ data (level 2A correction)[63] was employed,[58] which provided an estimate of dry $PM_{2.5}$ from the LCSs. Calibrations lasted 2 days and were conducted every 2 weeks during the study period to account for any drifts that occur. A linear fit was then used to calibrate the LCSs with the reference site measurements. The sensors' calibration data were then applied to the neighborhood sampling data by time-weighted averaging. The sampling frequency used in these samples was minute data; however, to be consistent with the NRN monitor data, levels were averaged hourly. A recent evaluation of the Plantower PMS3003 with a BAM in a US city

showed the BAM to have a high noise-to-signal ratio at low concentrations,[58] similar to levels that would be observed in Minneapolis; future work with the Plantower sensors may consider longer averaging times during the calibrations to smooth out the noise. Uncertainty was assessed from the slope and intercept uncertainty from the co-location calibration. Uncertainties were propagated through the sampling period for each hour's pollutant measurement.

While LCS can provide additional monitoring, they still do not provide comprehensive spatial coverage, so R-Line[64] was used to simulate on-road mobile source NO_x impacts for the same hours that the EWB assessments were conducted. Modeling of mobile-source impacts on $PM_{2.5}$ was not used because $PM_{2.5}$ impacts from on-road mobile sources are understood to be low,[65,66] leading to issues with relying on R-Line results. Mobile sources contribute to 18% of primary $PM_{2.5}$ emissions in Minneapolis (https://www.pca.state.mn.us/air/statewide-and-county-air-emissions). While NO_x was the only TRAP modeled here, those levels and spatial patterns would be indicative of exposure to other TRAP emissions, as well.

R-Line uses a similar approach to AERMOD, the EPA recommended regulatory dispersion model. R-Line is formulated specifically to address line (vs point or area) sources. In addition, R-Line has updated plume spread (σ_y and σ_z) parameterizations, specific for near-surface dispersion.[64,67] National land cover data from the multi-resolution land characteristic (MRLC) consortium were used in AERSURFACE to generate monthly surface properties in Minneapolis to estimate the Bowen ratio, surface roughness length, and albedo. This, in combination with surface data from the Minneapolis airport and upper air data from nearby Chanhassen, MN (WMO# 72649), was then processed in AERMET to generate meteorological fields, including hourly boundary layer heights.

On-road mobile source emission estimates were generated using annual average daily traffic (AADT) counts from the Minnesota Department of Transportation (MNDOT; http://www.dot.state.mn.us/traffic/data/data-products.html) in combination with representative emission factors used in the EPA National Emission Inventory (NEI). The AADT counts for each road link were from 2017 counts or from the most recent estimates on each road if 2017 data did not exist. Fleet composition data were available for 1040 links in Minneapolis. A weighted average by vehicle type and vehicle count was then used to estimate the fleet composition for the remaining road links used in the simulations (N~34 459). Diurnal and day-of-the-week trends measured in Minneapolis[68] were used alongside the AADT data to develop hourly vehicle counts for each link. Emission factors used to convert activity data to emissions were from the NEI and were a function of vehicle type, season (gasoline formulation), temperature, and RH. A 380 m (E-W) × 500 m (N-S) resolution receptor network spanning 46 km (E-W) × 60 km (N-S) was used in R-Line.

The R-Line simulations gave hourly on-road mobile source NO_x estimates, and concentrations were determined for each of the study neighborhoods. R-Line modeling has been found to lead to unrealistically high simulated pollutant values, which may be attributed to the model itself, that is, due to no default loss mechanisms or an overestimation of modeled emissions,[69,70] both of which led to approaches to calibrate simulated values.[71] Here, 24 correction factors were generated, one for each hour of the day. The correction was developed from linear fits between the R-Line simulation results for each hour of the day and an estimate of the true on-road mobile source impact from observations, (ie, the difference between the I-35/I-94 NRN monitoring site [AQS Site ID# 27-053-0962] and a background, regulatory EPA site observation [AQS Site IDs# 27-003-1002]). The correction approach resulted in the reduction of the model's initial, high-simulated concentrations (see SI Section 1 for more details on the correction methodology).

Emotional well-being assessments

Emotional well-being assessments were recorded using Daynamica™,[36] a smart phone application available on Android phones (SI Figure 4). Neighborhood residents took entry and egress surveys for demographic and personal characteristics. Survey respondents were not informed of the ongoing air pollution study. Residents of the 6 homes in which the LCSs were housed did not participate in the EWB assessments. Daynamica™ scaled EWB on a scale from 1 (not at all) to 7 (strongly), and 5 emotions were assessed: happiness, sadness, stress, pain, and tiredness.[36] The net affect, defined as the positive category (happiness) less the average of the 4 negative ones (sadness, stress, pain, and tiredness), was also assessed. This was the same approach that has been used in other studies to determine the U-index, an oft-applied misery index (ie, a measure of time that people spend in an unpleasant state).[72]

The application tracked the users' movements for a period of 7 consecutive days. Next, users would subsequently identify the activity completed and when it occurred and then respond to a series of EWB questions. There were 371 users, and 26 313 responses were gained from all users (see SI Section 2 for more details on the respondent selection criteria and respondent demographic and SES background). More detailed assessment of the EWB results can be found in Fan et al.[37] Oftentimes, the event to which the EWB recording was associated lasted over multiple hours. The midpoint of the start time and end time was used as the hour of the EWB recording for analysis. Because multiple responses existed in a given hour from a single person or from a person in the same neighborhood, the EWB assessment results in the same hour were averaged.

Linking air quality with neighborhood infrastructure and EWB

We analyzed the relationships between the EWB assessments with the neighborhood $PM_{2.5}$ measurements (home-based LCS exposure), the R-Line NO_x model results evaluated at the

same location where the $PM_{2.5}$ measurements existed (home-based R-Line exposure), and the R-Line NO_x model results at the location of the EWB respondent's activity (in situ R-Line exposure). Only the hours that included both an EWB neighborhood response and LCS $PM_{2.5}$ measurement or R-Line NO_x result were used in the analysis. Neighborhood averages for hours when the $PM_{2.5}$ observation/NO_x simulation and EWB response all existed were determined. The uncertainty for the R-Line simulations was not estimated (which was consistent with other R-Line studies).[65,71] The average EWB was reported with one standard deviation of all measurements. Tests for statistical significance (SI Section 3) on the regressions comparing LCS home-based $PM_{2.5}$, R-Line home-based NO_x exposures, and R-Line in situ NO_x exposures with EWB were performed. In each of these assessments, the exposures may occur in an indoor environment, but each of the assessments presented here is for ambient pollution concentrations. We use ambient concentrations, which is consistent with the approach used by the Global Burden of Disease (GBD) when assessing global mortality from air pollution exposure,[73] for the conducted comparisons. Indoor concentration to outdoor concentration ratios that have large uncertainties due to a multitude of factors including ventilation rates and infiltration rates have been assessed in US cities previously, but recent literature finds large pollution concentration differences even among indoor microenvironments.[74] Coupled with no detailed location of the respondents when indoors, we use ambient exposure estimates, consistent with the methods outlined by the GBD, for the analyses presented here.

The extent to which high-pollution events, including a 2-day lag period, affected EWB was also explored. We include the 2-day lag period as it is a lag time that is used in epidemiology studies involving air pollution exposure impacts with health outcomes.[75] Here, high-pollution events were considered as the top 10% of $PM_{2.5}$ observations or NO_x simulations for each of the neighborhoods, independently, or the top 10% of overall in situ NO_x concentrations where an EWB response existed. We also wanted to explore the EWB outcomes of National Ambient Air Quality Standard (NAAQS) exceedance events, but there were no exceedances of the 24-hour average $PM_{2.5}$ standard during the study period. There were 4 simulated hours that exceeded the 100 ppb NAAQS hourly NO_2 standard, but considering the inherent uncertainty of the simulations, the findings are not included in the main text (see SI Section 4).

Results and Discussion

Low-cost sensor $PM_{2.5}$ performance and neighborhood concentrations

The RH-corrected, ambient LCS $PM_{2.5}$ observations resulted in a linear relationship between the LCS data and regulatory instrument (BAM) at the NRN site, and Pearson correlation coefficients were consistently between 0.8 and 0.9 (see SI Figure 5 for a sample co-location calibration result and SI Table 2 for calibration fits for the entire study period). Elevated $PM_{2.5}$ levels were observed at the beginning of the study period in October/November and toward the end of the study period in April. Minnesota Pollution Control Agency (MPCA) sites within the study domain showed similarly elevated levels during the same hours (SI Figure 6). High concentrations are typically driven by meteorology (eg, low inversion heights, low wind speeds) though they also reflect increased emission events (eg, rush-hour traffic and residential wood burning, a common approach to home heating throughout Minneapolis).[76] The calibrated LCS observations were compared against the reference measurements for the entire study domain, and rough agreement was found between the neighborhood levels and the reference sites ($R^2 = 0.30$-0.61; SI Figures 6 and 7 and SI Table 4).

The LCS measurements showed similar average $PM_{2.5}$ concentrations in 5 of the 6 neighborhoods, with Blaine (the middle-income, suburban neighborhood) being statistically significantly ($\alpha = 0.05$) cleaner than each of the other 5 neighborhoods. Here, concentrations were compared only when observational data existed for all 6 neighborhoods. The highest observed average $PM_{2.5}$ concentration was in Prospect Park (the middle-income, urban with access to light rail neighborhood), but there was no statistical difference between the mean $PM_{2.5}$ in Prospect Park and each of the other neighborhoods except Blaine (Table 1). Although Brooklyn Center is a suburban neighborhood, it showed similar measured levels as the urban neighborhoods. Brooklyn Center is just outside the Minneapolis city boundary (SI Figure 1) and would thus be subject to similar urban emissions. The neighborhood $PM_{2.5}$ observations followed similar time series (SI Figure 6), which further supports that much of the particulate pollution in the area was from regional sources and/or driven by meteorological factors. The results suggest that there were no noticeable rail access impacts on $PM_{2.5}$ levels. It is understood that current-day $PM_{2.5}$ emissions from mobile-sources are generally low; the displacement of vehicles from riders choosing light-rail over personal vehicles will not affect local $PM_{2.5}$ levels. In addition, public transportation only accounts for 13% of Minneapolis' commute modeshare,[77] of which 68% is by bus commute and 29% by the light rail.[78] The light-rail system does not displace a large fraction of personal use vehicles.

R-Line on-road mobile source NO_x modeling calibration results and simulated concentrations

The re-scaling of on-road mobile source NO_x contributions resulted in improved agreement between the simulated mobile-source impact and the true mobile-source impact evaluated at the NRN site (SI Section 1). As expected, the modeled on-road mobile source impacts closely followed the major roadways in Minneapolis (Figure 2). A small NO_x concentration difference

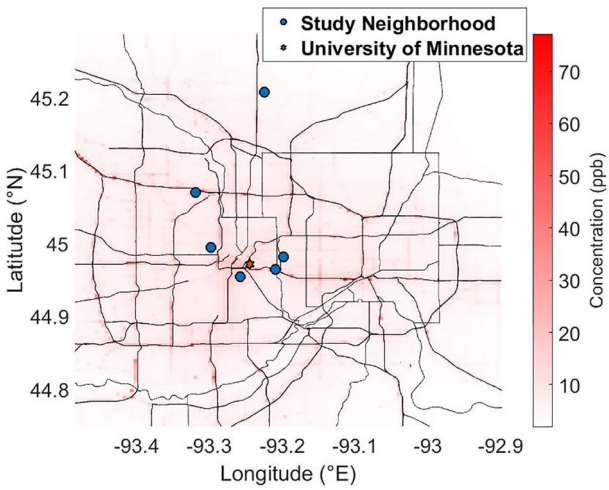

Figure 2. Average on-road mobile-source NO_x impacts simulated using R-Line for Minneapolis, MN, from October 2016 to April 2017. The blue dots indicate locations of neighborhoods where concurrent air quality measurements and emotional well-being (EWB) assessments were performed. The red star is the location of the University of Minnesota.

was found between urban neighborhoods with access to light rail (Phillips and Prospect Park) and neighborhoods without such access (Near North and St. Anthony Park). Access to light rail was expected to reduce mobile-source NO_x impacts considering the proximity of alternative-fuel transportation modes, that is, electric light rail. However, this can be offset by increased traffic arriving at the light-rail stations or because these 4 study neighborhoods were centrally located and thus subject to high vehicle counts along common routes. Phillips, Prospect Park, St. Anthony Park, and Near North (the urban neighborhoods) had the highest average simulated NO_x impacts with higher simulated NO_x concentrations than the 2 suburban neighborhoods (Brooklyn Center and Blaine; Table 1). This is due to the higher vehicle counts in the urban areas.

Linking LCS $PM_{2.5}$ and EWB

The findings in Minneapolis for the LCS $PM_{2.5}$ were negatively correlated (ie, a higher $PM_{2.5}$ concentration led to a lower EWB score) with happiness and positively correlated (ie, a higher $PM_{2.5}$ concentration led to a lower EWB score) with all of the negative emotions, including tiredness, stress, sadness, and pain (Figure 3). A negative correlation was also found for the net affect (sum of the 5 EWB indicators) assessment. There were 2806 hourly EWB responses used in comparison with home-based $PM_{2.5}$ observations (see Table 2 for neighborhood breakdown). None of the relationships were found to be statistically significant ($\alpha = 0.05$), which may in part be explained because among most of the neighborhoods, the difference between $PM_{2.5}$ concentrations was not significantly ($\alpha = 0.05$) different (Table 1). In addition, this assessment was conducted using home-based $PM_{2.5}$ exposures, which had limitations, as the respondents' $PM_{2.5}$ exposure pathways are not fully captured throughout the day.

Linking R-Line NO_x (home-based and in situ exposures) and EWB

Stress, sadness, and pain were positively correlated with simulated neighborhood on-road mobile-source NO_x levels, while tiredness and happiness were negatively associated with home-based NO_x concentrations (Figure 3). Net affect was also negatively associated with mobile-source NO_x concentrations (home-based exposure). For the in situ on-road mobile-source NO_x exposures, we found tiredness, sadness, and net affect to be positively associated with simulated NO_x concentrations and happiness, stress, and pain to be negatively associated. Happiness and net affect were expected to be EWB indicators negatively correlated with mobile-source NO_x concentrations. There were 4732 and 5126 hourly EWB responses used in comparisons with home-based and in situ NO_x simulations, respectively (see Table 2 for neighborhood breakdown).

All of the regression relationships between NO_x and EWB, for both home-based and in situ exposures were near zero, suggesting that the influence of mobile source pollution had little impact on immediate EWB (Figure 3). Although the majority of anthropogenic NO_x emissions (~59%)[32] come from on-road mobile sources in the United States, on-road mobile-source NO_x emissions have reduced ~80% as the Clean Air Act was passed in 1970,[66] resulting in relatively low average concentrations in the 6 study neighborhoods and at the locations where the associated activity for the EWB response took place (Table 1 and Figure 3). The range of average NO_x concentrations was 3.8-8.2 ppb in the 6 study neighborhoods, far below the annual NO_2 NAAQS standard of 53 ppb. Thus, the average NO_x levels might not have been high enough for its effects on EWB to be observed, and further, NO_2 has little impact on visibility at such low levels.[79]

Other factors that can influence the findings presented have not been controlled for in the analysis. The respondent took the survey at various times during the day (they could take the questionnaire right after completing an activity or hours after the activity), which could bias results. Confounding variables that could have major impacts on EWB assessments against a single indicator using this dataset are discussed further in Fan et al.[37] Briefly, EWB is a function of many factors in addition to air quality, including personality, age, sex, ethnicity, companionship, employment, and health. Recent work using the same survey data to carry out individual-level analyses has shown that general happiness and life satisfaction of a person predicts EWB during various activities. For example, Fan et al[37] used the same survey data and found that an individual's general happiness is associated with the individual's emotional experiences during daily trips. Ambrose and colleagues (https://www.sciencedirect.com/science/article/pii/S0169204619307297, 2020—accepted) used the same survey data and found that high levels of life satisfaction and optimism (personality traits) are associated with emotional experiences during gardening activities. This article aims to examine the air quality and EWB connection at the neighborhood level. Controlling for

individual attributes is out of the scope of the comparisons presented here. Future work should explore the effects of air quality on EWB at the individual level and the use of the sampling approach applied here can provide a fine time-series relating EWB to air quality, for example, at the hourly level. Furthermore, the EWB outcomes were not mutually exclusive of one another, that is, if someone is feeling pain, it is possible they feel stressed, too. This inter-relationship among the indicators was difficult to quantify and can influence results. Also, we have not included any correction or re-scaling of the data due to personality or

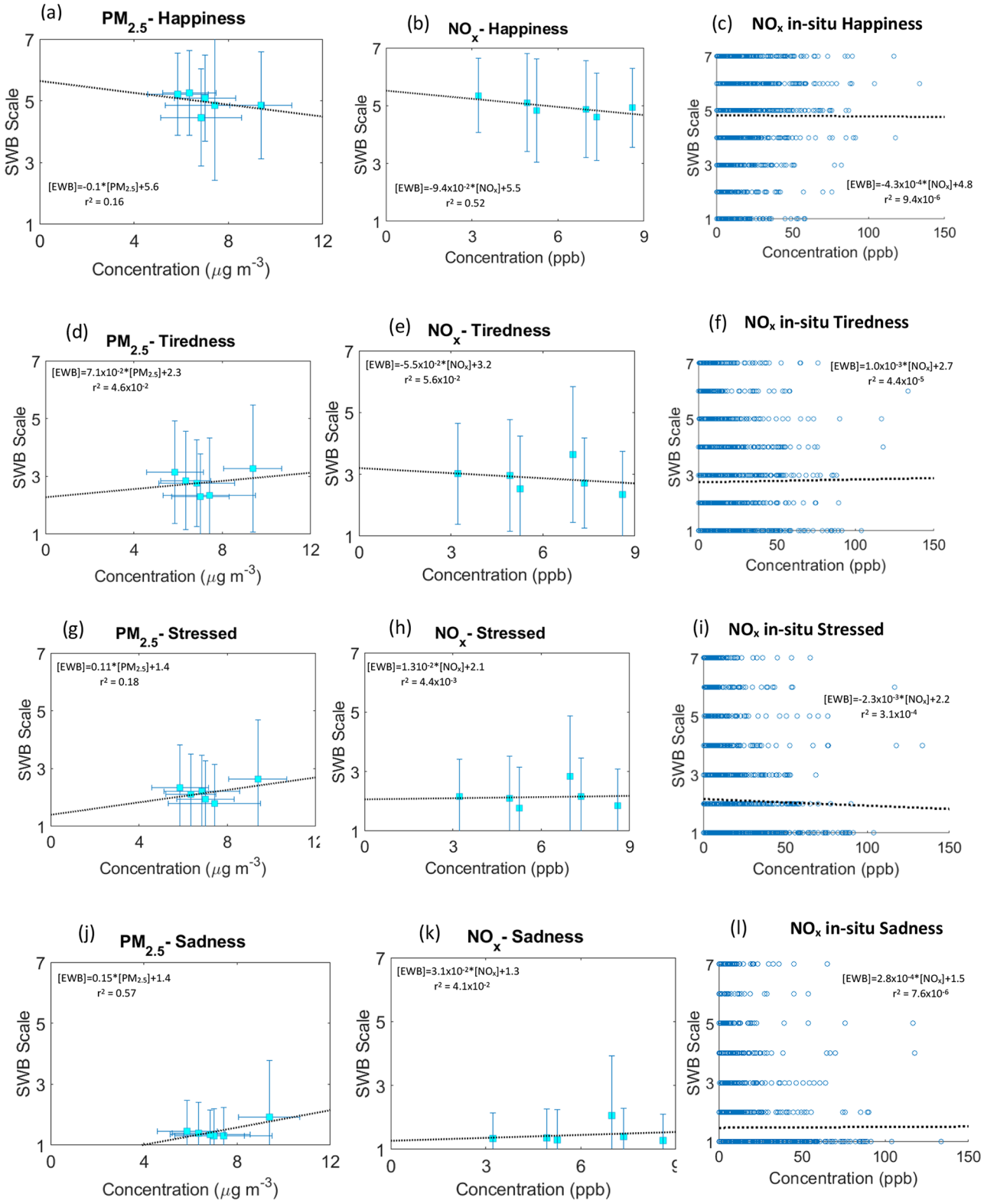

Figure 3. *(Continued)*

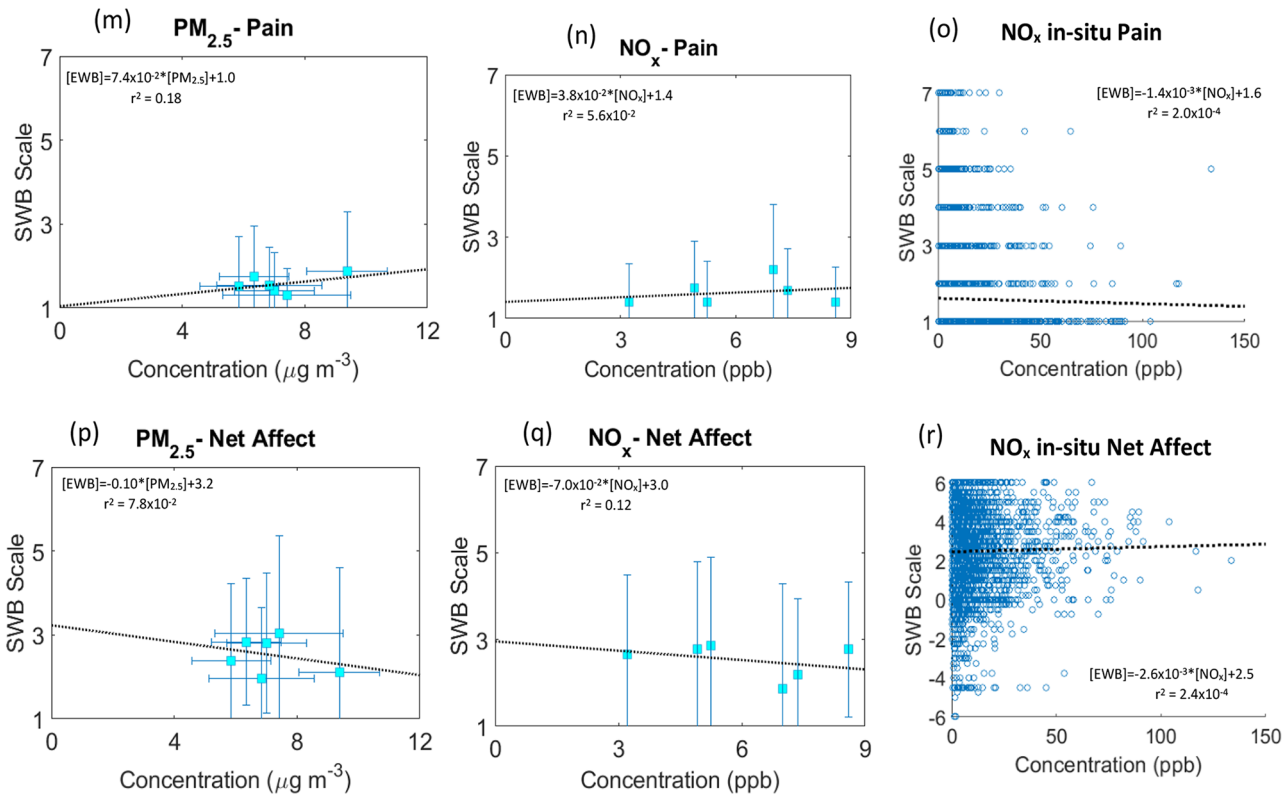

Figure 3. (Left column) Average neighborhood low-cost sensor (LCS) $PM_{2.5}$, (middle column) R-Line mobile-source NO_x home-based exposure, and (right column) R-Line mobile-source NO_x in situ exposure against concurrent emotional well-being (EWB) measurement (n = 5126) for (a-c) happiness, (d-f) tiredness, (g-i) stress, (j-l) sadness, (m-o) pain, and (p-r) net affect. A higher EWB score means "more" emotion (eg, a higher EWB happiness score means happier). None of the relationships were statistically significant ($\alpha = 0.05$).

Table 2. The number of emotional well-being (EWB) responses that aligned with an air quality (low-cost sensor $PM_{2.5}$, home-based R-Line on-road mobile-source NO_x, or in situ R-Line on-road mobile-source NO_x) data point during the same hour for each of the 6 study neighborhoods.

NEIGHBORHOOD	LCS $PM_{2.5}$ COMPARISON	HOME-BASED R-LINE MOBILE SOURCE NO_X COMPARISON	IN SITU R-LINE MOBILE SOURCE NO_X COMPARISON
Phillips	102	271	406
Near North	612	858	897
Prospect Park	520	833	861
St. Anthony Park	677	1172	1297
Blaine	496	805	778
Brooklyn Center	399	793	887
Total	*2806*	*4732*	*5126*

other demographic (eg, age, sex, ethnicity) effects. The relationships found in this manuscript should be interpreted with caution considering the high uncertainty associated with the variability in the air pollutant concentrations, uncontrolled factors of estimating personal EWB, and potential time lags in the response of EWB to air quality.

High-pollution events and EWB impacts

No noticeable trends were found when exploring the top 10% of neighborhood $PM_{2.5}$ concentrations, home-based mobile-source NO_x levels, or in situ mobile-source NO_x levels, including a 2-day lag, on any of the EWB outcomes (Tables 3, 4, and 5, and SI Figure 7). The $PM_{2.5}$ finding was likely due to the little difference between $PM_{2.5}$ concentrations in the top 10% of hours with the remaining concentrations (SI Table 5), while the NO_x finding could be explained from the low mobile-source NO_x to EWB relationship. There were no noticeable trends of EWB impacts from high NO_x or $PM_{2.5}$ events in the 6 neighborhoods with respect to access to light rail, income levels, or urban versus suburban.

Table 3. Average difference between EWB indicators for the top 10% of $PM_{2.5}$ hourly concentrations (including a 2-day lag) and the 90% cleanest hours in each neighborhood.

EWB INDICATOR	PHILLIPS	NEAR NORTH	PROSPECT PARK	ST. ANTHONY PARK	BLAINE	BROOKLYN CENTER
Happiness	−0.95*	-4.2×10^{-2}	−0.18	−0.51*	1.2×10^{-2}	0.15
Tiredness	0.21	0.49*	1.0*	−0.23*	−0.16	-6.6×10^{-2}
Stress	0.18	0.26	0.65*	-2.3×10^{-2}	−0.16*	1.3×10^{-2}
Sadness	0.11	0.12	0.41*	-7.3×10^{-2}	-3.6×10^{-2}	-1.9×10^{-2}*
Pain	0.33*	-3.8×10^{-2}	0.34*	−0.13	0.35*	-7.3×10^{-3}
Net affect	*−1.23**	*−0.13*	*−0.69**	*−0.34**	*−0.19*	*0.13*

Abbreviation: EWB, emotional well-being.
See SI Table 6 for the cutoff concentrations. Positive values indicate that the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high $PM_{2.5}$ days).
The asterisk (*) indicates the difference is statistically significant ($\alpha=0.05$).

Table 4. Average difference between EWB indicators for the top 10% of mobile-source NO_x hourly concentrations (including a 2-day lag) and the 90% cleanest hours in each neighborhood.

EWB INDICATOR	PHILLIPS	NEAR NORTH	PROSPECT PARK	ST. ANTHONY PARK	BLAINE	BROOKLYN CENTER
Happiness	0.16	−0.28*	−0.25*	−0.36*	−0.14	0.37*
Tiredness	−0.18	0.35*	0.20*	-1.6×10^{-2}	−0.16	−0.20
Stress	−0.37*	0.30*	7.3×10^{-2}	-1.6×10^{-2}	-6.0×10^{-2}	7.9×10^{-2}
Sadness	−0.12	0.59*	8.9×10^{-2}	-7.6×10^{-2}	-9.8×10^{-2}	0.13*
Pain	−0.32*	0.23*	−0.16*	−0.42*	1.8×10^{-2}	−0.10
Net affect	*0.64**	*−0.41**	*−0.21**	*−0.23**	*−0.23*	*0.26*

Abbreviation: EWB, emotional well-being.
See SI Table 6 for the cutoff concentrations. Positive values indicate the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high NO_x days).
The asterisk (*) indicates the difference is statistically significant ($\alpha=0.05$).

Table 5. Average difference between EWB indicators for the top 10% of in situ mobile-source NO_x hourly concentrations (concentrations > 19.6 ppb; including a 2-day lag) and the 90% cleanest hours in each neighborhood.

EWB INDICATOR	HAPPINESS	TIREDNESS	STRESS	SADNESS	PAIN	NET AFFECT
	−0.24*	−0.13*	−0.19*	-6.7×10^{-2}	1.5×10^{-2}	−0.11

Abbreviation: EWB, emotional well-being.
Positive values indicate the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high NO_x days).
The asterisk (*) indicates the difference is statistically significant ($\alpha=0.05$).

Conclusions

This exploratory research used a novel approach to characterize the relationships between air quality with EWB and neighborhood infrastructure. This study integrates low-cost sensing for $PM_{2.5}$ and R-Line modeling for mobile-source NO_x with a novel phone application for near real-time EWB assessments. From the observational data in 6 neighborhoods of varying SES and light-rail access, poorer neighborhoods tended to have higher $PM_{2.5}$ concentrations than their mid-SES counterparts in Minneapolis, MN, raising environmental justice concerns. Simulated NO_x levels from on-road mobile sources were significantly ($\alpha=0.05$) higher in the urban neighborhoods than the suburban ones, which was expected, considering higher average traffic counts in the urban neighborhoods. There was little influence of light rail access on neighborhood air quality (for both measured $PM_{2.5}$ and modeled mobile-source NO_x). When compared to concurrent EWB assessments from neighborhood respondents, neighborhood $PM_{2.5}$ had a negative response (ie, a higher $PM_{2.5}$ concentration resulted in a lower EWB outcome) for

happiness and net affect, but a positive response (ie, a higher $PM_{2.5}$ concentration resulted in a higher EWB outcome) for tiredness, stress, sadness, and pain. None of the air pollution relationships were found to be statistically significant ($\alpha = 0.05$) with EWB, and though from a relatively small sample size associated with this exploratory research, these results are suggestive of more measureable affects given larger sample sizes or greater pollutant variability. Both mobile-source and in situ NO_x had a minimal and near-zero regression relationship with all EWB indicators, which may have been a result of reductions in mobile source emissions as well as increased exposure measurement error versus having observed levels.

Future work linking air quality to EWB should consider personal pollution exposures with on-body monitors and consider personality, age, sex, ethnicity, companionship, employment, and health to better characterize environment impacts (ie, air quality) on EWB. The findings from this work and the novel methods introduced here may be used for policy directives specifically in Minneapolis and in other cities with similar neighborhood characteristics. Local interventions (eg, cleaner heating practices in the winter seasons), particularly in lower SES communities, may offer air quality improvements, which from the results presented here may results in improved well-being. More detailed assessments on the emission sources and activities will be needed to directly intervene in cities, but the methods presented here can be applied in other cities. The findings from this study are only applicable to relatively clean environments with similar infrastructure characteristics, but the relationship between air quality with neighborhood infrastructure and EWB may have more pronounced effects in developing countries (eg, Asian, African, and South American countries) where $PM_{2.5}$ levels can vary be 100s of $\mu g\,m^{-3}$ within the same day. Such studies would offer a unique opportunity to assess the relationship between air quality, infrastructure, and well-being.

Author Contributions

RML set up the LCSs in Minneapolis and analyzed their data, estimated mobile-source NO_x emissions and simulated NO_x impacts using R-Line in Minneapolis, linked EWB results with air quality, and wrote the manuscript. KD led the EWB sampling in Minneapolis. KKB designed and manufactured the LCSs. All authors assisted with manuscript preparation. AR, AGR, YF, and NB conceptualized the research.

ORCID iD

Raj M. Lal https://orcid.org/0000-0001-6024-0629

Data Availability

All data used in this study are openly available. Please email rlal6@gatech.edu or anu@princeton.edu for any data needs.

Supplemental Material

Supplemental material for this article is available online.

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