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Characterizing Urban Traffic Exposures Using Transportation Planning Tools: An Illustrated Methodology for Health Researchers

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ABSTRACT *Exposure to elevated levels of vehicular traffic has been associated with adverse cardiovascular and respiratory health effects in a range of populations, including children, the elderly, and individuals with pre-existing heart conditions, diabetes, obesity, and genetic susceptibilities. As these relationships become clearer, public health officials will need to have access to methods to identify areas of concern in terms of elevated traffic levels and susceptible populations. This paper briefly reviews current approaches for characterizing traffic exposure and then presents a detailed method that can be employed by public health officials and other researchers in performing screening assessments to define areas of potential concern within a particular locale and, with appropriate caveats, in epidemiologic studies examining traffic-related health impacts at the intra-urban scale. The method is based on two exposure parameters extensively used in numerous epidemiologic studies of traffic and health—proximity to high traffic roadways and overall traffic density. The method is demonstrated with publically available information on susceptible populations, traffic volumes, and Traffic Analysis Zones, a transportation planning tool long used by Metropolitan Planning Agencies and planners across the USA but presented here as a new application which can be used to spatially assess possible traffic-related impacts on susceptible populations. Recommendations are provided for the appropriate use of this methodology, along with its limitations.*

KEYWORDS *Traffic Analysis Zone (TAZ), Geocoding, Traffic density, Traffic proximity, Spatial density analysis, Metropolitan planning organizations*

INTRODUCTION

Residential traffic exposure is associated with a wide range of health effects for many populations.[1] Earlier large cohort studies of air pollution and health noted elevated cardiovascular and pulmonary risks in geographic areas where traffic burden was highest.[2,3] These studies prompted the next generation of studies focusing more closely on traffic-related impacts and refining the methods employed to characterize traffic-related exposures.

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The scale of traffic-related health assessments has ranged from large nationwide cohorts utilizing area-wide monitoring data or national databases[4,5] to more localized studies of specific regions,[6] air basins,[7,8] cities,[9–11] and neighborhoods[12–14] using air quality data of specific traffic-related pollutants collected to represent a more localized or even personal scale. Whether examining regional trends or local conditions, each scale of assessment faces the task of appropriately integrating spatial and temporal data regarding traffic impacts with available demographic and health outcome data to assess what has been termed "geographies of risk."[15]

A range of methods has been employed to characterize traffic exposures depending on the research hypothesis under examination, available budget, and time pressures. Many studies have focused on measuring and/or modeling the individual pollutants or classes of pollutants in traffic emissions including nitrogen dioxide (NO_2), carbon monoxide (CO), fine particulate matter less than or equal to 2.5 μm in aerodynamic diameter ($PM_{2.5}$), ultrafine particulates less than or equal to 0.1 μm in aerodynamic diameter (UFP), the elemental carbon content of PM, black carbon (BC), or volatile organic compounds such as benzene and toluene, attempting to identify the specific causal agent associated with adverse health effects.[16–19]

These studies have been conducted by positioning equipment on a residence or school building, in mobile vans, on carts that follow individuals through the course of their day, or in packs worn by study participants.[20–22] Air monitors have also been positioned at locations across a larger study area and data combined with statistical interpolation models, land-use regression models, dispersion models, meteorological-emission models, or some hybrid of these to estimate exposure concentrations for individuals in the study.[23]

The implementation costs and research time involved in establishing a comprehensive and representative air monitoring program are beyond the capabilities of many research projects. For this reason, numerous studies have developed exposure indices based on traffic volume data, which are generally publically available, rather than measured or modeled traffic pollution levels to perform screening level assessments in new study locales or to examine associations between level of traffic and previously unexplored health outcomes. These approaches are sometimes referred to as surrogate measures of traffic exposure.

Rationale for Using Surrogate Methods for Characterizing Traffic Exposures

Consensus has emerged regarding the presence of pollution gradients near major roadways. Several studies have demonstrated higher levels of several traffic-related air pollutants (TRAP) closer to roadways.[24–28] As compared with more aged emissions, fresh traffic emissions include larger amounts of UFP, which are strongly oxidative and may be particularly toxic,[29] black BC, CO, and oxides of nitrogen (NOx) are all elevated near highways with measurably significant declines beyond 200 m.[1] Evidence shows TRAP elevated near roadways with at least 30,000 vehicles per day, though some evidence suggests that roadways with lesser volumes may also generate pollution gradients with significant health effects.[1]

Residential proximity to high traffic roads and dense road networks have been linked to asthma,[7,30–32] respiratory symptoms,[33] and reduced lung function in children and adolescents.[34] Coronary heart disease risks have been reported to increase with levels of traffic,[11,35–37] as have the more discrete risks of acute myocardial infarction[10,38,39] and atherosclerosis.[40] Several studies indicate that older (65+) adults are at greater risk of the adverse effects of traffic exposures.[21,41,42]

Traffic density analyses provide a comprehensive and multi-directional assessment of airborne environmental burdens from roads within a certain radius of a residence.[5] In urban areas, roadway grids can be closer than 200 m, producing additive traffic-related effects that depend on the density of the road network.[43] Many areas within the city of Boston, for example, have streets less than 200 m or even 100 m apart. For dense urban areas, assessment of traffic exposure with respect to both proximity to major roads and the cumulative impacts of the roadway network is recommended.

Traffic density is a measure of the rate of traffic flow per unit time (usually day or year) along lengths of road within a specified area and is expressed as vehicle miles (or kilometers) traveled (VMT) per square mile (or kilometer), i.e., daily VMT/mi^2. Traffic density has been estimated at the county level,[5] the census block level,[44] and within selected radii (50–300 m) of a residence[10,11,30] using publically or commercially available sources or some combination thereof. The traffic density estimate may be based on only those roads for which actual traffic volume data are collected,[11,44] or traffic volumes may be assigned to neighboring roads using models or comparison to roads with similar capacities.[10,36] In one study, publically available data on roadway networks and traffic volumes were used to develop geographic information system (GIS)-derived cumulative traffic density scores identifying roads with greater than 8,500 cars/day.[14] Traffic density has been used together with several other methods, including proximity assessments and air measurements and has been identified as perhaps the strongest predictor variable in many of the recent land-use regression models.[45]

A Methodology to Characterize Urban Traffic Exposure Using City Planning Tools

A traffic exposure characterization methodology was developed to address both roadway proximity and traffic density. This methodology makes use of the Traffic Analysis Zone (TAZ). The TAZ is a small area transportation planning tool long used by Metropolitan Planning Agencies and planners across the USA. Use of these methods is illustrated with ArcGIS-based mapping and spatial analysis tools[46] that combine traffic level datalayers and the locations of sensitive receptors including (1) schools and long-term care facilities in the greater Boston area and (2) a sample of geocoded residential locations from an ongoing study, the Boston Puerto Rican Center for Population Health and Health Disparities Project (PRHDP), in the Tufts University School of Nutrition.[47] A cross-sectional analysis of health outcomes in this population and traffic exposure characterized using these methods is reported in a separate publication.[48]

Considerations for Traffic Exposure Assessment

Several interrelated issues addressed in the traffic and health literature remain active areas of research and warrant special consideration before initiating a traffic exposure assessment. These include (1) traffic volume and threshold of effects, (2) temporal and spatial scale of assessment, (3) acute and chronic exposures, (4) geocoding error and spatial misalignment, and (5) socioeconomic factors.

Traffic Volume of Concern. Traffic studies aim to answer the question, "Who is most susceptible to traffic exposure and which roadways and areas represent a concern?" Prior studies have provided guidance on who is most susceptible; however, what constitutes a roadway of concern in terms of traffic level remains a subject of study.

The lower level of traffic associated with adverse health effects has not been established. Several studies have reported adverse health effects associated with residing or attending school near “interstates, highways, and major arterials”[7,37] or near “major roads” with vehicle counts that ranged from 10,000 to 100,000.[35,40,49] Major arterials can range from 15,000 to 30,000 vehicles per day. These studies did not report the number or percentage of subjects living near the lower versus higher range of traffic volumes. Generally, unless selected on the basis of their exposure to traffic, a significantly smaller percentage of study participants live in the highest traffic areas suggesting that the more moderately exposed (10,000–75,000 vehicles per day) are also experiencing adverse effects. A recent study by this author suggests residence near roadways with traffic volumes as low as 20,000, common to many roads in the Greater Boston area, may be associated with adverse health effects, and on this basis, a lower volume threshold of 20,000 vehicles per day was used here.[48]

Scale of Assessment. Time and activity assessments consider the relative time spent inside and outside of the home or spent at school or work, in close proximity to traffic, or within one or more traffic analysis zones. A detailed exposure characterization model takes individual behavior into account and matches the geographic or spatial scale of the assessment to the study population. For certain populations, i.e., home-bound or less mobile individuals such as the elderly who spend a significant portion of their day in one place or reside in a long-term care facility, children who spend 6–8 h at school, or individuals working full time in one workplace, traffic conditions in those locales represent a significant portion of their total exposure. Roadway proximity and traffic density have been associated with adverse health outcomes based on school and residential locations, and it is therefore considered valid to use these same traffic indices for a residential or school-based study. When focused on only one domain such as school or residence, it is important to consider whether exposure levels in an individual’s other domains, including commuting, are significantly different. This could be especially important for people who commute between rural, suburban, and urban areas, an effect that may result in exposure misclassification and/or confound estimates of risk.

Acute and Chronic Exposures to Traffic. Both the traffic count and TAZ-level data employed here were collected and developed to reflect average weekday exposures for a 24-h period. Traffic counts are collected over a 48-h period but published as 24-h averages. These data are suitable for assessing chronic exposures. In almost all areas, but particularly in areas near major roadways, traffic-related exposures result in shorter-term daily peaks or intermittently higher levels during rush hours, as well as lower levels for the remainder of the day. The 24-h average traffic count and VMT/mi^2 estimates do not adequately reflect the acute exposure to which a commuter, pedestrian, or roadway worker may be exposed during daily peaks. Adverse traffic-related effects have been associated with both short-term and long-term exposures.[1] The underlying mechanisms for both cardiovascular and respiratory illnesses suggest that peak exposures in especially dense traffic areas (or resulting from unusual short-term weather events such as inversions) may act together with long-term somewhat lower level exposures to contribute to underlying vulnerability and then more severe events such as asthma attacks or myocardial infarction, especially among individuals with pre-existing health conditions.[17,50] Some traffic count data are available on an hourly basis from a smaller number of reporting stations. Assessment of health effects associated with peak traffic levels could be examined for individuals with localized exposures during those periods. The issue of acute versus chronic exposure and the degree to which health effects result from the former, latter, or both remains an ongoing research area.

Geocoding and Spatial Alignment of Data Sources. Geocoding is the process by which specific locations are located on digitized maps and assigned coordinates of longitude and latitude to enable spatial analysis. Errors in geocoding result from a number of sources, including positional and address errors in the geographic reference data set (e.g., street centerlines), errors or inconsistencies in the address information of the research participants, or in the geocoding algorithms themselves. Address verification and cleaning is the first step in the matching process. Misspellings, errors such as listing street when the address is an avenue, or missing or incorrect zip codes can reduce match rates significantly.

In a study of over 100,000 residential locations, a substantial median positional error of 41 m was reported, and the geocoding method consistently over-estimated the number of potentially exposed cases at small distances up to 250 m.[51] Geocoding against parcel boundary maps is generally considered a more spatially accurate method. In a study of 3,000 residential addresses, geocoding using property parcel maps was more accurate than street centerline files and was most accurate in urban areas where the distance between geocoded point and the true location determined by aerial imagery was within 21 m for 95% of the cases.[52] Not all cities or towns have available parcel maps, and depending on the study population, match rates using parcel maps can be lower than street network matching. For example, single parcels can be associated with duplex units, condominiums, and apartment complexes with several units, though the individual addresses may not be reflected in the parcel database.[51] Public housing sites, often comprising several units with individual addresses, may not be well represented in parcel matching for these reasons.

Before conducting any analysis functions in ArcGIS, it is imperative that all the data sets are in the same map projection/coordinate system, e.g., Universal Transverse Mercator, State Plane, with the same units, e.g., linear unit meters, and that the data frame is also in that coordinate system.[46] In one study, spatial misalignment of traffic data and the location of child care facilities obtained from different government agencies resulted in a substantial number of false positives and negatives with respect to facilities at risk.[53]

Socioeconomic Factors. Exposure to air pollution across a city may follow socioeconomic gradients that influence susceptibility as residents in poorer neighborhoods may live closer to roadways with higher traffic.[9] Differential personal exposure to particles, gaseous pollutants, and traffic pollution have been associated with lower socioeconomic position with respect to education, minority status, and income, and major roadways have been routed through lower-income areas with less political and economic power.[54] Studies to assess potential health impacts from elevated traffic exposures must account for a variety of socioeconomic and related lifestyle and behavioral factors that can confound the traffic pollution association.[54] Epidemiologic studies may collect some or all of these contextual variables for individual participants. For example, the PRHDP collected over 1,400 variables including an extensive list of socioeconomic, behavioral, and lifestyle and health status factors on study participants. A cross-sectional assessment of traffic exposure and cardiovascular risk factors in the Puerto Rican health study population used regression models that controlled for many of these contextual factors. Factors including educational levels, income, and percent of various ethnic minorities are available from the US Census at the level of blocks and block groups, a different scale of analysis. TAZ-level demographic statistics, developed as part of a larger Metropolitan Planning Organization (MPO) environmental justice analysis,[55] were developed by the Central Planning and Transportation Staff (CTPS).[56]

METHODS

Data Collection

Traffic count data were obtained from the Massachusetts Highway Department (MHD) and the CTPS of the Boston Region MPO, including a GIS-compatible file with traffic count station positions and measurement data from 2002 to 2006. Counts reflect traffic volumes in both directions. MHD conducts 48-h duration traffic counts each year utilizing automatic traffic recorders on various roadways throughout the state. The coverage count program consists of a total of 2,327 count locations spread across a 3-year counting cycle. Locations are repeated once every 3 years.

TAZ-level estimates of VMT and the size of the TAZ in total square miles and dry land square miles were obtained from the CTPS for the year 2000. Dividing VMT by dry land square mile gives an estimate of traffic density for each TAZ as VMT/mi^2. Quartiles and the 90th percentile values for VMT/mi^2 for the 447 TAZ in Boston were determined and used to construct color-coded traffic level data layers by importing the data into ArcGIS.

Table 1 provides a list of characteristics for the Boston Region MPO and MPOs in the USA that are relevant to consider when assessing the utility of TAZ data for health studies in a particular planning area. Important factors include: the median size of TAZ in that planning region, average number of links and nodes in the network, and the proportion of roads included in the network. All of these factors reflect the level of detail, resolution, and the extent of overall traffic that is included in the estimates and ultimately the strength of the exposure classification.

The geocoded locations of schools and long-term care in the greater Boston area were derived from the Commonwealth of Massachusetts Office of Geographic and Environmental Information (MassGIS.gov) on-line database. The locations of hospitals and community health centers are also available from the same source, though not included here. Both the traffic count data and all MassGIS files are registered to the NAD83 datum, Massachusetts State Plane Mainland Zone coordinate system. Developed from Department of Education datafiles, public, private, charter, collaborative programs, and approved special education schools attended by students in pre-kindergarten through high school were included. The Long Term Care Residences point datalayer contains the locations of licensed nursing homes, rest homes, and assisted living facilities in Massachusetts. Public agencies typically follow a geocoding protocol that combines an automated address matching component with manual refinement using digital ortho imagery or topographic imagery.

Residential addresses were collected as part of the ongoing PRHDP study, and address geo-coordinates were used to illustrate the traffic characterization methods.

Traffic Exposure Assessment

ArcGIS software (version 9.2) was used to review all of the traffic count station data and to identify and select the roads of interest based on a daily traffic volume

TABLE 1 Characteristics of US Metropolitan Planning Organizations and Boston region traffic analysis zones relevant to planning traffic exposure studies

MPO and TAZ characteristics	MPOs in US	Boston region MPO
Size of MPO[a]		
Small (n = 205)	<200,000	
Medium (n = 133)	200,000–1 million	
Large (n = 43)	>1 million	>3 million
TAZ per square mile (all MPOs)		
Small	0.9	
Medium	0.8	
Large	0.5	1.00
Average number of TAZ per planning region	836	
Small	463	
Medium	931	
Large	1,739	2,727
Average number of Links in the network	8,602	
Small	4,213	
Medium	8,719	
Large	20,038	40,000
Average number of nodes in the network	5,714	
Small	2,951	
Medium	6,859	
Large	11,367	15,000
Proportion of roadway miles included in network		
Freeways	Almost all	All
High occupancy vehicle lanes	Almost all	All
Major arterial	Almost all	All
Minor arterial	Almost all	All
Collector	Large range	All
Local	Large range	Some

[a]Survey based on responses received from 57%, 57%, and 84% of small, medium, large MPOs, respectively.[60]

threshold of 20,000. Studies that use proximity as a surrogate for near-roadway exposures often use a dichotomous exposure variable for living inside or outside a specified buffer zone of a roadway. Buffer distances typically range between 50 and 300 m.[30,35,36,40] Traffic-level data layers were developed to include 100- and 200-m buffers measured from the edge of roadways with traffic volumes over 20,000 vehicles per day. Centerline data for the buffers were based on the MassGIS Executive Office of Transportation roads data layer.

Some studies have expressed proximity as a continuous variable. Short of collecting measurements using geo-positioning devices, determining exact distances to roadways is difficult due to the problems inherent in the accuracy of geocoding (see "Considerations for Traffic Exposure Assessment").

Residential addresses of participants in the PRHDP study were geocoded using a three-tiered system consisting of parcel matching, street network matching, and manual refinement using Google Earth. *XY* coordinate pairs for latitude and longitude were assigned to the addresses by comparing or "matching" the address information (street number, name, city, and zip code) to a reference data base consisting of parcel boundary maps and associated addresses. The accuracy of the match is reflected in a score of between 0 and 100, with 100 being the highest match. For cases not matched to parcel maps or receiving match scores below 100, a second method of geocoding was conducted using ArcGIS StreetMap USA, a nationwide street network for map visualization, geocoding, and routing available as part of the ArcGIS software.[46]

For both methods, match scores were reviewed to determine the reason for scores less than 100 (on a scale of 0–100). Typical reasons for scores between 80 and 99 included slight misspellings of street name or the use of the abbreviation for street or road (st., rd) in the address database. Scores below 80 were manually resolved.

Data Analysis

After obtaining the GIS-compatible TAZ-level data, an initial TAZ assessment was conducted. Descriptive statistics on the range of density values, quartile values, and the 90th percentile value were generated and used to spatially display the data, noting whether observed patterns are generally consistent with known traffic geography. A spatial density assessment was conducted to evaluate the degree to which small TAZs may be influenced by the traffic levels of proximal TAZs.

Alternative methods of defining or classifying levels of VMT/mi^2 may be useful, depending on the population under study. In cases such as the present analysis, where traffic exposure assessment was not part of the initial hypotheses around which study participants were recruited, consideration should be given to having sufficient contrast across the study population in the traffic indices.

Traffic density and roadway proximity maps were overlaid to examine the extent to which high-impact areas identified by the two methods overlap. The variation in estimated traffic densities across adjacent TAZs was examined to assess potential exposure misclassification. A raster-based spatial density analysis was conducted to examine the degree to which small TAZs may be influenced by the traffic levels of their adjacent TAZ. Spatial density analysis accounts for the size of a TAZ with respect to the influences of other TAZs and calculates the density of traffic levels in the vicinity smoothing the variation between them. Using the kernel density option, which is based on the quadratic kernel function,[46,57] a running weighted average of vehicle miles traveled within cells 10 m^2 was calculated over a 1,000-m radius. The density is greatest at the point location and diminishes to zero at the specified radius.

The volume under the surface equals the population field (vehicle miles traveled) value for the point. The sum of the intersecting spreads is calculated for each output raster cell by adding the values of all kernel surfaces where they overlay the raster cell center. For mapping and visualization purposes, density contours were defined by natural breaks that best group similar values and maximize the differences between classes.[46]

RESULTS

The city of Boston is comprised of 447 out of a total of 2,727 TAZ in the larger MPO region (Table 2). TAZ Traffic density in the Boston area ranges from 600 to greater than 3,000,000 VMT/mi^2. In Boston, traffic density increases with population density, a trend consistent with many urban areas. The square area of a TAZ is generally smaller in the urban core of the city, though the highest-density TAZ (in darker colors) are generally coterminous with the major highways and arterials in the area (Figure 1). The smaller TAZ size in the urban core reflects the heterogeneity

TABLE 2 Traffic analysis zone characteristics—City of Boston, Massachusetts

	Traffic density (VMT/mi^2)	Mean TAZ size (mi^2)	Population[a]	Population density[b] (pop/mi^2)	% less than 15	% age 65 +
All TAZ (n = 447)	600–3,735,000	0.109	589,000	23,326	13.5	11.1
1st quartile	<69,000	0.166	191,460	23,773	15.2	11.5
2nd quartile	69,001–126,000	0.127	180,818	20,577	17.4	10.1
3rd quartile	126,001–335,000	0.086	130,769	23,147	11.9	11.9
4th quartile	>335,000	0.058	85,915	26,409	8.8	10.8
90th percentile	>798,000	0.065	28,918	19,718	7.9	9.7

[a]Source of population data: Boston Region MPO, Central Transportation and Planning Staff
[b]Mean for 371 TAZs with available data adequate data

of the inner-city roadway network and changing levels of traffic across relatively small distances. Zone homogeneity is a key criteria used to develop Boston area TAZ, and while the average TAZ size across the entire MPO region (2,727 total TAZ) is 1.0 mi^2, the average TAZ within the urban core of Boston is 0.109 mi^2.

A sizable population (>28,000) was estimated to live within the highest traffic density TAZs reflected by the 90th percentile of over 785,000 VMT/mi^2.[56] A study of all California census block groups defined 500,000 VMT/mi^2 as high traffic density, and a survey of the State of New York, the District of Columbia, and California found only 5% of census blocks and one US County (Manhattan) had traffic densities higher than 500,000 VMT/mi^2.[5] Approximately 8% of the population in the highest-density TAZ in Boston is under age 15, and nearly 10% is over age 65.

Forty roads in Boston were identified with traffic volumes greater than 20,000 vehicles per day. Volumes on the majority of roads were between 20,000 and 40,000 vehicles per day, with volumes on only four roads between 40,000 and 100,000 and volumes on two roads, Interstate 93 and the Massachusetts Turnpike, over 100,000 vehicles per day (Figure 2).

Several schools and long-term care facilities can be observed within the higher-density traffic areas and within the 100- and 200-m roadway buffers (Figures 1 and 2). The figures identify areas of potentially high traffic exposure, though actual exposures would be influenced by a number of road and building design factors, behavioral variables, and meteorological conditions.

Parcel maps were available for geocoding Boston addresses, though public housing sites with several units and individual addresses were not well represented. An estimated 25% of individuals from the PRHDP study resided in public housing, and it was necessary to geocode these cases using ArcGIS StreetMap USA.[46] Complicating the geocoding process, the city of Boston has 18 neighborhoods with over 200 instances of the same road name being used for two or more different non-contiguous roads.

Several high traffic density TAZ (darker colors), or portions of these TAZ, were outside of a 200-m buffer of a roadway (Figure 3a), and several of the geocoded addresses fell within a high traffic density area but were outside of a buffer (Figure 3b). In general, these high traffic density TAZ that were outside buffers were adjacent to very high traffic roadways such as Interstate 93 and the Massachusetts Turnpike with a dense network of arterials and ramps leading to the highway.

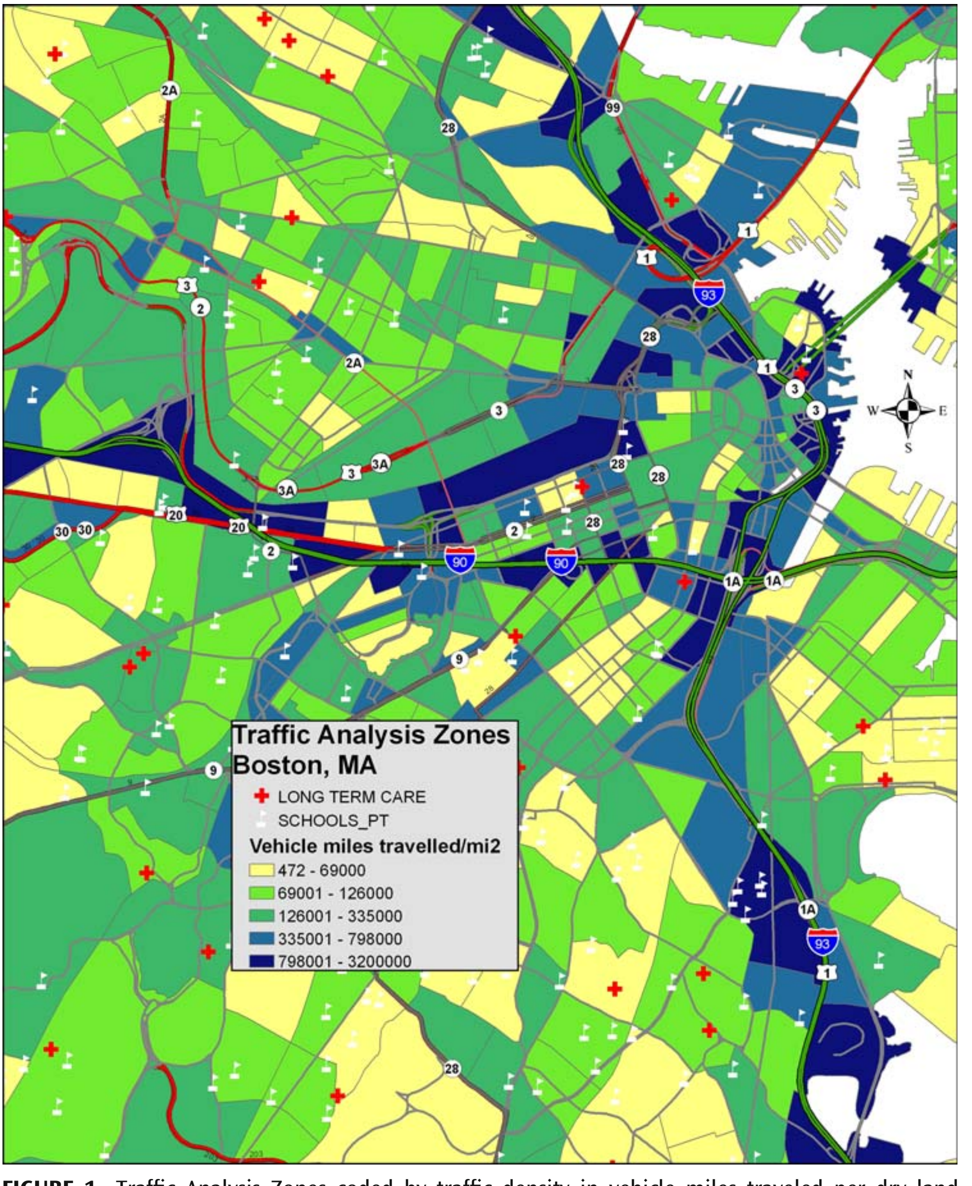

FIGURE 1. Traffic Analysis Zones coded by traffic density in vehicle miles traveled per dry land square mile (VMT/mi^2) and the location of schools and long-term care facilities—Greater Boston, MA.

Approximately 57% of individuals living in TAZ areas with the highest traffic density levels did not live within a 100-m buffer, and 26% did not live within a 200-m buffer (Table 3).

While demarcation of TAZ boundaries considers land use, demographics, roadway networks, and travel between TAZs, in some cases traffic density for adjacent TAZ, particularly those adjacent to major highways, were observed to be markedly different (Figure 4a). The traffic contributions of major and minor arterials and access points to the major highways contribute to this variation. TAZs adjacent to the Massachusetts Interstate 90 have traffic densities that range from the 25th to 90th percentiles, and in some cases adjacent TAZs display that level of

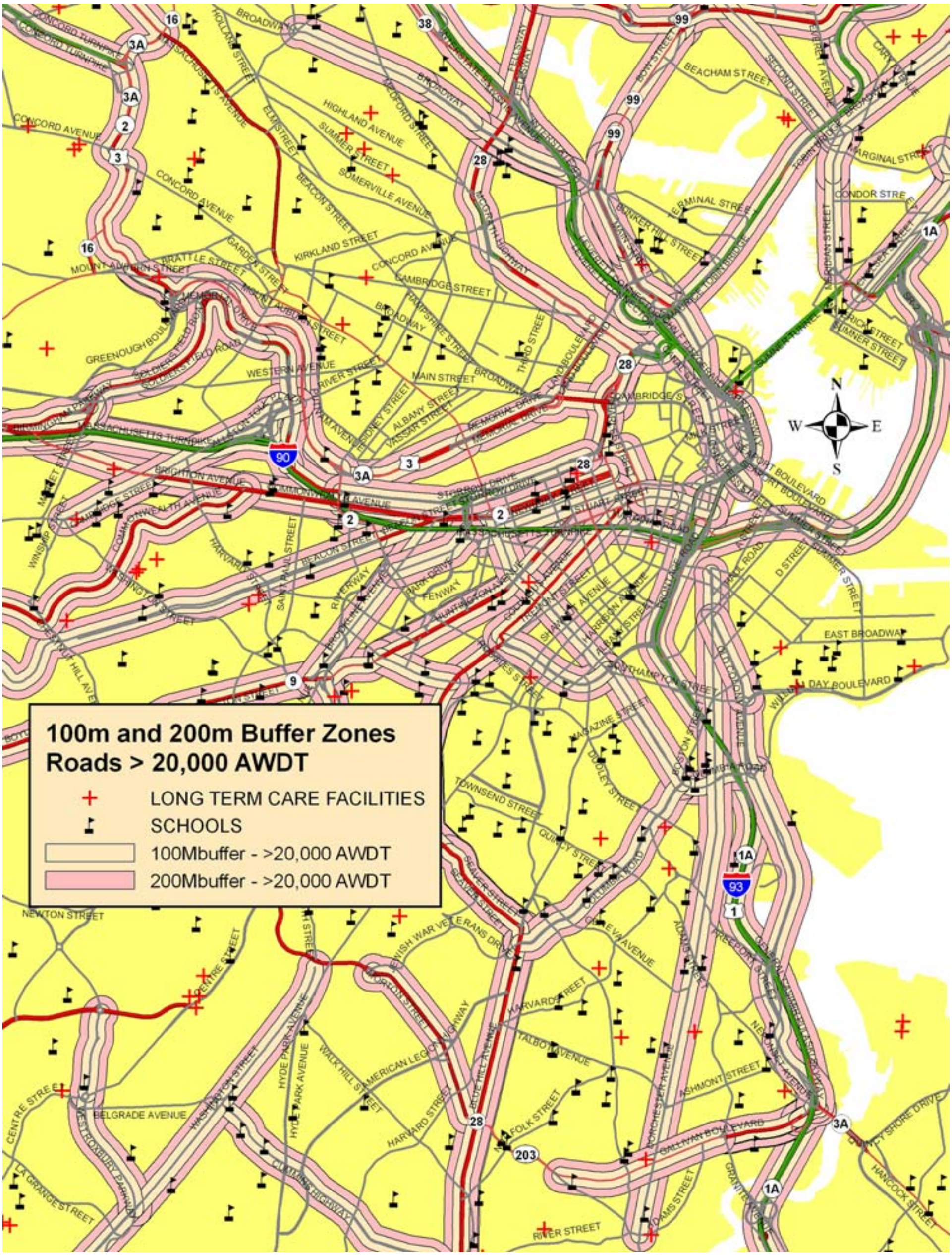

FIGURE 2. One-hundred- and 200-m buffers on roads with >20,000 vehicles per day and the location of schools and long-term care facilities—Greater Boston, MA.

variation. The impacts to residents living in adjacent TAZs, especially those living on the borders of these TAZs, may be subject to the traffic effects of the adjacent TAZ, depending on road geography, meteorology, and building design.

Raster-based spatial density analysis was conducted to address the issue of impacts across adjacent TAZ (Figure 4b). A running weighted average of traffic levels within cells 10 m^2 diameter was calculated over 500 and 1,000 (shown) m radii. Cell diameters did not substantially change the results, and the larger radii

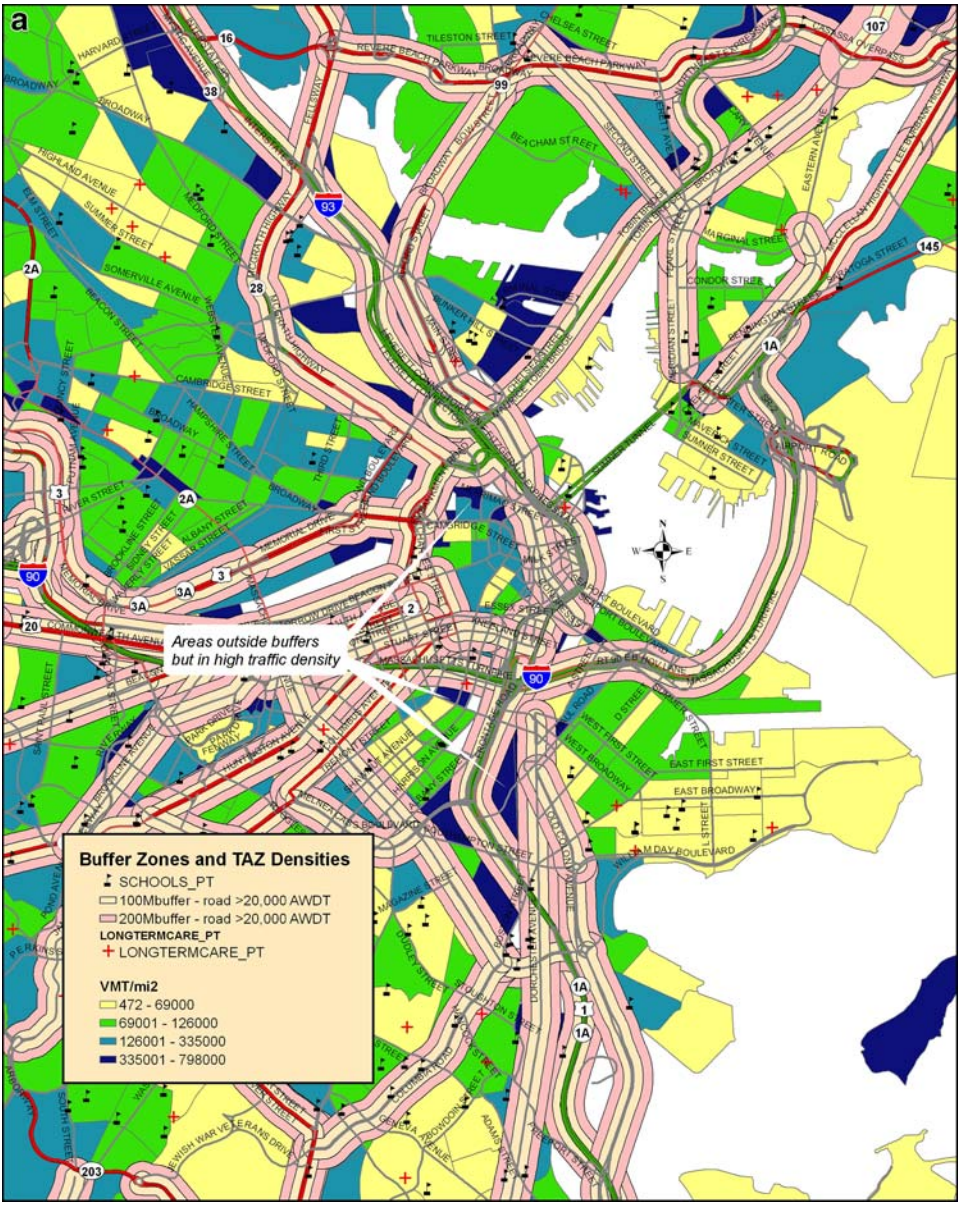

FIGURE 3. **a**, **b** Areas outside 100- and 200-m buffers but in high traffic density areas—Greater Boston, MA.

showed greater gradation over the study area. Traffic contours continued to follow along the major roadways. The number of TAZ and size of the overall area identified as highest traffic density was reduced in the smoothing process. Fewer geocoded addresses were located in the highest spatially contoured areas than in the highest traffic density TAZ areas (data not shown). Exposure contrast, i.e., the distribution of cases across the range of traffic exposure levels, was reduced. Figure 5 illustrates the spatially smoothed traffic density contours across the Greater Boston area along with the locations of sensitive receptors.

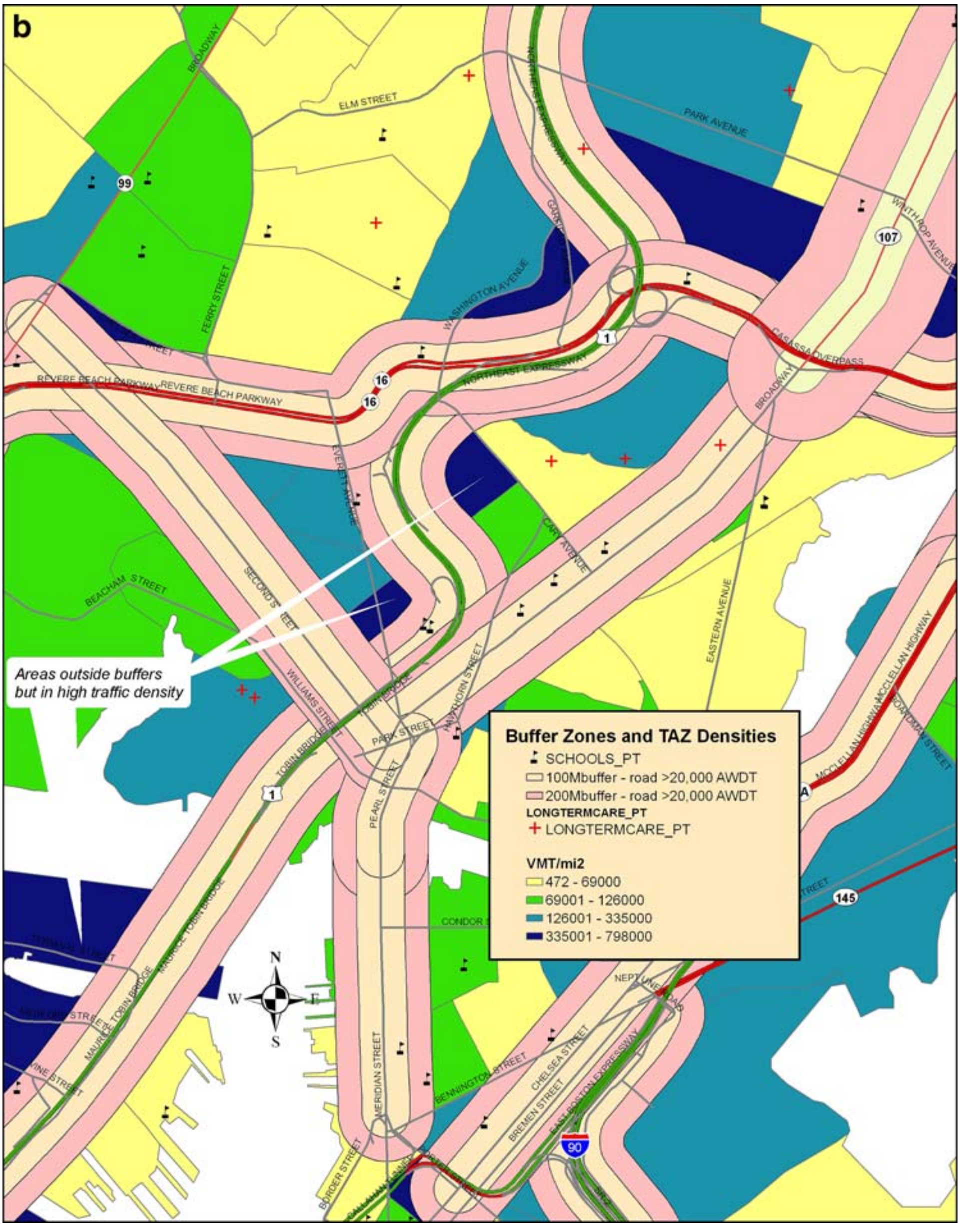

FIGURE 3. (continued)

DISCUSSION

Metropolitan areas, especially in older cities, comprise complex and heterogeneous inner-city roadway networks. Tree-lined streets and relatively quiet neighborhoods with natural buffers can quickly transition to densely traveled roads, congested intersections, and areas with high amounts of mobile and idling automobile, truck, and bus traffic at different time periods.

This study developed traffic exposure indices to reflect local gradients near roadways as well as the overall traffic density at the scale of the TAZ. The TAZ-level

TABLE 3 Comparison of number and percent of participants in the Boston Puerto Rican Center for Population Health and Health Disparities Project study residing within traffic proximity categories (<100 and <200 m of roadways) and traffic density quartiles (VMT/mi^2)

		VMT/mi^2 quartiles								
		1		2		3		4[a]		
		n	%	*n*	%	*n*	%	*n*	%	Total
<100 m	No	334	88	302	81	123	68	39	57	798
	Yes	47	12	69	19	74	41	29	43	219
Total		381		371		181	·	68	·	1,017
<200 m	No	275	72	213	57	79	40	18	26	585
	Yes	106	28	158	43	118	60	50	74	432
Total		381		371		197	·	68	·	1,017

[a]Highest traffic density quartile

traffic density variable VMT/mi^2 assessed cumulative impacts of an urban roadway network comprising mixed volume roads. In addition, a raster-based gradient assessment was developed to examine the degree to which small area TAZs may be influenced by the traffic levels of contiguous TAZs.

Strengths and Limitations

Indices of traffic exposures such as road proximity and traffic density, whether based on TAZ-level data or some other method, can capture a good deal of the variation in local traffic environments. An important limitation of these surrogates, however, is that they do not capture the dispersion and degradation profiles of the actual pollutant mix that originates from roadways and is the ultimate source of adverse health effects.[23]

The availability of traffic volume data, the coverage of roads in the traffic count station network (percentage of highways versus major and minor arterials and other surface roads), the spacing between stations, and the frequency with which counts are taken are all factors that influence the validity of roadway proximity exposure assessments. In Massachusetts, data on 2,327 traffic count locations spread across a 3-year counting cycle are published on-line, and additional data collected for special construction projects are on file but not automated. The majority of roads and road segments in Boston on which counts are collected had ≥10,000 vehicles per day, though some roads were as low as 2,100 vehicles per day. It is likely that the majority, if not all roads with ≥10,000 vehicles, are included in the network, thus providing adequate coverage to evaluate possible health impacts at the threshold of 20,000 we used here.

On average, the Boston region TAZ data incorporates a greater number of road links and nodes than other large MPOs, representing greater spatial resolution of the roadway network (Table 1). TAZ-level traffic density and emissions estimates for NOx, CO, and volatile organic compounds (VOCs) reflect automobile and truck traffic but not buses or commuter lines, which may be an important omission particularly in areas with a high density of bus lines or commuter rails.[12] Some MPOs develop estimates of the contribution of these sources to overall emissions, but at the least, any use of TAZ data should discuss this limitation.

Several studies have used measured air pollution concentrations to validate traffic density estimates, with a wide range of correlation coefficients reported. In one study, no correlation could be discerned between traffic density and background

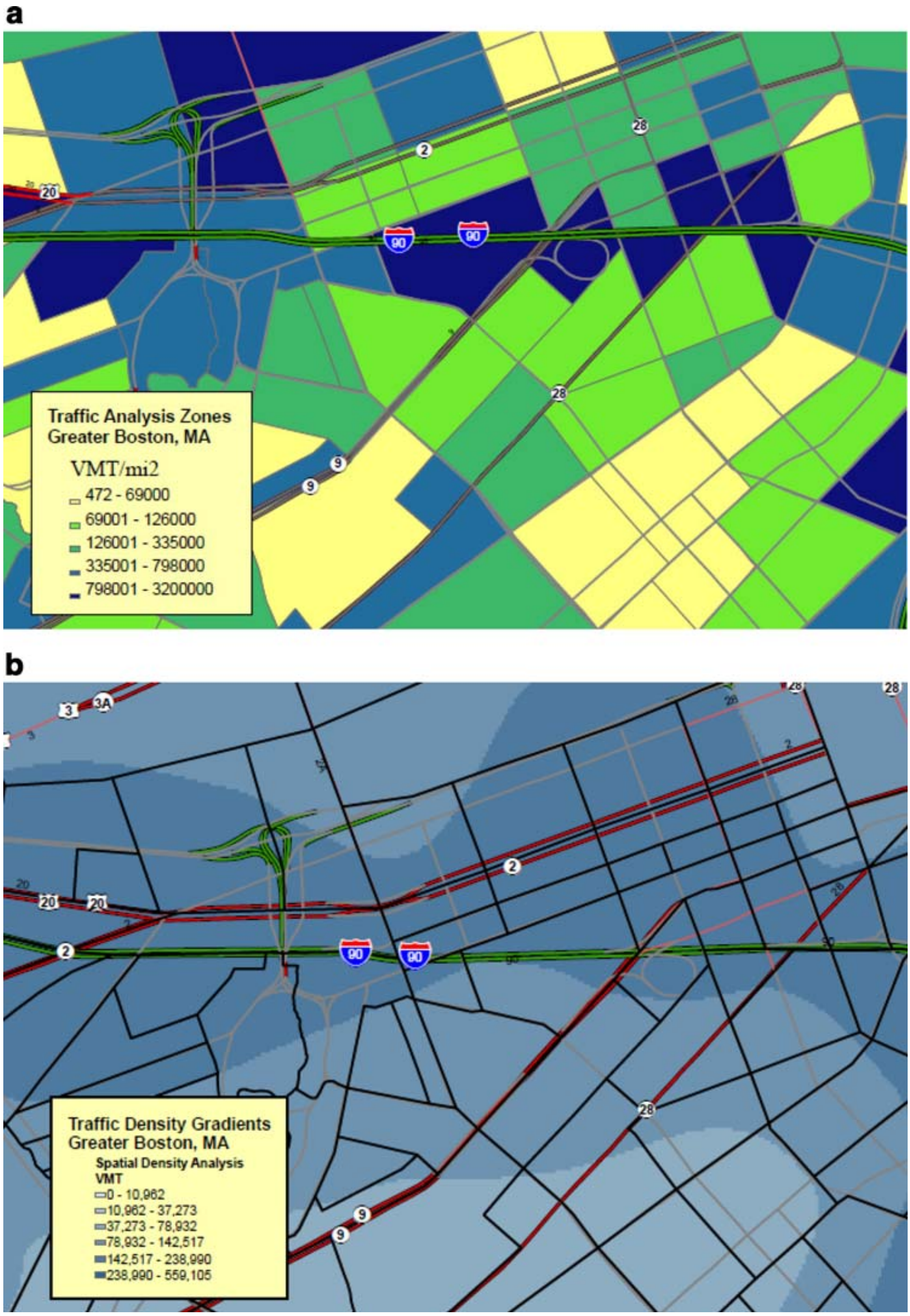

FIGURE 4. **a** Variation in traffic density in adjacent Traffic Analysis Zones—Greater Boston, MA. **b** Spatial density contours based on raster values re-define the variation in traffic density based on VMT/mi^2—Greater Boston, MA.

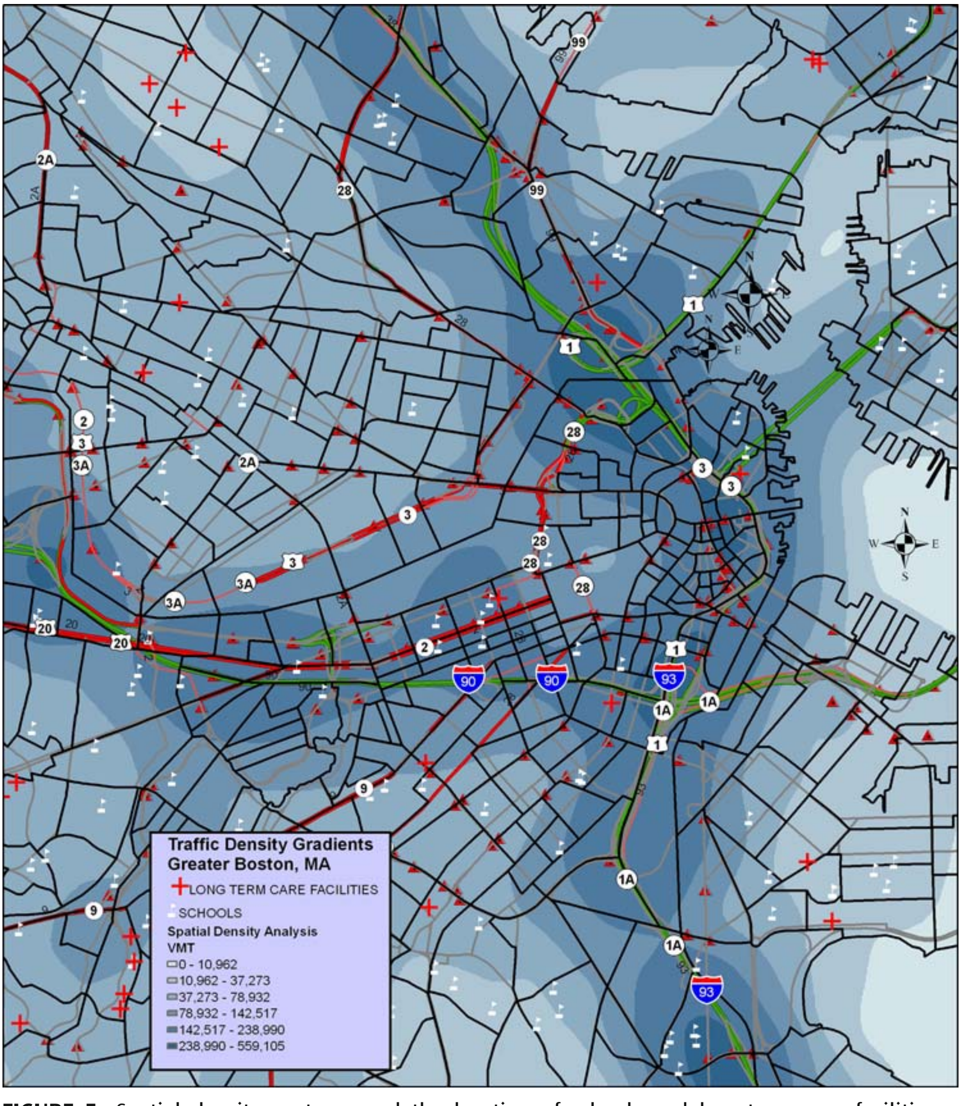

FIGURE 5. Spatial density contours and the location of schools and long-term care facilities—Greater Boston, MA.

levels of PM_{10} (particulate matter less than or equal to 10 μm in aerodynamic diameter), NO_2 (nitrogen dioxide), and O_3 (ozone) spatially interpolated to the residence of study subjects (correlation coefficients, –0.12, –0.04, and –0.10, respectively).[36] Data obtained from 93 state monitoring stations for CO, benzene, and 1,3-butadiene showed stronger correlations with census block level traffic density (correlation coefficients, 0.70, 0.69, and 0.57, respectively).[44] Possible explanations for these inconsistent results include spatial or temporal misalignment of the monitoring data and traffic density estimates or difference in the relative contribution of traffic versus non-traffic sources to parameter concentrations in a particular locale.

Land-use regression studies combine monitoring of air pollution at a small number of locations and development of stochastic models using data on land use, traffic characteristics, and meteorology to predict measured pollution concentrations at un-sampled locations.[45,58] In a review of 25 studies using land-use regression to characterize several parameters including NO_2, NOx, $PM_{2.5}$ (particulate matter less than 2.5 μm in aerodynamic diameter), the soot content of $PM_{2.5}$, and VOCs, traffic intensity, another term used for traffic density, was the most significant predictor or one of two strongest traffic predictor variables for pollution levels in a majority of the studies.[45]

Traffic proximity, or distance to roadway, was identified as a strong predictor in seven out of 25 studies. Coefficients of determination for the models ranged from an average of 0.72 for 24 studies evaluating NO_2, 0.57 for three studies evaluating NO, 0.82 for three studies evaluating NOx, and 0.72 for four studies evaluating various VOCs.[45]

Notable among the limitations of the TAZ approach was the potential for exposure misclassification for individuals residing near a TAZ boundary but who would be expected to be influenced to some degree by the traffic impacts of an adjacent TAZ. The raster-based density approach was developed to address these intra-TAZ influences

The screening level assessment identified areas of potentially high traffic exposure, though actual exposures would be influenced by a number of factors including building design and operation, extent of outdoor versus indoor activities, trees or other barriers that may mitigate traffic exposure, and the migration of pollutants or noise from roadways. People residing or children attending schools in high traffic areas may have very different exposure levels as a result of their exact distance from the road, the orientation of homes with respect to roadways, the location of apartments or classrooms within a building, the condition of windows, infiltration rates, and ventilation systems within the building. One such built environment feature is the "urban canyon." Urban canyons are streets cutting through blocks of buildings in a manner that influences wind speed, wind direction, noise levels, and ultimately air quality.[59] A review of wind direction distribution from Boston Logan Airport in Boston indicates a changing pattern of wind directions in the Boston area. Five months of the year, the predominant wind direction is from the west (fall and winter), 6 months from the east (spring and summer), and 1 month (July) from the south (www.windfinder.com/windstastic_boston_logan_airport.htm).

An air monitoring network of stations collecting traffic-related pollutants and their decay products positioned to characterize spatial and temporal variation at the local scale might be considered the gold standard for exposure characterization. Exposure misclassification would remain an important consideration based on time and activity relationships among the exposed population (e.g., portion of time spent indoors versus outside of the home), differences between ambient and indoor air concentrations, and measurement error. Because the implementation costs and research time involved in establishing a comprehensive and representative air monitoring program are beyond the capabilities of many research projects, a more efficient method is needed to perform screening level assessments in new study locales or to examine associations between level of traffic and previously unexplored health outcomes.

Using a set of exposure characterization methods can test associations with health outcomes thus calibrating the sensitivity of these associations. Using multiple traffic indices can also further understanding of the role of distance to roadway, traffic volume, dose–response, cumulative impacts from residing near multiple major roads, and high volume single source versus multi-directional overall traffic density for health outcomes studies. For epidemiologic purposes, assignment of exposure status on the basis of TAZ-based density versus spatially contoured density requires further exploration.

TAZ-level traffic density estimates have certain advantages to other traffic density estimates, e.g., using available traffic count data or link-based information for roads within a selected radius of a receptor. TAZ-level density estimates are more complete by including more roads, not only those with traffic counts, and by minimizing the error in traffic assignment for individual roadway links when competing nearby roadways can be used for travel.

To our knowledge, this is the first illustration of how TAZ data can be used for exposure assessment purposes. One of the goals of this review and screening level assessment was to evaluate the overall utility, transferability, reproducibility, and validity of TAZ data as a tool to identify potentially high-risk areas and populations and for use in future epidemiologic studies. MPOs across the country create TAZ boundaries using standard modeling tools, though the detail of the roadway networks captured in these data, the homogeneity of the individual TAZ, and the level of model validation employed will vary according to resources and expertise. Researchers interested in using TAZ data in health studies should obtain all available documentation on the travel demand model procedures used by the MPO along with the criteria used to delineate TAZ boundaries. Because MPOs are all public agencies, these data should be available to health scientists and researchers, though the level of documentation may vary considerably across MPOs. TAZ-level data on vehicle miles traveled, size of each zone, and associated geo-referenced material should be available in GIS-compatible format. In general, an urban area comprising smaller TAZs provides improved resolution of traffic density.

CONCLUSIONS

Growing evidence of the adverse effects of exposure to vehicular traffic highlights the need for transportation planners and health scientists to increasingly work in concert to understand the magnitude of the problem in their planning regions. Whether as a result of proximity to busy roads or residing in areas with dense road networks, it is clear that a substantial population resides and attends schools in areas of high volumes of vehicular traffic.

Future traffic-related health assessments should examine both proximity to roads and traffic density. It is recommended that assessments consider the extent of the overlap of these two indices and whether different population subgroups are classified as “exposed” by the two methods. Risks may be under-estimated and/or subjects misclassified when health studies use only roadway proximity or traffic density to assess traffic exposure.

TAZ data generated by MPOs across the USA represent a widely available, straightforward, and useful set of metrics to assess the impact of traffic density by employing standardized and widely used models subject to oversight and validation. Environmental epidemiologists are often required to adapt methods originally developed for purposes other than health studies to accomplish their goals. The present paper is yet another example of this phenomenon. With appropriate scrutiny, health scientists can make use of these data within a GIS format to spatially assess the relative burdens of localized versus larger-scale traffic-related impacts on susceptible populations. Use of these transportation planning tools in future health studies provides an opportunity for collaboration among transportation and public health scientists that can help advance policy initiatives aimed at both the characterization and potential mitigation of transportation-related health effects.

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