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Inhalation of motor vehicle emissions: effects of urban population and land area

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Abstract

Urban population density may influence transportation demand, e.g., as expressed through average daily vehicle-kilometers traveled in private motor vehicles per capita. In turn, changes in transportation demand influence total passenger vehicle emissions to which populations are exposed. Population density can also influence the fraction of total emissions that are inhaled by the exposed urban population. Equations are presented that describe these relationships for an idealized representation of an urban area. Using analytic solutions to these equations, we investigate the effect of three changes in urban population and urban land area (infill, sprawl, and constant-density growth) on per capita inhalation intake of primary pollutants from passenger vehicles. For the system considered, the magnitude of these effects depends on density–emissions elasticity (ε_e), a normalized derivative relating change in population density to change in vehicle emissions. For example, based on the idealized representation of the emissions-to-intake relationship presented herein, if urban population increases, then per capita intake is less with infill development than with constant-density growth if ε_e is <-0.5, while for $\varepsilon_e > -0.5$, the reverse is true.

Keywords: Population density; Infill; Sprawl; Land-use planning; Transportation planning; Smart growth

1. Introduction

Motor vehicles are a major source of the criteria pollutants and hazardous air pollutants that are ubiquitous to urban areas in the US and worldwide. Traditionally, air-quality engineers have investigated the connection between transportation demand (measured, for example, in terms of total vehicle-miles traveled) and emissions, and between emissions and ambient concentrations. Recently, air-quality managers have begun to consider the extent to which urban planning may reduce transportation demand and motor vehicle emissions. Increasing population density is expected to reduce average daily vehicle-kilometers traveled in private motor vehicles per capita (VKT) for several reasons (Ewing and Cervero, 2001). For example, increasing

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population density increases accessibility: people in more dense areas do not need to travel as far to reach common destinations such as stores, theaters, and employment centers (Cervero, 1997; Levinson, 1998). Public transit and nonmotorized private transportation such as walking and biking have higher mode shares in more densely populated regions (Crane, 2000; Messenger and Ewing, 1996). Certain disincentives to driving, such as congestion delays and limited parking availability, occur more frequently in densely populated areas.

A broad definition for infill development is "any type of new development that occurs within existing built-up areas" (US EPA, 1999a). The potential association between density and VKT has led some planners to implement policies to accommodate growing urban population that encourage infill development rather than sprawl (APA, 2002; Burchell et al., 2002; US EPA, 2001a). To understand the air-quality impacts of such policies, two questions can be considered: (1) Under what circumstances does increasing population density reduce vehicle emissions? (2) Under what circumstances does reducing emissions by increasing population density reduce people's inhalation intake of vehicle emissions? A few publications have commented on these questions. An international study of motor vehicle use concluded that "whilst *per capita* [transportation] emissions may be higher in the low-density automobile-dependent regions, the rate of [transportation] emissions per urbanized hectare [is] clearly lower. We thus have the situation in the high-density cities… where emissions output is highly concentrated. This leads to more concentrated impacts and higher exposure…" (Kenworthy and Laube, 2002). Cervero (2000) summarizes the dilemma: "exposure levels (and thus health risks) are lower with sprawl, but tailpipe emissions and fossil-fuel consumption are greatly increased."

Many urban areas are growing in population or land area or both, and this growth may impact emissions and emissions-to-intake relationships. Such impact will vary with urban conditions (e.g., urban population) and with the nature of growth. To our knowledge, no prior research has quantified how changes in urban land area and urban population would affect the population inhalation of transportation emissions. Nor has previous research addressed the necessary conditions such that increased population density is accompanied by reduced inhalation of vehicle emissions. This paper contributes to filling these gaps. In addition to offering insights for air-quality management and urban planning, our work can inform expectations in the absence of strong planning.

We start with the premise that population inhalation of vehicle pollutants is more appropriate than emissions or individual exposures as an indicator of the health impacts attributable to air pollution (Bennett et al., 2002). In this paper, we develop and present an exploratory analysis that considers a hypothetical, idealized representation of an urban area. Using this representation, we investigate, quantitatively and parametrically, how three changes in urban land area and urban population influence population inhalation of motor vehicle emissions: (1) increasing population while land area remains constant (denoted "infill" in this paper), (2) increasing land area while population remains constant ("sprawl"), and (3) increasing land area and population while density remains constant ("constant-density growth"). Note that as employed in this paper, these terms have a narrower and more precisely defined scope than in common usage.

There is debate in the literature as to whether and how much population density and other aspects of urban form influence VKT. Some investigations have found that increasing density reduces VKT while others have found no connection (Badoe and Miller, 2000). Some research suggests that the correlation between density and VKT is not causal, but rather that density serves as a proxy for income, which is itself causally connected to VKT (Boarnet and Sarmiento, 1998). Others disagree, finding that both density and income are important (Kenworthy and Laube, 2002). This paper does not take a position on this debate. Because there is variability and uncertainty in the impact of density on VKT and vehicle emissions (Badoe and Miller, 2000; Gordon and Richardson, 1997), we allow a range of values (including zero) for the density–emissions elasticity, and we identify the minimum elasticity necessary for a given change in urban population and land area to reduce intake.

2. Methods

Because this paper represents the first attempt to quantify the relationship between population density and the inhalation intake of primary traffic-related air pollutants, we aim for a direct approach that clarifies underlying relationships, aids in elucidating causal connections, and permits the problem to be analytically tractable. We consider population density, passenger vehicle emissions, attributable ambient concentrations for primary pollutants, and the resulting attributable intake per capita. Below we describe our method for connecting these elements of the source–intake relationship for primary pollutants from motor vehicles.

2.1. Density–emissions elasticity

Population density has the potential to influence vehicle emissions (Holtzclaw et al., 2002) as well as the fraction of emissions inhaled by people (Lai et al., 2000). Population density is a key aspect of urban form, and one that can be influenced by urban planning.

If there were no relationship between density and VKT, then an increase in population density would cause an increase in both transportation emissions per km^2 and per capita inhalation of transportation emissions. On the other hand, if an increase in population density were to result in a reduction in per capita emissions, then the same two variables (emissions per km^2 and per capita inhalation of emissions) might either increase or decrease, depending on the density–emissions elasticity. Eq. (1) defines density–emissions elasticity (ε_e) and density–VKT elasticity (ε_v):

$$\varepsilon_e \equiv \frac{dE/E}{d\rho/\rho}, \quad \varepsilon_v \equiv \frac{dV/V}{d\rho/\rho}. \tag{1}$$

Here, E is the total vehicle emission rate of a pollutant ($g\,s^{-1}$), ρ is the population density (km^{-2}), and V is the average daily vehicle kilometers traveled per person (km $person^{-1}\,d^{-1}$). If ε_e is negative and large in magnitude, then increasing population density could reduce both vehicle emissions and per capita inhalation of vehicle emissions. However, if the magnitude of ε_e is small (but still negative), then increasing population density could reduce vehicle emissions, yet increase per capita inhalation of vehicle emissions. In this paper, we allow ε_e to vary, and explore how the relationship between changes in population, land area and per capita inhalation of vehicle emissions depends on ε_e.

2.2. Pollutant classification

The relationship between emissions and inhalation intake depends, among other factors, on the dynamic behavior of the pollutant. Pollutants are classified as *primary* or *secondary*, according to whether they are emitted directly from sources or are formed in the atmosphere from precursors (Seinfeld and Pandis, 1998). Pollutants are further classified as *nonreactive* or *reactive* according to their level of atmospheric reactivity. For the present purposes, a nonreactive pollutant is one for which the pollutant's characteristic atmospheric lifetime is significantly greater than the characteristic residence time of air in an urban basin (typically in the range of several hours to a day).

Vehicular emissions of concern include primary nonreactive species (e.g., CO and benzene), primary reactive species (e.g., 1,3-butadiene and ultrafine particles), and secondary reactive species (e.g., ozone and NO_2). The analysis in this paper focuses on primary nonreactive pollutants as the logical and important first step toward a complete treatment of all pollutant classes. In the discussion, we outline how one would extend the methods to address reactive primary and secondary pollutants.

2.3. Ambient concentrations

In this paper, we use a single compartment model to describe the relationship between emissions and ambient concentrations. The model, which has been used extensively (Benarie, 1980; Lyons et al., 2003), assumes air concentrations are uniform throughout an air basin. To explore the accuracy of this assumption, we analyzed year-2002 annual average CO concentrations at the 497 monitoring stations in the US Environmental Protection Agency (EPA) AIRData website (http://www.epa.gov/air/data). We chose CO because it is nonreactive, because there are a large number of monitoring stations in the US, and because most urban CO emissions are attributable to motor vehicles (US EPA, 2001b). First, we removed from the dataset the 60 monitors that did not meet EPA's reliability criterion (>75% reporting rate). Then, we removed the 30 monitors that did not have an associated metropolitan statistical area (MSA) code. Among the remaining 407 monitors, 189 (46%) were located in one of the 28 MSAs with five or more monitors. We evaluated intra-MSA variability among these 189 monitors. The coefficient of variability (the standard deviation divided by the mean) for each MSA has a small average value of 0.31 (range: 0.13–0.53). Furthermore, the concentration difference between a monitor and the associated MSA average is always less than 65%. Low intra-MSA variability in annual average ambient CO concentrations suggests that the one-compartment model is useful for estimating the average emissions-to-concentration relationship for primary nonreactive vehicle emissions in urban areas. At the same time, the limitations of the one-compartment model are such that the results reported here should be considered as preliminary and suggestive rather than conclusive.

The steady-state mass-balance equation for a square plan, one-compartment model yields the following expression for attributable concentration of a primary nonreactive pollutant:

$$C = \frac{E}{uH\sqrt{A}} = \frac{FVP}{uH\sqrt{A}} \times \frac{1}{86\,400}. \tag{2}$$

Here, C is the average ambient concentration attributable to vehicles ($g\,m^{-3}$), u is the wind speed ($m\,s^{-1}$), H is the mixing height (m), A is the urban land area (m^2), F is the average motor vehicle emission factor ($g\,km^{-1}$), P is the population size, and 86 400 converts time units from seconds to days. The group (uH) indicates how rapidly local meteorology dilutes and removes emissions from an area, the group ($PA^{-0.5}$) is a linear population density, and the group (FV) is the average per capita emission rate.

2.4. Intake

Given Eq. (2), average daily per capita intake of motor vehicle emissions, I (units: g person^{-1} d^{-1}), can be estimated as

$$I = QC = \frac{QFVP}{uH\sqrt{A}} \times \frac{1}{86\,400}. \quad (3)$$

Here, Q is the average breathing rate for an individual (m^3 person^{-1} d^{-1}).

Of the variables urban planning can influence, we explore three: V, P, and A. We define a normalized intake (I^*, units: d^{-1}) to highlight the influence on intake of these three variables:

$$I^* \equiv I\left(\frac{uH}{QF} \times 86\,400\right) = \frac{VP}{\sqrt{A}}. \quad (4)$$

Although potentially important, we do not explore here intra-urban concentration variability, the influence of urban population and area on emission factors (e.g., by changing traffic flow conditions), or the role of urban form on mixing height (e.g., via the urban heat island effect).

Exposure concentrations can be subdivided based on the distance to the attributable emission source: e.g., global (>3000 km), regional (150–3000 km), urban (5–150 km), local (200 m–5 km), and microenvironmental (3–200 m) (Colvile et al., 2003; Watson and Chow, 2001). For the analysis presented here, we consider exposures from urban and local emissions. The importance of regional and global emissions will depend on the pollutant and the emission rate upwind of an urban area (Tsuang et al., 2003). An urban area's population and land area are unlikely to strongly affect exposures attributable to emissions that are upwind of the urban area. The importance of microenvironmental factors depends on the amount of time spent in a microenvironment and the concentration difference between a microenvironment and ambient air. Exposures in near-source microenvironments contribute a greater fraction of total intake for rapidly decaying primary pollutants (e.g., ultrafine PM) than for nonreactive species. Because of the transport and dispersion that occurs during the interval between precursor release and secondary pollutant formation, local and microenvironment emissions will be less important for secondary pollutants that take ~0.5 h or more to form than for primary pollutants.

Both intra-urban concentration heterogeneity and microenvironments might play important roles influencing the relationship between urban form and inhalation intake of primary vehicle emissions. However, in addition to the analysis of ambient CO monitoring station data presented above, evidence from the literature also indicates that average outdoor concentrations are relatively homogeneous for primary nonreactive pollutants from motor vehicles. For example, an investigation of population exposure to CO from motor vehicles in California's South Coast Air Basin (Marshall et al., 2003) presented results for two analyses. The first analysis accounted for spatial variability of population density and ambient concentrations, temporal variability of concentrations and breathing rates, and microenvironments such as in- and near-vehicle and indoors near a freeway. The second analysis considered only the air basin-wide annual average ambient concentration. Estimated average intake values in the second analysis were ~70% of the values in the first analysis, indicating that the ambient concentration analysis captured most of the average population exposure to motor vehicle emissions. In a second example, Watson and Chow (2001), studying conditions in Mexico City, reported that "65% of the 24-h black carbon was part of the urban mixture, 23% originated in the neighborhood surrounding the monitor, and only 12% was contributed from nearby sources [within ~km]." For primary nonreactive pollutants, if there are removal mechanisms as air moves from outdoors to indoors (e.g., ventilation system air filters that can remove diesel PM), then the average attributable exposure concentration will be less than the average attributable ambient concentration. But if such removal mechanisms do not exist (e.g., for CO), then the average attributable exposure concentration will more nearly equal the average attributable outdoor concentration. In addition to these considerations, the present study explores how *changes* in urban population and area lead to *changes* in inhalation. This approach reduces the importance to our results of differences between the average attributable ambient concentration and the average attributable exposure concentration.

3. Results

3.1. Changes in urban population and area

Fig. 1 illustrates the three changes in urban population and area considered in this paper (infill, sprawl, and constant-density growth). We present the effect of increases in urban population and area on per capita inhalation of vehicle emissions; a reduction would cause the opposite effect as an increase. Equations describing the three changes in urban population and area are given in Table 1. The entries in Table 1 follow from Eqs. (1) and (3) and from the assumption that, among the variables considered, per capita transportation emissions are only a function of population density. The entries do not assume any specific functional form for the density–emissions relationship.

Fig. 2 summarizes key results. For the system considered here, constant-density growth always increases per capita intake. Infill and sprawl may either increase or decrease per capita intake, depending on the density–emissions elasticity. Infill reduces per capita intake when ε_e is less than -1.0. Sprawl reduces per capita intake when ε_e is greater than -0.5.

Rather than plotting numerical values on the ordinate axes, Fig. 2 shows mathematical expressions. To calculate the value for the derivatives in a specific city, one needs to know values of parameters such as the city's population and land area. The term on the ordinate axis of the $\partial I/\partial P$ plot (Fig. 2, left) contains $A^{-0.5}$, indicating that—all else being equal—changes in per capita intake attributable to changes in population would be more significant in small cities than in large cities. The term on the ordinate axis of the $\partial I/\partial A$ plot (Fig. 2, right) contains $PA^{-1.5}$, indicating that—all else being equal—changes in per capita intake attributable to changes in land area would be more significant in densely populated small cities than in sparsely populated large cities.

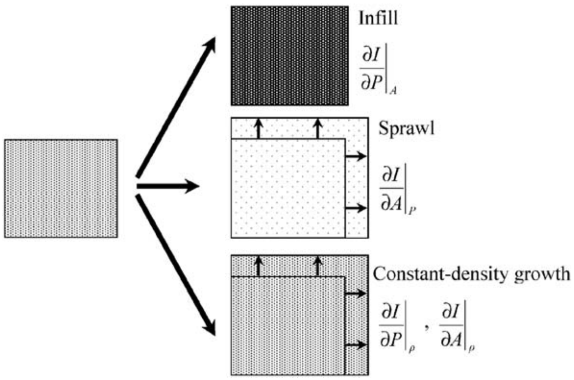

Fig. 1. Three changes in urban population (P) and urban area (A) investigated in this work, in terms of the impact on the incremental change in per capita intake (I). The first change (infill, $\partial I/\partial P|_A$) is population increase at constant land area. The second change (sprawl, $\partial I/\partial A|_P$) is land area increase at constant population. The third change (constant-density growth, $\partial I/\partial A|_P$) is increase in population and land area, at constant population density. Not shown is the opposite of sprawl: a land-area decrease at constant population (contraction).

Table 2 presents the results in terms of a question raised in the introduction: which change in urban population and land area minimizes per capita intake? The answer depends on density–emissions elasticity, ε_e, and on whether population is increasing, decreasing, or remaining constant. For example, consider the case of an increasing population. If ε_e is <-0.5, then infill minimizes per capita intake; if ε_e is >-0.5 then constant-density growth minimizes per capita intake.

3.2. Density–emissions elasticity

The general analysis presented in this paper develops results that depend on the relationship between population density and transportation emissions. Only a few studies have investigated this relationship. A comparison between two Nashville neighborhoods found that one neighborhood was 68% more dense, had 25% fewer VKT, and 7% less toxic-emissions per capita per day from vehicles, than the other (NRDC, 2003). These findings suggest $\varepsilon_e = -0.10$ and $\varepsilon_v = -0.37$. The study did not consider changes in population intake. Using an international dataset, Newman and Kenworthy (1989) reported a density-fuel consumption elasticity between

Table 1
Mathematical description of the three changes in urban population and area[a]

Name	Change in urban population and area	Incremental change in normalized pollutant intake associated with incremental change in urban population and area
Infill	Population increases; land area is constant.	$\left.\frac{\partial I^*}{\partial P}\right\|_A = \frac{V(1+\varepsilon_e)}{\sqrt{A}}$
Sprawl	Population is constant; land area increases.	$\left.\frac{\partial I^*}{\partial A}\right\|_P = -\frac{PV}{2\mathrm{A}^{1.5}}[2\varepsilon_e+1]$
Constant-density growth	Both population and land area increase; density is constant.	$\left.\frac{\partial I^*}{\partial P}\right\|_\rho = \frac{1}{\rho}\left.\frac{\partial I^*}{\partial A}\right\|_\rho = \frac{V}{2\sqrt{A}}$

[a]Here, I^* is the normalized intake (d^{-1}), P is the population, A is the urban land area (km^2), V is the average daily per capita vehicle-kilometers traveled (km person^{-1} d^{-1}), ε_e is the density–emission elasticity defined in Eq. (1), and ρ is the population density (km^{-2}).

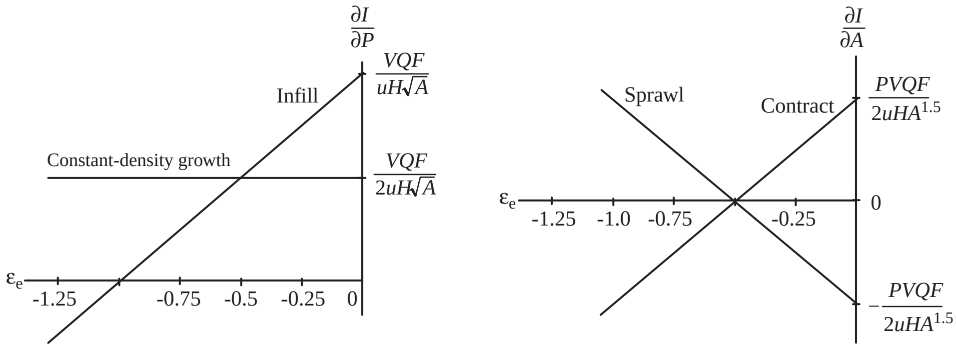

Fig. 2. Influence of density–emissions elasticity (ε_e) on the incremental change in per capita intake (I) with respect to a change in urban population (P) or urban area (A). The left plot ($\partial I/\partial P$) shows the impact of increasing population on intake when urban land area is constant (infill) and when population density is constant (constant-density growth). The right plot ($\partial I/\partial A$) shows the impact of increasing (sprawl) and decreasing (contraction) urban land areas on intake when population is constant. In each plot, the change in urban form that minimizes intake is the lower line. A negative value on the ordinate axis indicates an absolute reduction in I.

Table 2
The change in urban population and area that minimizes intake, depending on the density–emissions elasticity and the change in population[a]

	Population is increasing	Population is constant	Population is decreasing
$\varepsilon_e < -0.5$	Infill ($dA/dt = 0$)	Contraction ($dA/dt < 0$)	Constant-density contraction ($d\rho/dt = 0$)
$\varepsilon_e > -0.5$	Constant-density growth ($d\rho/dt = 0$)	Sprawl ($dA/dt > 0$)	Constant-land-area contraction ($dA/dt = 0$)

[a]Here, t = time (y), ε_e = density–emissions elasticity, A = land area (km^2), and ρ = population density (km^{-2}).

-0.4 and -0.5. Fuel consumption is likely a better surrogate for vehicle emissions than distance traveled (Pokharel et al., 2002; Singer and Harley, 1996). On-road remote-sensing techniques used to determine vehicle emissions in these studies may prove valuable in direct investigations of density–emissions elasticity.

Because data from empirical studies of ε_e are sparse, we use empirical information about ε_v as a surrogate. The relationship between ε_e and ε_v is

$$\frac{\varepsilon_e}{\varepsilon_v} = \frac{dE/dV}{E/V} = \frac{F^*}{F}, \quad (5)$$

where F^* (g km^{-1}) is the marginal change in emissions attributable to a marginal change in VKT. Using reported values for ε_v in place of robust estimates for ε_e assumes $F^* \approx F$, i.e., that F is not strongly dependent on population density. Because density and other urban-form attributes affect congestion (Dunphy and Fisher, 1996) and because emission factors are related to average speed (Kean et al., 2003; Ntziachristos and Samaras, 2000), distance traveled is an imperfect indicator of emissions. We expect in many situations that the density–emissions elasticity would be greater than the density–VKT elasticity (e.g., if both terms were negative, we expect the density–emissions elasticity would be less negative than the density–VKT elasticity). Because of start-up emissions (Heeb et al., 2003), reductions to average trip length would reduce emissions less than it would reduce VKT. Furthermore, increasing density may increase congestion and driver aggressiveness, which would increase emission factors (De Vlieger et al., 2000). If future research better quantifies the relationship between density and emissions, that information could be applied directly to the approach presented in this paper.

There is debate in the literature regarding the nature of the density–VKT relationship. Some investigations have found little or no relationship between density and VKT, suggesting that ε_e may be approximately zero, while other investigations have found a strong relationship between density and VKT (Badoe and Miller, 2000; Mindali et al., 2004). Published ε_v values are between 0 and -0.7 (Holtzclaw et al., 2002). Empirical evidence of density–VKT elasticity comes from both intra- and inter-urban comparisons. Fig. 3a presents an inter-urban comparison of density and VKT (US DOT, 2003). These data exhibit a clear inverse relationship and suggest $\varepsilon_v \approx -0.3$. A 1996 study of four areas in Toronto (urban core, core ring, inner suburbs, and outer suburbs) found that urban core residents traveled half as far (motorized distance traveled) and had about four times the residential density (persons per sq. km. of urbanized land) as outer suburb residents (CST, 1998), suggesting that $\varepsilon_v = -0.5$. Transportation demand modeling of two hypothetical housing developments in each of three US metropolitan areas (Montgomery County, MD; San Diego, CA; and West Palm Beach, FL) concluded that VKT would be 40–50% lower for infill than for "greenfield" development (US EPA, 1999b). Holtzclaw (1991, 1994) reported that ε_v is between -0.3 and -0.5 after accounting for demographic variables such as income and cars per household. Internationally, a strong relationship has been observed between urban density and travel patterns (Kenworthy et al., 1999). For example, in a comparison of 100 cities worldwide, Kenworthy and Laube (2002) concluded, "The data show how the higher car use cities are low in population density and more decentralized… while the higher density and more centralized cities have reduced car use per person."

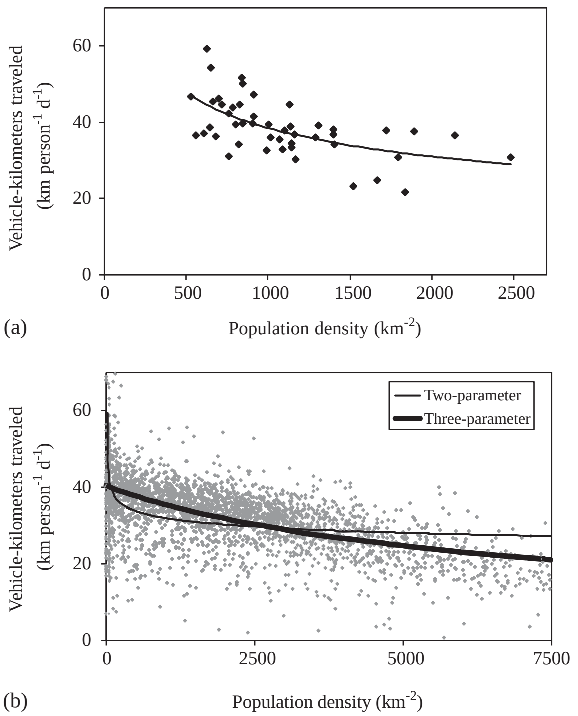

Fig. 3. Comparisons of population density and average daily per capita VKT. (a) Data for the 47 urban areas in the US with population exceeding 750,000. For this dataset, the two- and three-parameter regression lines are indistinguishable. (b) Data for the 2834 Traffic Analysis Zones in the Chicago, Los Angeles and San Francisco metropolitan areas. In (b), not plotted are the 5% of the population density values that are greater than 7500 km^{-2} and the 0.8% of the VKT values that are greater than 65 km person^{-1} day^{-1}. Both datasets show an inverse relationship, with more dense areas having lower per capita VKT.

Empirical elasticity values cited here are from intra- and inter-urban comparisons, rather than from changes over time in a single urban area. By comparing available estimates for density–VKT elasticity with the results presented in this work, we implicitly assume that existing intra- and inter-urban cross-sectional data are informative about the longitudinal conditions that would apply in any given urban area. This assumption is common in the literature, but, to our knowledge, it has not been rigorously tested.

Comparing our analyses with reported values for ε_v, we find that whether infill is an effective strategy for minimizing intake of vehicle emissions depends on the circumstances. Within the range of reported ε_v values, infill and constant-density growth both tend to increase per capita intake. If the elasticity is strong ($\varepsilon_v < -0.5$), then the intake increase is less for infill than for constant-density growth. However, in the case of weak elasticity ($\varepsilon_v > -0.5$), the reverse is true. *Merely* increasing population density, while holding constant all other aspects of urban form, will likely not reduce VKT enough to reduce average per capita intake. Rather, to reduce inhalation intake of air pollutants emitted from motor vehicles, our analysis suggests that infill development must include urban design features that strengthen the density–VKT relationship, such that the density–emissions elasticity satisfies the condition $\varepsilon_e < -0.5$.

4. Discussion

4.1. Applying intake results to a specific urban area

Applying the intake results presented in this paper to a specific urban area would require an estimate of ε_e or ε_v. The results presented in Table 2 and Fig. 2 do not depend on a specific functional form for ε_e or ε_v. However, estimating ε_e or ε_v for a given situation may require specifying this function.

Empirical studies of the density–VKT relationship often report results as "doubling density reduces VKT by X%." These observations can be represented mathematically using the following two-parameter relationship:

$$V = k\rho^{[\log(1-(X\%/100\%))/\log(2)]}. \quad (6)$$

Here, k is a constant (km person^{-1} d^{-1}), and X is the percent reduction in VKT attributable to a doubling of population density. The exponent in Eq. (6) is the density–VKT elasticity (ε_v). For example, if doubling density reduces VKT by 40%, then $\varepsilon_v = -0.74$. As an alternative to Eq. (6), Holtzclaw et al. (2002) suggested the following three-parameter relationship:

$$V = a(\rho + b)^c. \quad (7)$$

Here, a, b, and c are empirical constants.

To compare the two functional forms found in the literature (Eqs. (6) and (7)), we determined the correlation parameters for the neighborhood-scale data used by Holtzclaw et al. (2002) (Fig. 3b) and for the urban-scale data reported by the US Department of Transportation (US DOT, 2003) (Fig. 3a). The neighborhood-scale dataset contains VKT and density for each traffic analysis zone in three urban areas (Chicago, Los Angeles, and San Francisco). The urban-scale dataset contains VKT and density for the 47 urban areas in the US with population greater than 750,000. Correlation parameters for the two- and three-parameter density–VKT equations, and a summary of the input datasets used to derive these parameters, are presented in Table 3. We report the neighborhood-scale density–VKT relationship for three cities (Chicago, San Francisco, Los Angeles). We also report the urban-scale density–VKT relationship for two representative urban areas (Atlanta and New York) from among the 47 urban areas in the dataset. There is almost no difference in the goodness-of-fit parameter (r^2) for the two- and three-parameter equations.

Table 3 also contains changes in normalized intake attributable to the three hypothesized changes in urban population and area. Intake differences in Table 3 between the two- and three-parameter equations are $<14\%$ and $<4\%$ for the neighborhood- and urban-scale datasets, respectively.

Fig. 4 presents the relationship between elasticity and population density for the functional fits to the empirical neighborhood-scale data presented in Fig. 3b. Elasticity is independent of density for the two-parameter equation. However, for the three-parameter equation, elasticity magnitude increases as density increases ($\varepsilon_v = c/(1 + (b/\rho))$).

The normalized intake results in Table 3 and Fig. 2 provide relative estimates of the exposure impact of changes in urban population and area. To quantify intake (Eq. 3) for a specific pollutant in a specific location, one must specify average breathing rate (Q), average emission factor (F), and typical meteorological conditions in terms of wind speed and mixing height

Table 3
Two- and three-parameter density–VKT equations and attributable changes in normalized intake[a]

	Neighborhood-scale data			Urban-scale data	
	Chicago	Los Angeles	San Francisco	Atlanta	New York City
Population (million)	7.3	14.0	5.9	3.0	17.1
Land area (km^2)	9700	23,400	17,700	4600	10,300
Average density (km^{-2})	753	597	336	650	1660
Total vehicle-kilometers traveled per day (million)	136	256	112	162	424
Average vehicle-kilometers traveled per capita per day	29.9	29.5	30.4	54.4	24.8
Number of data points	315	1471	1048	47[b]	47[b]
Using $V = k\rho^e$					
k	69	52	56	335	335
e	−0.10	−0.07	−0.08	−0.31	−0.31
r^2	0.57	0.20	0.27	0.35	0.35
ε_v	−0.10	−0.07	−0.08	−0.31	−0.31
Infill ($\partial I^*/\partial P\|_A$, units: d^{-1} $person^{-1}$)	0.27	0.18	0.21	0.55	0.17
Sprawl ($\partial I^*/\partial A\|_P$, units: d^{-1} km^{-2})	−91	−49	−32	−97	−76
Constant-density growth ($\partial I^*/\partial P\|_\rho$, units: d^{-1} $person^{-1}$)	0.15	0.10	0.11	0.40	0.12
Using $V = a(\rho + b)^c$					
a	2100	1800	2900	343	343
b	1800	2800	4200	20	20
c	−0.51	−0.48	−0.52	−0.32	−0.32
r^2	0.74	0.31	0.43	0.35	0.35
ε_v	−0.15	−0.08	−0.04	−0.306	−0.312
Infill ($\partial I^*/\partial P\|_A$, units: d^{-1} $person^{-1}$)	0.26	0.18	0.22	0.56	0.17
Sprawl ($\partial I^*/\partial A\|_P$, units: d^{-1} km^{-2})	−80	−48	−35	−101	−76
Constant-density growth ($\partial I^*/\partial P\|_\rho$, units: d^{-1} $person^{-1}$)	0.15	0.10	0.11	0.40	0.12

[a]Here, ε_e = density–emissions elasticity, I^* = Normalized intake (d^{-1}), P = population, A = land area (km^2), and ρ = population density (km^{-2}). The urban-scale and neighborhood-scale datasets are shown in Fig. 3.

[b]Atlanta and New York City each represent one of the 47 cities in the urban-scale data set.

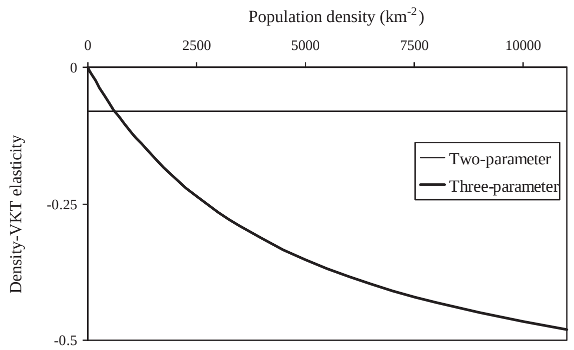

Fig. 4. Density–VKT elasticity as a function of population density, based on data for the 2834 Traffic Analysis Zones in the Chicago, Los Angeles and San Francisco metropolitan areas. Elasticity is independent of density with the two-parameter regression. With the three-parameter regression, elasticity is seen to increase in magnitude as population density increases.

(uH). Appropriate values for these parameters are presented next.

Estimates of the US population-average breathing rate vary. Commonly used values (units: $m^3\,person^{-1}\,d^{-1}$) include 12 (Layton, 1993; US EPA, 1997), 15 (Marty et al., 2002), and 17 (OEHHA, 1996). Emission factors are available for many pollutants, based on techniques such as on-road measurements and laboratory dynamometer tests. There can be significant variability and uncertainty in estimates of F (Abu-Allaban et al., 2003). An estimate of the overall average value of F can be obtained as the ratio of total vehicle emissions to total VKT. For example, dividing reported year-2000 $PM_{2.5}$ tailpipe emissions for gasoline vehicles in California's South Coast Air Basin ($6.2\times10^6\,g\,d^{-1}$) (CARB, 2004) by the total distance traveled by gasoline vehicles ($5.1\times10^8\,km\,d^{-1}$) (CARB, 2002) yields a value of F for tailpipe fine particulate matter of $\sim$12 mg km^{-1}. This value is consistent with experimentally measured values (Abu-Allaban et al., 2003). Meteorology varies among locations and times. We computed the harmonic mean value of Hu for each of the 73 meteorological stations in the EPA SCRAM database (www.epa.gov/ttn/scram). The median value among the stations is $\sim 500\,m^2\,s^{-1}$. Combining the above values, for $PM_{2.5}$, I^* can be converted to I by multiplying by 4.2×10^{-9} mg person^{-1}.

Results in Table 3, combined with conversion factors such as those given above, can provide information that is helpful to cost–benefit analyses and to understanding the health impacts of urban development. For example, the value in Table 3 for infill development in Atlanta, $\partial I^*/\partial P|_A = 0.55\,d^{-1}\,person^{-1}$, is converted to $\partial I/\partial P|_A = 2.3\times10^{-9}\,mg\,d^{-1}\,person^{-2}$ for $PM_{2.5}$. This means if the population of Atlanta were to increase by 100,000 people via infill development, we estimate that the average increase in inhalation intake of $PM_{2.5}$ would be $0.2\,\mu g\,person^{-1}\,d^{-1}$. Per Table 3, if the same population growth were to occur via infill development in New York City, then the expected average increase in per capita inhalation intake of $PM_{2.5}$ would be three times lower.

4.2. Applying the results in this work to specific pollutants or pollutant classes

The analysis presented in this paper is directly applicable to inhalation of primary conserved passenger vehicle emissions, such as benzene and CO. Our results can inform considerations beyond this subset of pollutants. For example, at equal emission rates, the average ambient concentration of a primary conserved pollutant would be higher than for a primary reactive pollutant. All else being equal, intake for a primary nonreactive pollutant is an upper-bound estimate of intake of primary, reactive (or depositing) pollutants. Similarly, the estimated *change* in intake of a primary nonreactive pollutant that results from a change in urban form (e.g., as given in Table 3) is an upper bound estimate of the *change* in intake of a primary reactive pollutant.

For rapidly reacting pollutants (i.e., those for which the characteristic reaction time is much less than the time for removal from the air basin by advection), concentrations are likely to exhibit a high degree of spatial heterogeneity. For all primary vehicle pollutants, concentrations will be higher near roadways than elsewhere, but the concentration difference between near-source and not-near-source areas is greater for rapidly reacting pollutants than for nonreactive pollutants. One implication of this difference is that, when estimating population inhalation of vehicle emissions, proximity to the emission source is more important for rapidly reacting pollutants than for slowly reacting pollutants. A second implication is that the difference between the population average exposure and exposures for people who live or work in proximity to major roadways will be greater for rapidly reacting pollutants than for slowly reacting pollutants.

Two important pollutants associated with transportation are diesel PM (predominantly from nonpassenger vehicles) and ozone (a highly reactive, secondary pollutant). To our knowledge, estimates of density–emissions elasticity for diesel PM do not exist, and we do not expect ε_e for passenger vehicles to be an accurate estimator of ε_e for diesel PM. Because diesel vehicle emissions are concentrated near specific land uses such as highways and freight centers, we expect ambient concentrations to be more spatially heterogeneous for diesel emissions than for passenger vehicle emissions (SCAQMD, 1999). The density–emissions elasticity for diesel PM may be negative, because increasing population density is likely to increase the efficiency with which organizations can deliver the goods and services that require diesel consumption. However, there is currently no good basis for estimating this parameter.

The approach for primary pollutants developed in this paper could be extended to secondary pollutants (Marquez and Smith, 1999). For example, investigations of how changes in VKT affect ozone concentrations can yield a pseudo-emission factor, defined as the attributable change in the average mass of ozone in an urban area divided by the change in VKT (Carter, 1989). Similar metrics could be explored for changes in the size of an urban area or the spatial distribution of precursor vehicle emissions. Factors influencing such metrics include climate and meteorology, topography, total precursor emissions (i.e., including nonvehicle emissions), and the spatial and temporal distribution of emissions and of changes in emissions. Vehicle emissions may reduce ozone concentrations locally (because fresh NO emissions remove ozone) but increase ozone concentrations in areas that are downwind of the emissions. Average ozone concentrations are lower indoors than outdoors because the absence of direct sunlight reduces ozone formation and because reactions with indoor surfaces increase ozone destruction (Weschler, 2000). Uncertainty and variability in the emission-to-intake relationship tend to be larger for secondary pollutants than for primary pollutants.

4.3. Other impacts

The health effects attributable to inhalation of emissions are only one of the many impacts associated with motor vehicles and urban form (Delucchi, 1996). Emissions occur throughout the lifecycle of all components of the transportation infrastructure, including vehicles, fuels, and roads. Impacts of the transportation system include local and global environmental damage (e.g., habitat loss, urban heat island effects, and global climate change). Among nonpollution health effects, urban form may influence exercise levels, obesity, mental health, and other "quality of life" issues (Frank and Engelke, 2001; Frumkin, 2002).

Actions that reduce one impact may or may not reduce other impacts. As an example, Table 4 presents policies that influence greenhouse gas (GHG) and toxic emissions, and population inhalation of vehicle emissions. Some actions exhibit co-benefits between these impacts; others exhibit trade-offs.

4.4. Other issues

An important limitation to the approach employed in this paper is the assumption that individuals are exposed to the same attributable concentration. Differences in exposures among individuals and among sub-populations are important components of society's overall air-quality concerns. While the results of this paper indicate that in some cases sprawl may reduce total population inhalation of motor vehicle emissions, the exposure change is not expected to be uniform across the population. Sprawl may reduce the population average exposure while increasing exposures for persons living near transportation corridors, especially if people living at the urban edge commute to downtown locations.

A second important limitation is that we use the average ambient concentration as a proxy for the average exposure concentration. In some situations (e.g., benzene concentrations in vehicles), attributable exposure concentrations are likely to be greater than attributable ambient concentrations; in other situations (e.g., particulate matter in a mechanically ventilated building), the reverse is true. In a specific urban area, correlations are likely among population density, building type and age, the ratio of indoor-to-outdoor pollution concentrations, and time spent in or near vehicles. Such considerations may be important in understanding a specific individual's or sub-population's exposures.

Finally, our analysis does not address the effects of changes in fuels and vehicle technologies. Aggressive programs have led to demonstrable and substantial reductions in on-road emissions of many criteria and toxic air pollutants (Kean et al., 2001; Kean et al., 2000). In cases where inhalation intake of vehicle emissions is not reduced by infill development alone, combining infill with efforts to further reduce vehicle emissions may permit overall inhalation intake to decrease.

Table 4
Examples of actions that increase and reduce two impacts from vehicles[a]

		CO_2 and toxic emissions	
		Reduction	Increase
Inhalation of emissions	Reduction	Increased fuel-efficiency	Sprawl, if $-0.5<\varepsilon_e<0$
	Increase	Infill development, if $-1.0<\varepsilon_e<0$	Reduced fuel-efficiency

[a]Here, ε_e = density–emissions elasticity.

5. Conclusion

Urban land area and population change over time, with or without planning. We have analyzed the impact of changes in land area and population on per capita inhalation of primary passenger vehicle emissions. Depending on the density–emissions elasticity (ε_e), infill development has the potential to reduce motor vehicle emissions yet increase per capita inhalation of these emissions, while sprawl has the potential to increase vehicle emissions but reduce inhalation of these emissions. Under the idealized conditions considered here, for ε_e greater than -0.5, constant-density growth and sprawl minimize intake for increasing and constant population, respectively. For ε_e less than -0.5, infill and contraction minimize intake for increasing and constant population, respectively. Data on density–emissions elasticity (ε_e) are lacking, but published values for density–VKT elasticity (ε_v) are between 0 and -0.7. To interpret our model results (which are based on ε_e), we assume in this paper that ε_v is a reasonable proxy for ε_e, and also that data on ε_v from cross-sectional studies provide useful predictive information for describing changes in response to growth over time in any given urban area. To the extent that these assumptions are reasonably accurate, merely increasing population density while all other aspects of urban form are unchanged appear unlikely to reduce VKT enough to reduce average per capita intake. Rather, to reduce health impacts of transportation emissions relative to constant-density growth, infill development would have to include urban design features that strengthen the density–VKT relationship, such that the condition $\varepsilon_e < -0.5$ is satisfied.

An ultimate goal in air-quality management is to minimize adverse health effects of air pollution. In the case of motor vehicle emissions, major progress has been achieved through technological developments such as fuel reformulation and on-board emission controls. Urban planning may also reduce vehicle emissions and their associated health effects. To do so will require a better understanding of the relationships among urban form, vehicle use, vehicle emissions, and inhalation intake of those emissions. This paper offers early progress toward such understanding.

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