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Inhalation of Primary Motor Vehicle Emissions: Effects of Urban Population and Land Area

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Abstract

Urban population density can influence transportation demand, as expressed through average daily vehicle-kilometers traveled per capita (VKT). In turn, changes in transportation demand influence total passenger vehicle emissions. 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. 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, if urban population increases, per capita intake is less with infill development than with constant-density growth if ε_e is less than –0.5, while for ε_e greater than –0.5 the reverse is true.

Key words: 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 can reduce average daily vehicle-kilometers traveled per capita (VKT) for several reasons (Ewing and Cervero, 2001). For example, increasing 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 non-motorized 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 association between density and VKT has led some planners to implement policies encouraging 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 reducing VKT by increasing population density reduce vehicle emissions? (2) Under what circumstances does reducing emissions by increasing population density reduce people’s inhalation intake of these 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."

Most urban areas are growing, with or without planning, and this growth will have an impact on emissions and emissions-to-intake relationships. This 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 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 aims to fill 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 inhalation of vehicle pollutants is more appropriate than emissions as a measure of environmental health impacts (Bennett et al., 2002; Delucchi, 1996). 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"). We consider a hypothetical, idealized urban area. 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 for the density-emissions elasticity and 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 density-intake relationship, we aim for a direct approach that clarifies underlying relationships, aids in elucidating causal connections, and makes the problem analytically tractable. We consider population density, passenger vehicle emissions, attributable ambient concentrations for primary pollutants, and attributable intake per capita. Below we describe our method for connecting these elements of the source-intake relationship for primary pollutants from motor vehicles.

Density-Emissions Elasticity

Population density has the potential to influence both vehicle emissions (Holtzclaw et al., 2002) and 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.

An increase in population density while per capita emissions remain constant 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 results in a reduction in per capita emissions, then the same two variables (emissions per km^2 and per capita inhalation of emissions) may either increase or decrease, depending on the density-emissions elasticity. Equation 1 defines density-emissions elasticity (ε_e) and density-VKT elasticity (ε_v):

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

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}). Because density and VKT are often inversely related (Holtzclaw et al., 2002), ε_v is usually negative, and ε_e is likely to be negative. If ε_e is negative and large in magnitude, increasing population density can reduce both vehicle emissions and per capita inhalation of vehicle emissions. However, if the magnitude of ε_e is small (but still negative), increasing population density can 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.

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. In the discussion, we outline how one would extend the methods to address reactive primary and secondary pollutants.

Ambient Concentrations

In this paper, we use a one-box 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. Evidence indicates this assumption is approximately true for average ambient concentrations of primary nonreactive pollutants from distributed sources in large air basins. To explore the accuracy of this assumption, we analyzed year-2002 annual average CO concentrations at the 497 monitoring stations in the US 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%) are 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-box model is useful for estimating the average emissions-to-concentration relationship for primary nonreactive vehicle emissions in urban areas.

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

$$C = \frac{E}{uH\sqrt{A}} = \frac{FVP}{uH\sqrt{A}} \times \frac{1}{86400}. \tag{2}$$

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 local urban land area (m^{2}), F is the average motor vehicle emission factor (g km^{-1}), P is the population size, and 86400 converts time units from seconds to days. The group (uH) indicates how rapidly local meteorology dilutes and removes emissions from an area; the group ($P\,A^{-0.5}$) is a linear population density; and, the group (FV) is the average per capita emission rate.

Intake

Average daily per capita inhalation intake (g person^{-1} d^{-1}) is the product of total emissions (g d^{-1}) and the average fraction of emissions that are inhaled by an individual (i.e., the individual intake fraction) (Bennett et al., 2002; Marshall et al., 2003). Alternatively, given equation (2), average daily per capita intake of motor vehicle emissions, I, can be estimated as

$$I = QC = \frac{QFVP}{uH\sqrt{A}} \times \frac{1}{86400}. \tag{3}$$

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 these three variables:

$$I^* \equiv I\left(\frac{uH}{QF} \times 86400\right) = \frac{VP}{\sqrt{A}}. \tag{4}$$

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

Exposure concentrations can be subdivided by 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 affect exposures attributable to emissions that are upwind of the urban area (i.e., regional and global emissions). 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. Local and microenvironment emissions will be less important for secondary pollutants that take ~ 0.5 hour or more to form than for primary pollutants, because of the transport and dispersion that occurs during the interval between precursor release and secondary pollutant formation.

Outdoor concentrations are relatively homogeneous for primary nonreactive pollutants from motor vehicles. For such 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. 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. 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. Watson and Chow (2001), studying conditions in Mexico City, reported that "65% of the 24-hr 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 ~ 1 km]." 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

Changes in urban population and area

Figure 1 illustrates the three changes in urban population and area considered in this paper (infill, sprawl, and constant-density growth). We explore 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 equations (1) and (3) and from the assumption that, among the variables considered, transportation emissions are only a function of population density. The entries do not assume any specific functional form for the density-emissions relationship.

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

Table 2 presents our 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, when population is increasing, infill minimizes per capita intake if ε_e is less than –0.5; constant-density growth minimizes per capita intake if ε_e is greater than –0.5.

Density-emissions elasticity

The general analysis presented in this paper is based 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 $\varepsilon_v = -0.37$. Using an international dataset, Newman and Kenworthy (1989) reported a density-fuel consumption elasticity of between –0.4 and –0.5. Some researchers have suggested fuel consumption is 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

$$\frac{\varepsilon_e}{\varepsilon_v} = \frac{\frac{dE}{dV}}{\frac{E}{V}} = \frac{F^*}{F}, \tag{5}$$

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. Since density and other urban-form attributes affect congestion (Dunphy and Fisher, 1996) and 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 is greater than the density-VKT elasticity. For example, 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.

Published ε_v values are between –0.2 and –0.7, with typical values between –0.3 and –0.5 (Holtzclaw et al., 2002). Empirical evidence of density-VKT elasticity comes from both intra- and inter-urban comparisons. Figure 3 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 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). Transportation demand modeling of two hypothetical housing developments in each of three US metropolitan areas (Montgomery County, Maryland; San Diego, California; and West Palm Beach, Florida) concluded that VKT would be 40 – 50% lower for infill than for "greenfield" development (US EPA, 1999b). Holtzclaw (1991; 1994) reported 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."

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 cross-sectional data are informative about the longitudinal conditions that would apply in any given urban area. Evidence against which to test this assumption does not exist.

Comparing our analyses with reported values for ε_v, we find that infill may or may not be an effective strategy for minimizing intake of vehicle emissions. Infill development is unlikely to reduce per capita intake: our analysis suggests this outcome would require a density-VKT elasticity of less than minus one ($\varepsilon_v < -1.0$). Within the range of reported ε_v values, infill and constant-density growth both increase per capita intake, but at $\varepsilon_v < -0.5$, the intake increase is less for infill than for constant-density growth. At $\varepsilon_v > -0.5$, the reverse is true. Thus, based on typical values for ε_v, we conclude that merely increasing population density, while holding constant all other aspects of urban form, will not reduce VKT enough to reduce average per capita intake. Rather, to reduce inhalation intake of air pollutants emitted from motor vehicles, 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

Comparing two- and three-parameter density-VKT relationships

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

$$V = k\rho^{\left[\frac{\log\left(1-\frac{X\%}{100\%}\right)}{\log(2)}\right]} . \tag{6}$$

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 equation (6) is negative when there is an inverse relationship between density and VKT.

Using equation (6) to establish the relationship between VKT and population density requires specifying two parameters: k and X. Alternatively, one can specify the value for V at a specific density (i.e., given $V=V_1$ when $\rho=\rho_1$) and X, in which case equation (6) can be written as

$$V = V_1\left(\frac{\rho}{\rho_1}\right)^{\left[\frac{\log\left(1-\frac{X\%}{100\%}\right)}{\log(2)}\right]} . \tag{7}$$

The exponent in equations (6) and (7) is the density-VKT elasticity (ε_v). For example, if doubling density reduces VKT by 40%, then $\varepsilon_v = -0.74$.

Equations (6) and (7), although common, have a weakness in that they do not incorporate an upper limit to VKT. As density becomes infinitesimally small, equations (6) and (7) erroneously suggests that VKT grows infinitely large. The bounded exponential equation used by Holtzclaw et al. (2002) overcomes this limitation:

$$V = a(\rho + b)^c . \tag{8}$$

Equation (8) is a more realistic description of the density-VKT relationship than equation (6), but it requires specification of three constants (*a*, *b*, and *c)* rather than two (*k* and *X*). Perhaps because of its simplicity, most previous studies have used the two-parameter relationship.

The results presented in Table 2 and Figure 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. To compare the two functional forms found in the literature (equations 6 and 8), we determined the correlation parameters for the neighborhood-scale data used by Holtzclaw et al. (2002), and for urban-scale data reported by the US Department of Transportation (US DOT, 2003). The neighborhood-scale dataset contains VKT and density for each traffic analysis zone in three urban areas (Chicago, Los Angeles, and San Francisco). We also analyzed the combined three-city dataset. 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), and for a hypothetical urban area formed by combining the three neighborhood-scale datasets. 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. Regression residuals for the neighborhood-scale data are heteroscedastic, i.e., differences between the regression lines and the data vary non-randomly. For example, as Figure 3 shows, the two-parameter three-city regression over-predicts VKT at population densities above ~ 5,000 km^{-2}.

We concur with Holtzclaw et al. (2002) that the three-parameter equation offers a better fit of the neighborhood-scale data than does the two-parameter equation. On the other hand, for the urban-scale data, the third parameter is unnecessary: there is almost no difference in the goodness-of-fit parameter (r^2) for the two- and three-parameter equations. These results indicate that, as expected, the three-parameter equation only improves on the two-parameter equation when the dataset includes very small population-density values.

Table 3 also contains normalized changes in intake attributable to the three hypothesized changes in urban population and area. Differences in Table 3 between the two- and three-parameter equations are <14% and <4% for the neighborhood- and urban-scale datasets, respectively. For the datasets and equations employed in this work, the functional form of the density-VKT relationship is not important in estimating ε_v.

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

Among the three changes in urban population and area considered, and based on reported values for the density-VKT elasticity, only sprawl reduces per capita inhalation intake (i.e., changes in intake are negative). Sprawl increases emissions but reduces per capita inhalation of these emissions, while infill reduces emissions but increases per capita inhalation of these emissions.

Applying intake results to specific pollutant classes

The normalized intake results in Table 3 and Figure 2 provide relative estimates of the exposure impact of changes in urban population and area. To quantify intake (equation 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 (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 (6.2×10^6 g d^{-1}) (CARB, 2000) by the total distance traveled by gasoline vehicles (5.1×10^8 km d^{-1}) (CARB, 2002) yields a value of F for tailpipe fine particulate matter of ~ 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 ~ 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 $\partial I/\partial P|_A = 2.3 \times 10^{-9}$ 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 expect that the average increase in inhalation intake of $PM_{2.5}$ would be 0.2 μg $person^{-1}$ 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 3 times lower.

The analysis presented in this paper is directly applicable to inhalation of primary conserved passenger-vehicle emissions, such as benzene and the primary component of $PM_{2.5}$. 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 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 non-passenger 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 a particularly useful 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). We hypothesize that, as with passenger vehicles, the density-emissions elasticity for diesel PM is negative, because increasing population density is likely to increase the efficiency with which organizations can deliver goods and services that require diesel consumption. However, given the lack of research in this area, there is currently no good basis for estimating the magnitude of the density-emissions elasticity for diesel PM.

The approach for primary pollutants developed in this paper could be extended to secondary pollutants. For example, investigations of how changes in VKT affect ozone concentrations can estimate 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 non-vehicle 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.

Other impacts

The health effects attributable to inhalation of emissions are only one of 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 non-pollution 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 might 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.

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 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. We have argued that *changes* in average attributable ambient concentrations are a reasonable proxy for *changes* in average attributable exposure concentrations, for primary nonreactive pollutants. This approximation is less appropriate for reactive pollutants. 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 well-sealed 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.

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. 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 are lacking, but typical values for density-VKT elasticity (ε_v) are between –0.3 to –0.5. We have assumed in this paper that ε_v is a reasonable proxy for ε_e, and also that data on ε_v from cross-sectional studies provides useful predictive information for describing changes in response to growth in any given urban area. To the extent that these assumptions are reasonably accurate, then merely increasing population density while all other aspects of urban form are unchanged will not reduce VKT enough to reduce average per capita intake. Rather, to reduce health impacts of transportation emissions, infill development must include urban design features that strengthen the density-VKT relationship, such that the condition $\varepsilon_e < -0.5$ is satisfied.

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Table 1

Mathematical description of the three changes in urban population and area*

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.	$\left.\frac{\partial I^*}{\partial A}\right\|_P = -\frac{PV}{2A^{1.5}}\left[2\varepsilon_e + 1\right]$
Constant-density growth	Both population and land area increase; density is constant.	$\left.\frac{\partial I^*}{\partial P}\right\|_\rho = \frac{1}{\rho}\left.\frac{\partial I^*}{\partial A}\right\|_\rho = \frac{V}{2\sqrt{A}}$

* 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 equation (1), and ρ is the population density (km^{-2}).

Table 2

The change in urban population and area that minimizes intake, depending on the density-emissions elasticity and the change in population†

	$\mathrm{d}P/\mathrm{d}t > 0$	$\mathrm{d}P/\mathrm{d}t = 0$	$\mathrm{d}P/\mathrm{d}t < 0$
$\varepsilon_e < -0.5$	$\mathrm{d}A/\mathrm{d}t = 0$ (infill)	$\mathrm{d}A/\mathrm{d}t < 0$ (contraction)	$\mathrm{d}\rho/\mathrm{d}t = 0$ (constant-density growth)
$\varepsilon_e > -0.5$	$\mathrm{d}\rho/\mathrm{d}t = 0$ (constant-density growth)	$\mathrm{d}A/\mathrm{d}t > 0$ (sprawl)	$\mathrm{d}A/\mathrm{d}t = 0$ (infill)

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

Table 3

Two- and three-parameter density-VKT equations and attributable changes in normalized intake‡

	Neighborhood-scale data				Urban-scale data	
	Chicago	Los Angeles	San Francisco	Three-city dataset	Atlanta	New York City
Population (million)	7.3	14.0	5.9	27.2	3.0	17.1
Land area (km^2)	9,700	23,400	17,700	50,800	4,600	10,300
Average density (km^{-2})	753	597	336	536	650	1,660
Total vehicle-kilometers traveled per day (million)	136	256	112	504	162	424
Average vehicle-kilometers traveled per capita per day	29.9	29.5	30.4	29.8	54.4	24.8
Number of data points	315	1471	1048	2834	47	
Using $V=k\rho^e$						
k	69	52	56	55	335	
e	–0.10	–0.07	–0.08	–0.08	-0.31	
r^2	0.57	0.20	0.27	0.26	0.35	
ε_v	–0.10	–0.07	–0.08	–0.08	-0.31	
Infill ($\partial I^*/\partial P\|_A$, units: d^{-1} $person^{-1}$)	0.27	0.18	0.21	0.12	0.55	0.17
Sprawl ($\partial I^*/\partial A\|_P$, units: d^{-1} km^{-2})	-91	-49	-32	-30	-97	-76
Constant-density growth ($\partial I^*/\partial P\|_\rho$, units: d^{-1} $person^{-1}$)	0.15	0.10	0.11	0.07	0.40	0.12
Using $V=a(\rho+b)^c$						
a	2100	1800	2900	13800	343	
b	1800	2800	4200	4800	20	
c	-0.51	-0.48	-0.52	-0.69	-0.32	
r^2	0.74	0.31	0.43	0.40	0.35	
ε_v	-0.15	-0.08	-0.04	-0.07	-0.306	-0.312
Infill ($\partial I^*/\partial P\|_A$, units: d^{-1} $person^{-1}$)	0.26	0.18	0.22	0.12	0.56	0.17
Sprawl ($\partial I^*/\partial A\|_P$, units: d^{-1} km^{-2})	-80	-48	-35	-31	-101	-76
Constant-density growth ($\partial I^*/\partial P\|_\rho$, units: d^{-1} $person^{-1}$)	0.15	0.10	0.11	0.07	0.40	0.12

‡ Here, ε_e = density-emissions elasticity, I^* = Normalized intake (d^{-1}), P = population, A = land area (km^2), and ρ = population density (km^{-2}).

Table 4

Examples of actions that increase and reduce two impacts from vehicles[††]

		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

[††] Here, ε_e = density-emissions elasticity.

Figure 1

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, $\partial I/\partial A|_\rho$) 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).

Figure 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 (1) urban population (*P*) or (2) 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*.

Figure 3

Fig. 3. Comparisons of population density and average daily per capita VKT. Fig. 3a shows 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. Fig. 3b shows data for the 2,834 Traffic Analysis Zones in the Chicago, Los Angeles and San Francisco metropolitan areas. Not plotted are the 5% of the population density values that are greater than 7,500 km^{-2} and the 0.8% of the VKT values that are greater than 65 km person^{-1} day^{-1}. Both dataset show an inverse relationship, with more dense areas having lower per capita VKT.

Figure 4

Fig. 4. Density-VKT elasticity as a function of population density, based on data for the 2,834 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.

Fig. 1

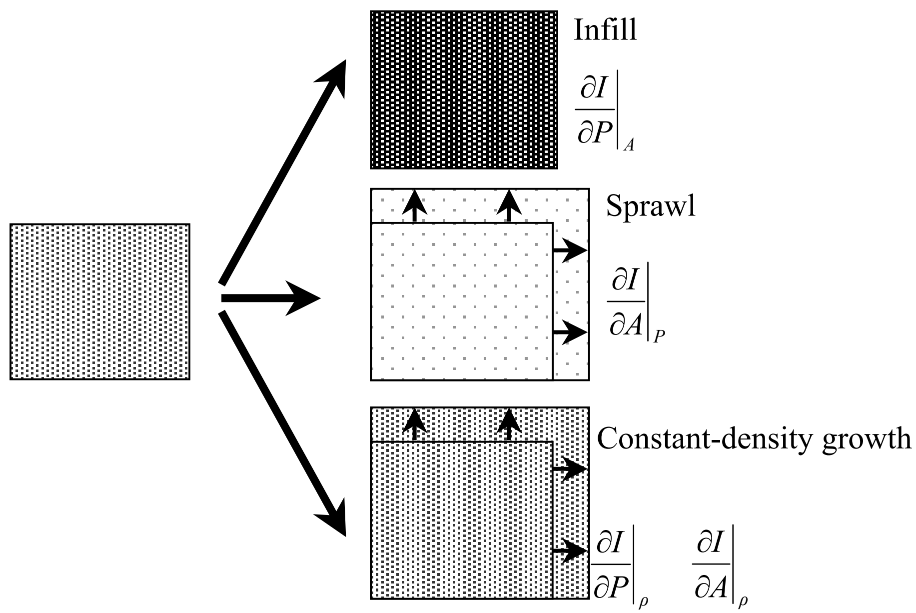

Infill
$\left.\frac{\partial I}{\partial P}\right|_{A}$
Sprawl
$\left.\frac{\partial I}{\partial A}\right|_{P}$
Constant-density growth
$\left.\frac{\partial I}{\partial P}\right|_{\rho}$
$\left.\frac{\partial I}{\partial A}\right|_{\rho}$

Fig. 2

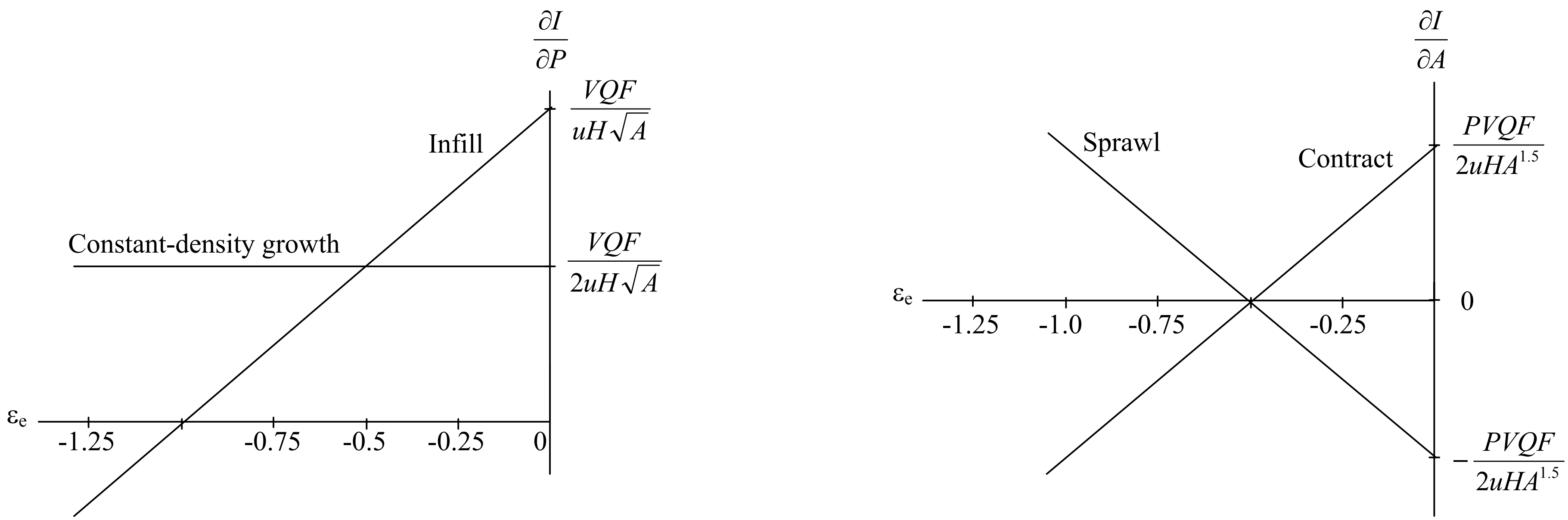
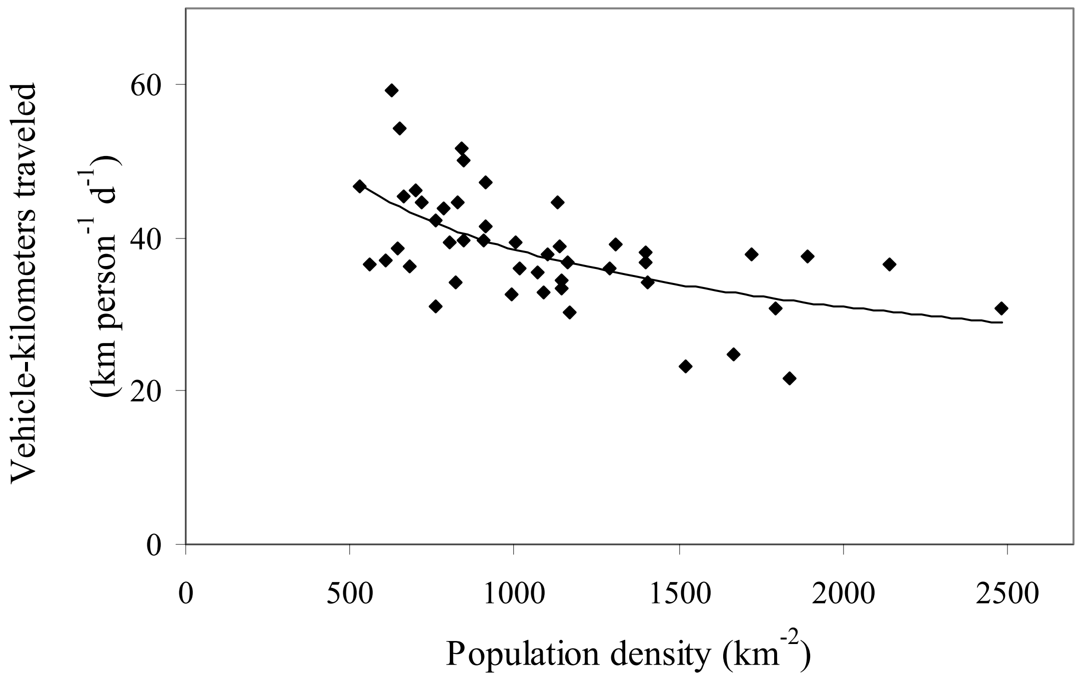
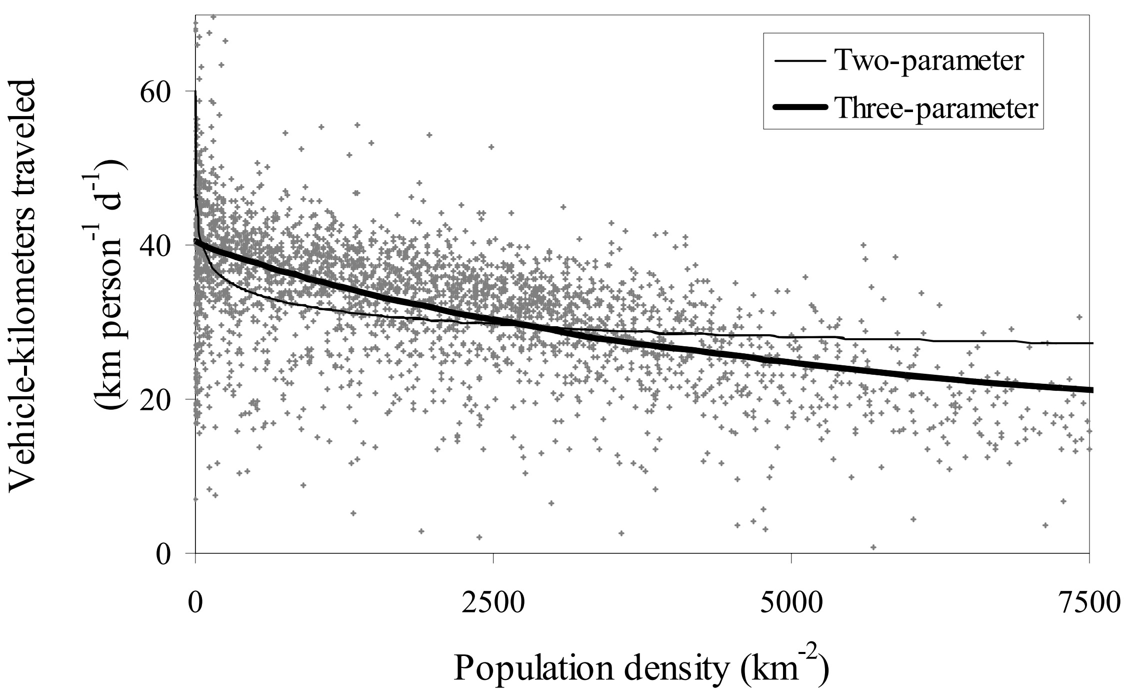

$\frac{\partial I}{\partial P}$
$\frac{VQF}{uH\sqrt{A}}$
Infill
Constant-density growth
$\frac{VQF}{2uH\sqrt{A}}$
ε_e
-1.25
-0.75
-0.5
-0.25
0
$\frac{\partial I}{\partial A}$
Sprawl
Contract
$\frac{PVQF}{2uHA^{1.5}}$
ε_e
-1.25
-1.0
-0.75
-0.25
0
$-\frac{PVQF}{2uHA^{1.5}}$

Fig. 3a



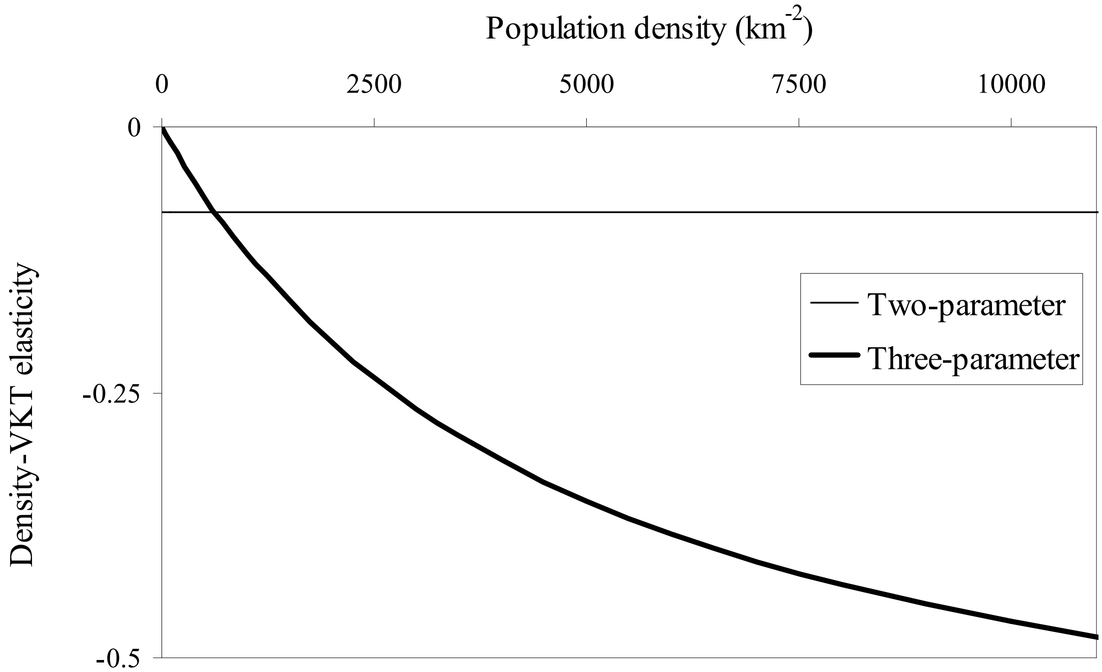
Vehicle-kilometers traveled
(km person^{-1} d^{-1})
0
20
40
60
0
500
1000
1500
2000
2500
Population density (km^{-2})

Fig. 3b



Vehicle-kilometers traveled
(km person^{-1} d^{-1})
Two-parameter
Three-parameter
0
20
40
60
0
2500
5000
7500
Population density (km^{-2})

Fig. 4


Population density (km^{-2})
0
2500
5000
7500
10000
0
-0.25
-0.5
Density-VKT elasticity
Two-parameter
Three-parameter