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Land use policies and transport emissions: Modeling the impact of trip speed, vehicle characteristics and residential location

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ABSTRACT

This study employs a multilevel model to compare the influence of land use on transportation emissions in urban and suburban areas when considering trip speed and vehicle characteristics. In the existing literature, transportation emissions are calculated with aggregate travel activity and emissions factors, however, emissions factors are sensitive to trip speed and vehicle characteristics, implying that considering those factors can change transportation emissions as well as the estimated effects of the built environment. Our results show that indeed this true.

1. Introduction

There is a large body of work investigating the influence of urban form on travel that has sought to examine whether land use planning can be an effective tool for environmental improvement. A particular theme has been the consideration of the role that denser and appropriately "mixed" neighborhoods can encourage the transfer of people to public transit or non-motorized transportation modes.

Two approaches are generally used to estimate emissions from transportation; the first directly measuring pollutants, and the second estimating emissions as a function of vehicle activity. The general finding being that design has a positive effect on the environment. However, there has been limited work involving the detailed modeling of travel speed and vehicle characteristics, although this may impact the more general picture. Spatial setting is also likely to have an impact. Here we focus on such gaps by incorporating the impact of speed variations and vehicle characteristics on emissions estimates and estimating the effect of the built environment according to urban and suburban settings.

2. Methods

CO_2 equivalent emissions are estimated in four ways. First, road speed emissions are calculated using road segment speed estimated by the Puget Sound Regional Council's (PSRC's) regional transportation model as well as diverse vehicle characteristics and road types. We first estimate emissions factors for Pierce County, Washington State, US using the Motor Vehicle Emission Simulator (MOVES) considering: 16 speed categories; motorcycles, passenger cars and trucks, school buses, and transit buses; vehicle age; and highway and local roads[1]. We use emissions factors developed for Pierce County in the Puget

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[1] MOVES is a tool that has been developed by the US Environmental Protection Agency (EPA) and provides estimates of emissions from mobile sources. It also includes a default vehicle database however users are recommended to use local data for the State Implementation Plans or conformity determinations to reflect the local fleet more accurately.

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Sound Region of Washington State because it has the most complete local MOVES data. We assume Pierce County emissions factors are representative of the four counties of the Puget Sound.

The PSRC 2006 Household Activity Survey is used to determine vehicle choice and route. The survey includes 4746 households living in the Puget Sound region and asks respondents to record where, when and how they traveled for two days, as well as basic socio-demographic information. All trips are grouped by am-peak, mid-day, pm-peak, evening, and night periods. We define the routes used by assuming the shortest time path is selected, accounting for different speeds during the relevant periods. The route information is merged with the number of passengers, road segment speed, vehicle characteristics, and road type to match with emissions factors. We assume 11.29 and 12.59 passengers travel in the off-peak and peak periods on buses, based on the average bus utilization of King County Metro Transit (Frank et al., 2011); King County being where Seattle is located. The data is, then, connected to emissions factors estimated by MOVES, and transportation emissions for road segments of all routes are calculated. Mode shares are known from the PSRC travel journal. Emissions per trip are allocated per traveler; i.e. a traveler incurs a larger CO_2 footprint when travelling in a single occupancy vehicle (SOV). Finally, road speed emissions are estimated by adding the estimates for each trip, person and household (Eq. (1)). In this way, transportation emissions reflect unique speed estimates for each road segment and can provide more accurate emissions than average speed emissions.

$$\sum_{k}^{K}\sum_{j}^{J}\sum_{i}^{N}\text{Road length per passenger}_{\text{for road}_i\ \text{in trip}_j\ \text{of person}_k\ \text{in household}_l} * \text{EF}_{\text{road speed, vehicle characteristics and road type for road}_i} \tag{1}$$

Second, average speed emissions are calculated based on average trip speed, vehicle characteristics and road type. The same emissions factors from MOVES are used, however, with the average trip speed calculated by dividing travel distance on the network with travel time for each trip instead of road segment speed. Compared to road speed emissions, average speed emissions can smooth out the influence of travel speed.

$$\sum_{k}^{K}\sum_{j}^{J}\sum_{i}^{N}\text{Road length per passenger}_{\text{for road}_i\ \text{in trip}_j\ \text{of person}_k\ \text{in household}_l} * \text{EF}_{\text{average speed, vehicle characteristics and road type for road}_i} \tag{2}$$

Third, vehicle type emissions are calculated by employing emissions factors by vehicle types from US Environmental Protection Agency (2008) that provides methodologies for estimating greenhouse gases (GHGs) based on CO_2, CH_4, N_2O, and global warming potential (GWP) by various modes. Different formulas are used to estimate GHGs for each vehicle type:

$$\begin{aligned}
&\text{Motorcycle}: \sum_{k}^{K}\text{VMT per passenger}_{\text{for person}_k\text{in household}_l} * (\text{EF}_{\text{CO2}}(0.167) + \text{EF}_{\text{CH4}}(0.070) * 0.021 + \text{EF}_{\text{N2O}}(0.007) * 0.310)\\
&\text{Passenger car}: \sum_{k}^{K}\text{VMT per passenger}_{\text{for person}_k\text{in household}_l} * (\text{EF}_{\text{CO2}}(0.364) + \text{EF}_{\text{CH4}}(0.031) * 0.021 +\\
&\text{EF}_{\text{N2O}}(0.032) * 0.310)\\
&\text{Light-duty Truck}: \sum_{k}^{K}\text{VMT per passenger}_{\text{for person}_k\text{in household}_l} * (\text{EF}_{\text{CO2}}(0.519) + \text{EF}_{\text{CH4}}(0.036) * 0.021 + \text{EF}_{\text{N2O}}(0.047) * 0.310)\\
&\text{Bus}: \sum_{k}^{K}\text{VMT per passenger}_{\text{for person}_k\text{in household}_l} * (\text{EF}_{\text{CO2}}(0.107) + \text{EF}_{\text{CH4}}(0.0006) * 0.021 + \text{EF}_{\text{N2O}}(0.0005) * 0.310)
\end{aligned} \tag{3}$$

Finally, generalized emissions are calculated using a single generalized emission factor (0.435 kg CO_2 per passenger mile for SOV trip) making use of data from Federal Transit Administration (2010). This ignores the variations in both travel speed and vehicle characteristics, and assumes that transportation emissions are only a function of vehicle miles traveled.

$$\sum_{k}^{K}\text{VMT per passenger}_{\text{for person}_k\text{in household}_l} * 0.435 \tag{4}$$

3. Multilevel model

Multilevel model approaches have been often employed in correlated data analysis (Duncan and Jones, 2000; Hong and Shen, 2013). This type of model can consider the correlation among elementary units in the same cluster by introducing random effects. In this study, it is possible that residents in the same geographic unit, that is, the same traffic analysis zone (TAZ) behave in a similar way due to unobserved factors. A TAZ is the unit of area most commonly used in transportation planning models. The size of a zone varies, but typical metropolitan planning, a zone of under 3000 residents is common. For example, even though we consider diverse aspects of built environment in our analysis there may be unmeasureable factors such as

Table 1
Density, diversity, and design.

Measure	Aggregated within TAZ
Density	Net residential density (residential building floor area/residential land area)
Diversity	Entropy $= -\sum_j \frac{P_j^* * \ln(P_j^*)}{\ln(J)}$
Design	Intersection density (Number of four-way intersections/land area)

* The six ($J = 6$) land use types are employed; residential, commercial, industrial, office, government, and others.

pedestrian-friendless that could cause correlation among travelers. Therefore, we adopt the Bayesian multilevel approach (i.e., varying intercept model) to analyze the effects of the built environment on transportation emissions. In addition, we assume that the variance of the multilevel model can vary across TAZs to alleviate the homogeneity assumption in a linear regression model. It is plausible that people living in compact areas may have higher variances because of different responses to the reduced travel cost, so we model the variance as a function of built environment factors. With non-informative prior, our final model can be written as follow:

$$\begin{aligned} y_i &\sim N(\alpha_{j[i]} + \beta_{SES}^T X_{iSES} + \beta_{PTA} X_{iPTA}, \sigma_{j[i]}^2), \quad \text{for } i = 1, \ldots, n. \quad \text{and} \\ \alpha_j &\sim N(\gamma + \gamma_{BE}^T X_{jBE}, \sigma_\alpha^2), \quad \text{for } j = 1, \ldots, J \\ \sigma_j &\sim N(\delta + \delta_{BE}^T X_{jBE}, \sigma_\delta^2), \quad \text{for } j = 1, \ldots, J \end{aligned} \tag{5}$$

where y represents transportation emissions and X_{SES}, X_{PTA}, X_{BE} indicate various socio-economic factors, public transit accessibility (distance to the nearest bust stop), and built environment variables, respectively. Table 1 shows three built environment factors often called "3D (Density, Diversity, and Design)".

4. Results

Transportation emissions per household are calculated under the various emissions assumptions, and compared in Fig. 1. We see that differences, while not dramatic, are significant. Employing the average speed and vehicle characteristics generates an average, 3.13 kg smaller than generalized emissions calculated from a single generalized emission factor. However, because the emissions factors for each vehicle type and a single emission factor are from other sources, it is not easy to directly compare the absolute values of transportation emissions and their differences.

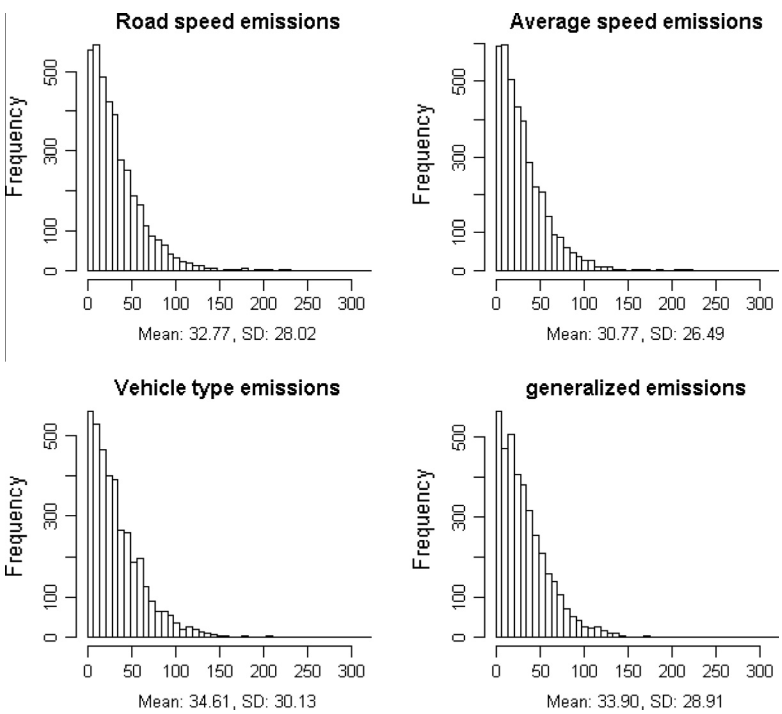

Fig. 1. Transportation emissions based on various assumptions.

To analyze the effects of different assumptions on the connection between land use and transportation emissions, we use a multilevel-model and the results are compared in Tables 2 and 3 for urban and suburban areas. Residential location (i.e., urban or suburban) is defined according to the response when people were asked if their current homes are located in an urban, suburban, or rural/exurban areas. Since we employ a Bayesian approach the mean and 95% credible interval (CI) of estimates are presented instead of *p*-value. If the 95% CI does not include zero, it implies the coefficient is statistically significant at the 95% CI. We also include the results for the varying variance for the comparison.

As the number of individuals in a household increases, more transportation emissions are generated due to the cumulated VMT. In addition, wealthier households tend to produce more emissions associated with their economic ability to drive. Number of workers is positively associated with transportation emissions suggesting that commuters tend to travel more miles than non-commuters. Transit accessibility, measured by the distance to the nearest bus stop, shows different results according to location. That is, its impact is only significant in the suburban models. In general, most urban areas have good transit accessibility, and differences are not observed.

In terms of the built environment factors, households located in denser and well-mixed neighborhoods tend to be responsible for smaller amount of emissions. In addition, intersection density has a negative impact on emissions, showing that

Table 2
Results from urban models.

	Road speed emissions		Average speed emissions		Vehicle type emissions		Generalized emissions	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Intercept	1.771	(1.606, 1.937)	1.720	(1.549, 1.880)	1.818	(1.608, 2.011)	1.827	(1.632, 2.024)
Household size	0.175	(0.126, 0.220)	0.172	(0.128, 0.216)	0.182	(0.132, 0.231)	0.141	(0.096, 0.190)
Total income	0.028	(0.016, 0.040)	0.026	(0.014, 0.039)	0.028	(0.015, 0.040)	0.029	(0.015, 0.042)
Number of vehicles	0.256	(0.196, 0.315)	0.257	(0.197, 0.319)	0.246	0.188, 0.307)	0.312	(0.245, 0.378)
Worker 1	0.438	(0.331, 0.546)	0.436	(0.323, 0.549)	0.438	0.323, 0.562)	0.426	(0.306, 0.555)
Worker 2+	0.566	(0.426, 0.708)	0.564	(0.417, 0.707)	0.569	0.420, 0.707)	0.550	(0.396, 0.705)
Transit accessibility	0.096	(−0.010, 0.248)	0.094	(−0.024, 0.241)	0.083	(−0.044, 0.226)	0.078	(−0.051, 0.231)
Residential density	−0.263	(−0.366, −0.136)	−0.255	(−0.360, −0.145)	−0.268	(−0.373, −0.161)	−0.375	(−0.508, −0.218)
Entropy	−0.314	(−0.539, −0.079)	−0.320	(−0.541, −0.096)	−0.316	(−0.551, −0.085)	−0.315	(−0.556, −0.081)
Intersection density	−0.592	(−0.852, −0.340)	−0.590	(−0.835, −0.318)	−0.654	(−0.940, −0.392)	−0.624	(−0.933, −0.330)
Varying variance								
Intercept	−0.467	(−0.578, −0.344)	−0.461	(−0.577, −0.342)	−0.438	(−0.563, −0.322)	−0.466	(−0.598, −0.334)
Residential density	0.075	(0.014, 0.139)	0.075	(0.015, 0.141)	0.073	(0.013, 0.134)	0.086	(0.023, 0.156)
Entropy	0.518	(0.292, 0.750)	0.518	(0.292, 0.749)	0.508	(0.284, 0.752)	0.613	(0.338, 0.874)
Intersection density	0.368	(0.097, 0.624)	0.348	(0.111, 0.592)	0.354	(0.118, 0.613)	0.606	(0.359, 0.874)
σ_α	0.104		0.094		0.118		0.143	
σ_j	0.926		0.908		0.926		1.033	
σ_δ	0.294		0.288		0.282		0.372	
R^2	0.363		0.361		0.359		0.340	

Table 3
Results from suburban models.

	Road speed emissions		Average speed emissions		Vehicle type emissions		Generalized emissions	
	Mean	95% CI	Mean	95% CI	Mean	95% CI	Mean	95% CI
Intercept	2.396	(2.256, 2.550)	2.338	(2.193, 2.477)	2.483	(2.346, 2.629)	2.573	(2.431, 2.711)
Household size	0.135	(0.107, 0.164)	0.132	(0.103, 0.159)	0.137	(0.109, 0.168)	0.113	(0.087, 0.141)
Total income	0.036	(0.028, 0.046)	0.037	(0.027, 0.046)	0.037	(0.028, 0.046)	0.032	(0.023, 0.041)
# of vehicles	0.140	(0.105, 0.176)	0.140	(0.105, 0.175)	0.129	(0.095, 0.165)	0.138	(0.105, 0.171)
Worker 1	0.214	(0.132, 0.302)	0.216	(0.128, 0.305)	0.208	(0.118, 0.296)	0.211	(0.120, 0.299)
Worker 2+	0.506	(0.409, 0.599)	0.509	(0.407, 0.606)	0.507	(0.405, 0.600)	0.506	(0.407, 0.608)
Transit accessibility	0.076	(0.049, 0.106)	0.074	(0.047, 0.104)	0.074	(0.048, 0.103)	0.069	(0.042, 0.099)
Residential density	−1.090	(−1.619, −0.584)	−1.150	(−1.692, −0.634)	−1.233	(−1.717, −0.725)	−1.347	(−1.906, −0.770)
Entropy	−0.275	(−0.456, −0.086)	−0.263	(−0.452, −0.077)	−0.260	(−0.477, −0.059)	−0.277	(−0.471, −0.070)
Intersection density	−0.920	(−1.453, −0.412)	−0.879	(−1.367, −0.387)	−0.924	(−1.443, −0.413)	−0.769	(−1.398, −0.152)
Varying variance								
Intercept	−0.548	(−0.656, −0.443)	−0.548	(−0.648, −0.453)	−0.546	(−0.647, −0.443)	−0.617	(−0.733, −0.506)
Residential density	0.378	(−0.108, 0.863)	0.396	(−0.148, 0.950)	0.463	(−0.05, 0.963)	0.703	(0.151, 1.265)
Entropy	0.355	(0.123, 0.593)	0.372	(0.140, 0.607)	0.377	(0.137, 0.606)	0.462	(0.204, 0.726)
Intersection density	0.481	(−0.014, 1.044)	0.456	(−0.048, 0.960)	0.450	(−0.043, 0.944)	0.715	(0.185, 1.228)
σ_α	0.173		0.165		0.168		0.174	
σ_j	0.769		0.774		0.783		0.834	
σ_δ	0.312		0.313		0.301		0.385	
R^2	0.376		0.370		0.372		0.344	

Table 4
Elasticities of built environments.

	Urban				Suburban			
	Road speed	Average speed	Vehicle type	Generalized	Road speed	Average speed	Vehicle type	Generalized
Residential density	−0.079	−0.077	−0.080	−0.108	−0.120	−0.126	−0.134	−0.146
Entropy	−0.109	−0.112	−0.110	−0.109	−0.076	−0.073	−0.072	−0.077
Intersection density	−0.123	−0.123	−0.135	−0.127	−0.042	−0.040	−0.042	−0.035
Total	−0.312	−0.312	−0.325	−0.344	−0.237	−0.239	−0.248	−0.258

improving the walking environment can encourage people to use non-motorized transportation modes. The influence of the built environment, however, varies according to how transportation emissions are measured. For example, the generalized emissions model produces the largest influence of residential density on transportation emissions for both urban and suburban models. High density is related to slow travel speed because of congestion, and slow speed produces more emissions per mile. Ignoring variations in speed can thus overestimate the impact of density. In addition, both urban and suburban models show built environment factors to be significantly associated with variances, indicating that denser, well-mixed, and more walkable areas tend to have greater variations. People living in these areas may travel less due to increased accessibility but they can also travel more due to reduced travel costs. Assuming homoscedasticity can, therefore, lead to incorrect statistical test of significance.

Elasticities of built environments are presented in Table 4. We find that a 100% increase in all three built environment factors in urban areas can generate 31.2–34.4% reductions in transportation emissions. The absolute value of difference is marginal although, the relative difference is substantial. For suburban areas, the results show that the impacts of land use factors are smaller than those of urban areas. In addition, the influences of entropy and intersection density for urban areas are larger than those of suburban areas, implying that there could be possible synergy impacts with high density. The effect of residential density in the urban model is, however, much smaller than that in the suburban model.

5. Conclusions

In examining how the built environment affects transportation emissions we find large reductions in emissions as residential density, entropy and intersection density increase. In other words, there is a strong relationship between the built environment and transportation emissions in both urban and suburban areas. The effects of the built environment can, however, be overstated if the characteristics of travel speed and vehicles are ignored. Finally, we see that urban and suburban characteristics influence travel and the environment with, for example, residential density impacting more on suburban than urban areas.

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