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A bottom up approach to on-road CO_2 emissions estimates: improved spatial accuracy and applications for regional planning.

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Abstract

On-road transportation is responsible for 28% of all U.S. fossil-fuel CO_2 emissions. Mapping vehicle emissions at regional scales is challenging due to data limitations. Existing emission inventories use spatial proxies such as population and road density to downscale national or state-level data. Such procedures introduce errors where the proxy variables and actual emissions are weakly correlated, and limit analysis of the relationship between emissions and demographic trends at local scales. We develop an on-road emission inventory product for Massachusetts based on roadway-level traffic data obtained from the Highway Performance Monitoring System (HPMS). We provide annual estimates of on-road CO_2 emissions at a 1km x 1km grid scale for the years 1980 through 2008. We compared our results with on-road emissions estimates from the Emissions Database for Global Atmospheric Research (EDGAR), with the Vulcan Product, and with estimates derived from state fuel consumption statistics

reported by the Federal Highway Administration (FHWA). Our model differs from FHWA estimates by less than 8.5% on average, and is within 5% of Vulcan estimates. We found that EDGAR estimates systematically exceed FHWA by an average of 22.8%. Panel regression analysis of per-mile CO_2 emissions on population density at the town scale shows a statistically significant correlation that varies systematically in sign and magnitude as population density increases. Population density has a positive correlation with per-mile CO_2 emissions for densities below 2,000 persons km^{-2}, above which increasing density correlates negatively with per-mile emissions.

Introduction

The transportation sector comprises 33% of U.S. greenhouse gas emissions.[1] On-road sources (i.e. excluding aviation and rail) account for 28% of total U.S. CO_2 emissions.[1] The largest component of vehicle greenhouse gas (GHG) emissions is CO_2 generated by the combustion of motor gasoline and diesel fuel. CO_2 emissions contribute to global climate change[2], but the United States has yet to formulate a coherent national policy to mitigate domestic emissions of greenhouse gases. In the absence of national policy, states have pursued their own abatement initiatives such as the Regional Greenhouse Gas Initiative (RGGI) and California's Global Warming Solutions Act.[3] Both policies set emissions reduction targets for power plants and other point sources, but California's also sets future fuel economy standards for vehicles. Regulating transportation sector carbon emissions presents a unique challenge, as sources' mobility results in a change in the spatial distribution of emissions over time. A prerequisite for regulating mobile emissions is therefore accurate, spatially explicit emission inventories which serve to establish the baseline level of GHGs and validate the extent of sources' compliance with abatement targets. This remains incomplete for the on-road sector, and is the contribution of this paper.

In addition to their value for treaty and regulatory compliance, emissions inventories play a vital role in the calibration of general circulation models used to understand and predict global, national and regional climate and ecosystem dynamics. The temporal and spatial distribution of anthropogenic emissions is a fundamental input to most terrestrial carbon cycle models and is typically obtained from emissions inventories developed at a variety of scales using multiple data sources.[4,5] Reducing uncertainties in emission inventories remains an important challenge, and is considered essential for improving the accuracy of regional carbon cycle models.[6-10]

Uncertainty in the spatial and temporal distribution of emissions can produce significant variations in estimates of carbon sequestration in the terrestrial biosphere.[7,8] Gurney et al.[11] compared the results of an atmospheric inversion model estimating net ecosystem carbon exchange (NEE) using the 10 km resolution Vulcan emissions product with results from the same model using a 1° resolution emissions product,[12] and found differences on the order of 100% in local estimates of NEE between the two models. This is on the same order as the uncertainty associated with CO_2 emissions estimates based on directly measured CO_2 concentrations from sampling towers,[10] unacceptably high given these models' critical importance. Emissions inventories were initially developed as accounting exercises based on national fossil fuel consumption. Typically, national statistics on fossil fuel consumption are used to estimate carbon emissions and the results are downscaled to higher spatial resolution using proxies to distribute the emissions across a grid. For example, in the Emissions Database for Global Atmospheric Research (EDGAR) produced by the European Commission, Joint Research Center,[13] on-road emissions are spatially allocated using road density as a proxy. A key limitation to this approach is its assumption of a fixed relationship between emissions and the proxy, whereas the correlation between road density and actual emissions is likely to vary widely across roadway types and between rural and urban areas. Vehicle miles travelled (VMT) has been observed to vary significantly across roadway types and VMT is highly correlated with CO_2 emissions from vehicles.[1,14] Thus, while EDGAR offers a time series of emissions spanning 1975 to 2008, trends in its spatial distribution of on-road CO_2 emissions may be biased by trends in the proxy variable that are weakly correlated with the true spatial pattern of vehicle emissions.

The Vulcan Project[15] produced a high-resolution map of hourly U.S. carbon emissions for the year 2002. Its on-road emissions are derived from mostly state-level estimates of VMT, which were downscaled to the county level and allocated to a GIS Road Atlas using a combination of population density and road density. This method allows for broad spatial coverage for the inventory, but does not account for variations in the spatial distribution of travel demand within counties. Using state-level source data greatly improves the spatial accuracy of on-road emissions relative to EDGAR, but on-road emissions estimates from Vulcan are only available for a single year. Vulcan does report total emissions for the years 1999-2008 at the state/county level but does not break these out by sector. This temporal limitation precludes analysis of trends in the spatial distribution of emissions across time, and requires researchers to use scaling factors to back out emissions in subsequent years.

Several researchers have made improvements to the spatial resolution of emissions estimates by incorporating local data sources. Brondfield et al.[16] developed a model that used impervious surface area (ISA) and volume-weighted road density to estimate CO_2 emissions for eastern Massachusetts on a 1km grid. They used linear regression to model the relationship between these scaling factors and emissions estimates generated at the scale of Traffic Analysis Zones (TAZ) by the regional Metropolitan Planning Organization. They also modeled emissions estimates from the Vulcan Product, and found that both TAZ and Vulcan emissions could be well represented by ISA and volume-weighted road density. By incorporating locally-sourced data, Brondfield et al.[16] were able to construct a high resolution emissions inventory that avoided using coarser spatial proxies, but their estimates were still limited by the spatial and temporal extent of both source and proxy data.

Gurney et al.[17] used a large database of local traffic data to downscale Vulcan on-road emissions for the City of Indianapolis to the level of individual roadways. By combining a high-resolution map of the local road network with traffic counts provided by the local MPO they were able to assign hourly carbon emissions to each road in the city. The use of local data on traffic flows to spatially allocate on-road emissions reduces the uncertainty associated with downscaling county or state level data to such high resolutions. Despite the richness of the local data, the control totals are still drawn from Vulcan's downscaled state-level VMT.[17] Our premise is that uncertainty in spatial imputation of on-road emissions due to downscaling can be substantially reduced by using source data for VMT available at roadway scales.

Unlike Vulcan, which uses downscaled state-level VMT from the National County Database (NCD),[18] in this study we make use of roadway-level traffic volumes and road characteristics obtained from archived raw data of the Highway Performance Monitoring System HPMS.[19] We construct estimates of on-road CO_2 emissions for the state of Massachusetts on a 1km grid for the years 1980-2008. We chose Massachusetts as an initial case study because it has per-capita on-road CO_2 emissions similar to the national average, a recent state-wide greenhouse gas inventory[20] is available for comparison, and the state has made freely available a GIS layer of the complete road network for mapping purposes.[21] We also believe Massachusetts is a suitable example to demonstrate our methodology as it contains a wide range of land-use types, population densities and road network densities, all contained within a spatial extent that does not exceed reasonable computational requirements. As our plan is to extend our analysis to other states, we have kept our methodology as simple and as flexible as is reasonably possible, and limited our model's data requirements to publicly available sources. We expect that the only modifications required to extend this work to other states will be the partitioning of the model domain to avoid exceeding available computational resources.

The broad temporal scope of our data permitted the construction of a time series of emissions estimates at high spatial resolution, which allowed us to analyze trends in on-road emissions across space and time, and to compare our results with other inventories. Since our estimates do not rely on spatial proxies such as population density or road density, we were able to conduct a full cross-section/time-series panel regression of population density on vehicle emissions at the scale of local towns (for Massachusetts, approximately census tracts). Our analysis is valuable in the context of urban planning, as the intensity of emissions is likely to be strongly correlated with characteristics of the built environment such as household and population density, jobs-housing balance and the diversity of land uses.[22,23] To accurately quantify the relationship between these variables and emissions it is necessary to characterize vehicle emissions at the same spatial scale as the built environment while minimizing reliance on the variables of interest as proxies for spatially allocating the emissions estimates. By doing this, our method provides the wherewithal to investigate the co-evolution of emissions, population, income, and land uses.

Methods and Data

We combined data on average daily traffic volumes with the distribution of vehicle miles travelled among different vehicle types to estimate average annual per-mile CO_2 emissions for each roadway section in the state of Massachusetts. We summarize our methodology below. A full description is available in the Supplementary Information.

Our main data source is average daily traffic volumes reported for each road section in the Highway Performance Monitoring System.[19] The HPMS is a roadway-scale national database managed by the Federal Highway Administration (FHWA) that contains data on annual average daily traffic volumes (AADT) and centerline mileage for all Federal-Aid roads and most other major and minor roads. For all road sections in the Massachusetts HPMS we calculated annual vehicle miles travelled (VMT) as the product of AADT and road length in miles, multiplied by 365. The AADT values in HPMS have already been adjusted to account for seasonal and day-of-the-week variations as per the submission requirements of HPMS.[24]

The roadway-scale HPMS data does not include all of the VMT that occurred on local roads. To impute Massachusetts total VMT, it was necessary to use a partial downscaling approach only for local road VMT. We used state-level data on minor and local road VMT from FHWA[25] and distributed it by county using each county's fraction of total state VMT as calculated from the HPMS roadway-level dataset for each year. HPMS road sections are not explicitly geocoded, but do contain codes for county, urban/rural context and HPMS functional class.[24] In order to assign our roadway-level VMT to a spatial location, we were therefore required to aggregate our data to the county level, partitioned by functional class and urban/rural context.

Since vehicle emission rates are a function of fuel type,[26] we estimated diesel and gasoline fuel consumption by functional class and urban/rural context within each county. Our first step was to distribute annual vehicle miles travelled amongst five different vehicle types: passenger cars, passenger trucks (includes SUVs, vans and pickup trucks), buses, single-unit trucks and combination trucks. State-level data on the distribution of VMT among different vehicle types is available for the years 1993 through 1999 and for 2009 and 2010.[27] For model years 1999 through 2008 we interpolated linearly between the state-level distributions for 1999 and 2009; for years prior to 1993, we applied the 1993 distribution for all years. Our vehicle type distribution accounts for variation in the types of vehicles on different types of roads by assigning different distributions for six different functional classes of road, three rural and three urban.[27] This captures the variation in the composition of traffic on different classes of roads and between urban and rural areas.

We used the national average fuel economy for each vehicle type for each year[14] to estimate fuel consumption for each roadway functional class, county and year. Fuel consumption was calculated by dividing distance travelled by average fuel economy. Fuel consumption was converted to CO_2 emissions using the emission factors of 8.91 kg CO_2 per gallon gasoline and 10.15 kg CO_2 per gallon diesel fuel.[26] Emissions from both fuels were aggregated to obtain total emissions for each functional class of road at the county scale.

Emissions were assigned to a road network using the 2009 GIS Road Inventory provided by the Massachusetts Department of Transportation.[21] We calculated the total centerline mileage of each functional class of road in each county, and then divided our relevant CO_2 emissions by this mileage to generate average per-mile CO_2 emissions. These average per-mile emissions were then assigned by functional class, urban/rural context and county to the road network for each year in the study period.

For comparability with prior estimates, we aggregated our roadway-scale emissions to multiple scales: a 1km grid, a 0.1 degree grid, and summed to the level of local towns.

Results and Discussion

Using our HPMS data model, we produced on-road CO_2 emissions estimates at the scale of towns, and at a 1 km and 0.1 degree grid for Massachusetts for the years 1980 through 2008. The 1 km gridded results show the strong influence on emissions of major urban areas as well as both urban and rural interstates and highways (figure 1).

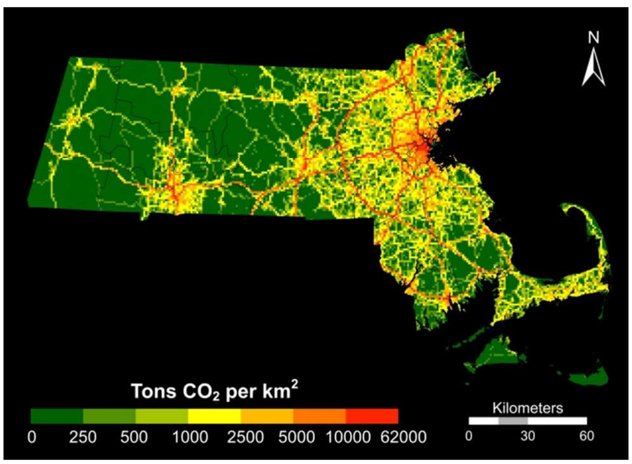

Figure 1. 1 km gridded on-road CO_2 emissions (metric tons CO_2) estimated by HPMS-based model for the year 2008.

We compared our total state-wide estimates to the estimates produced by EDGAR, Vulcan, the Massachusetts Greenhouse Gas Emissions Inventory (MGGEI),[20] the National Emissions Inventory (NEI),[28] the EPA's Motor Vehicle Emission Simulator (MOVES),[29] and with emissions estimates derived by applying emissions factors[26] to statewide fuel consumption reported by FHWA[30] (figure 2). We found that EDGAR emissions estimates significantly exceeded FHWA estimates, our model estimates, and most other inventory products. Since we assume the

FHWA fuel consumption data to be the closest to actual “ground-truth” for statewide on-road CO_2 emissions, it is of concern that EDGAR estimates exceed these values by as much as 9.3 million tons, or more than 33%, and systematically exceed FHWA estimates by an average of 22.8% across the study period. The EDGAR emissions are closest to the MGGEI. However, the discrepancy may be accounted for by the fact that the MGGEI emissions represent the entire transportation sector,[20] including emissions associated with rail and air transportation that are absent from other inventories.

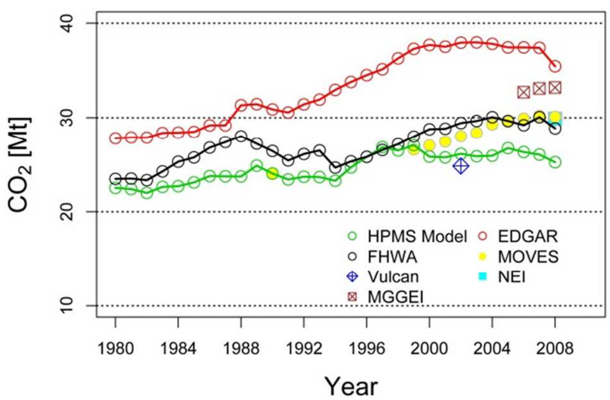

Figure 2. Comparison of total Massachusetts on-road CO_2 emissions estimates from our HPMS model with EDGAR, FHWA, MOVES, Vulcan, MGGEI and NEI inventories. Emissions for FHWA estimated using emissions factors for fuel combustion from Energy Information Adminstration.[26]

Our HPMS-based model is in better agreement with the FHWA estimates, but does show a systematic under-prediction. The best fit between our model and FHWA data is for the years that we used state-level data for distribution of VMT among vehicle types (1993-1999).[27] In the years that we estimated this distribution, our model show larger deviations from FHWA, which suggests that our estimated distribution may underestimate the miles travelled by lower fuel economy vehicles during those years. It is also possible that FHWA overestimates the amount of fuel that is consumed by drivers in the state, since state totals are derived from the volumes of fuel sold—but not necessarily consumed—within the state’s boundaries. This discrepancy is likely to be larger in states such as Massachusetts, which have both a small areal extent and substantial cross-border traffic flows.

Our model also exhibits generally good agreement with results generated by the EPA MOVES software for 1990 and 1999, but diverges in later years where MOVES estimates are observed to match the trend in FHWA estimates. We ran the MOVES software for the state of Massachusetts using the built-in default values for fleet age and vehicle type distribution. The trend in our estimates matches that in MOVES, which suggests that both models are capturing the same underlying processes that drive changes in emissions.

The divergence of our estimates from EDGAR and FHWA are fundamentally explained by their underlying methodological differences. EDGAR's use of a national emission control total in conjunction with road density as a downscaling proxy,[31] combined with the fact that Massachusetts has the third-highest road density of all U.S. states,[32] tends to bias its estimates upward. Symmetrically, for states with lower than average road densities EDGAR will tend to systematically under-predict emissions relative to inventories calibrated to state-level data.

The EDGAR emissions product plays an important role in carbon cycle modeling, as many inverse atmospheric models, such as CarbonTracker,[4] use EDGAR as an input term in the calculation of terrestrial carbon fluxes. Spatial misallocation of anthropogenic emissions introduces error to these models, and may bias estimates of carbon storage in terrestrial ecosystems.[11] A key implication of our results is that out of an abundance of caution, future U.S.-focused regional- or national-scale carbon-cycle modeling studies would be well advised to compare EDGAR's regional estimates to FHWA's state-wide fuel consumption estimates, which are available from 1980 to present, and provide a simple validation of on-road CO_2 emissions at the regional scale.

We next compared our results with on-road CO_2 emissions estimated by Vulcan and the EDGAR inventory (figure 3) for the year 2002, the only year for which all three inventories generate on-road CO_2. When summed to total statewide emissions, we find good agreement between our model and Vulcan: 26,127,254 tons CO_2 for HPMS and 24,838,683 tons CO_2 for Vulcan, a difference of roughly 5%. This is an improvement compared to the EDGAR product, which estimates total emissions of 37,942,510 tons CO_2 in the year 2002, 45% greater than our HPMS estimates and 53% greater than Vulcan. We also calculated cell-by-cell differences between HPMS and Vulcan, which show a mean difference of 6,190 tons. Difference maps and additional details are available in the Supplemental Information.

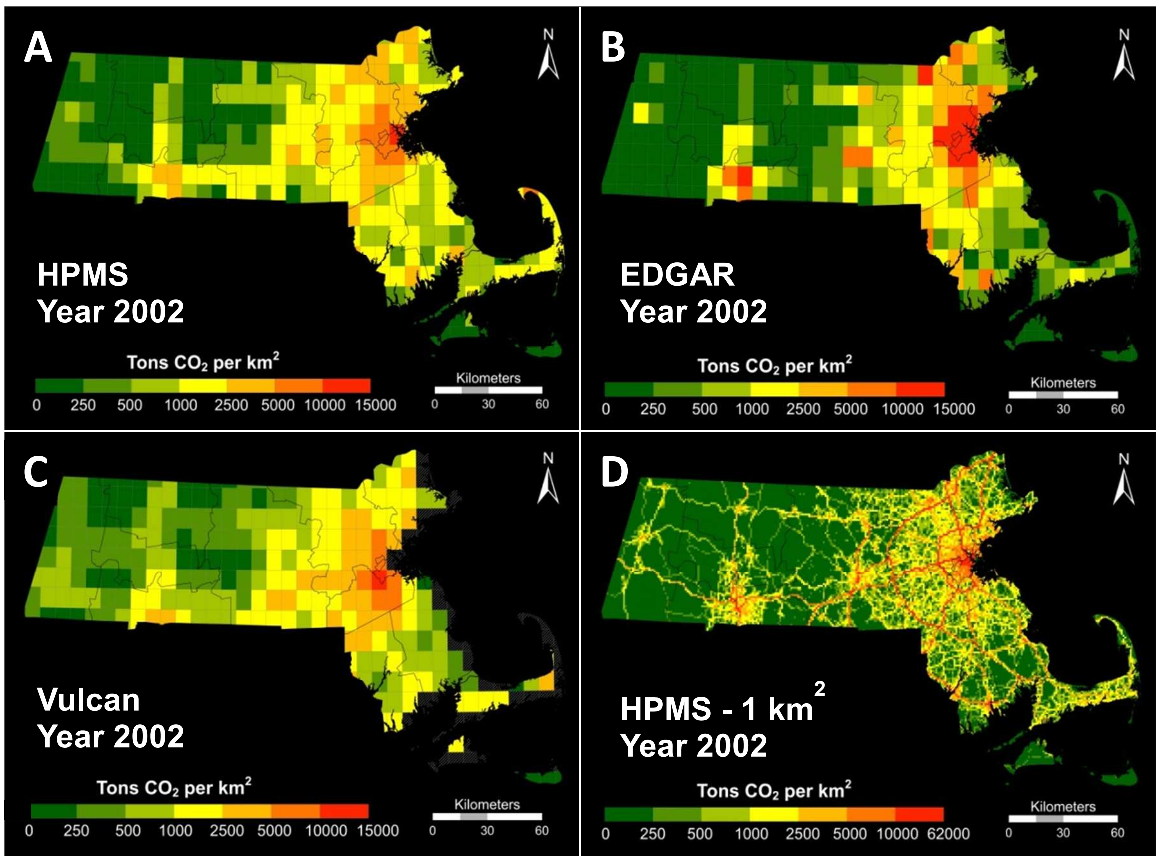

Figure 3. Comparison of CO_2 emission inventories for Massachusetts at 0.1 degree grid scale. Panel A shows HPMS-based estimates, Panel B shows EDGAR Product estimates, Panel C shows Vulcan Product estimates. Panel D shows HPMS-based estimates at 1 km grid scale. Note the difference in the highest legend value for the 1km^2 estimates versus the 0.1 degree estimates. This is a demonstration of how aggregation to the 0.1 degree scale masks the

presence and location of the significantly higher emissions intensities that are present in the cores of urban areas.

Despite the good aggregate correspondence between our results and Vulcan, we observed differences between all three models in the spatial allocation of emissions (figure 3). The EDGAR product shows emissions declining relatively sharply outside the densest urban areas in eastern Massachusetts and the Springfield Urbanized Area in the south-central part of the state. Vulcan shows the most gradual decline in emissions moving from dense urban areas to less dense suburban and rural areas, while our HPMS-based emissions inventory falls between EDGAR's and Vulcan's urban-rural emission gradients. Per our discussion above, EDGAR's spatial distribution of emissions corresponds tightly to the spatial extent of the road network, but, crucially, its estimates do not distinguish either roads' functional classes or their rural-urban context, both of which are predictors of traffic patterns. Vulcan partially addresses this issue by using a combination of population density, road density, and functional class to spatially allocate CO_2 emissions. In urban areas Vulcan emissions correlate well with both our model and with the EDGAR product. However Vulcan distributes rural VMT by roadway class in each county using the county's share of total state rural-area population.[18] Given that only five counties comprise nearly all of the predominantly rural western and central parts of Massachusetts, each spatial unit represents a sizeable share of total state rural population. And, since Vulcan assigns rural VMT uniformly across each road type within a county, it is likely that some areas are assigned VMT in excess of that actually occurring on their constitutent local roads. This explanation is consistent with Vulcan's higher emission values in grid cells in the rural western areas of the state compared to non-population based techniques. Our 1km resolution estimates (Figure 3D) show clearly the underlying Massachusetts road network and the consequent sparseness of emissions in the western part of the state. For both our model and EDGAR, rural-area emissions only exceed 250 tons CO_2 per km^2 in areas that contain large freeway segments. To recapitulate, it seems likely that Vulcan over-allocates CO_2 emissions to rural roads in Massachusetts, a result which is consistent with other recent findings.[16,33]

Sources of Uncertainty

We take pains to elaborate two potentially significant sources of uncertainty in our HPMS model: uncertainty associated with the values of AADT reported by HPMS and uncertainty in our fuel economy estimates of each vehicle type. Uncertainty in the fuel economy of each vehicle type arises from variation in the average travel speed of each vehicle and from variations in vehicle age. Older model-year vehicles tend to have lower fuel economy than newer ones, due to tightening of the Corporate Average Fuel Economy (CAFE) standards over the period of our sample.[34] As well, fuel economy is substantially reduced by travel at lower speeds, as occurs when traffic flow is congested. This effect also varies by vehicle type.[35] Our ability to account for local heterogeneity in fuel economy's response to these regulatory changes is limited by our use of a national average fuel economy for each vehicle type, which is averaged across all vehicle ages, all road types, and all travel speeds.[14] Therefore to the extent that the age distribution of vehicles or the level of traffic congestion in Massachusetts diverges from the national average, our model's fuel economy values will be biased. Although the uncertainty associated with the vehicle age distribution for Massachusetts is difficult to estimate without access to data on individual vehicle registrations, a recent study by Mendoza et al.[36] estimated that the impact on fuel economy of variations in vehicle age to be less than 2% for most vehicle types. Data from the most recent Urban Mobility Report[37] indicate that the major urban areas in Massachusetts have levels of congestion similar to the national average. However, given that, first, our model does not directly account for the effects of traffic congestion on fuel economy, and, second, we under-predict FHWA fuel consumption by on average 8.5%, it is reasonable to suspect that some of this difference may be accounted for by this particular uncertainty.

There are two types of uncertainty associated with AADT: uncertainty in actual traffic measurements and uncertainty in estimates of AADT that FHWA impute for roads that are not directly measured. The latter type of uncertainty stems from the practice of using seasonal and geographic factoring to assign AADT from permanent or portable automated traffic recorder stations (ATRs) to similar road links in the network that lack ATR data. Several researchers have used state data to estimate this uncertainty. Ritchie[38] estimated uncertainties in factored AADT of 7-18 % for Washington State. Gadda et al.[39] found average uncertainties of 12-14% for Minnesota and Florida roads. The FHWA Guidelines for Data Quality Measurement[40] set uncertainty targets of less than 10% mean absolute error for most road classes in HPMS.

Mendoza et al.[36] use reported confidence interval and precision estimates from the HPMS Field Manual[24] to estimate one-sigma percent uncertainties for HPMS reported AADT that range from 3.04% to 7.8% depending on functional class. One-sigma uncertainties are roughly equivalent to a 68.3% confidence interval. To evaluate the impact of AADT uncertainty on our model results, we calculated upper and lower bound estimates of AADT for each road section using both a one-sigma percent difference and a two-sigma percent difference. Two-sigma uncertainties (equivalent to a 95.4% confidence interval) were obtained by doubling the one-sigma values reported by Mendoza et al.[36] Using these higher and lower AADT values our model generated CO_2 estimates that ranged from ±7.4% to ±7.6% for one-sigma differences in AADT and from ±14.7% to ±15.2% for two-sigma differences, relative to our original estimates. Both ranges are in general agreement with the micro-level studies cited above, and give us additional confidence in the veracity of our estimation procedure. As well, the upper boundary estimates encompass the values for FHWA emissions for most but not all of the years of this study. Further details are included in the Supplemental Information.

Analysis of On-road CO_2 Emissions and Population Density

A key issue in the debate over how to reduce on-road CO_2 is the nature of the relationships between emissions and VMT, and between VMT and other features of the built environment such as the density of roads, residences and commercial activity. These issues have been the subject of intensive study for several decades, with recent work focusing on the influence of road infrastructure,[41-43] the effect of fuel prices and vehicle fuel economy[44,45] and the influence of land-use, population density and other demographic factors.[46-48] A recent National Research Council investigation[22] found that the majority of studies report an inverse relationship between VMT and population density, with VMT decreasing by 5% to 12% given a doubling of population density.[22] Quantifying the effect on VMT of changes in population density is important, as it informs policymakers considering planning policies such as infill development or lot-size restrictions that aim to reduce vehicle CO_2 emissions by traffic in and around large urbanized areas.

To accurately characterize the effects of population density on CO_2 emissions, it is necessary to account for trends in these variables across both time and space. As our method for estimating emissions does not rely on population density as a spatial proxy, we were able to use the results of our emissions inventory to conduct a cross-sectional time-series regression analysis of CO_2 on population density at the scale of local towns. We used population data for each of the 351 Massachusetts towns for the years 1980 through 2008, as reported by the Massachusetts Department of Revenue.[49] We aggregated our emissions estimates to the town scale and normalized CO_2 emissions by dividing them by the total length of roads in each town. We ran a panel regression of CO_2 mile^{-1} on population km^{-2}, estimating town and year fixed effects for the whole dataset. The town fixed effects capture heterogeneous unmeasured influences on emissions that are unique to the spatial area covered by each town, such as the spatial structure of the road network or local zoning practices, but which are stable across time. The year fixed effects represent exogenous impacts that affect all towns in the sample but vary over time, such as changing demand for travel and VMT, and trends in unmeasured economic variables such as fuel prices and income. We employ a semi-parametric stratification of our estimates by population density to allow the marginal effect of population density on emissions to vary with different densities. Our model showed excellent goodness-of-fit with an R^2 value of 0.93 and a statistically significant negative correlation between population density and CO_2 emissions per mile of roadway.

To evaluate whether the sign and magnitude of the relationship between emissions and population density changes across different levels of density, we pooled our population density data and used the estimated regression coefficients to predict CO_2 emissions over the range of observed densities. The general functional form of the relationship is characterized as a sequence of linear splines, each with its own confidence interval (figure 4). As the data are pooled across all towns and years, each spline segment represents the common marginal impact of density in a collection of different towns in different years. The shape of the curve in figure 4 reflects the effect of increasing population density on CO_2 emissions, independent of the year- and town-fixed effects.

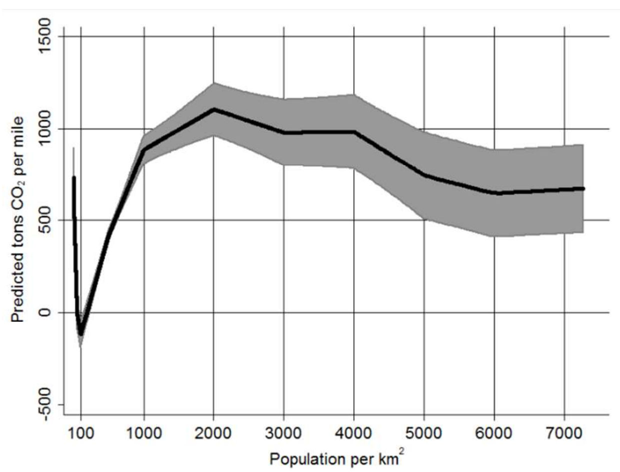

Figure 4. Plot of predicted CO_2 emissions per mile vs. population density, with town and year fixed effects excluded. Observations are pooled across all towns and years. Grey area represents extent of 95% confidence intervals.

Population density is positively correlated with vehicle emissions at densities less than 2000 persons km^{-2}. However, above this level the correlation becomes negative, and emissions decline slowly until densities exceed 4000 persons km^{-2}, and then more rapidly thereafter.

These results suggest that it is only at the higher population densities associated with dense, urban-core towns that we would expect to see on-road emissions decline with rising density. For lower-density towns, increasing population density is more likely to result in an increase rather than a decrease in vehicle emissions occurring within the town. This result may be a consequence of adding new resident-drivers to the roads, or an indirect effect of denser development drawing more travelers into the area from neighboring towns. Since our emissions estimates only consider the emissions that occur within each town's boundary, we cannot distinguish emissions emitted by residents of the town versus those emitted by drivers from other towns.

Our estimates reflect emissions generated by four different categories of vehicle travel: (1) trips that occur entirely within the given town; (2) trips that originate in the town and terminate outside the town; (3) trips that originate outside the town and terminate within the town; and (4) trips which pass through the town, but start and end elsewhere. We would expect a town's population density to have a stronger direct effect on emissions from categories 1 and 2 and a weaker effect on emissions from categories 3 and 4. That is, higher local population density should reduce per capita vehicle emissions by reducing VMT by the residents of the town, both for trips within the town (category 1) and trips outside the town (category 2). This effect could be generated by increasing the availability of trip destinations such as employment or retail centers or by induced shifts to alternative modes of travel such as walking, bicycling or public transit.

Density's impact on category-3 trips is less straightforward, as a town with high density may draw vehicle trips from neighboring towns if it contains destinations that attract these trips. Indeed in urban areas the availability of trip destinations has been shown to be a stronger predictor of VMT than population density.[23,46] Across the state, we would expect this effect to vary depending on local relationships between population density and destination availability. Emissions from category-4 trips are probably influenced more strongly by the nature of the road network that transits the town than by the town's population density. We expect this effect to be most pronounced in the rural towns containing sections of interstate highway in the western part of the state, and this is reflected in the higher marginal impact of density close to the origin in Figure 4. Disentangling the proportions of total emissions that originate from the four categories listed above requires a far more data-intensive process of conducting a full traffic assignment using origin and destination survey data for the entire road network, which is a task that we leave for future research. Nevertheless, our results still show clearly that population density influences on-road emissions through a combination of direct and indirect pathways, with high density towns showing a decrease in per-mile CO_2 emissions relative to low density towns. That this decrease is only observed in towns above a relatively high density threshold highlights the potential magnitude of the indirect effects of density described in category 3, and suggests that at low to medium densities, the attraction of vehicle trips from surrounding towns may counteract the decline in per-capita emissions caused by increased local density.

These results highlight the value of using an emissions inventory with high spatial and temporal resolution. At coarser spatial scales, much of the variation in population density and on-road emissions between towns is lost in the aggregation to larger grid cells. By preserving this local variation, and by generating emissions estimates that did not rely on population density as a proxy for spatial allocation, we were able to highlight the shape of the response surface between on-road CO_2 emissions and population density at the scale of local municipalities in Massachusetts. Lastly, our finding of a highly nonlinear relationship between bottom-up emission estimates and a spatially-varying proxy variable used in prior studies highlights the potential pitfalls of relying on linear predictors in the construction of downscaled emission inventories.

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Supporting Information: Contains detailed methodology, panel regression statistics, and additional figures. This material is available free of charge via the Internet at http://pubs.acs.org.

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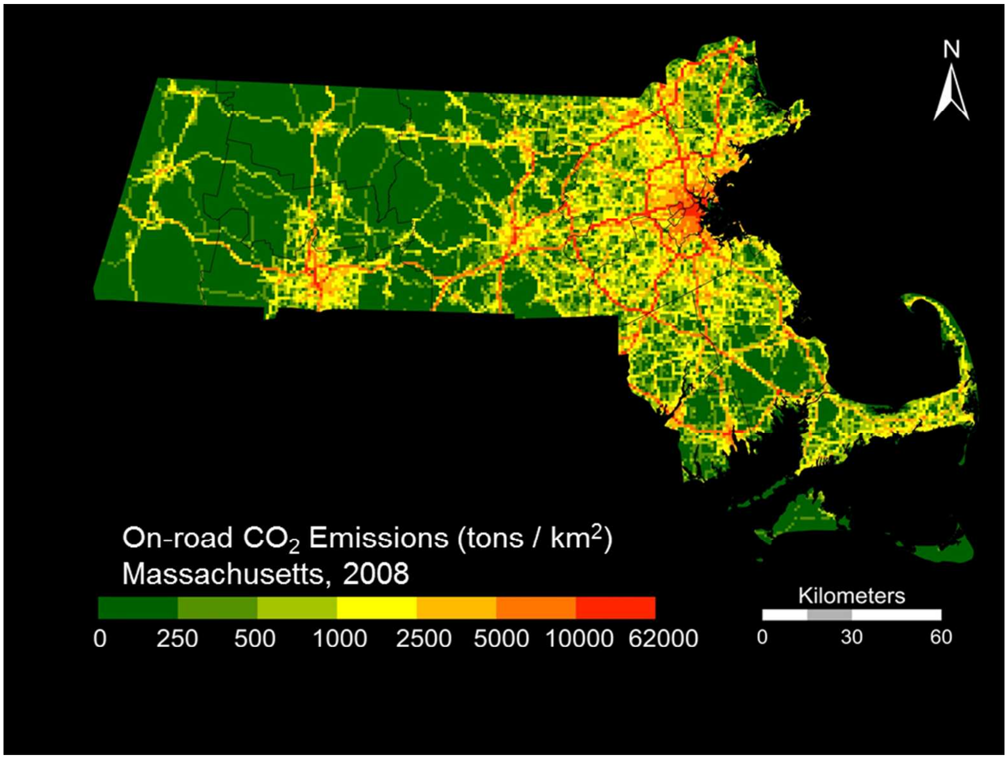

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