Energy Policy 55 (2013) 386–395

Contents lists available at SciVerse ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Implications of uncertainty on regional CO_2 mitigation policies for the U.S. onroad sector based on a high-resolution emissions estimate

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HIGHLIGHTS

- State-level biases of road groupings are twice as large as biases of vehicle groupings.
- State-level fleet composition is a large driver of the biases.
- Emissions uncertainty is driven by uncertainties in VMT and fuel efficiency and less by fleet composition variation.
- Errors of $\pm 60\%$ corresponding to ± 0.2 MtC at the state level for 10% emissions mitigation when using national averages.
- Recommendations are made on reducing uncertainty in onroad CO_2 emissions.

ARTICLE INFO

Article history:
Received 27 March 2012
Accepted 5 December 2012
Available online 3 January 2013

Keywords:
Transportation CO_2 emissions
Transportation emissions bias and uncertainty
Transportation sector policy

ABSTRACT

In this study we present onroad fossil fuel CO_2 emissions estimated by the Vulcan Project, an effort quantifying fossil fuel CO_2 emissions for the U.S. in high spatial and temporal resolution. This high-resolution data, aggregated at the state-level and classified in broad road and vehicle type categories, is compared to a commonly used national-average approach. We find that the use of national averages incurs state-level biases for road groupings that are almost twice as large as for vehicle groupings. The uncertainty for all groups exceeds the bias, and both quantities are positively correlated with total state emissions. States with the largest emissions totals are typically similar to one another in terms of emissions fraction distribution across road and vehicle groups, while smaller-emitting states have a wider range of variation in all groups. Uncertainties in reduction estimates as large as $\pm 60\%$ corresponding to ± 0.2 MtC are found for a national-average emissions mitigation strategy focused on a 10% emissions reduction from a single vehicle class, such as passenger gas vehicles or heavy diesel trucks. Recommendations are made for reducing CO_2 emissions uncertainty by addressing its main drivers: VMT and fuel efficiency uncertainty.

1. Introduction

Global warming is a leading environmental challenge currently faced by the world. Carbon dioxide (CO_2) is the most abundant anthropogenic greenhouse gas and projections of fossil fuel energy demand show CO_2 concentrations increasing indefinitely into the future (Denman et al., 2007).

After electricity production, the transportation sector is the second largest CO_2 emitting economic sector in the United States, accounting for 32.3% of the total U.S. emissions in 2002 (Gurney et al., 2009). Over 80% of the transportation sector is composed of onroad emissions, with the remainder of emissions shared by the nonroad, aircraft, railroad, and commercial marine vessel transportation (United States Environmental Protection Agency, 2011b).

No national policy exists to regulate greenhouse gases in the United States, but legislation has been passed in the European Union to reduce fossil fuel CO_2 emissions from the transportation sector (Council of the European Union, 2009). Though CO_2 is not declared a pollutant in the US, its increase has been deemed a threat to the "public health and general welfare of current and future generations" and the passage of climate mitigation measures seems imminent (United States Environmental Protection Agency,

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http://dx.doi.org/10.1016/j.enpol.2012.12.027

2009). Some states and localities, such as California, have passed emission reduction regulations independent of national policy-making (California Air Resources Board, 2009). Both national and local legislation have recognized the importance of the transportation sector. Because localities have considerable control over transportation planning and policy, interest in the potential of the transportation sector to offer effective mitigation options is increasing on both local and national levels (Vadas, 2007).

In order to construct effective mitigation policies for the onroad transportation sector and more accurately predict CO_2 emissions for use in atmospheric transport models and measurements, analysis must incorporate the dominant components that determine onroad transport CO_2 emissions. These include, but are not necessarily limited to, vehicle miles traveled (VMT) and vehicle fuel efficiency. Furthermore, effective policy must be based upon directly quantified CO_2 emissions with local granularity—municipal, city, or county levels and hourly timescales—while simultaneously linking to national scale systems. This enables strategies such as improved fuel efficiency to be undertaken and progressively monitored at both national and local levels (Fuller et al., 2009; United States Congress, 2009; United States Environmental Protection Agency, 2005). Due to the ability of localities to institute policy, emission reduction approaches must accommodate the particular needs of a community.

Studies to date, have either focused on only one of these three components, have been completed only at the national scale, or have not explicitly represented CO_2 emissions (Puentes, 2008; Southworth et al., 2008; Stone et al., 2009).

Southworth et al. (2008) analyzed VMT and CO_2 emissions for the 100 largest metropolitan areas in the U.S. but only disaggregated vehicles into trucks and passenger cars and used a single national estimate of vehicle fuel efficiency for each of the two vehicle types. Furthermore, the heterogeneity of emissions in space was not fully addressed, as there was no disaggregation by road type. Finally, only 100 metropolitan areas were studied, which accounted for only about 65% of the total U.S. population at the time of the study.

Puentes (2008) presented a thorough analysis of national-level VMT from 1966 to 2008 and further subdivided the analysis into vehicle classes, road classes and the largest metropolitan areas. While this study explored VMT in detail, there was no analysis of CO_2 emissions.

Stone et al. (2009) discussed the impact of Hybrid Electric Vehicle (HEV) introduction on urban mobile CO_2 emissions. The study involved a sample of eleven cities located in six states in the Midwestern United States. However, the study assumed there was no variation in the vehicle fleet across the six states and hence, the vehicles had the same CO_2 emissions per mile of travel.

In this paper, we overcome many of the previous limitations by analyzing onroad CO_2 emission differences between a new, high-resolution emissions data product and a "low-resolution" or "national-average" approach, typical of previous studies. Our aim is to demonstrate the quantitative impact of a highly-resolved approach on emissions estimation and mitigation in the U.S. onroad transportation sector. We perform this analysis at the state spatial scale and disaggregate results by road, vehicle, and fuel classifications. In Section 2, we describe the methodology used in constructing both the high-resolution and national-average approach in addition to uncertainty quantification. In Section 3, we compare the high-resolution results to the national-average approach, quantifying the onroad CO_2 emissions bias resulting from using a national-average approach. Section 4 discusses the implications of this study for constructing national and regional policies for mitigating onroad CO_2 emissions. We also make a series of recommendations to lower and better quantify the uncertainty associated with our high-resolution emissions data product.

2. Methodology

2.1. Data

The onroad CO_2 emissions analyzed here are a product of the Vulcan Project, an effort aimed at quantifying hourly fossil fuel CO_2 emissions for the entirety of the United States at fine space/time resolution (Gurney et al., 2009). The onroad mobile emissions are constructed from a series of existing databases and modeling efforts to generate CO_2 emissions for the year 2002 at the spatial scale of a U.S. county every hour for the entire U.S. Further spatial allocation is performed in order to place these emissions onto U.S. roads and onto a common 10 km $\times$ 10 km spatial grid.

The Vulcan 2002 emissions data product is used for this analysis, as it is currently the only product available at this resolution, as the multiyear product is still forthcoming. Changes in composition and characteristics of urban and rural transportation, as well as LD and HD fleet makeup, have predictably occurred throughout the U.S. since the 2002 product was established. With respect to this fact, this paper aims to emphasize the potential biases and uncertainties that can be calculated from the distributions inherent to a particular year and is not intended to reflect contemporary conditions. The calculations and methodology are presented to highlight the importance of using localized data for accuracy in terms of emissions estimates as well as policy formulation.

2.2. Emissions calculation

The Vulcan onroad transportation emissions calculation utilizes the total vehicle miles traveled (VMT) from the National Mobile Inventory Model (NMIM) County Database (NCD) in which the data is provided for each combination of 28 vehicle types, 6 road types, county, and month (see Appendix A for details).

To obtain onroad transportation CO_2 emission factors (grams CO_2/mile driven), EPAs MOBILE6.2 onroad combustion model was utilized (Harrington, 1998; United States Environmental Protection Agency, 2001). MOBILE6.2 calculates CO_2 emission factors for each vehicle type based on fuel carbon content (grams CO_2/gallon of fuel), a vehicle fuel efficiency (miles/gallon of fuel), a vehicle age distribution, and a carbon oxidation factor (% oxidation) (see Appendix A for details). The product of VMT and corresponding CO_2 emission factor yields the county CO_2 emissions for each road and vehicle type combination. This can be expressed as

$$C_c^{v,x} = VMT_c^{v,x} \times CF^v \tag{1}$$

where $C_c^{v,x}$ is the CO_2 emissions for vehicle type V on road type X in county C; $VMT_c^{v,x}$ is the total vehicle miles traveled in county C, for vehicle class V and road type X; and CF^v is the CO_2 emission factor (mass of CO_2/mile) for vehicle type V. Each county-specific fleet is therefore defined by the combination of the vehicle type mix and their respective VMT.

2.3. Comparison method

In order to compare results from the Vulcan high-resolution emissions data product to a "low-resolution" or "national-average" approach, we estimate state level emissions by creating average CO_2 emissions factors for aggregate vehicle and road type groups. Vehicles are grouped into either a light-duty (LD) or heavy-duty (HD) vehicle group (all fuels combined) and an urban or rural road group (see Appendix A for details). All groups are analyzed at the U.S. state spatial scale. The national-average approach attempts to reflect the type of analysis typically employed prior to the availability of the Vulcan data product (Southworth et al., 2008; Stone et al., 2009).

The difference between these two approaches can be considered a bias that can be quantified for each of the vehicle and road groups. We attempt to quantify two qualities of this bias: (1) the ratio of the bias from each of the aggregate vehicle and road groups to the CO_2 total in a given state and (2) the ratio of the bias from each of the aggregate vehicle and road groups to the national total group-specific CO_2 emissions. These metrics can be expressed as

$$\Delta S\%_S^G = 100 \times \frac{LEM_S^G - VEM_S^G}{VEM_S} \quad (2)$$

$$\Delta N\%_S^G = 100 \times \frac{LEM_S^G - VEM_S^G}{VEM_N^G} \quad (3)$$

where $\Delta S\%_S^G$ and $\Delta N\%_S^G$ are the percent differences between the Vulcan CO_2 and national-average CO_2 emissions for state S and group G for state and national group-specific totals, respectively. VEM_S^G is the CO_2 emissions for state S and group G obtained from the Vulcan data product; LEM_S^G is the CO_2 emissions for state S and group G obtained from the national-average approach; VEM_S is the total (summed across all groups) CO_2 emissions for state S obtained from the Vulcan data product; VEM_N^G is the national total CO_2 emissions for group G.

Positive values for Eqs. (2) and (3) imply that the national-average approach overestimates emissions relative to the Vulcan estimate, and vice-versa. Eq. (2) quantifies the difference in state-level CO_2 emissions between the national-average approach and the Vulcan estimate for each of the groups relative to the Vulcan state total. Eq. (3) quantifies the difference in state-level CO_2 emissions between the national-average approach and the Vulcan estimate for each of the groups relative to the Vulcan national total. Hence, Eq. (2) provides information about what is driving the biases present at the state-level while Eq. (3) provides information about where across the nation, the biases are most important.

2.4. Uncertainty

There are two central variables in the calculation of onroad transportation CO_2 emissions in the Vulcan system, each with an associated uncertainty. The first is the uncertainty associated with the estimate of VMT. The other is the assignment of the CO_2 emission factor to vehicle class. As shown below, the uncertainties are centered symmetrically about the calculated Vulcan result with an equal magnitude of uncertainty in both the positive and negative directions.

2.4.1. VMT uncertainty

The VMT uncertainty stems from the precision of the measurements and estimates of VMT produced by the FHWA. These estimates may be found in Appendix C of the HPMS Field Manual and are shown in Appendix A, Table A.8 (Federal Highway Administration, 2005). Samples designated at a "90–10" confidence interval and precision level contain VMT estimation within ± 10 percent of the true value, 90 percent of the time. In order to convert these values to a one-sigma VMT variation, the stated confidence interval and precision level were combined into a single estimate of uncertainty as follows:

$$U_X = \frac{V_X}{S_X}. \quad (4)$$

where U_X is the uncertainty percent value associated with road type X; V_X is the percent variation from the true value for road type X (10 for 90–10); S_X is the number of standard deviations within a normal distribution that is within variation V_X of the true value for road type X ("90" for 90–10). In case of road types with missing data, the lowest confidence and precision level (80–10) was used. The VMT uncertainty calculated for each road type using Eq. (4) is shown in Table 1.

2.4.2. Age distribution uncertainty

The CO_2 emission factor per mile driven is derived from the results of the MOBILE6.2 combustion model and is a function of fuel carbon content (grams CO_2/gallon of fuel), a vehicle fuel efficiency (miles/gallon of fuel), a vehicle age distribution, and a carbon oxidation factor (see Appendix A).

The age distribution has an impact on fleet emissions levels due to the fact that for a particular vehicle class, a newer fleet has higher fuel efficiency than does an older fleet, and thus lower CO_2 emissions per mile. However, with the exception of the light-duty diesel vehicle (LDDV) and small light duty diesel truck classes (LDDT12) whose age distribution uncertainties are 2.71 and 4.06%, respectively, none of the age distribution uncertainties exceed 2%. These figures are small compared to the fuel efficiency and VMT uncertainties and are shown in Appendix A, Table A.9.

2.4.3. Fuel efficiency uncertainty

The other source of uncertainty considered for the CO_2 emission factor is the vehicle fuel efficiency or the well-known miles per gallon or "MPG" rating for a given vehicle type and model year (central values provided in Appendix A, Table A.4).

The goal is to quantify how much variation about the mean values presented in Appendix A, Table A.4 is present in a population of drivers operating a particular vehicle class in a particular vehicle age cohort. This translates into asking how much variation is there in the idle time, stop/starts, acceleration rates, etc.

For Vulcan uncertainty estimation, we use the percent difference between the "5-cycle" and "Current EPA Label" estimates obtained from tests performed by the EPA (see Appendix A for details). The percentage difference values are assumed to be symmetric uncertainties (both "hi" and "low") and are considered one-sigma variations. The estimated uncertainties are shown in Table 2.

Table 1
VMT uncertainty levels used in Vulcan defined by road classification.

Road description	***Uncertainty*** (%)
Interstate: Rural	3.04
Other principal arterial: Rural	3.04
Minor arterial: Rural	6.08
Major collector: Rural	7.8
Minor collector: Rural	7.8
Local: Rural	7.8
Interstate: Urban	7.8
Other freeways and expressways: Urban	7.8
Other principal arterial: Urban	7.8
Minor arterial: Urban	7.8
Collector: Urban	7.8
Local: Urban	7.8

2.4.4. Total uncertainty

The uncertainty ranges obtained for VMT, age distribution, and fuel efficiency are then used to estimate extreme-case values for VMT and emissions factors. The total uncertainty is obtained by using these extreme-case values as inputs for Eq. (1), effectively yielding a combined correlated total that represents the maximum or minimum possible emissions for each road and vehicle type, specific to each county. When the extreme-case total is subtracted from the corresponding average emissions total, the absolute result is the total one-sigma emissions uncertainty. The total uncertainty is not additive, and, in fact, has a smaller value than would be expected with an additive total. This is because Eq. (1) forces a multiplicative combination of the fractional changes in VMT and emissions factors that are due to uncertainty.

Table 2
Uncertainty by vehicle class and road category due to one sigma variations in fuel efficiency.

Vclass #	Vclass abbr.	City uncertainty (%)	Highway uncertainty (%)
1	LDGV	14	10
2	LDGT1	13	7
3	LDGT2	13	7
4	LDGT3	13	7
5	LDGT4	13	7
6	HDGV2B	13	7
7	HDGV3	13	7
8	HDGV4	13	7
9	HDGV5	13	7
10	HDGV6	13	7
11	HDGV7	13	7
12	HDGV8A	13	7
13	HDGV8B	13	7
14	LDDV	13	11
15	LDDT12	13	7
16	HDDV2B	13	7
17	HDDV3	13	7
18	HDDV4	13	7
19	HDDV5	13	7
20	HDDV6	13	7
21	HDDV7	13	7
22	HDDV8A	13	7
23	HDDV8B	13	7
24	MC	14	10
25	HDGB	13	7
26	HDDBT	13	7
27	HDDBS	13	7
28	LDDT34	13	7

3. Results

3.1. Onroad fossil fuel CO_2 emissions uncertainty

In order to place the uncertainty of the Vulcan onroad CO_2 emissions in context, we calculate a "normalized" uncertainty for each state. This quantifies uncertainty from each of the uncertainty contributors (VMT, age distribution, fuel efficiency) and from each of the aggregate road and vehicle type groups as a fraction of the state total CO_2 onroad emissions. This can be expressed as

$$\Delta\%_S^{U,G} = 100 \times \frac{HEM_S^{U,G} - VEM_S^{U,G}}{VEM_S} \tag{5}$$

where $HEM_S^{U,G}$ is the high uncertainty Vulcan CO_2 emissions for state S, group G, and uncertainty type U; $VEM_S^{U,G}$ is the central Vulcan CO_2 emissions for state S, group G, and uncertainty type U; VEM_s is the central Vulcan CO_2 emissions for state S. The uncertainty type is either uncertainty due to VMT, age distribution, fuel efficiency, or the combination of all three uncertainty factors. A group represents either the aggregate vehicle type group (HD or LD) or aggregate road type group (rural or urban). The normalized uncertainty is presented in Fig. 1 and a comparison of total state emissions with the corresponding fractional uncertainties is presented in Appendix B, Table B.1.

As specified in the uncertainty construction, the largest contributors to the total uncertainty are the VMT and fuel efficiency uncertainties which are an order of magnitude larger than the Fleet Age uncertainty in all aggregate groups. The LD uncertainty generally

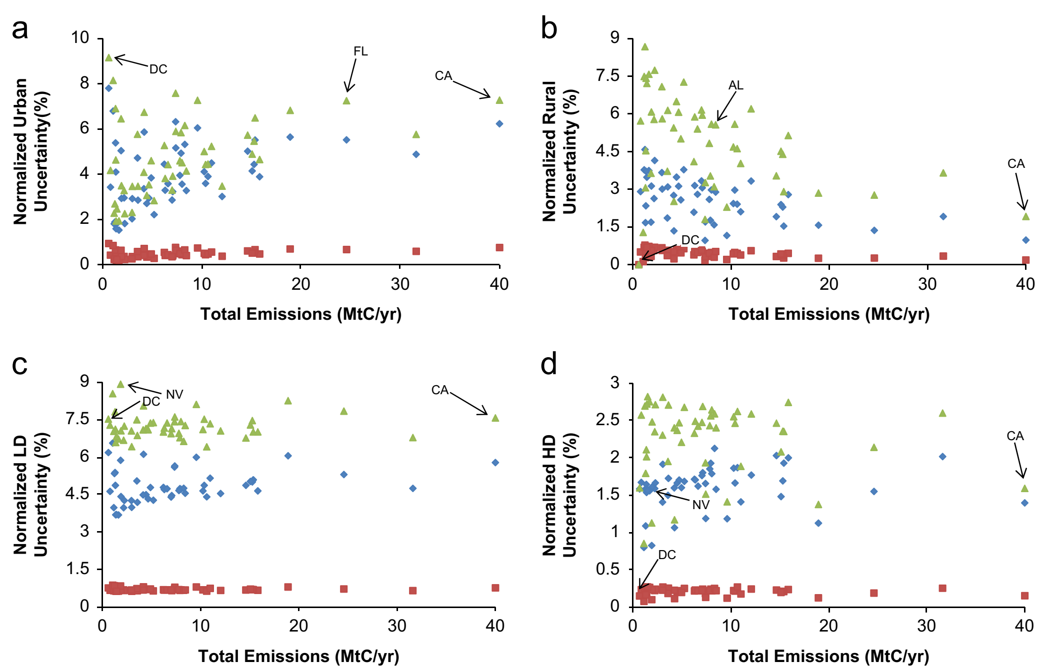

Fig. 1. Vulcan state-specific normalized onroad fossil fuel CO_2 uncertainties vs. emissions. (a) Normalized urban uncertainty vs. total emissions; (b) normalized rural uncertainty vs. total emissions; (c) normalized LD uncertainty vs. total emissions; (d) normalized HD uncertainty vs. total emissions. VMT uncertainty (blue diamonds), fuel efficiency uncertainty (green triangles), fleet age uncertainty (red squares). The y-axis scales are different in each panel. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

shares characteristics of the urban uncertainty since the majority of vehicles on urban roads are within the LD group.

VMT uncertainty is dependent only on road type, as outlined in Section 2.4.1. Hence, the magnitude of the VMT uncertainty in the rural and urban road type groups (Fig. 1a, b) reflects the proportion of state VMT on rural vs. urban roads and these magnitudes are inversely related for a given state. For example, Washington DC, which contains only urban roads, has a normalized urban VMT uncertainty of 7.8%, and a normalized rural VMT uncertainty of 0%. Furthermore, states with smaller total emissions exhibit a much more heterogeneous mix of urban vs. rural VMT represented by the greater scatter in normalized VMT uncertainty in Fig. 1a/b. This heterogeneity declines as total onroad CO_2 emissions increase and reflects the fact that states with larger total onroad emissions have a greater proportion of their total VMT on urban roads.

Unlike the road group VMT uncertainty, the magnitude of the two vehicle group VMT uncertainties reflects the relative proportion of state VMT in the LD vs. HD vehicle groups, and the distribution of each vehicle group on either urban or rural roads. Because VMT uncertainty is sensitive to road type only, the vehicle group VMT uncertainty magnitude reflects the correlation between vehicle type and road type. Hence, the VMT uncertainty for the LD group is much larger and closer to the urban VMT uncertainty (7.8%) when compared to the HD vehicle group, the vehicles of which are more likely to travel on rural roads.

Fuel efficiency uncertainty is dependent on both vehicle and road type ("city" vs. "highway") in the uncertainty construction used in this study (see Section 2.4.3). However, the magnitude of the uncertainty only varies with road type, being a fixed value across all vehicle types. As with the VMT uncertainty, the fuel efficiency uncertainty is greater for urban road types because of the greater proportion of "stop-and-go" traffic which results in greater fuel efficiency variation.

Fleet age uncertainty is dependent only on the vehicle type (see Section 2.4.2). It exhibits the smallest uncertainty due to the small observed variation in state-to-state fleet age distribution. However, despite the fact that the uncertainty in age distribution is small, it results almost exclusively from variation in the LD fleet as opposed to the HD fleet. HD fleets are commercially-owned and maintained by companies that have fleet management policies in place to maximize fleet efficiency (Galletti et al., 2010). A major component of fleet efficiency maximization is regular vehicle replacement, decreasing variation within the age distribution of HD fleets (Port of Long Beach, 2008). In contrast, LD vehicles are generally privately owned and display a larger spread in age distribution. As a result, the mean of fleet age uncertainty for the LD group in Fig. 1c is 0.7% as opposed to a mean of 0.2% for the HD group in Fig. 1d.

3.2. Bias of a national-average approach

Fig. 2 shows the state-specific biases (Eq. (2)) of the national-average results relative to the Vulcan data product organized into the road and vehicle type groups. We find a spread of positive and negative biases for both the road and vehicle type groups. These are driven by the road and vehicle type compositions of each state, which differ from the national-average. We find a larger spread of state-specific bias values in the road type groups than in the vehicle type groups.

Fig. 2 also highlights the correlation between the road and vehicle type group emissions biases that results from the underlying relationships. For example, traffic on urban roads is comprised mostly of LD vehicles ($r=0.64$; $p<0.0001$), while rural roads have a comparatively larger percentage of HD vehicle traffic ($r=0.74$; $p<0.0001$) (Pechan, 1996).

In the case of the vehicle group bias, the magnitudes are driven by states having a greater/lesser proportion of LD/HD vehicles within their total state fleet when compared to the national-average. For example, the LD vehicle class has emission factors ranging from 177.4 grams CO_2/mile (motorcycles) to 577.0 grams CO_2/mile (LD diesel trucks). If the amount of motorcycles in a state is greater than the national-average, the national-average approach will yield a positive emissions bias compared to the Vulcan approach. The standard deviation of these biases is 2.0% and 0.8% for the LD and HD groups, respectively.

The road group bias is driven by a combination of two factors: (1) the amount of rural vs. urban VMT within each state relative to the national average and (2) the vehicle class distribution comprising the rural/urban VMT and its difference from the national average. Hence, states having a larger amount of rural VMT relative to the national average, but for which the vehicle class composition of the rural VMT matches the national average, will still result in a negative bias. If the vehicle class composition within the rural VMT contains a greater proportion of higher-emitting LD vehicle types than the national average, this will compound the negative bias. Similarly, states in which the amount of rural VMT matches the national average may still arrive at a bias were the vehicle class composition within the rural VMT to contain a larger proportion of higher-emitting LD VMT than the national average. These factors account for the larger bias values in the road groups. The standard deviation of these biases is 3.2% and 2% for the urban and rural groups, respectively.

The correlation of road and vehicle type groups hides a more revealing classification—'larger' vs. 'smaller' roads. For example, larger road types (interstates and arterials) are used as commerce routes to transport goods and have a larger fraction of HD vehicles than smaller road types (collector and local roads) (Lindhjem and Shepard, 2007). Hence, those states displaying negative urban

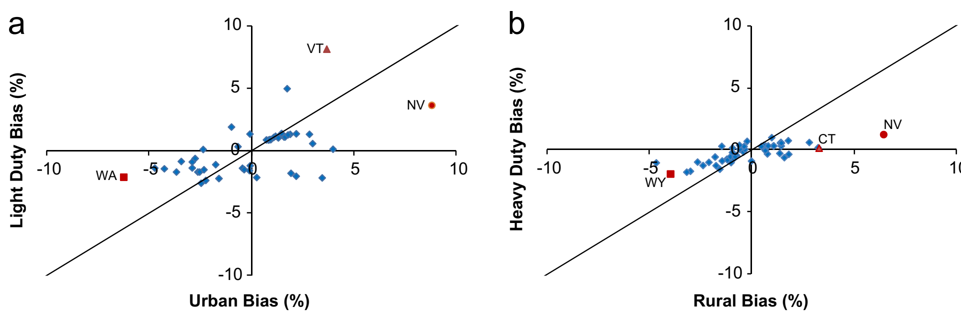

Fig. 2. State-specific biases of the national-average results relative to the Vulcan data product for road and vehicle aggregate groups. (a) Light duty vs. urban groups; (b) heavy duty vs. rural groups. A one-to-one line is present in each panel as a reference and large values are denoted by red symbols. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

biases are states whose percentage of traffic on these larger road types exceeds the national average.

A few values are found outside of the central cluster in Fig. 2a. For example, Washington has 28.9% of urban VMT residing on interstates and freeways compared to the national average (23.8%). Since these two road types have a larger proportion of HD traffic compared to smaller urban roads, they will have a larger average CO_2 emission per mile of travel, creating the negative bias evident in Washington's urban road group. Conversely, Vermont and Nevada have a smaller amount (3.8% and 19.2%, respectively) of urban VMT comprised of interstate and freeway travel, accounting for the positive urban group biases. Vermont and Nevada have more (78.4% and 75.6%, respectively) LD VMT from the lesser-emitting LD vehicle class, LDGV, than the national average (59.4%) creating the positive LD group bias. The negative bias for Washington State's LD vehicle group results from a smaller amount (48.8%) of LD group VMT from the lesser-emitting LDGV type.

The largest values in Fig. 2b are attributed to Wyoming, Connecticut, and Nevada. Wyoming has 28.2% of its HD VMT arising from the eight lowest-emitting HD vehicle classes, less than the national average (38.0%), causing the negative bias for Wyoming's HD group. Nevada and Connecticut have a larger amount (51.6% and 40.0%, respectively) of their HD VMT stemming from the same eight lowest-emitting HD vehicle classes, accounting for the positive HD group biases. Wyoming has greater rural interstate VMT (37.6%), compared to the national average (24.8%), accounting for the negative rural group bias. Conversely, Connecticut has less rural interstate VMT (21.3%), accounting for its positive rural group bias. Nevada has greater rural local and minor collector VMT (20.2%), compared to the national average (18.1%), accounting for the positive rural group bias.

Fig. 3 shows the biases of Fig. 2 but normalized by the national total, group-specific fossil fuel CO_2 emissions (Eq. (3)). When normalized by national totals, the biases highlight states with large amounts of onroad emissions that also deviate significantly from the national average. For example, although Connecticut has the fifth largest rural road group bias (Fig. 2b), the state accounts for less than 0.25% of the national emission total and hence, is not an outlier value in Fig. 3b.

The vehicle class distribution is a significant contributor to the observed LD and HD biases (Appendix A, Fig. A.1). States that exhibit a positive LD bias (Fig. 3a: Texas, Florida, California) have

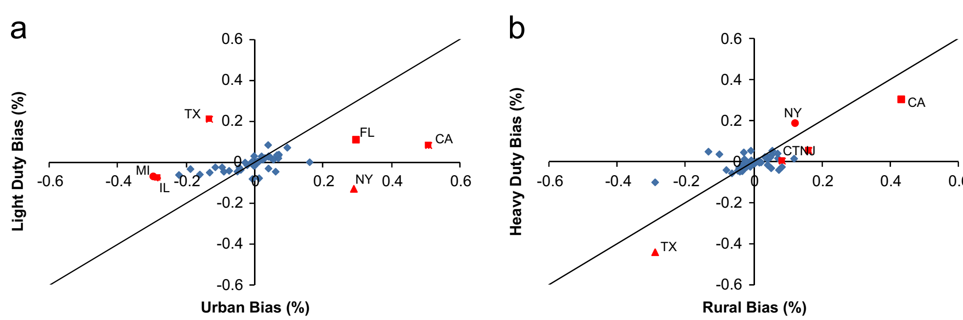

Fig. 3. As in Fig. 2 but normalized by the national total CO_2 emissions in each road and vehicle group. A one-to-one line is present in each panel as a reference and large values are denoted by red symbols. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

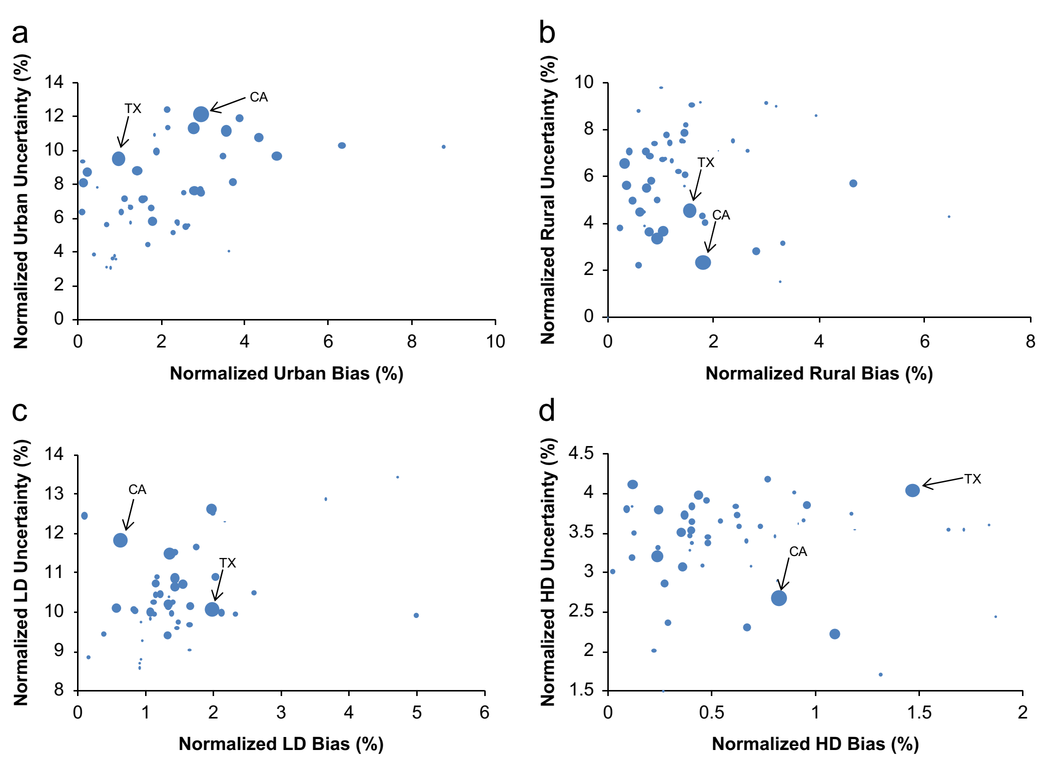

Fig. 4. Total normalized state-specific uncertainty vs. total absolute normalized state-specific bias. Symbol size is proportional to total state emissions. (a) Urban; (b) rural; (c) LD; (d) HD. Note that scales are different in each panel.

large contributions from the lowest-emitting vehicle classes. Conversely, the states showing a negative LD bias (Fig. 3a: Michigan, Illinois, New York) have larger fractions than the national average of emissions from the highest-emitting vehicle classes. A similar pattern is shown in Appendix A, Fig. A.1b for the HD group.

3.3. *Bias and uncertainty comparison*

Fig. 4 compares the normalized absolute bias (Eq. (2)) to the normalized uncertainty (Eq. (5)) for each of the aggregate groups. Since the uncertainty is $+/-1$ sigma, the sign of the bias relative to the uncertainty is impossible to ascertain. Thus we utilize the absolute bias, as its sign is of little value.

In nearly all cases, the total Vulcan uncertainty exceeds the calculated bias and exhibits no obvious relationship. However, the largest-emitting states exhibit less variation in both normalized bias and uncertainty for the aggregate groups than the smallest-emitting states, as shown in Appendix B, Table B.2. A state may emit a small amount of emissions, with the majority of these emissions occurring on urban roads, while other small-emitting states have predominantly rural emissions. Likewise, similar trends are present for the vehicle groups, where small states display larger standard and relative standard deviations when compared to the same quantities for the larger states (Appendix B, Table B.3). This heterogeneity in road and fleet composition is associated with the wide range of bias and uncertainty values seen for small-emitting states for all four aggregate groups.

4. Discussion

4.1. *Policy implications*

Uncertainty analysis in the context of environmental models is a means to improve data collection and measurement as well as calculation methods. After identifying the parameters with highest uncertainty, steps can be taken to improve current and future emissions estimates (Lieberman et al., 2007). For example, the IPCC's guidance on national inventory construction suggests that uncertainty analysis is intended to "improve the accuracy of inventories in the future and guide decisions on methodological choice" (Intergovernmental Panel on Climate Change, 2000). Furthermore, quantification of emissions uncertainty is necessary in order to accurately assess the impact of mitigation policy. If uncertainty levels exceed the reductions expected from mitigation policies, it will be difficult to confirm policy effectiveness. Accurate emissions estimation with realistic, unbiased uncertainties are critical in assuring that reported emissions reductions are credible. The Kyoto Protocol sets forth emissions reductions targets of 7% from 1990 amounts by 2008–2012, a target that was agreed upon but not ratified by the United States. The California Senate proposed 8% reductions from 2005 amounts by 2020 and 15% reductions by 2035 (California State Senate, 2008; United Nations Framework Convention on Climate Change, 2008). These targets are the same size or smaller than the uncertainty found in the rural, urban, and LD groups. Therefore even if the targets proposed by the Kyoto Protocol and California Senate were achieved, the reductions would not necessarily be detectable for three out of the four road and vehicle groups.

Transportation sector policy formulation based on a US national-average emissions approach is poorly suited for cities, states and regions that differ from the national mean. Policies based on the specific emission profiles of a county or state will address specific regional needs and idiosyncrasies and thereby, maximize emissions mitigation across the entire nation. For example, a county or state with an older passenger car composition could be encouraged to discard the older, more inefficient vehicles via a policy such as the Consumer Assistance to Recycle and Save Program (United States Congress, 2009). In a similar manner, states with a larger heavy-duty diesel truck composition could focus on improving the fleet fuel economy by mandating corporate participation in programs dedicated to this purpose, such as the U.S. Environmental Protection Agency (USEPA) SmartWay Program (United States Environmental Protection Agency, 2011c).

Fig. 5 demonstrates the differential impact to state-level emissions of a nationwide 10% reduction in emissions from the Light Duty Gasoline Vehicle (LDGV) class and a Heavy-Duty Diesel Vehicle (HDDV8B) class. These two vehicle classes were chosen because they account for the largest fraction of emissions within their respective vehicle groups. These reductions are comparable to the fuel efficiency standards set forth by the EPA for LD and HD vehicles (National Highway Traffic Safety Administration, 2011; United States Environmental Protection Agency, 2011a; United States Environmental Protection Agency, 2010. The reductions are expressed as the difference between the actual percent reduction and the expected emission reduction if using a national-average fleet composition. Fig. 5 shows this difference as a function of the proportion each specific vehicle class represents within the larger vehicle groups used in this study.

Nationally, 51.9% of an average state's LD group emissions are due to the LDGV class. Fig. 5a shows the large spread of LDGV proportion values, with some states having as little as 42.7% of their LD group emissions accounted for by LDGV class and some states as large as 75.2%. A 10% emissions reduction for the LDGV class would yield a 3.8% average reduction in total state emissions, but for a given state this value can range from 3.0 to 6.1%.

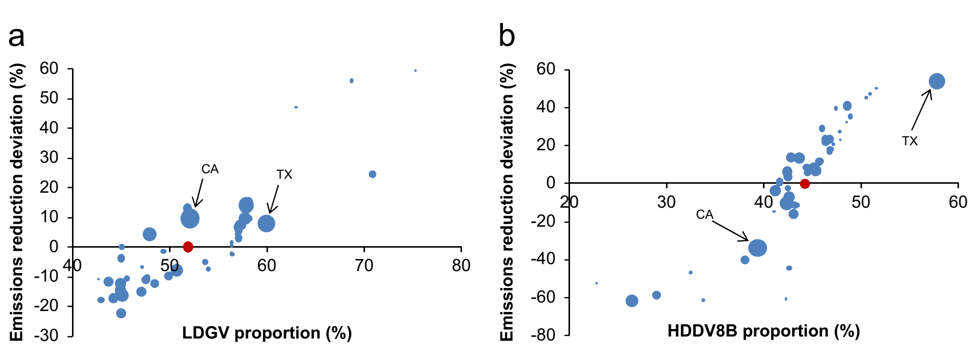

Fig. 5. Difference between the actual state emission reduction and expected (%) associated with a nationwide vehicle-specific 10% emissions reduction vs. the proportion of vehicle class. (a) Reduction difference vs. LDGV proportion of LD; (b) reduction difference vs. HDDV8B proportion of HD. Symbol size is proportional to total state emissions. The red symbol represents the national average. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

This results in a range of deviation of -25% to 60% from the expected emissions changes based on the national average. For example, the LDGV proportion in Texas exceeds the national average; the total reduction for this state would be subsequently underestimated by 0.1 MtC/yr.

Similarly, 44.2% of an average state's HD group emissions are due to the HDDV8B class (Fig. 5b). This figure corresponds to a 1.2% total emissions reduction in an average state if a policy advocating a 10% HDDV8B emissions reduction were implemented. However, because the HDDV8B proportion ranges from 22.8% to 57.7% overall reductions vary by state from 0.5 to 1.8%. The range of deviation from expected changes is $\pm 60\%$ from the national average. This would yield an overestimation of emissions reductions by 0.2 MtC/yr in the State of California.

Montgomery County, Maryland passed the first county-wide carbon tax in the U.S. in 2010 calling for payments of $5 per ton of CO_2 (Montgomery County Council, 2010). Using the national-average fleet as a baseline, the difference in expected and actual emissions reductions obtained by a 10% emissions reduction would cause California to be undercharged by nearly $800,000 under this policy due to its smaller fraction of HDDV8B vehicles. Conversely, Texas would overpay by $500,000 due to its larger fraction of LDGV vehicles.

4.2. Uncertainty improvement

The uncertainty in emissions due to VMT can be traced to a number of sources. For example, missing VMT data for a given state is gap-filled with data from a neighboring state. Additional uncertainty can arise from undersampling annual average daily travel (AADT) data on large and complicated road networks.

Poorly placed or distant traffic monitoring stations may lead to vehicle miscounting. If stations are too far apart or placed illogically with respect to exit and entry points on a given road segment, vehicles may enter and/or exit without being recorded (undercounting). The opposite problem may occur if a vehicle enters just before the monitoring station and exits immediately or shortly after being counted (overcounting). In order to reduce all three of these sources of VMT uncertainty, a larger and more representative set of monitoring stations is required, with optimal placement.

Finally, uncertainty is introduced when state-level VMT estimates are downscaled to counties, as described in Section 2.2. If there are significant differences in road network composition between individual counties and the state, bias results. One example of this is a situation in which the proportion of interstate to arterial roads varies significantly between an individual county and the state in which it is located (Barrett et al., 2001; Bostrom and Mayes, 2002; Federal Highway Administration, 2011).

An option to reduce the uncertainty associated with these problems is a periodic review of the variables involved in the VMT calculation. This assessment would be used to adjust the variables to current values that reflect actual conditions. Such a procedure would update scope of influence and lane-mile values for each station and ensure that any gaps in data readings are filled in the most accurate way possible. Additionally, the administration of driver surveys or a sampling of odometer readings for vehicles traveling within the domain associated with a particular station would contribute to a more realistic characterization of local VMT.

Though the smallest contributor to the overall onroad CO_2 emissions uncertainty, the age distribution uncertainty could be improved by obtaining registration information from the Bureau of Motor Vehicles databases instead of relying on state-provided data, as is currently done in the publicly available fleet data.

Analyses of new fuel efficiency regulations for the HD fleet and revised corporate average fuel economy (CAFE) standards have the potential to aid the formulation of a more accurate fuel efficiency estimate, thereby lowering the fuel efficiency uncertainty (United States Environmental Protection Agency, 2011a; United States Environmental Protection Agency (2010). Available data on annual vehicle sales by class may help to accurately represent the particular fleet makeup of each state or region. Such a portrayal, in conjunction with a larger, more representative sampling of vehicle classes, would provide the level of detail necessary for a more comprehensive and accurate uncertainty estimate. Additionally, because the fuel efficiency of the fleet is dependent on its composition, an improvement in age distribution accuracy will improve fuel efficiency accuracy.

Because the traffic on each road type can vary by location, fuel efficiency uncertainty has spatial dependence. City roads are classified as small roads regardless of the city in which they are located. However, a city road located in a major urban center may experience significantly different traffic patterns from those on small town roads. These disparities go unaccounted for in the fuel efficiency uncertainty calculation and affect its accuracy. In order to account for these obvious differences, revisions and expansions must be made to the current road type classification system. By accounting for location-specific differences, improved uncertainty will enable more informed policy decisions to be made on the basis of a more comprehensive and accurate assessment of road network biases.

Atmospheric CO_2 inversions use measurements of atmospheric CO_2 coupled with atmospheric transport models to infer exchanges of carbon with the planetary surface (Enting, 2002; Gurney et al., 2003). Given the importance of understanding carbon exchange with the terrestrial environment and how it might change with a warmer world, inversions have become an important tool to understanding carbon budgets. The accuracy of atmospheric CO_2 inversion results depends on many factors, including the spatial and temporal resolution of the fluxes being estimated, the transport model, and prior estimates of the flux (Gurney et al., 2003; Kaminski and Heimann, 2001). In particular, biases in the prior flux have been shown to alias the residual flux (Gurney et al., 2005; Peylin et al., 2011; Schuh et al., 2010). The space and time distribution of the prior fossil fuel emissions data product has become more important as inversions attempt to solve for smaller space and time scales. As the second largest emitting sector in most industrial economies, accurate representation of the onroad transportation sector space/time patterns are thus, critical.

Although the state-level biases resulting from the national-average emissions estimation approach in this study have been found to be smaller than the uncertainty (less than 10%), they remain relevant because they vary in space. This study has been performed at the state level, thus the results would impact atmospheric measurements and transport at the regional scale. For example, Schuh et al. (2010) demonstrated that differences of up to $150\ g/m^2$ in the annual net ecosystem exchange (NEE) estimate were obtained when the Vulcan fossil fuel fluxes were used instead of a previously established flux inventory of lower resolution. The magnitude of the observed differences is significant and comparable to that of the maximum annual sinks associated with the inversion.

5. Conclusions

As one of the largest sectoral sources of fossil fuel CO_2 emissions in the United States, onroad fossil fuel CO_2 emissions, are an important component of carbon cycle budget studies and figure prominently in policies designed to mitigate greenhouse gas emissions. Although onroad CO_2 emissions in the United States have been studied extensively, these efforts lack sub-national spatial detail. Such detail is essential because both scientific questions and greenhouse gas policies are being explored at the urban landscape scale and current analysis cannot adequately support quantitative decisions at these scales. Onroad CO_2 emissions are dependent on a variety of driving factors, all of which are known to vary significantly at these smaller spatial scales. Hence, in order to study, project and mitigate onroad CO_2 emissions, a high-resolution onroad emissions data product is paramount.

Three sources of uncertainty are quantified in this study: vehicle miles traveled (VMT), fleet age, and fuel efficiency. VMT and fuel efficiency normalized (by state total emissions) uncertainty range from 2 to 12% and are approximately 5 to 10 times larger than fleet age uncertainty. The total normalized uncertainty is 2 to 15 times larger than the normalized bias. Uncertainty quantification and reduction measures focused on VMT and fuel efficiency would yield the maximum benefit. VMT uncertainty reduction strategies involve a revision of the formula for conversion of vehicle counts to VMT, as well an increased number of traffic monitoring stations with optimal placement to minimize inaccuracies in vehicle counting. A fuel efficiency uncertainty improvement strategy would involve creating more spatially explicit calculations of possible fuel consumption scenarios and driving habits.

Although it is desirable to reduce uncertainty, it is of equal importance to improve the accuracy of uncertainty estimates. This can be accomplished by a more accurate spatial portrayal of the sources of uncertainty through methods such as a more representative sampling of vehicle classes and assessments of regionally-explicit VMT estimates. Downscaling the temporal domain for comparison to the county level is a realistic and attainable goal due to the nature of the Vulcan data product. Due to the heterogeneous distribution of roads and vehicles within a state, this level of resolution is necessary for policy formulation at this level.

Additionally we have compared onroad CO_2 emissions based on a national-average approach to a high-resolution onroad CO_2 emissions estimate. In order to represent the differences in these two approaches, we group emissions into either urban or rural roads and either light-duty (LD) or heavy-duty (HD) vehicles. Biases are obtained from the difference between the high-resolution and national-average emissions.

We find that using group-specific national averages is consistently associated with state-level emissions bias; however, the range of bias estimated is strongly dependent on how the emissions are classified. A vehicle group classification yields a state-level normalized bias range of -2.6% to 8.1% while a road group classification yields a state-level normalized bias range of -6.3% to 16.8%. When normalized to the national total, these differences account for bias ranges of -0.4% to 0.3% for a vehicle type classification and -0.3% to 0.5% for a road type classification. These biases are the direct result of regional heterogeneity in road and fleet composition. There exists a positive correlation between HD and rural biases and between LD and urban biases because urban traffic is comprised mainly of LD vehicles and rural traffic has a comparatively larger HD component.

Policy measures aimed at reducing emissions from a particular group within the vehicle fleet must take into account regional differences in fleet composition. Vehicle-specific mitigation strategies based upon national-average fleet composition have been shown to display errors of up to 60% in expected state level emissions reductions for the passenger car and heaviest diesel truck classes. If a 10% emissions reduction from an individual vehicle class is assumed, these estimation errors can be as large as $\pm 60\%$ corresponding to ± 0.2 MtC reductions in state totals.

Additionally, policy must be drafted keeping its scope of predictable influence in mind. The largest-emitting states have similar distributions of rural, urban, LD, and HD emissions, while small-emitting states show greater heterogeneity in these groups. Policy drafted for nationwide application should consider that recommendations based on a national-average would affect large-emitting states similarly and in a predictable manner, while the results in smaller-emitting states would differ from the expected reductions. Because of the nature of the HD group, policy aimed at this group would benefit most strongly from a regionally motivated approach as opposed to a national-average approach.

Carbon cycle science similarly requires high-resolution fossil fuel CO_2 emissions data products to accurately isolate the net terrestrial and oceanic fluxes. Atmospheric CO_2 inversion studies have already demonstrated the impact of high-resolution fossil fuel CO_2 prior fluxes on the spatial patterns of biospheric exchange. As the second largest single sectoral source within the total fossil fuel CO_2 emissions in the United States, high-resolution onroad emissions are a critical element in advancing inversion studies. Furthermore, atmospheric CO_2 inversions are sensitive to the prior flux uncertainty, placing particular emphasis on prior fluxes with well-quantified uncertainties.

Acknowledgments

This work was supported by NASA grant NNX06AB37G and NSF CAREER award 0846358. We would like to thank Broc Seib and William Ansley for assistance with information systems and the Rosen Center for Advanced Computing for in-kind support.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2012.12.027.

References

Barrett, M.L., Graves, C.R., Allen, D.L., Pigman, J.G., 2001. Analysis of Traffic Growth Rates. University of Kentucky Transportation Center, Lexington, KY, USA.
Bostrom, R., Mayes, J., 2002. Highway Speed Estimation for MOBILE6 in Kentucky. Kentucky Transportation Cabinet.
California Air Resources Board, 2009. Resolution 09-53, Amendments to Assembly Bill 1493, Pavley Regulations.
California State Senate, 2008. Senate Bill 375, Chapter 278, SB-375, Sacramento, California.
Council of the European Union, 2009. Regulation (EC) No. 443/2009: Setting Emission Performance Standards for New Passenger Cars as Part of the Community's Integrated Approach to Reduce CO_2 Emissions from Light-Duty Vehicles. Official Journal of the European Union, L140/141-115.
Denman, K., Brasseur, G., Chidthaisong, A., Ciais, P., Cox, P.M., Dickinson, R.E., Hauglustaine, D., Heinze, C., Holland, E., Jacob, D., Lohmann, U., Ramachandran, S., Leite da Silva Dias, P., Wofsy, S.C., Zhang, X., 2007. Couplings between changes in the climate system and biogeochemistry. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Avery, K.B., Tignor, M., Miller, H.L. (Eds.), Climate Change 2007: The Physical Science Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK, New York, NY, USA.
Enting, I.G., 2002. Inverse Problems in Atmospheric Constituent Transport. Cambridge University Press, Cambridge, UK.
Federal Highway Administration, 2005. Highway Performance Monitoring System for the Continuing Analytical and Statistical Database. United States Department of Transportation, Office of Highway Policy Information.
Federal Highway Administration, 2011. Sample Methodologies for Regional Emissions Analysis in Small Urban and Rural Areas. Office of Planning, Environment, and Realty.

Fuller, M.C., Kunkel, C., Kammen, D.M., 2009. Guide to Energy Efficiency & Renewable Energy Financing Districts for Local Governments. Renewable and Appropriate Energy Laboratory (RAEL). University of California, Berkeley.
Galletti, D.W., Lee, J., Kozman, T., 2010. Competitive benchmarking for fleet cost management. Total Quality Management & Business Excellence 21, 1047–1056.
Gurney, K.R., Chen, Y., Maki, T., Kawa, S.R., Andrews, A., Zhu, Z., 2005. Sensitivity of atmospheric CO_2 inversions to seasonal and interannual variations in fossil fuel emissions. Journal of Geophysical Research, 110.
Gurney, K.R., Law, R.M., Denning, A.S., Rayner, P.J., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y., Ciais, P., Fan, S., Fung, I.Y., Gloor, M., Heimann, M., Higuchi, K., John, J., Kowalczyk, E., Maki, T., Maksyutov, S., Peylin, P., Prather, M., Pak, B.C., Sarmiento, J., Taguchi, S., Takahashi, T., Yuen, C., 2003. TransCom3 CO_2 inversion intercomparison: 1. Annual mean control results and sensitivity to transport and prior flux information. Tellus, Series B 55, 555–579.
Gurney, K.R., Mendoza, D.L., Zhou, Y., Miller, C., Geethakumar, S., Fischer, M.L., De la Rue du Can, S., 2009. The Vulcan Project: high resolution fossil fuel combustion CO_2 emissions fluxes for the United States. Environmental Science & Technology 43, 5535–5541.
Harrington, W., 1998. A Behavioral Analysis of EPA′s MOBILE Emission Factor Model. Resources for the Future, Washington, D.C.
Intergovernmental Panel on Climate Change, 2000. Good practice guidance and uncertainty management in national greenhouse gas inventories. In: Penman, J., Kruger, D., Galbally, I., Hiraishi, T., Nyenzi, B., Emmanuel, S., Buendia, L., Hoppaus, R., Martinsen, T., Meijer, J., Miwa, T., Tanabe, K. (Eds.), IPCC/OECD/IEA/IGES. Hayama, Kangawa, Japan.
Kaminski, T., Heimann, M., 2001. Inverse modeling of atmospheric carbon dioxide fluxes. Science 294, 259.
Lieberman, D., Jonas, M., Winiwarter, W., Nahorski, Z., Nilsson, S., 2007. Accounting for climate change: introduction. Water Air Soil Pollution Focus 7, 421–424.
Lindhjem, C.E., Shepard, S., 2007. Development Work for Improved Heavy-Duty Vehicle Modeling Capability Data Mining—FHWA Datasets. Prepared for United States Environmental Protection Agency by ENVIRON Corporation, Novato, CA.
Montgomery County Council, 2010. Expedited Bill No. 29-10; Article XIII, Excise Tax on Major Emitters of Carbon Dioxide, Montgomery County, Maryland.
National Highway Traffic Safety Administration, 2011. Summary of Fuel Economy Performance. U.S. Department of Transportation, NHTSA.
Pechan, E.H., 1996. Analysis of the Effects of Eliminating the National Speed Limit on NO*x* Emissions. United States Environmental Protection Agency, Springfield, VA, USA.
Peylin, P., Houweling, S., Krol, M.C., Karstens, U., Rödenbeck, C., Geels, C., Vermeulen, A., Badawy, B., Aulagnier, C., Pregger, T., Delage, F., Pieterse, G., Ciais, P., Heimann, M., 2011. Importance of fossil fuel emission uncertainties over Europe for CO_2 modeling: model intercomparison. Atmospheric Chemistry and Physics 11, 6607–6622.
Port of Long Beach, 2008. 2006 Air Emissions Inventory, pp. 143–163.
Puentes, R., 2008. The Road Less Traveled: An Analysis of Vehicle Miles Traveled Trends in the U.S. Metropolitan Policy Program at Brookings.
Schuh, A.E., Denning, A.S., Corbin, K.D., Baker, I.T., Uliasz, M., Parazoo, N., Andrews, A.E., Worthy, D.E.J., 2010. A regional high-resolution carbon flux inversion of North America for 2004. Biogeosciences 7, 1625–1644.
Southworth, F., Sonnenberg, A., Brown, M.A., 2008. The Transportation Energy and Carbon Footprints of the 100 Largest U.S. Metropolitan Areas. Ivan Allen College, Georgia Institute of Technology, Atlanta, GA.
Stone, B., Mednick, A.C., Holloway, T., Spak, S.N., 2009. Mobile source CO_2 mitigation through smart growth development and vehicle fleet hybridization. Environmental Science & Technology 43, 1704–1710.
United Nations Framework Convention on Climate Change, 2008. Kyoto Protocol Reference Manual: On Accounting of Emissions and Assigned Amount.
United States Congress, 2009. Consumer Assistance to Recycle and Save Act, 111th Congress ed, United States of America.
United States Environmental Protection Agency, 2001. Fleet Characterization Data for MOBILE6: Development and Use of Age Distributions, Average Annual Mileage Accumulation Rates, and Projected Vehicle Counts for Use in MOBILE6.
United States Environmental Protection Agency, 2005. Light-Duty Automotive Technology and Fuel Economy Trends: 1975 through 2004.
United States Environmental Protection Agency, 2009. Greenhouse Gases Threaten Public Health and the Environment/Science Overwhelmingly Shows Greenhouse Gas Concentrations at Unprecendented Levels Due to Human Activity, EPA News Release, Washington DC, USA.
United States Environmental Protection Agency, 2011a. Final Rulemaking to Establish Greenhouse Gas Emissions Standards and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles. Office of Transportation and Air Quality, National Highway Traffic Safety Administration, United States Department of Transportation.
United States Environmental Protection Agency, 2011b. Inventory of U.S. Greenhouse Gas Emissions and Sinks, pp. 1990–2009.
United States Environmental Protection Agency, 2011c. SmartWay Transport Overview. Office of Transportation and Air Quality.
United States Environmental Protection Agency, United States Department of Transportation, National Highway Traffic Safety Administration, 2010. Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards, Final Rule. Federal Register, vol. 75, no. 88, pp. 25324–25728.
Vadas, T., 2007. Local-scale analysis of carbon mitigation strategies: Tompkins County, New York, USA. Energy Policy 35, 5515–5525.