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Detailed assessment of global transport-energy models' structures and projections

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ABSTRACT

This paper focuses on comparing the frameworks and projections from four global transportation models with considerable technology details. We analyze and compare the modeling frameworks, underlying data, assumptions, intermediate parameters, and projections to identify the sources of divergence or consistency, as well as key knowledge gaps. We find that there are significant differences in the base-year data and key parameters for future projections, especially for developing countries. These include passenger and freight activity, mode shares, vehicle ownership rates, and energy consumption by mode, particularly for shipping, aviation and trucking. This may be due in part to a lack of previous efforts to do such consistency-checking and "bench-marking." We find that the four models differ in terms of the relative roles of various mitigation strategies to achieve a 2 °C/450 ppm target: the economics-based integrated assessment models favor the use of low carbon fuels as the primary mitigation option followed by efficiency improvements, whereas transport-only and expert-based models favor efficiency improvements of vehicles followed by mode shifts. We offer recommendations for future modeling improvements focusing on (1) reducing data gaps; (2) translating the findings from this study into relevant policy implications such as gaps of current policy goals, additional policy targets needed, regional vs. global reductions; (3) modeling strata of demographic groups to improve understanding of vehicle ownership levels, travel behavior, and urban vs. rural considerations; and (4) conducting coordinated efforts in aligning historical data, and comparing input assumptions and results of policy analysis and modeling insights.

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1. Introduction

Transportation accounts for a significant portion of global fossil fuel use and greenhouse gas (GHG) emissions (IPCC, 2014b). Therefore, reductions in transportation-sector emissions will play an important role in any comprehensive carbon reduction strategy. Abatement in the sector will be multifaceted, and may include emissions reductions through increased efficiency of vehicle fleets, lower carbon intensity (CI) of fuels, and/or reduced demand for vehicle-kilometers travelled (Creutzig et al., 2015). Several recent studies comparing global transportation models have looked into the growth trajectories of transportation demand and potentials of mitigation options to meet climate mitigation goals (Edelenbosch et al., 2016; Pietzcker et al., 2014; Girod et al., 2013). These modeling comparison studies generally focus on projections of fuel use, GHG emissions and technology and fuel mixes in business-as-usual (BAU) and in GHG abatement scenarios, and are for the most part based on results of whole-systems and integrated assessment models (IAMs).

This paper presents the results of a model comparison effort called iTEM (International Transportation Energy Modeling). It focuses on comparing the frameworks and scenario projections from four major global transportation models that have a high degree of technology details compared with most major IAMs, allowing a deeper level of analysis than has been performed in the previous literature to date. Our goal is to conduct a detailed comparison of modeling framework, underlying data, assumptions, intermediate parameters, and projections, to gain a better knowledge of the sources of divergence or consistency. We also aim to identify potential knowledge gaps in data, new model methods and transportation topics.

2. Comparison of model structure

The four models compared in this work include:

- Global Change Assessment Model (**GCAM**) by Pacific Northwest National Laboratory (PNNL) with modification for the transportation sector by the Institute of Transportation Studies (ITS), University of California, Davis.
- **MESSAGE-Transport** (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) by the International Institute for Applied Systems Analysis (IIASA).
- Mobility Model (**MoMo**) by the International Energy Agency (IEA), and
- **Roadmap** by the International Council on Clean Transportation (ICCT).

The four models differ in terms of scope and model structure. GCAM and MESSAGE cover all sectors of the energy system, including linkages with global land use, energy/economic, and/or climate systems, whereas MoMo and Roadmap cover the global transportation sector only. GCAM and MESSAGE tend to rely on cross-sectoral endogenous functions to project future development, whereas MoMo and Roadmap rely more heavily on expert judgment and detailed, country-specific research and expertise. Yet, owing to these differences, the models are highly complementary and in some cases can be used jointly to answer questions that no single model can address in isolation.

In this section we provide a brief overview of each of the model, and compare the model structure and key mechanisms that drive the major differences in these models.

2.1. Global transportation models

The **Global Change Assessment Model (GCAM)** is a global (multi-region, multi-sector) dynamic-recursive partial equilibrium model with technology-rich representations of the economy, energy sector, land use and water (Kim et al., 2016) linked to a climate model. The model has participated in many international modeling comparison efforts involving integrated assessment models, including those in climate change scenarios (Fawcett et al., 2015), natural gas (McJeon et al., 2014), land use (Di Vittorio et al., 2014), and transportation (Girod et al., 2013). The new transportation module of GCAM was developed in a collaborative effort between PNNL (Kyle and Kim, 2011) and ITS at the University of California, Davis (Mishra et al., 2013).

The **MESSAGE** model is a global (multi-region, multi-sector) systems engineering, inter-temporal optimization model that has rich technological detail, particularly on the supply side of the energy system (Riahi et al., 2012). MESSAGE is linked to other models for studying impacts of the energy system on land use and forestry, macro-economics, air pollution, and climate change. More recently a significant amount of technology detail has also been added to the transportation sector of MESSAGE (McCollum et al., 2016). The model has also participated in many international modeling comparison efforts involving integrated assessment models, including van der Zwaan et al. (2013), Tavoni et al. (2015), McJeon et al. (2014), IPCC (2014a); recently the model is also part of a model comparison focusing on transportation (see also (Edelenbosch et al., 2016)).

The **Mobility Model (MoMo)** (Fulton et al., 2009) is a "stand alone" transportation-only model that interacts with IEA's annual Energy Technology Perspectives (ETP) TIMES-based optimization modeling system. MoMo uses a manually iterative process to achieve consistency in energy use and GHG emissions with the ETP scenarios. The 2013 version of MoMo and the scenarios run for ETP 2014 were evaluated in the iTEM model comparison. MoMo tracks transportation activity, energy use, GHG and local pollutant emissions, material use and infrastructure. The model allows the user to create "what-if" scenarios

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to explore the impacts of various technological, economic, demographic, and policy trends. The calculation of final energy consumption and emissions performed in MoMo is based on the ASIF methodology (Schipper et al., 2011) that decomposes GHG emissions into the multiplication of four major components: activity (passenger-km or tonne-km for freight), mode shares (% of total passenger or tonne-km carried by each mode), fuel intensity of each mode (energy use per passenger (or tonne-) km using fuel or energy source), and carbon content of each fuel used in a particular mode.

The **Roadmap** model has been developed for the purpose of estimating current and future well-to-wheel emissions and energy consumption by the transportation sector under different policy scenarios (Façanha et al., 2012). The model was built using the best available data from public sources and in-country partners, with much of the data for aggregate (multi-country) regions coming from the IEA's MoMo model. Therefore it is structurally similar to the MoMo model. The model was developed to assess transportation systems in the top eleven vehicle markets and in five aggregate regions, enabling global analyses that are based on up-to-date policy information and take into account administrative and technical considerations of implementing new policies.

2.2. Model system boundary, resolution, and structure

The four models vary in structure, scope, and the variables included in calculations and projections. The transportation sectors of GCAM and MESSAGE are both part of larger, multi-sector IAMs whereas MoMo and Roadmap are "stand-alone" transportation models, with no endogenous feedback from sectors outside the transportation system to changes in transportation sector assumptions or projections (such as energy use impact on energy prices). As mentioned earlier, however, MoMo outputs are iterated with IEA's ETP scenarios exogenously to achieve consistency in energy use and GHG emissions with global economy-wide ETP scenarios. On the other hand, MoMo and Roadmap tend to have more detailed representations of the transportation sector, such as vehicle characteristics, near-term policy goals and implementation, and detailed tracking of vehicle pollutant emissions as a function of vehicle emission control levels and utilization. Table S1 in the Supporting Information (SI) provides a basic comparison of the models' system boundary, resolution, and structure.

2.3. Projections of service demand, vehicles sales and fuel uses

Across the four models, population and income (GDP) are the exogenous drivers of passenger service demand in passenger kilometers travelled, PKT (GCAM, MESSAGE, Roadmap) and new vehicle demand (MoMo), as shown in Table 1 and Fig. 1. In GCAM and MESSAGE, the passenger service demands by mode are estimated endogenously based on the total travel costs (monetary cost per passenger kilometer travelled, $/PKT) by mode, fuel, technology, and time cost of travel that is a function of the average hourly wage rate of the employed population, mode-specific value of travel time (VTT), and travel speed). In MoMo, vehicle and 2-wheeler travel demands are estimated based on private vehicle ownership rates that are modeled with Gompertz curves as a function of per-capita GDP, while air travel activity is projected based on historical trends. In Roadmap, PKT is projected based on exogenous changes in GDP, population, and fuel prices. Freight service demand is based on simple functions of population, GDP, and fuel prices (except MoMo) in these models.

The competition between vehicle technologies, including alternative fuel vehicles, is estimated differently by each model (Table S3). In GCAM, it is based on a nested-logit function where the share of technology/mode is determined endogenously based on the average levelized costs of service of each technology/mode in $/PKT (Mishra et al., 2013; Clarke and Edmonds, 1993). Alternatively, technologies are selected based on least-cost optimization of the discounted net present cost of each technology in MESSAGE, subject to constraints on annual sales growth rate and vehicle stock turnover, among others (McCollum et al., 2013). In contrast, technologies are chosen based on expert judgment and what-if analysis in both MoMo and Roadmap. While the rate of efficiency improvement of each represented vehicle technology is exogenous in all four models, the average improvement in energy intensity for modes or classes of technology is endogenous in all four models (Tables S4 and 1). Table S3 describes the level of detail used to characterize different modes and sectors in the models, and how vehicle stocks, efficiency (Table S4) and fuel demands are determined in these models.

Modeling transportation energy use in these models is either done by estimating how far people travel and what mode of transportation they choose, or by estimating how many vehicles there are and how far each one travels. These are complementary approaches, and in principle they should both lead to similar answers, given a consistent set of assumptions. The former approach, used in "service demand" models, can be more intuitive and appropriate when one wants to model societal shifts in modes of transportation, either in emerging economies as they develop or in developed economies as they decarbonize (Schäfer et al., 2009; Schäfer and Victor, 2000); but collecting reliable and consistent data on service demand (including passenger travel demand in PKT, and freight demand in tonne-kilometers travelled, TKT, across all modes of transportation) is quite challenging particularly for developing countries. In contrast, vehicle stock models rely upon readily-available vehicle sales data, but are less well suited for projecting future-state, what-if scenarios (particularly in estimating modal shift behaviors) and thus require special attention by experts. On the other hand, the later approach is more responsive to non-cost based policy or social changes that lead to mode shifts or demand reductions. Fig. 1 compares the service demand model (GCAM, MESSAGE, and Roadmap) with the car stock (MoMo) model. The figure shows the basic logic, in the form of flow charts, of the four models, illustrating the exogeneity vs. endogeneity of variables, and their general connectedness. Table S2 provides a high level comparison of endogeneity/exogeneity of key model drivers and parameters.

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Table 1
Comparison of exogenous and endogenous variables used in the models.

	Integrated assessment model		Transportation model	
	GCAM	MESSAGE	MoMo	RoadMap
Socioeconomic factors and demand drivers				
GDP	Ex	Ex	Ex	Ex
Population	Ex	Ex	Ex	Ex
Passenger service demand	En	En	En	En
Freight service demand	En	En	En	En
Mode share	En	En	Ex	Ex
Fuels and vehicle technologies				
Fuel prices	En	En	Ex	Ex
Energy intensity of fuel production	En	En	Ex	Ex
Shares of fuel types within modes	En	En	Ex	Ex
Efficiency levels of individual technologies	Ex	Ex	Ex	Ex
Efficiency levels within service, mode, fuel type	En	En	En	En
Consumer behaviors				
Average transit speed	Ex	Ex	n.c	n.c
Time cost (mode choice)	Using wage rate and mode-specific value of travel time (VTT) multipliers to determine the value of time in each mode	Using wage rate and mode-specific value of travel time (VTT) multipliers to determine the value of time in each mode. Also include travel time and budget constraints	n.c	n.c

Notes: En: Endogenous, results are calculated by the models or by authors based on exogenous drivers; Ex: Exogenous, values taken directly from external sources; n.c.: Not considered.

2.4. CO_2 emission accounting

The four models have different system boundaries for CO_2 emission accounting, with implications for how these emissions are accounted for in the policy analysis, and how they are reported to communicate the impacts of policies. These differences are illustrated in Fig. S1. In GCAM and MESSAGE, carbon sequestration and emissions associated with biomass growth and land use changes are included in the agriculture and land use sectors, respectively. Both MoMo and Roadmap include upstream production and transportation CO_2 and non-CO_2 greenhouse gases (CO_2e) emissions, and Roadmap also includes indirect land-use change (ILUC) emissions based on literature reviews. This is likely due to the fact that ILUC emissions are included in US biofuel policies (U.S. EPA, 2012; ARB, 2012) (reflected in the Roadmap model) but not in the EU renewable energy policies (EC, 2009) (reflected in the MoMo model). However, in order to have consistent reporting across studies, this study focuses only on tailpipe CO_2 emissions and biofuel-derived carbon is not included here. The system boundaries of CO_2 emissions by each model characterized in this study are compared in Fig. S1. These differences are particularly important in the analysis of biofuels and carbon policies.

2.5. Mechanisms for policy analysis

All four models have been applied extensively for policy analysis, in particular for energy efficiency standards, carbon policies (e.g. carbon taxes, temperature or emissions targets), monetary policy (e.g. subsidies), air pollution policies, etc. The mechanisms of policy analysis (e.g. exogenous vs. endogenous, constraints vs. cost-minimization vs. what-if analysis) are described in detail in Table S4. In general, GCAM and MESSAGE solve for travel activity and energy-related variables as a function of cost; thus are suited for price-based policies relying on cost adjustments (such as carbon prices) to drive change. MoMo and Roadmap are run primarily as backcasting analyses or for regulatory impact analysis, where parameters, such as the average rate of efficiency improvement, mode shares or activity levels, are typically set exogenously by the modelers.

3. Base year (2010) and global projections in the baseline scenario

This section compares the consistency in the base year data and explores the baseline scenario projections in each of the four models. We discuss the reasons for similarities and differences in the base year and projections.

3.1. Uncertainty in the base year (2010) estimates

A key finding of the iTEM exercise is that there are considerable discrepancies in historical data, both globally and for individual countries. There are many reasons for data discrepancies across models. Calibration to different sources of historical data, or different versions of the same source (specifically the IEA Energy Balances https://www.iea.org/statistics/relateddatabases/worldenergystatisticsandbalances/) partly account for differences in transportation fuel consumption at

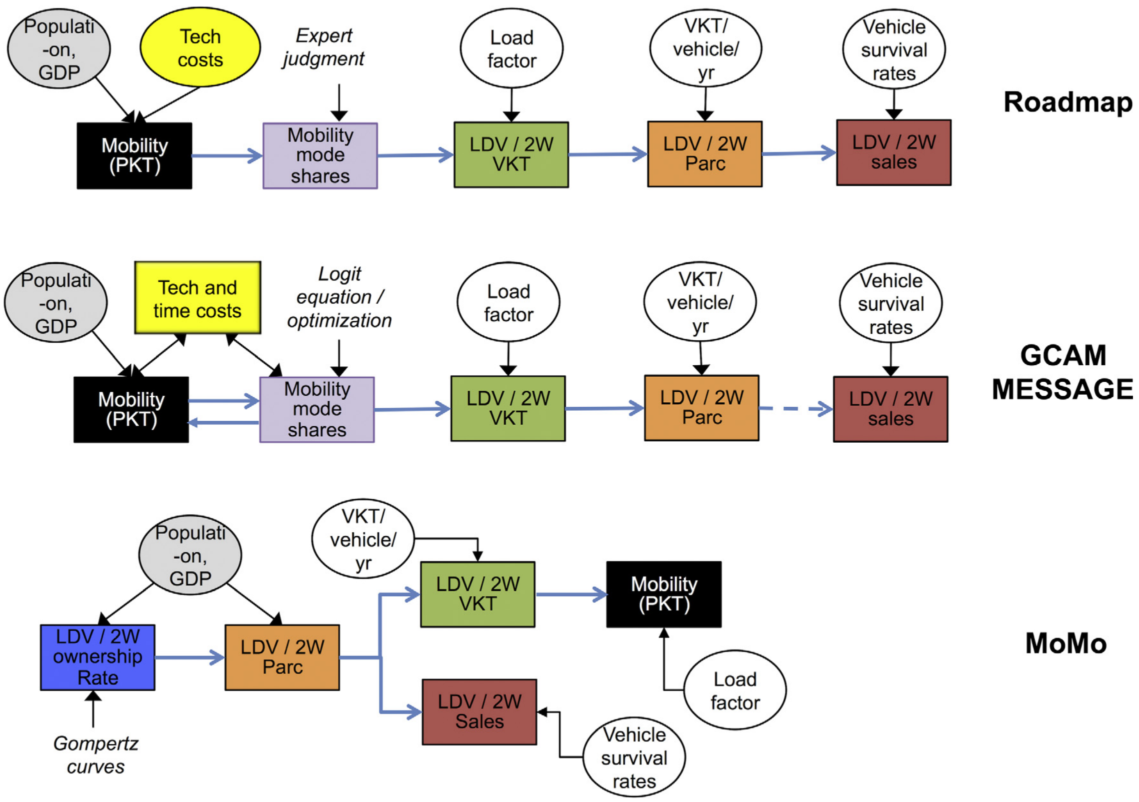

Fig. 1. Simplified representation of how models solve for personal light-duty vehicle (LDV) and two wheelers (2W) demand. Circles are exogenous variables, boxes are endogenous calculations by the model and text without boxes are methods of solving for a particular variable. Color of the boxes represents similar variables across different models. Parc stands for "population of vehicles on the road." VKT is vehicle kilometers travelled whereas PKT is passenger kilometers travelled. (PKT is related to VKT through the number of passengers per vehicle, which is sometimes called the load factor or the occupancy rate. Vehicle survival rate is the lifetime of vehicles). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

an aggregate level (Fig. S2). Models also make independent assumptions to disaggregate IEA energy balances to individual modes and technologies – for example to road, aviation, shipping; and within road energy consumption is further allocated to some combination of light-duty vehicles (LDVs), two and three-wheelers, buses, and freight heavy-duty trucks (HDT). As a result, mode-specific differences are even larger (Fig. S3), especially for developing regions where there are relatively few data points for calibration to reconcile the differences.

Differences in energy consumption quantities also reflect differences in the estimates of (a) load or occupancy factors, (b) vehicle kilometers travelled (VKT) per vehicle, (c) the number of vehicles in operation, and/or (d) different estimates of the energy intensity of these technologies. Variability in estimates of transportation activity – vehicle kilometers travelled (VKT) or service demand (PKT), and tonne-km for freight – are often much larger than the differences in estimated energy use (Figs. S3 and S4). Detailed data for developing countries are sparsely available, if at all, necessitating assumptions largely on the basis of historical trends or data from other countries. Given the sparsely available data, models differ substantially in terms of assumed 2010 values for mode-specific vehicle stocks, energy intensity of service, annual VKT per vehicle, and occupancy factors by country (Fig. 2). For example, estimated global passenger travel in buses for the year 2010 ranges from 6 to 20 trillion PKT and estimates of global road freight range from 9 to 18 trillion tonne-km. These differences are even greater for individual countries/regions (Fig. 2). For China, the estimated PKT across all modes of transportation range from 4.4 to 10.3 billion PKT/year in 2010, a factor of two difference. Similarly, the estimated total energy use for transport for 2010 range from 7.5 to 12.4 EJ. Uncertainty in these input parameters is much higher for developing regions like India where there are no reliable nation-wide travel surveys, systematic traffic counts or vehicle odometer readings, or a comprehensive database of on-road vehicles.

3.2. Baseline scenario of global fuel consumption and CO_2 emissions

Across the four models, global transportation fuel consumption in a baseline scenario is projected to grow by anywhere from 1.5 to 2.5 times the 2010 level to reach 160–250 EJ by 2050 (Fig. 3). All models project continued importance of liquid

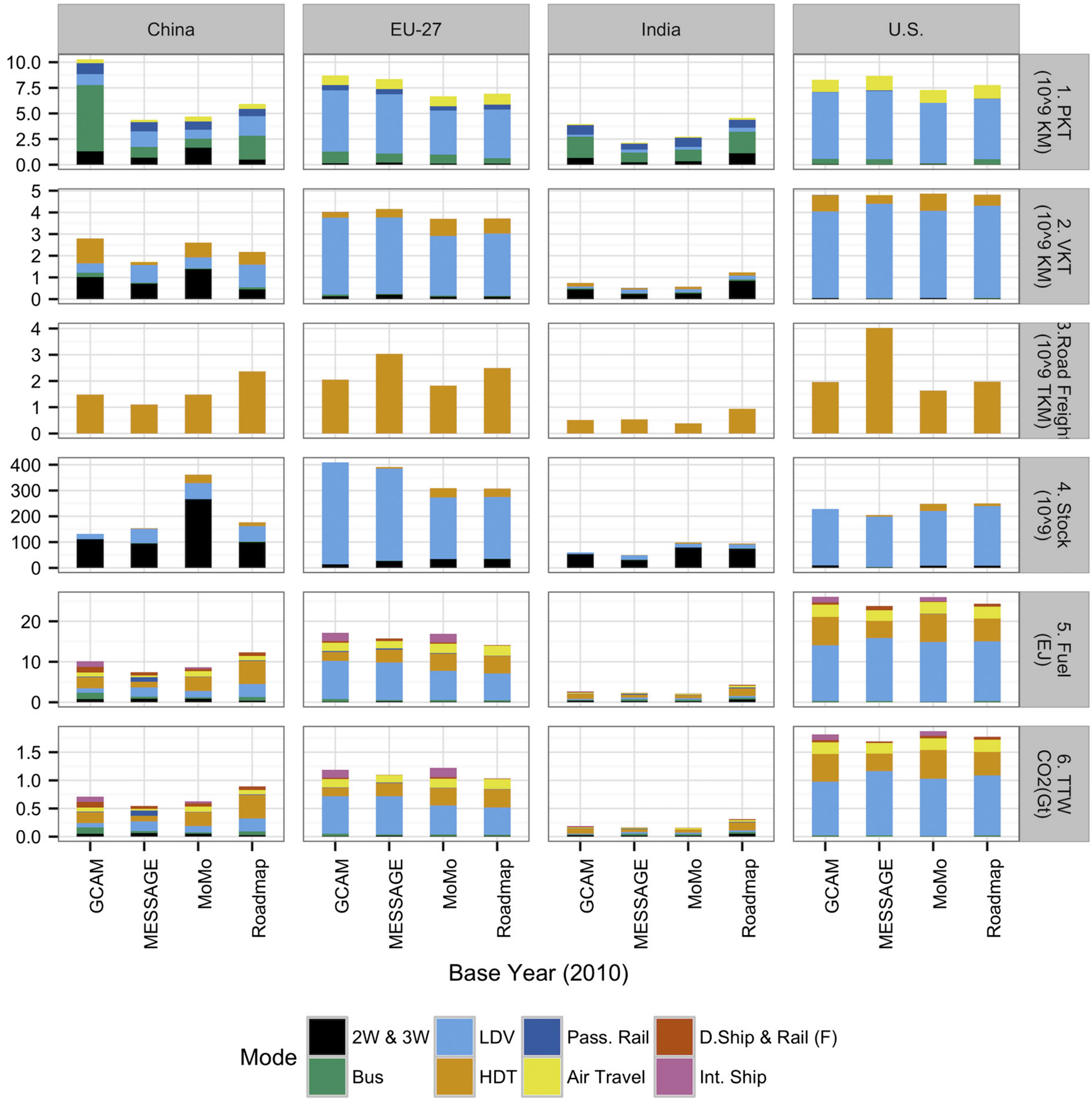

Fig. 2. Base year (2010) estimates of transportation activity by mode in China, India, EU-27 and the U.S. 2W & 3W: two- and three-wheelers; LDV: light-duty vehicle; HDT: heavy-duty truck; Pass. Rail: passenger rail; D. Ship & Rail (F): domestic freight shipping & rail (Freight); Int. Ship: international shipping; PKT: passenger kilometers travelled; VKT: vehicle kilometers travelled; TTW: Tank-to-wheel (or tailpipe) CO_2 emissions (biofuel-derived carbon is not included here in order to have consistent accounting across studies).

fuels – both fossil- and bio-based – and dominance of developing regions, which account for around two-thirds of total transportation energy consumption by 2050, from around half today. The modes that use the most energy continue to be car and light-duty trucks and heavy-duty trucks, though the share of aviation increases rapidly. The fastest growth is expected in the aviation sector (150–400%) and road freight, or heavy-duty trucking (HDT), sector (100–160%).

As discussed earlier in Section 2.4 and Fig. S1, models differ in terms of the accounting of CO_2 emissions, and how these emissions are reported in the iTEM exercise. The fossil CO_2 emissions from transportation are estimated to be 11–18 Gigatonnes of CO_2 in 2050 for the tank to wheel (TTW, or tailpipe) emissions. Biofuel-derived carbon is not included here in order to have consistent accounting across studies) (Fig. 3).

Some of the variation in projected growth of transportation fuel consumption may be explained by differences in assumed growth in income (per capita GDP) – historically the key driver of vehicle ownership and travel (Schäfer et al., 2009). For example, China's per capita income in 2050 is assumed to range from $24,000 (MESSAGE) to $42,000 (MoMo) (2005 U.S. dollars, measured in purchasing power parity) (Fig. S6), with corresponding estimates vehicle ownership of

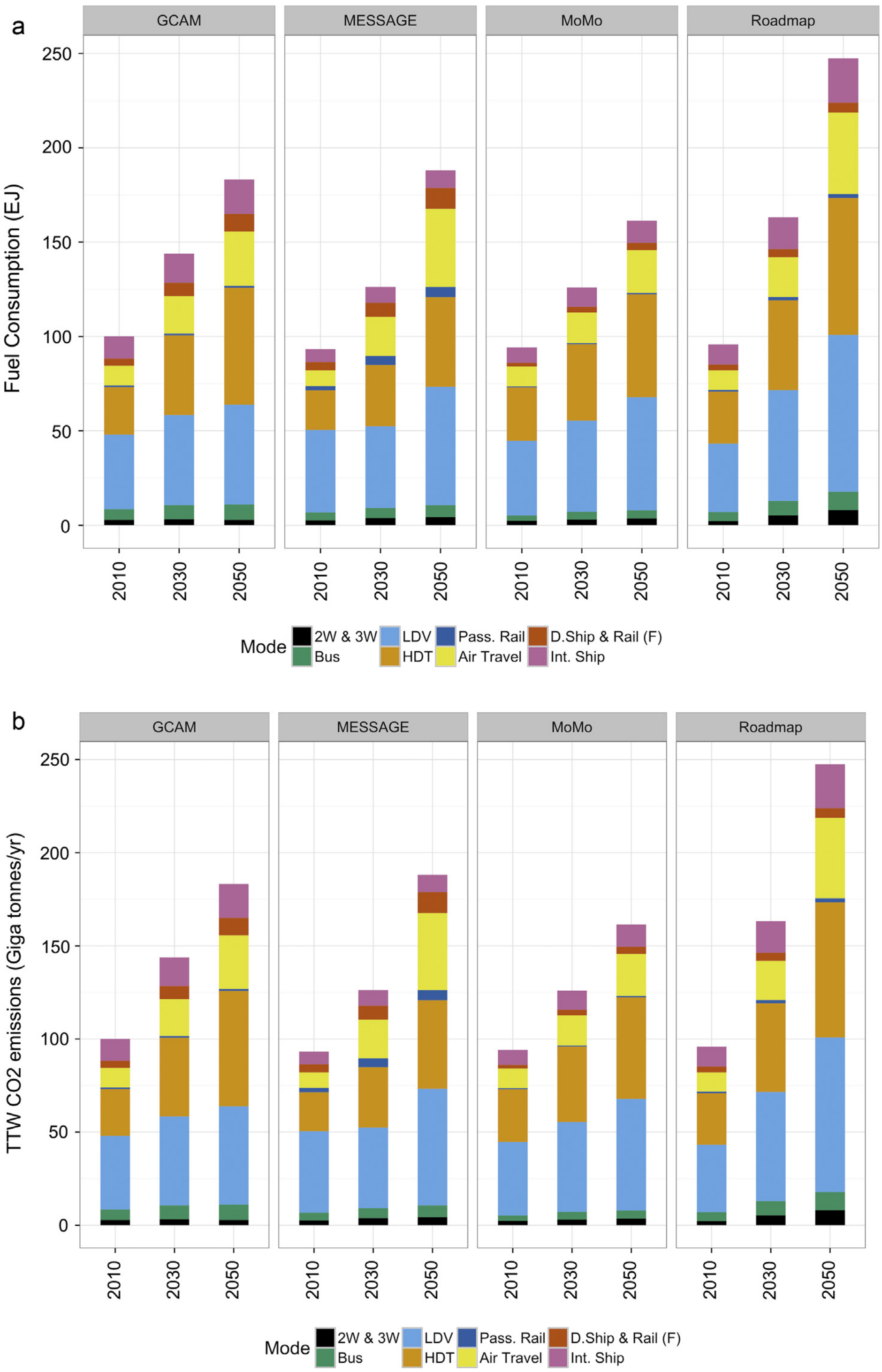

Fig. 3. Global fuel use and CO_2 emission projections by mode to 2050 in the baseline scenario. 2W & 3W: two- and three-wheelers; LDV: light-duty vehicle; HDT: heavy-duty truck; Pass. Rail: passenger rail; D. Ship & Rail (F): domestic freight shipping & rail (Freight); Int. Ship: international shipping; PKT: passenger kilometers travelled; VKT: vehicle kilometers travelled; TTW: Tank-to-wheel (or tailpipe) CO_2 emissions (biofuel-derived carbon is not included here in order to have consistent accounting across studies).

172 (MESSAGE) to 426 (MoMo) per 10,000 people. On the other hand, MoMo in general has a lower-than-average service demand projection, while Roadmap to have a higher one across all modes. Taking all these into account (assumptions about regional GDP growth, vehicle ownership, service demand, etc), global passenger mobility is expected to increase by 1.9–3.3

times from 2010 to 2050, ranging from 37 (MoMo)–59 (GCAM) trillion PKT in 2010 to 78 (MoMo)–136 (Roadmap) trillion PKT in 2050 (Fig. S7). Air travel is expected to grow from 4.4 to 4.6 trillion PKT in 2010 to 17 (GCAM)–27 (Roadmap) trillion PKT in 2050, constituting 13–20% total passenger transportation service demand by 2050, from today's 8–12%.

3.3. Light-duty vehicles and two-wheelers ownership projections

Perhaps one of the most important uncertainties in projecting future fuel use is the level of vehicle ownership and use. Population and income growth are the key drivers of the expected increase in car ownership, though GCAM, MESSAGE, and Roadmap models predict ownership as a function of total travel, modal shares, and annual VKT per vehicle, MoMo estimate it directly from basic population and income data, as shown in Fig. 1. Globally, baseline projections of global LDV (cars and light trucks) ownership rates (vehicles per 1000 people) increase from around 120–160 in 2010 to 220 (GCAM)–320 (MESSAGE) in 2050 (Fig. S6). This implies a growth in on-road stock from around 0.85–1.1 billion LDVs in 2010 to 1.6–2.2 billion LDVs in 2030 and 2.0–3.0 billion LDVs in 2050, when the world will have about 10 billion people (Fig. S8). The range is consistent with the auto industry's own projections for the year 2035 (Navigant Consulting, 2015). There are wide ranges in estimated vehicle ownership across countries: 700–1075 for the US by the middle of the century (US is around 700 today), 40–430 for China, and 20–250 for India across the four models (Fig. S6). In general, GCAM and MESSAGE project higher vehicle ownership for developed countries, and MoMo and Roadmap have higher projections for developing countries (Fig. S6).

The amount of travel per vehicle per year was also found to be a significant source of uncertainty across the models. For some countries, models had widely varying assumptions for annual vehicle travel, especially for certain vehicle types (e.g. from 3000 to 10,000 km per year for motor scooters in India). Since these assumptions link vehicle stock to total activity and fuel use, they need to be better understood. Improving the representation of car ownership and use across the models was identified as a priority, perhaps second only to data improvements.

3.4. Freight projections

All four models rely on GDP forecasts to project future freight demand (with different system boundaries, see Table S2). Regions have very different starting points for modal shares (trucks vs. rail vs. ship), and projections across the four models tend to hold the base year modal shares roughly constant through 2050. In reality, future evolution will depend on the characteristics of products (e.g. type of commodities) being shipped, availability of efficient freight technologies, and development policies and infrastructure. For example, policies can affect the type of fuel used (e.g., the upcoming MARPOL Annex VI on regional and global marine fuel oil (HFO) and marine diesel fuel use), as well as commodities transported domestically (e.g., reduced coal use in China to improve air quality and reduce GHG emissions) and internationally (e.g., liquefied natural gas (LNG) and oil exports from US).

4. Climate policy scenario

Comparing the results of policy impacts from multiple models with different solution mechanisms can improve our understanding of the robustness of the results. We compare a scenario consistent with the deep economy-wide decarbonization needed to reach a 2 °C/450 ppm target by the end of the century. In GCAM, this means applying carbon prices at levels that increase at a Hotelling schedule of 5% per year from 2020 to 2050 such that CO_2 emissions follow a 450 ppm pathway. Similarly, a carbon budget is imposed in the MESSAGE model in order to reach the target of GHG concentration (including all forcing agents) peaks at just over 500 ppm GHG around mid-century and then drops to 477 ppm by 2100. This leads to a globally-harmonized carbon price (across all countries and energy/land-use sectors) that grows over time with the prevailing model discount rate of 5%. The price first comes into effect in 2020 at 43 \$/tCO_2eq and then reaches 186 \$/tCO_2e in 2050. For MoMo, the 2 °C scenario is consistent with the ETP analysis that lays out a secure and affordable energy system deployment pathway and an emissions trajectory consistent with at least a 50% chance of limiting the average global temperature increase to 2 °C by 2100 (IEA, 2014). Roadmap's low-carbon scenario only projects to 2030, and is based on identified policy potential to expand the adoption of new vehicle efficiency standards; increase uptake of electric-drive passenger vehicles; improve the efficiency of marine vessels and aircraft; shift some road-based travel to less carbon-intensive modes; and improve road freight logistics (Miller and Façanha, 2014; Façanha et al., 2012).

Because of the different interpretations of the 2 °C scenario, this translates to different transportation sector GHG emission reduction levels across models. In addition, because GCAM and MESSAGE are IAMs, GHG emission reductions in transportation will compete with emission mitigation options elsewhere in the economy based on costs. What this implies is that both the level and timing of mitigation can vary considerably across models. The overall GHG reductions range is estimated between 0.86 (MESSAGE) and 2.1 (Roadmap) Gt CO_2/yr in 2030, and between 2.0 (GCAM) and 3.6 (MESSAGE) Gt CO_2/yr in 2050 (Roadmap's low-carbon scenario only projects to 2030). The overall magnitude of transportation emissions reduction estimated is consistent with the range found by the literature assessment of the IPCC AR5 WGIII (IPCC, 2014a). However the four models compared here provide more details on mode-specific mitigation measures, and better insight regarding the regional-level policies and measures necessary to mitigate in a manner that is consistent with the global goals. Here we compare the results in changes in per capita travel (Section 4.1), energy intensity of transportation service (Section 4.2), and carbon intensity of fuels (Section 4.3). We present the results of a decomposition analysis in Section 4.4.

4.1. Passenger travel activity and fuel use

In general, in response to a climate policy the four models project a decrease in overall private travel volumes (5–15% reduction in 2050, except for Roadmap which does not generate 2050 results), but an increase in travel by public modes (Figs. 4 and S9 by region). In MoMo and Roadmap, these changes are estimated based on expert judgment (what-if scenarios). In GCAM and MESSAGE, travel demands are a function of income and travel time costs (both are exogenous), and other costs including fuel, levelized vehicle costs, and carbon taxes. Thus, the demand response in these IAMs is entirely a function of increase in travel costs as a result of implicit carbon tax, and the adoption of low-carbon fuels and vehicle technology. Corresponding to the reduction in average per capita travel is a decline in the stocks of LDVs and two-wheelers (7–25% reduction of LDVs globally, equivalent to 150–740 million less cars and light trucks in 2050 in the policy scenario compared to the baseline scenario) (Fig. S10).

The overall fuel use by scenario, model, and transportation mode in 2030 and 2050 are shown in Fig. 5. Even in the climate policy scenario, liquid fuels (including biofuels which are not separately reported by the models) are still dominant in the transportation sector in 2050, despite greater penetration of other alternative fuels, particularly electricity (in bus and rail, and in car and light-duty trucks) and natural gas (in car and light-duty trucks, heavy-duty trucks, and in international shipping). Overall fuel use decreases by 5–26% in the climate policy scenario to 97–127 EJ in 2030 and 12–41% to 95–162 EJ in 2050 (Fig. 5). Liquids constitute 87–99% of total fuel use in the baseline scenario compared to 74–84% in climate policy scenario in 2050.

4.2. Energy intensity of transportation service

All four models assume improvements in energy efficiency of vehicle technologies and show a gradual penetration of alternative fuel vehicles across all transportation technology/modes. In the baseline scenario, there are underlying trends shifting passenger service demand to faster modes (i.e. from public transit to cars and air travel), as discussed in Sections 2 and 3. Despite increases in the efficiency of vehicles (Fig. S11), the overall energy intensity of passenger travel decreases much more slowly across all transportation modes, or even increases slightly for some regions such as China (Fig. S11). These increases are due to modal shifting, toward more energy-intensive transportation modes, as well as income-related decreases in LDV occupancy factors. Climate policy results in greater reduction in energy intensity or slower increases in energy intensity in countries such as China. These changes reflect the combined effects of: (1) greater efficiency improvements of transportation technology including vehicles (Fig. S11); (2) shifts to more energy-efficient low-carbon technologies such as electric vehicles; and (3) shifts to more energy-efficient low-carbon modes. In the climate policy scenario, the levelized costs of travel in energy intensive modes – air travel and LDV – rise more than those of buses and rail. As a result, the share of more energy-efficient public transit modes increases, leading to slower increases or decreases in average MJ/PKT.

It is interesting to note that the reductions in energy intensity from the baseline to policy scenarios are greater for the transportation-only models (MoMo and Roadmap) than the energy-economic systems models (GCAM and MESSAGE) (Fig. 6). One possible explanation for the difference between the two types of models is that in the energy-economic systems models, the costs of mitigation are compared across all sectors, and the costs of efficiency improvement (particularly through the adoption of advanced vehicles such as electric vehicles). Similarly, the energy intensity of road freight (HDT) also has the similar trend: the energy intensity of freight shows almost no change in the energy-economic systems models between the baseline and policy scenarios while the reductions in the expert-based models can be much larger.

4.3. Carbon intensity of fuels

As discussed earlier in Sections 2.4 and 3.2 and Fig. S1, models differ in terms of their accounting of carbon emissions, and how these emissions are reported in the iTEM exercise. Hence, a consistent comparison of fuel CI trends across models is not possible. However, within a given model, the relative trends between the baseline and climate policy scenarios highlight the extent of transportation sector decarbonization estimated by the models. All models except Roadmap include substantial decarbonization of all transportation fuels especially liquids (via biofuels) in the climate policy scenario (Fig. 7). The largest CI reduction comes from GCAM and MESSAGE, followed by MoMo and least reductions from Roadmap.

4.4. Decomposition of GHG emission reduction

Here we decompose the relative roles of various mitigation drivers in achieving carbon emissions reductions from the passenger transportation sector from 2010 to 2050. Understanding how models use these different "levers" to achieve CO_2 reductions can yield insights into the potential contribution of different strategies. Following the Kaya relationship developed previously (Zhang and Ang, 2001; Ang, 2004), CO_2 emission reductions from passenger transportation sector in any given year can be represented by changes in travel demand, mode share, load factor (LF, or occupancy factor), energy

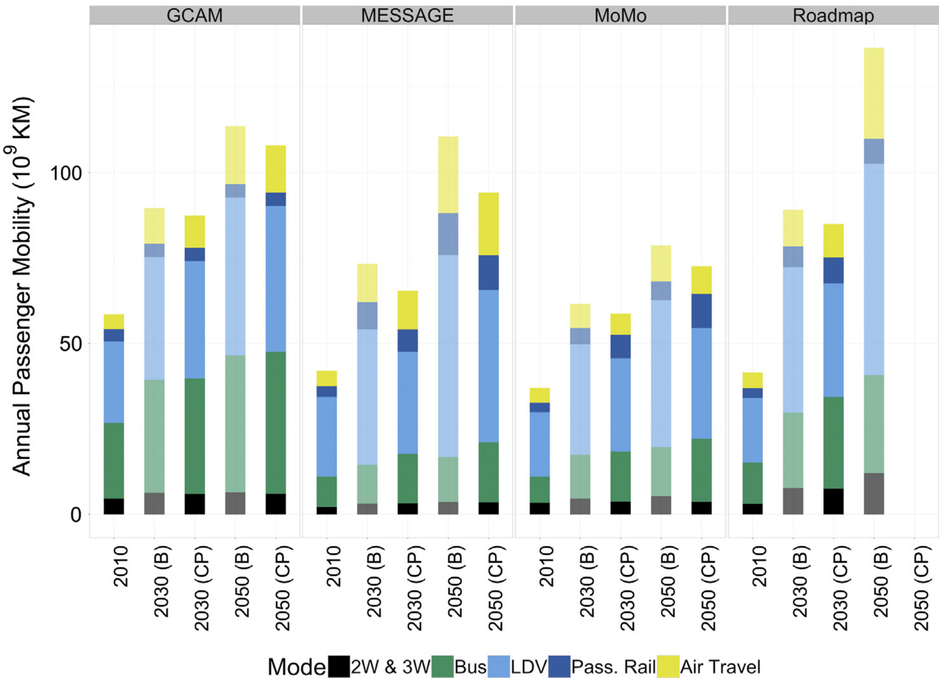

Fig. 4. Global passenger activity in the baseline (B) and climate policy (CP) scenarios in 2010, 2030 and 2050.

intensity of modes, and the carbon intensity of fuels (Mishra et al., 2014). The equations for the decomposition analysis are listed in Appendix A of the SI. Fig. 8 shows the results of the decomposition.

Among all mitigation options, all four models seem to indicate that efficiency improvements and low carbon fuels are the most important emission reduction strategies over the first half of the century, followed by mode shift, changes in LF of a particular mode, and travel demand reduction. The economic-based IAMs (GCAM and MESSAGE) favor the use of low carbon fuels as the primary mitigation option (most cost-effective transportation solution across the entire transportation sector, considering other options in transportation and other sectors) followed by efficiency improvements, whereas transportation-only and expert-based models (MoMo and Roadmap) favor efficiency improvements of vehicles followed by mode shifts. Roadmap, though going only to 2030, appears to be headed in a fairly similar direction as MoMo (despite higher baseline emissions), in particular in relying on vehicle efficiency improvements to achieve CO_2 reductions. In the energy-economic system models (GCAM and MESSAGE), the cost of travel demand reduction and mode shifts are dominated by wage rate and thus are simply too expensive compared with other mitigation options. None of the models shows significant CO_2 reductions related to load factor changes or reductions in overall travel demand relative to the baseline. Despite 2–5% reductions in total PKT between the baseline and the climate policy scenarios (Fig. 4), it translates to only 0.3–4% of total GHG emission reductions in 2030 and 2050. In the case of MoMo, this reflects a modeling choice to hold the low CO_2 travel levels the same as for the BAU; the goal was to achieve a low-carbon future without any reductions in mobility, as measured by PKT.

Note that because GCAM and MESSAGE only report combustion emissions in this iTEM exercise and biofuels are reported as carbon neutral, land use emissions (both direct and indirect) associated with increased demand for biofuels are reported elsewhere in the IAMs (mainly in the agriculture and land use sectors) instead of the transportation sector, the principle focus of iTEM. Nonetheless, the IAMs still find biofuels a cost-effective solution across the entire system.

5. Policy insights and recommendations for future work

The four models selected for this exercise have a long tradition of providing insights related to transportation-related activity, energy, economic and environmental projections and scenarios that are used to inform policy makers in many countries. Our goals in undertaking this modeling comparison focus on the details of the transportation models that are important for reported high-level outcomes. In particular, we seek to understand how differences in the models' structures, key assumptions and data sources contribute to differences and similarities in the base year data and future projections. More importantly, given the policy relevance of these models, we seek to translate the findings from this study into relevant policy implications such as additional policy targets needed, feasibility of policy goals, regional vs. global reductions, etc. Through this effort, we also seek to identify major gaps, new efforts in modeling and data collection, future comparisons, and other next steps that would be of value to modelers and policymakers. Compared with previous modeling comparison efforts that are limited to IAMs (Pietzcker et al., 2014; Girod et al., 2013; Edelenbosch et al., 2016), we include two prominent

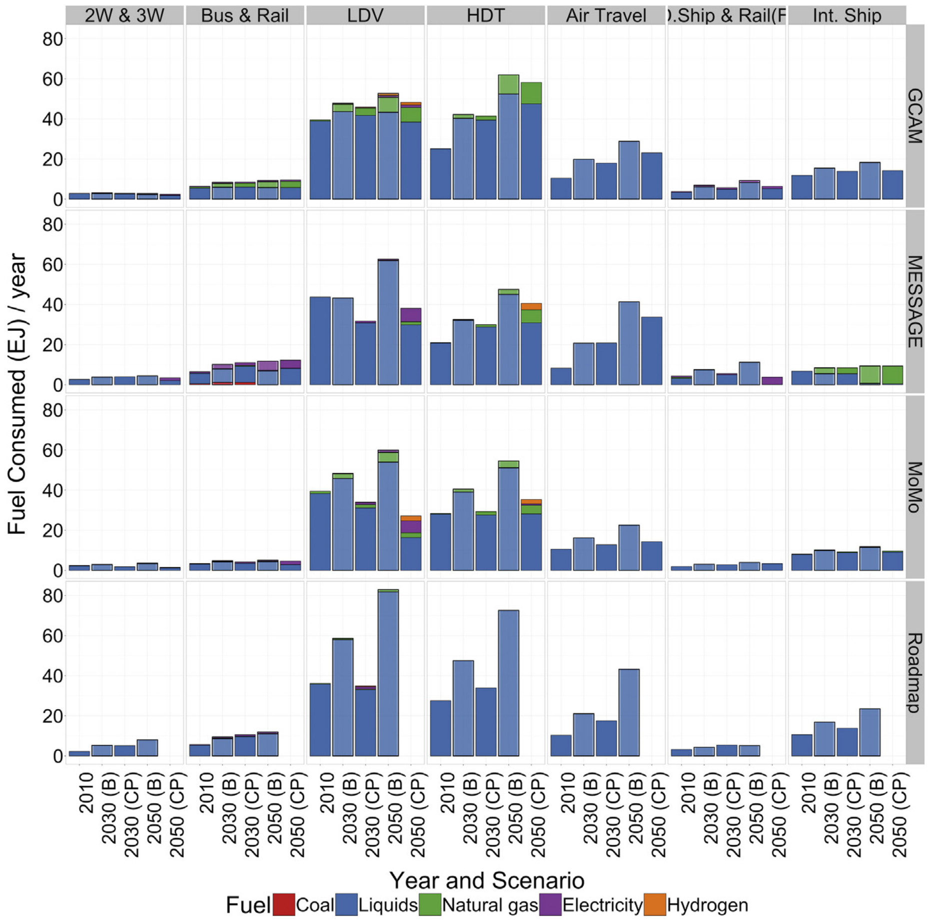

Fig. 5. Global fuel use in the baseline (B) and climate policy (CP) scenarios in 2010, 2030 and 2050. Liquids include crude oil, other fossil-fuel based liquids like CTL and GTL, and biofuels.

transportation-only expert models that have been relied heavily in the past to inform policymakers about regional/country-specific/global transportation challenges. The value of this workshop extends beyond modeling comparison by bringing the academic institutions, NGOs, industry, and policymakers to have a real dialog about model assumptions and real-world policy targets (see Section 5.1 on the EV vehicle goals and the vehicle efficiency legislation in different countries). Our workshop also results in a list of survey of experts' recommendations for future work, summarized in Section 5.2.

5.1. Policy insights

One useful exercise is to compare modeling results with planned policy targets to gain insights such as possible policy gaps, or the feasibility of modeling results. For example, the modeling results suggest that in order to be consistent with the global target of 2 °C/450 ppm the *fleet average (stock) efficiency* target for light-duty vehicles (cars and light trucks) should be around 2.2 MJ/km (1.8–2.8) for the US and 1.7 MJ/km (1.5–2.0) for China in 2030 and 1.7 MJ/km (1.3–2.3) for US and 1.4 MJ/km (1.1–1.7) for China in 2050[1] (Fig. S11). Since US vehicle stocks are historically less efficient and bigger sizes, the expected vehicle stock efficiency improvement to meet the 2 °C/450 ppm has a wider range compared to China depending on each model's assumptions regarding size changes and consumers' preference for changes toward smaller and more efficient vehicles. Based on Fig. 9, the current and proposed fuel economy standards for *new* light-duty vehicles[2] in US and China are probably insufficient to meet the fleet-average target for 2030.[3] Though if future standards continue to be tightened at rates consistent with current policies, efficiency could certainly deliver its contribution to the 2 °C/450 ppm CO_2e target.

[1] 2.2 MJ/KM is equivalent to 34 miles per gasoline gallon equivalent (mpgge), and 1.7 MJ/KM is roughly equivalent to 44 mpgge.

[2] Note that these numbers have not been adjusted for the new European Worldwide Harmonized Light Vehicles Test Procedure that better reflects the real-world driving conditions. It is estimated that the new testing procedure will add on average 5–7 gCO_2/km to the 2020/2021 EU standard (Mock et al., 2014) though the difference will be even larger for plug-in hybrid electric vehicles (Plötz et al., 2015).

[3] The average vehicle lifetime in the US is about 15 years, and it takes about 16–20 years for the entire vehicle stock to reach the same energy efficiency level of the new vehicles sold in a given year.

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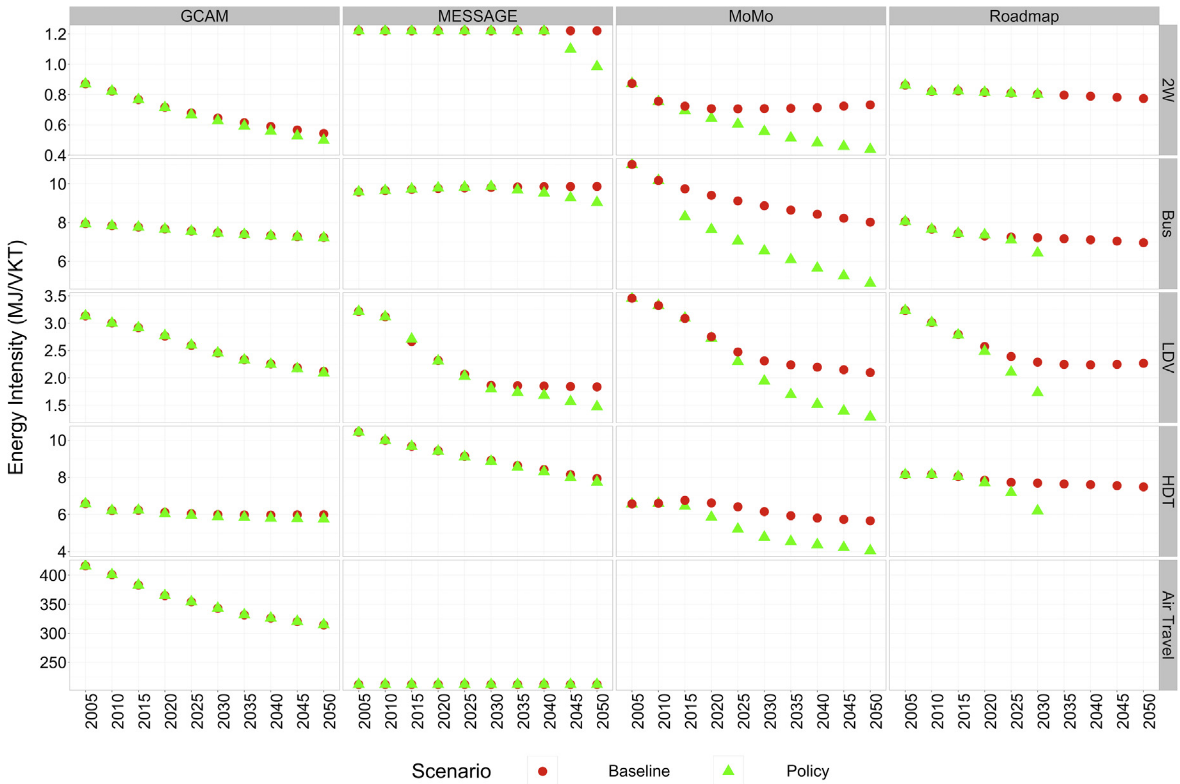

Fig. 6. Average energy intensity of selected modes of transport. VKT: vehicle kilometers travelled. HDT: heavy-duty truck. LDV: light-duty vehicle.

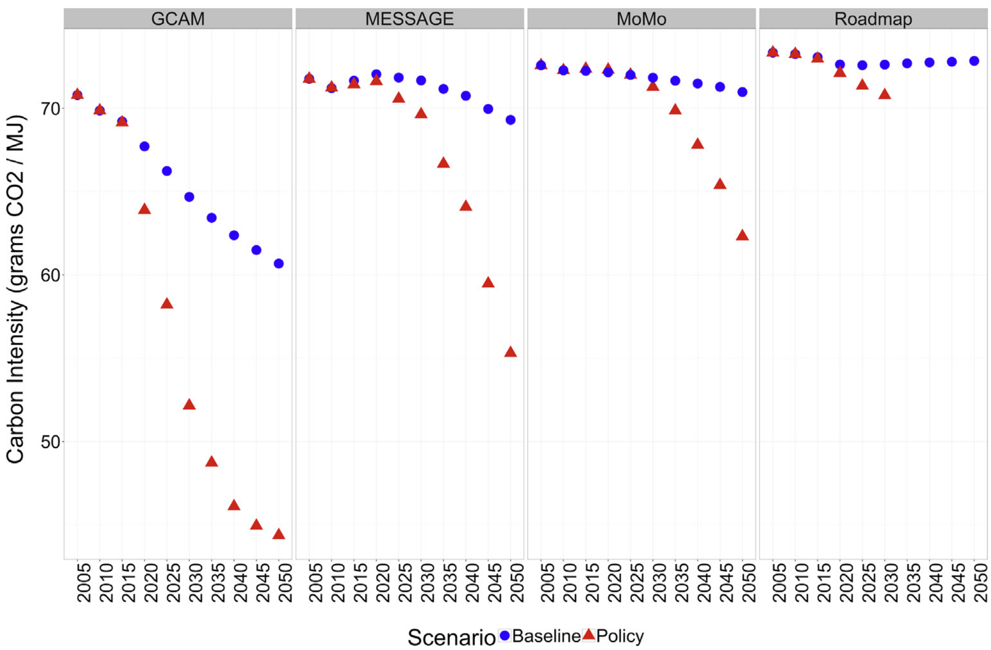

Fig. 7. Carbon intensity of all transportation fuels in baseline and climate policy scenarios. Only fossil emissions are reported here; biofuels are reported here as carbon neutral.

Another policy insight, as shown in Table 2, is the comparison between existing policy commitments for zero-emission vehicles (ZEVs) and partial ZEVs (plug-in hybrid vehicles and hydrogen fuel cell vehicles) and the projected levels that the

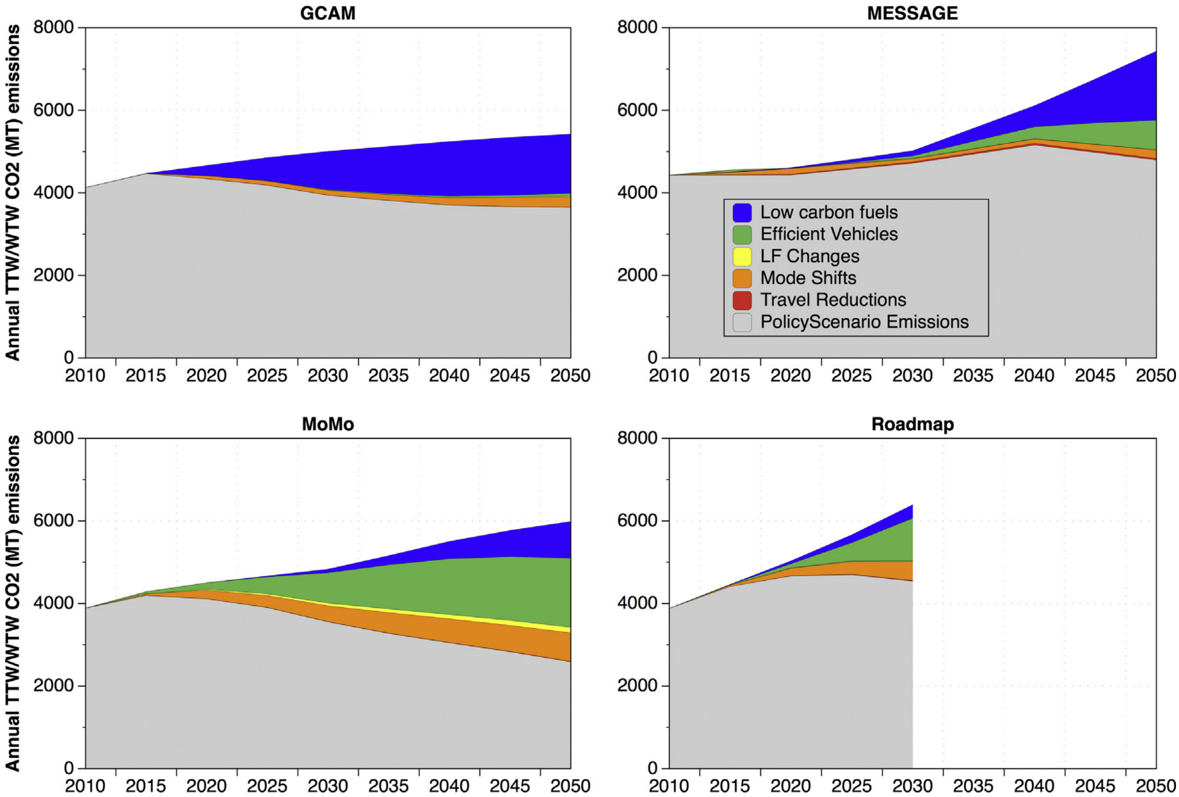

Fig. 8. Decomposition of the relative roles of mitigation options in reducing global carbon emissions from passenger transportation (including 2W & 3W, bus, LDV, passenger rail, and air travel).

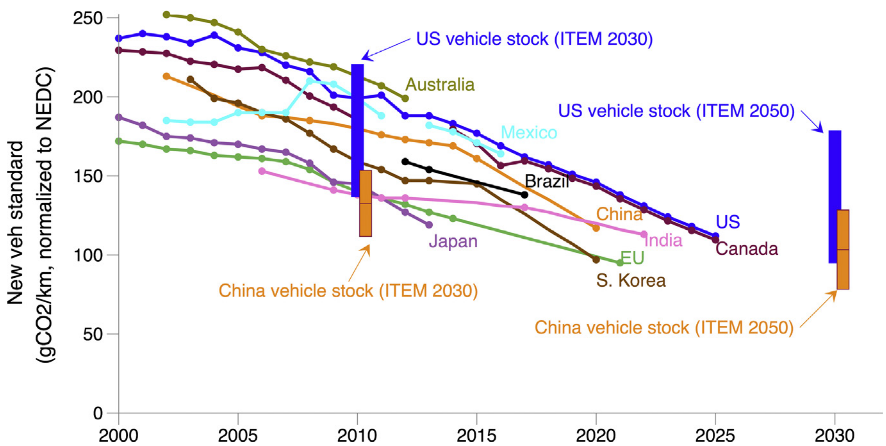

Fig. 9. Comparison of iTEM results with current and planned energy intensity policies for new passenger LDVs, by country (ICCT, 2015), and the ranges of *average energy intensity for the entire vehicle stock* for 2030 and 2050 across the iTEM models. The stock averages are overlapped onto new vehicle standards by a 20-year lag.

models suggest need to be on the road by 2020/2025 in order for the transportation sector to be consistent with the 2 °C target. This comparison suggests that the current policy commitments toward EVs and PHEVs for 2020/2025 may be far below the number of vehicles suggested needed in 2025 by these models. The electric vehicle landscape is changing rapidly, however. For instance, the IEA's ETP 2016 suggests that EV sales growth in 2015 puts them potentially 'on-track' to meeting the two-degree targets by 2025 (assuming annual growth in sales can be sustained at levels close to those of that year) (IEA, 2016). In general, the modeled low-carbon scenarios will require much more aggressive market uptake of EVs than targeted by policy commitments to date. This seems to indicate the need for stronger, coordinated policies to realize the combined

Table 2
Comparison of announced policy targets with model-projected number of electric vehicles needed to be on the road by 2020/2025 in order for the transportation sector to be consistent with the 2 °C target. Average values across models are shown; full ranges in parentheses.

	China	U.S.	Global
iTEM	28 million *(2–47)*	29 million *(9–42)*	113 million *(35–180)*
Policy/Target	5 million by 2020[a]	1 million EVs by 2015[b] 3.3 million by 2025[c]	20 million by 2020, 100 million in 2030[d]

[a] Energy Saving and New Energy Auto Industry Development Plan (2012–2020) (State Council, 2012).
[b] President's pledge (https://www.whitehouse.gov/sites/default/files/other/fact-sheet-one-million-advanced-technology-vehicles.pdf).
[c] MOU, 8 states (http://www.arb.ca.gov/newsrel/newsrelease.php?id=620).
[d] IEA Electric Vehicles Initiative (EVI) (http://www.iea.org/topics/transport/subtopics/electricvehiclesinitiative/).

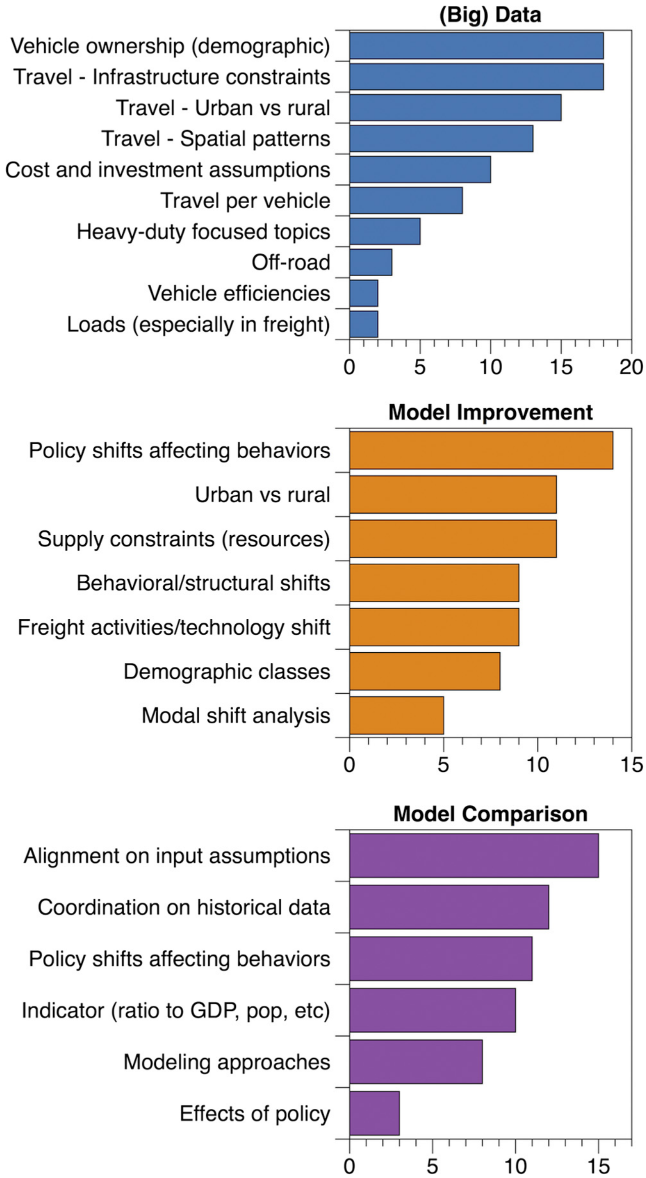

Fig. 10. Survey of experts' recommendations for future improvement in data, modeling and modeling comparison.

mitigation potential of fuel economy standards and ZEV targets in both the near-term and long-term. As we illustrate in Fig. 8, however, when comparing specific mitigation options (such as technology adoption or low carbon fuels) across models, it is worth noting that results must be understood in the context of emissions *tradeoffs* made in the models (i.e. more aggressive reliance on low carbon fuels will require less EVs to meet a particular target, and vice versa). Therefore, to the extent that greater reductions can be achieved from other measures such as mode shifts or demand reductions, the demand for EVs to meet the policy targets can be smaller.

5.2. Recommendations for future work

A survey was conducted with external experts not previously involved in the iTEM exercise (selected participants are listed in Acknowledgement and a full list of participants is available upon request), seeking inputs for key research priorities in the areas of data collection/development, model improvement, and model comparison. Each participant cast up to two votes in each category, and the results are summarized in the following bar graphs (Fig. 10). Overall, experts see importance in improving the quality and the availability of data, as well as making improvements in model structure to enhance our capability of making better projections, especially of vehicle ownership and travel behaviors. The results are briefly discussed below.

Data. Given the great uncertainty observed in base year data across models, there is a great need to increase the collection of data, particularly in developing countries where systematic efforts in collecting transportation relevant data at the national level are lacking.

Model improvement. The lack of modeling of behavioral aspects in vehicle adoption rates, mobility/mode choices, urban vs. rural considerations, and so on are considered as critical to improve modeling efforts in the future. For example, modeling saturation in vehicle ownership and use as a function of income distributions, urban form, and infrastructure requirements and constraints, was discussed as an important enhancement that could be made to these models. An improved representation of the freight sector is also an area of future research. A few recent modeling efforts have started to address these critical issues: Bunch et al. (2015), McCollum et al. (2016), Ó Broin and Guivarch (2016), Carrara and Longden (2016).

As we have shown in this paper, detailed comparison of modeling data and results at country/regional level and specific modes show greater uncertainties and differences than the global and aggregated data for the base year, baseline projections and the climate policy scenario. Better regional and demographic detail could improve the capacity of models to better inform policy goals and estimate policy impacts. Further, for large regions like China, variation at the sub-regional level in current and projected income, urbanization rates, vehicle ownership, levels of infrastructure, types of industry, etc. may add further value to the analysis (Kishimoto et al., 2014). Similarly, modeling strata of demographic groups can provide better understanding of vehicle ownership levels, travel behavior, response to GDP growth and policies, etc.

Modeling comparison. In future model comparison work, external experts see great value in conducting on-going, coordinated efforts in aligning input assumptions and historical data, more analysis of vehicle ownership, and more policy analysis, among other topics.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2016.11.001.

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