Decomposing passenger transport futures: comparing results of global integrated assessment models

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Abstract

The transport sector is growing fast in terms of energy use and accompanying greenhouse gas emissions. Integrated assessment models (IAMs) are used widely to analyze energy system transitions over a decadal time frame to help inform and evaluating international climate policy. As part of this, IAMs also explore pathways of decarbonizing the transport sector. This study quantifies the contribution of changes in activity growth, modal structure, energy intensity and fuel mix to the projected passenger transport carbon emission pathways. The Laspeyres index decomposition method is used to compare results across models and scenarios, and against historical transport trends. Broadly-speaking the models show similar trends, projecting continuous transport activity growth, reduced energy intensity and in some cases modal shift to carbon-intensive modes - similar to those observed historically in a business-as-usual scenario. In policy-induced mitigation scenarios further enhancements of energy efficiency and fuel switching is seen, showing a clear break with historical trends. Reduced activity growth and modal shift (towards less carbon-

intensive modes) only has a limited contribution to emission reduction. Measures that could induce such changes could possibly complement the aggressive, technology switch required in the current scenarios to reach internationally agreed climate targets.

Keywords: passenger transportation, energy modelling, model comparison, low emission scenarios

1. Introduction

The increased use of motor vehicles and airplanes has led to a higher mobility, flexibility and accessibility of the current population. At the same time, this has also resulted in social and environmental impacts at both the international/national and local scales [1]. At the local scale, transport activities cause urban air pollution, noise, congestion, water and soil degradation, asthma, obesity, road deaths and social and urban fragmentation [1]. At the international/national scale, mobility contributes to greenhouse gas emissions, trans-boundary air pollution, and the depletion of oil resources. Global greenhouse gas emissions from transport doubled over the 1970–2010 period to 7.0 $GtCO_2$-eq, increasing at a faster rate than any other end-use sector [2]. Strategies to decrease transport energy use, or even demand growth, can clearly lead to many co-benefits [3].

Integrated assessment models (IAMs) are commonly used to explore energy system transitions over the long term to meet global climate targets. Their strength lies in analyzing trade-offs and synergies across economic sectors, and providing insights in the costs and benefits of different policies [4]. Due to the importance of the transport sector as a final energy consumer, most of these models also include a relatively detailed representation of developments in this sector and its potential to contribute to mitigating GHG emissions. Girod et al. [5] and Pietzcker et al. [6] have performed comparison studies of transport sector representation in energy system models, including IAMs. Both studies show that, in these models transport CO_2 emission reduction potential depends highly technological change and changing fuel composition, which would breakthrough in the second half of the century. However, there is a large difference across models regarding the relative potential of the sector to mitigate.

There are different possible Interventions to reduce the impact of transport: 1) lower transport demand, 2) shift transport modes towards low carbon-intensity modes, 3) reduce the energy intensity of technologies and 4) reduce the emissions intensity of fuels [7]. Creutzig et al. [8] argue that limiting demand growth by shifting to more efficient modes and reducing the distance traveled has limited application in global IAM scenarios and emissions could be further reduced than currently suggested. Local studies often show that behavioral and infrastructure policy interventions, especially in urban areas, impacting modal shift, distance travelled and technological change could be effective measures to decrease emissions [7]. Moreover these measures can already impact transport emissions in the short term and can in fact potentially avoid infrastructure path dependency [8, 9].

In this study we look at a large set of IAM transport model projections and determine the relative contribution of energy efficiency, fuel shift, modal shift and activity change through decomposition analysis. This allows us to improve the understanding of these scenarios and to compare the application of the models in a transparent manner, by relating model structure to scenario results. Moreover, the disaggregation can provide further insight into how specific projected components compare against historical transport trends and, by extension, can potentially improve translation into and comparison with local measures, such as those highlighted by Creutzig et al. [8]. Secondly, input data on technology costs are compared in an attempt to further understand uncertainties underlying model differences in projections of vehicle and fuel choice.

The article is structured as follows: Section 2 discusses the method applied. The subsequent Section 3 discusses the results of a GHG mitigation scenario that is evaluated against a common baseline, focusing on specific GHG mitigation interventions. In Section 4, specific attention is given to technology input data representation in the USA affecting light-duty vehicle (LDV) choice. In Section 5, we discuss the results and identify key transport model developments that rank high in terms of policy relevance, and in Section 6 we come to our conclusions.

2. Method

2.1 Description of the IAM models

Eleven IAMs were included in this study, namely AIM/CGE, DNE21+, GCAM, GEM-E3, Imaclim-R, IMAGE, POLES, MESSAGE, REMIND, TIAM-UCL and WITCH. A qualitative questionnaire was sent to the modeling teams to take stock of their transport sector representations. This section discusses the concept and solution method of these models, along with the transport modes accounted for. In addition, Tables A.1 and A.2 in the supplementary material provide a summary of the responses. Several papers in this special issue include more detailed presentations of the transport modeling in GEM-E3 [10], MESSAGE [11], AIM/CGE [12], Imaclim-R [13] and WITCH [14].

IAMs differ in the way they represent the transport sector. The ones with greater transport detail (i.e., compared to the ones described herein) use a hybrid approach to model the transport demand and use of energy in the transport sector. In the hybrid approach a top-down demand formulation, relating demand to population and economic growth, is combined with the explicit modelling of modes and technology options per mode. Clearly, the degree of detail determines how well models are able to represent the key dynamics of the various transport sub-sectors and the different ways to mitigate emissions.

Transport demand in AIM-CGE is derived using a top-down method, where energy demand is input to a production function driven by gross domestic product (GDP) growth. In WITCH, the service demand of the explicitly modeled LDV mode is related to GDP and population, while the rest of the transport sector is indirectly comprised in the more general non-electric sector which is an input to a nested constant elasticity of substitution (CES) production function. Also the REMIND transport projections are based on a nested CES production function, but includes a second step in which three different technology options for the LDV mode and one generic end-use technology representation for the other modes. In POLES, DNE21+ and TIAM-UCL, GDP per capita drives modal service demand through income elasticities, while being sensitive to fuel prices. GEM-E3 transport demand depends on bilateral trade flows and on consumer preferences and budgets.

To capture modal shift dynamics and the transition between modes as countries develop (i.e., wealthier individuals use higher-speed modes [15]), a few models relate the demand per mode to mode speed and cost, MESSAGE and IMAGE both use travel money budget (TMB) and travel time budget (TTB) as top-down elements to constrain per capita person kilometers per mode in combination with the price and speed of the modes to project transport service demand per mode [16]. GCAM uses a similar approach, where the speed of the transport mode and vehicle operating cost affect the service price, which is related to income levels to determine the energy service demand. Imaclim-R travel demand and modal split are calculated endogenously from household utility maximization under constraint of revenues and time spent, assuming that mode speed is affected by utility of infrastructure. Girod et al. [5] previously found that income-induced shifts to faster modes are more pronounced in the models that consider travel time.

Most IAMs are able to meet the overall service demand with different transport modes (see Table 1, e.g. cars, buses, air planes and trains), with the number of discrete modes in passenger transport ranging from one to seven modes. In several models, including DNE 21+, AIM-CGE and TIAM-UCL, the share of each mode is set exogenously. IMAGE, MESSAGE, Imaclim-R, POLES, REMIND, GEM-E3 and GCAM calculate the modal shares endogenously based on cost and, in some models, time and saturation constraints. WITCH features LDVs only.

Within any mode, vehicle technologies compete on the basis of cost, either through a logit distribution (GEM-E3, GCAM, POLES, IMAGE and Imaclim-R) or least-cost optimization (MESSAGE, REMIND, TIAM-UCL, WITCH and DNE21+). AIM/CGE does not explicitly model technologies. POLES takes exogenous assumptions on infrastructure development into account as a constraint to vehicle choice. The parameters used to describe the costs of transport technologies as well as their future development differ per model. REMIND, GEM-E3 and WITCH, for example, assume that the investment costs for currently immature technologies (battery-electric vehicles (BEV), plug-in hybrid vehicles(PHEV), fuel cell vehicles (FCV)) decrease endogenously as a function of deployment, following a global learning rate. In Imaclim-R, technology learning rates are applied to all technologies. In other models, the costs of some or all technologies decrease exogenously over time.

Table 1 Model description and passenger mode represented in the IAMs.

	AIM/CGE[1]	DNE21+[2]	GCAM[3]	GEM-E3[4]	IMACLIM-R[5]
Model concept	General equilibrium	Partial equilibrium	Partial equilibrium	General equilibrium	General equilibrium
Solution method	Mixed complementarity	Intertemporal optimization	Recursive simulation	Recursive dynamic model solved with mixed non-linear complementarity	Recursive dynamics
Passenger modes	Train, aviation, bus, LDV	LDV, bus	LDV, bus, 2W&3W, aviation, train	LDV, aviation, train, bus, ship	Aviation, bus & rail, cycling & walking, LDV

IMAGE[6]	**POLES[7]**	**MESSAGE[8]**	**REMIND[9]**	**TIAM-UCL[10]**	**WITCH[11]**
Partial equilibrium	Partial equilibrium	Partial equilibrium model soft-linked to general equilibrium mode	Hybrid model that couples an economic growth model with a detailed energy system model	Partial equilibrium	Hybrid model that couples an economic growth model with a detailed energy system model
Recursive dynamic	Recursive simulation	Linear optimization	Inter-temporal optimization	Linear optimization	Non-linear inter-temporal optimization and game theoretic setup
LDV, bus, train, aviation, cycling and walking	LDV, bus aviation, train	LDV, bus, 2W, aviation, train	LDV, rail, aviation and bus	LDV, bus, 2W&3W, train, aviation	LDV

1)Fujimori, Masui [17], 2)Sano, Wada [18], 3)Kyle and Kim [19], 4)Karkatsoulis, Kouvaritakis [20], 5)Waisman, Guivarch [21] 6)Girod, van Vuuren [16], 7)Girod, van Vuuren [5],8)Riahi, Dentener [22], 9)Luderer, Bosetti [23], 10)Anandarajah, Pye [24], 11)Bosetti and Longden [25],and Longden [26], 1:11EU-FP7-ADVANCE [27]

2.2 Transport model scenarios

Two scenarios have been used to examine the main passenger transport model outputs (freight transport projections are not compared for the purposes of this paper):

- a baseline scenario (no explicit climate policies beyond those already in place);
- a mitigation scenario (aiming to stabilize atmospheric concentrations of GHGs at 450 ppm CO_2-eq in 2100, compatible with the long-term target of achieving a 2°C increase in global temperature at the end of the century with respect to pre-industrial levels);

The baseline is the standard run scenario of the IAMs that represents a business-as-usual state where no explicit climate policy is assumed but current policy trends (e.g. efficiency) are in some cases extrapolated. Most model teams[1] are currently using or have harmonized their drivers to the population and income projections of the "middle of the road" shared socioeconomic pathway (SSP2) scenario, which assumes that economic and social trends continue in the future following the current patterns [28]. Projected GDP and population are shown in Figure 1; in some models these are scenario drivers while in others they are model outputs. There are some differences in GDP/capita visible already in the base year but in particular in the long term. Population projections are very similar, with the exception of POLES after 2030.

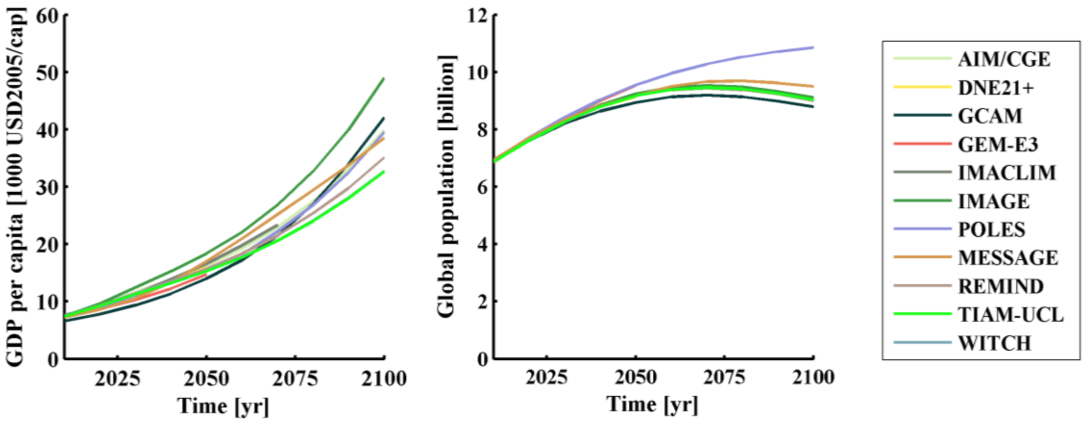


Figure 1 a) global population b) global GDP (MER) per capita.

2.3 Data analysis

The Laspeyres index decomposition method is used to quantify the contribution of the changes in components (corresponding to the earlier mentioned potential intervention strategies) to the aggregate emissions in the IAM transport model projections. This method has been used in energy research in recent decades to understand historical trends. There

[1] Models not harmonized to the SSP drivers are POLES, using UN projections of demographic drivers, and MESSAGE which is based on a Global Energy Assessment (GEA)-Mix storyline for population and GDP growth. GEM-E3 drivers are not fully harmonized but close to SSP2 projections.

are different decomposition methods and the advantages and disadvantages have been discussed extensively in the literature [29] [30]. Even though there are more sophisticated decomposition methods with factor and time reversal properties, the Laspeyres index is easy to interpret which, in this large multi-model comparison study, is an advantage. Moreover this method has been used in several studies to analyze historical transport sector developments across global regions and for a straight forward comparison the same method is applied [31-33]. We use the following variant of the IPAT formula [29] to compute the index:

$$Transport\ CO_2\ emissions = \sum_{i,j} population(P) * activity(A) * modal\ share\ (S)_i * energy\ intensity\ (I)_i * fuel\ mix\ (F)_{i,j} \quad \text{(Eq. 1)}$$

The formula shows a disaggregation of total CO_2 emissions from the transport sector into a combination of:

i) population in capita;
ii) the average per capita distance travelled in passenger km/capita (activity);
iii) the share of the different transport modes in fulfilling this travel demand in passenger-km/passenger-km (modal share of each mode i);
iv) the energy used per passenger km traveled for each mode in MJ/passenger-km (energy intensity of each mode i);
v) the CO_2 emissions per unit of energy consumed in g/MJ (fuel mix of each fuel j used per mode i).

Combining the last two components, the CO_2 emissions per passenger kilometer can be derived, which represents the CO_2 intensity per mode. Changes in these components are not necessarily independent from each other; for example, an increase in fuel prices can lead to a change in modal share as well as a decrease in travel activity. It does however give a measure of the relative importance of the change in each of the components in the development of CO_2 emissions.

The Laspeyres index indicates the contribution of the annual change in a single component to the projected CO_2 emissions, holding the others at their base year levels (in this analysis 2010, 2030 or 2050). For example activity growth affecting CO_2 emissions is calculated as:

$$CO_{2}{}_t^A = \frac{A_t}{A_{t0}} \quad \text{(Eq. 2)}$$

where A_t is the total passenger kilometers in year t and A_0 is the total activity in the base year. The Laspeyres index represents the annual average change δ^A in the period between the years t and t0:

$$\delta_{a,b}^A = exp\left[\frac{logCO_{2}{}_t^A - logCO_{2}{}_{t0}^A}{t-t0}\right] - 1 \quad \text{(Eq. 3)}$$

The index calculation shown in Equation 3 has been used 1992 by Scholl et al. [33] to compare developments in energy use and CO_2 emissions in – amongst others – the USA,

Japan, France, former West Germany, Italy, the UK, Denmark, Norway and Sweden over the 1973–1992 period. The study found that activity growth is the main contributor to the increase in CO_2 emissions in these regions. In the countries that are part of the Organization for Economic Co-operation and Development (OECD), passenger kilometers per capita grew by 37% on average in the 1973–1992 period. In most countries the modal structure shifted from bus and rail to automobiles and airplanes. The increase in car ownership, driven by growth in income, expanding suburbs, and greater female participation in the workforce, led to an increase in activity. Higher income along with a decrease in the cost of flying led to a larger share of air travel.
The change in CO_2 emissions as a result of the modal shifts was however relatively small compared to the contribution made by activity growth. Scholl et al. found that shifting modes in some countries led to unexpected effects and that the impact on total CO_2 emissions can be time dependent [33]. In Japan, for example, the CO_2 intensity of air travel dropped from the most intensive mode to just below the value of cars in 1992. Shifting to air transport therefore would result in a decrease in total CO_2 emissions, while in earlier years it had the opposite effect [33].

A more recent study running up to 2008 showed that the combination of slower activity growth and decline in energy intensity has led to stable or even declining transport GHG emissions in some OECD countries in recent years [31]. These examples illustrate the relevancy and type of analysis that can be performed through the decomposition method, that can improve understanding of developments contributing to GHG emissions.

3. Global trends in IAM transport projections

3.1 Transport carbon emission pathways

Figure 2 shows the direct and indirect passenger transport emissions[2] projected by the eleven IAMs in the baseline and GHG mitigation scenarios at the global level. All models, show an increase in direct emissions between 2010 and 2050 in the baseline, although the size of this increase clearly differs. In 2100, the projected emissions range (between 4 and 12 Gt/year) is further amplified. The models have followed different baseline emission pathways, either continuous increase until 2100, saturation, or even peak-and-decline. In the mitigation scenario, all models show a significant decrease in transport emissions compared to the baseline; this is necessary to achieve the stringent, long-term climate target. However, whereas direct emissions are less than one Gt in some models, in others they are comparable to base year values.

The lower panel of Figure 2 shows the indirect emissions from electricity and hydrogen use in the transport sector, calculated by using the average emission intensities of the models of

[2] The passenger projections of REMIND and WITCH only account for LDV transportation. GEM-E3, POLES and TIAM-UCL emissions include total aviation, and not specific aviation for passenger transport purposes. DNE21+ and Imaclim-R do not account for rail transport explicitly (see Table 1). DNE21+ and GEM-E3 projections run to 2050 and Imaclim-R to 2070.

electricity and hydrogen production[3] to enable straight-forward comparison across the models. Zero carbon emissions are assumed for biofuels, thus the indirect emission figure indicated the degree of electrification. Transport electrification takes place in all models, especially between 2050 and 2100. Whether electrification of transport will actually lead to lower emissions will depend on the fuel production process.

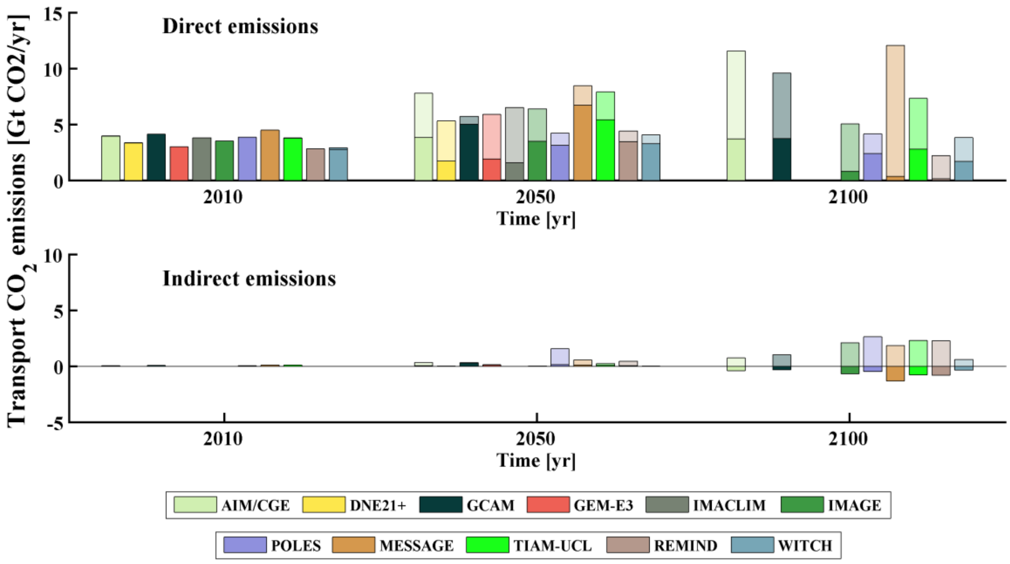


Figure 2: Passenger transport direct (top) and indirect (bottom) CO_2 emissions projected by IAMs in baseline (transparent color) and mitigation (solid color) scenarios. Average CO_2 intensity factors for hydrogen and electricity production across models are used for the indirect emissions calculation. REMIND and WITCH results only include LDV emissions.

3.2 Laspeyres index scenario decomposition

To untangle the underlying dynamics that lead to the models projected pathways, the Laspeyres indices are calculated for several components (Table 2): *activity* (pkm), *structure, energy intensity* (MJ/pkm) and *fuel mix* (g/MJ). The analysis focuses on direct emissions. The Laspeyres index is calculated for three time periods, namely 2010–2030, 2030–2050 and 2050–2100. As REMIND and WITCH only model LDV explicitly as a passenger mode, structural change – which refers to mode shifting – does not play a role in these models projections. The results of eleven IAMs are compared to Millard-Ball et al. [31] for a selection of OECD countries in the 1973–2007 period, which is summary of data collected by Scholl et al. [33] and Schipper [34] over a long time frame.

Table 2: Laspeyres index decomposition of activity, structure, energy intensity and fuel mix contributing to direct CO_2 emissions in IAM passenger transport model projections. The index value indicates the annual rate of change in emissions with respect to the base year

[3] In the mitigation scenario the average electricity emission factor across models is negative (this is not the case for all models) at the end of the century due to biofuel use combined with carbon capture and storage use for electricity production.

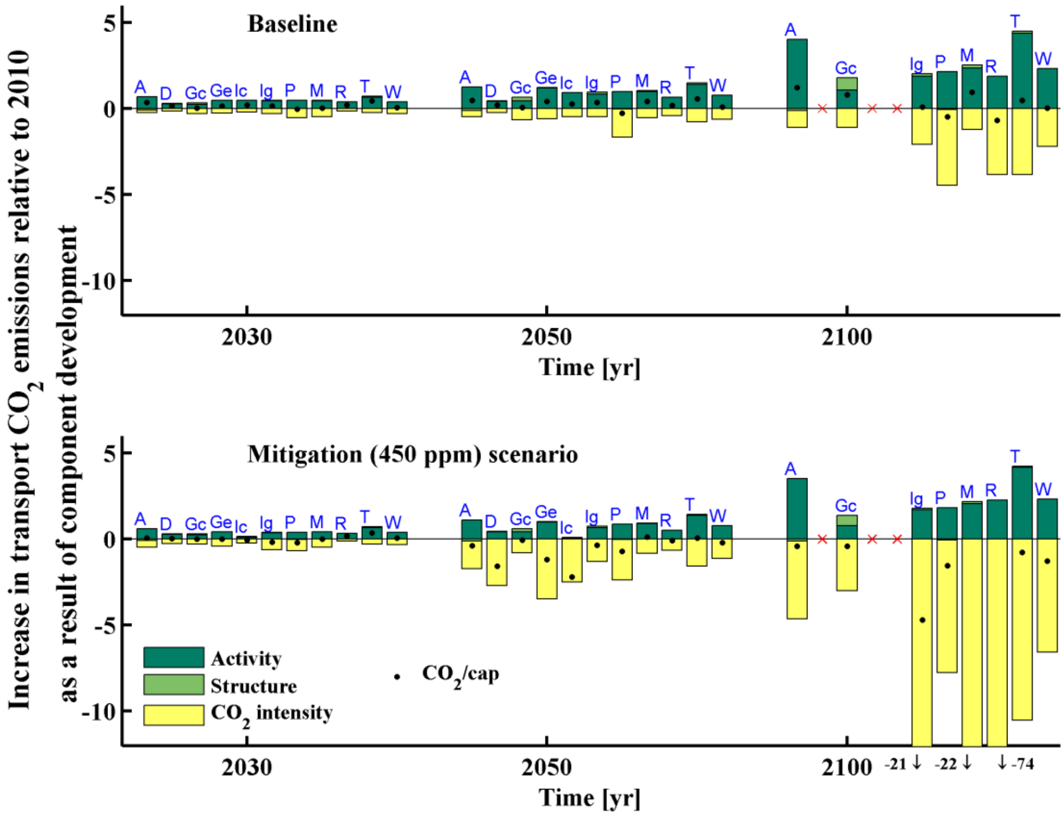
***if only* that component changes while the other components remain constant. WITCH and REMIND show results at the LDV level. Annual change rates higher than 1% are highlighted in bold.**

		Activity		Structure		Energy intensity		Fuel mix	
		BAU	450	BAU	450	BAU	450	BAU	450
AIM/CGE	2010-2030	**1.1%**	**1.0%**	-0.2%	-0.2%	-0.2%	-0.5%	0.0%	-0.2%
	2030-2050	0.6%	0.6%	0.0%	-0.1%	-0.4%	**-1.2%**	0.0%	-0.2%
	2050-2100	0.9%	0.8%	0.0%	0.0%	-0.4%	-0.6%	0.0%	-0.2%
DNE21+	2010-2030	0.5%	0.5%	0.1%	0.1%	-0.3%	-0.3%	0.0%	-0.2%
	2030-2050	0.2%	0.2%	0.0%	0.0%	-0.1%	**-1.2%**	-0.1%	**-1.2%**
GCAM	2010-2030	0.5%	0.5%	0.2%	0.1%	-0.5%	-0.5%	-0.1%	-0.1%
	2030-2050	0.3%	0.3%	0.2%	0.2%	-0.3%	-0.3%	-0.2%	-0.4%
	2050-2100	0.4%	0.2%	0.4%	0.3%	-0.1%	-0.2%	-0.1%	-0.6%
GEM-E3	2010-2030	0.8%	0.7%	0.0%	0.0%	-0.5%	-0.7%	0.0%	-0.1%
	2030-2050	0.9%	0.7%	0.1%	0.1%	-0.5%	**-1.0%**	0.0%	**-1.5%**
IMACLIM	2010-2030	0.9%	0.2%	0.0%	0.1%	-0.3%	-0.3%	-0.1%	-0.1%
	2030-2050	0.6%	-0.1%	0.0%	0.0%	-0.3%	**-1.0%**	-0.2%	-1.3%
IMAGE	2010-2030	0.8%	0.7%	0.1%	0.0%	-0.5%	-0.9%	0.0%	-0.1%
	2030-2050	0.5%	0.4%	0.2%	0.1%	-0.1%	-0.5%	-0.1%	-0.3%
	2050-2100	0.5%	0.5%	0.0%	0.0%	-0.4%	-0.7%	-0.6%	**-1.6%**
POLES ADVANCE	2010-2030	0.8%	0.7%	0.0%	0.0%	-0.6%	-0.7%	-0.4%	-0.4%
	2030-2050	0.6%	0.6%	0.0%	0.0%	-0.5%	-0.7%	-0.7%	-0.9%
	2050-2100	0.5%	0.5%	0.1%	0.1%	-0.2%	-0.3%	-0.6%	-0.7%
MESSAGE[4]	2010-2030	0.8%	0.8%	0.0%	0.0%	-0.8%	-0.8%	0.0%	0.0%
	2030-2050	0.7%	0.6%	0.1%	0.1%	-0.1%	-0.2%	-0.1%	-0.3%
	2050-2100	0.6%	0.5%	0.1%	0.0%	-0.2%	-0.4%	-0.2%	**-2.3%**
REMIND	2010-2030	0.7%	0.6%			-0.2%	-0.2%	-0.1%	-0.1%
	2030-2050	0.4%	0.3%			-0.3%	-0.2%	-0.2%	-0.6%
	2050-2100	0.6%	0.8%			-0.6%	**-1.0%**	-0.8%	**-3.1%**
TIAM-UCL	2010-2030	**1.1%**	**1.1%**	0.1%	0.1%	-0.5%	-0.6%	0.0%	0.1%
	2030-2050	0.8%	0.8%	0.1%	0.0%	-0.6%	**-1.1%**	-0.1%	-0.4%
	2050-2100	0.9%	0.9%	0.0%	0.0%	-0.7%	-0.4%	-0.3%	-0.9%
WITCH	2010-2030	0.7%	0.7%			-0.6%	-0.6%	0.0%	0.0%
	2030-2050	0.5%	0.5%			-0.5%	-0.6%	-0.1%	-0.5%
	2050-2100	0.7%	0.7%			-0.3%	-0.6%	-0.4%	-0.8%
OECD[5]	*1973-2007*	*1.0 to 3.1%*		*0.0 to 0.8%*		*-0.6 to 0.3%,*			
	2000-2007	*-0.8 to 1.8%.*		*-0.3 to 0.2%*		*-1.2 to 0.8%*			

[4] The MESSAGE transport module used in this study is a simpler version than used in other papers of the special issue (e.g.. McCollum et al., 2016). Specifically, this version is MESSAGE-Transport V.5; yet, for the purposes of this paper, the model did not make any explicit assumptions about heterogeneous behavioral features among consumers

[5] The historical OECD Laspeyres decomposition index values are based on the analysis performed by Millard-Ball et al., 2011.

Activity growth makes a large contribution to the total CO_2 emissions pathways; in some models, it increases by a factor five between 2010 and 2100



. In the baseline scenario, all models except REMIND and WITCH show a deceleration in activity growth in the second half of the century. The average annual activity change between 2010 and 2100 varies across models and ranges from -0.1% to 1.1%. Between 1973 and 2007, activity growth ranged from 1.0% to 3.1% per year in the six OECD countries studied. Activity growth reduced over time ranging from -0.8% to 1.8% between 2000 and 2007 [31]. This small set of countries shows a large variation in activity across the regions studied. Although the models' activity growth projections are well within that range, the variation in global activity increase across models over the century has a significant impact on total CO_2 emissions. Moreover, activity level differences between models within a single scenario are more pronounced than for a single model between the two scenarios. In other words: activity reduction in the mitigation scenario compared to the baseline scenario as a measure to decrease emissions has a limited effect according to the models.

Energy intensity increased over time in some of the OECD regions evaluated by Millard-Ball et al. [31] but decreased in others, ranging from -0.6% to 0.3% between 1973 and 2007, and from -1.2% to 0.8% in more recent years (2000-2007). All models project that the global average energy intensity of motorized passenger transportation will decrease in the baseline, even though historically this has not always been the trend. Several models project that the energy intensity will drop more strongly in the first half of the century than in the second half in the baseline. REMIND, AIM/CGE and TIAM-UCL show the opposite effect over time and Imaclim-R and GEM-E3 show a constant decrease. In all models energy intensity reduces further in the mitigation scenario; it still remains within the range of reduction rates measured across OECD regions historically, although at the high end.

Fuel mix has not been reported by Millard-Ball et al. [31] as historically shifting to alternative fuels has had limited application. 94 % of transport final energy is currently fueled by oil [2]. Even in the baseline all models move away from this trend with changing fuel mix impacting the projected transport CO_2 emissions. This impact is more pronounced in IMAGE, POLES, WITCH and TIAM-UCL towards the end of the century. This effect is even larger in the mitigation scenario where the majority of the models show a high reduction in direct CO_2 emissions as a result of changing fuel mix, especially in the second half of the century. This could be related to electrification or increased shares of less CO_2 intensive fuels such as biofuels or natural gas.

Modal shift contribution might be underestimated as a result of using the Laspeyres method where all other factors remain at their base year level. The reason for this is that aviation, rail and LDV have similar base year energy intensity and CO_2 intensity levels. Table 2 indeed shows that modal shift plays a limited role in emission changes. Consistent with historical trends, modal shift leads to increasing emissions in the baseline projections with the exception of AIM/CGE. In the mitigation scenario this trend is not reversed and is hardly applied as a mitigation measure in the policy scenario.

Looking across the different models, we see that TIAM-UCL, AIM/CGE and MESSAGE – with high activity growth assumption – project high emissions. GCAM includes a structural shift towards carbon intensive modes, which explains why even with relatively low activity growth the projected emissions are at the higher end of the model range. Similarly, activity and structural change lead to increasing emissions in IMAGE and POLES, but a strong decrease in CO_2 intensity – as a result of energy intensity and fuel mix change – resulting in lower total CO_2 emissions: the decline in CO_2 intensity of transport strongly offsets the increase in transport service demand. The models are comparable in their behavior in the sense that they show activity growth and reduced CO_2 per passenger kilometer, which further declines as measures to meet the climate target are set. Even though the direction of change is the same, the differences in extent – which is especially pronounced in fuel mix change, but it also true for energy intensity or activity change – leads to large differences in projected CO_2 pathways over the century. Figure 3 further illustrates this, depicting the increase in CO_2 emission development resulting from change in a component following Equation 2. IMAGE and MESSAGE for example project that CO_2 intensity developments will reduce emissions by a factor as high as 21–22, if all other components remain at their base year value, and REMIND (only accounting for LDV) even goes as far as a factor -74, reaching full decarbonization of transport fuels.

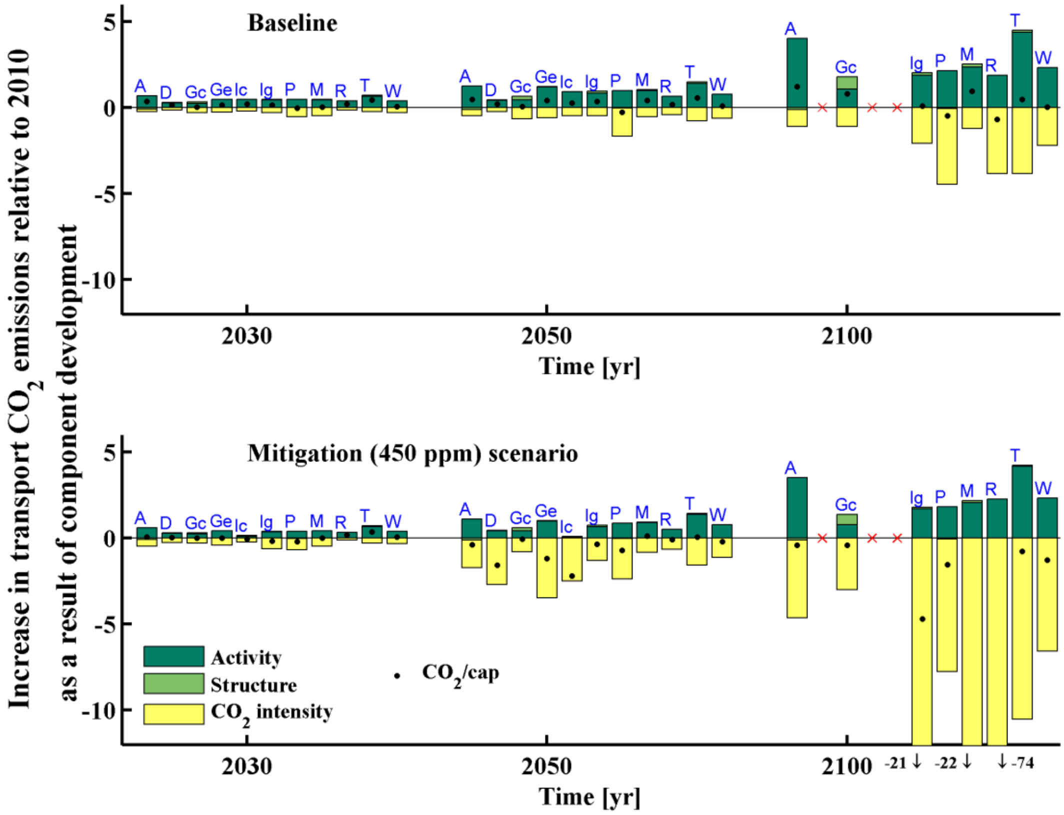


Figure 3: Passenger transport direct CO_2 emission increase relative to 2010 due to activity, structure or CO_2 intensity development, in accordance with Equations 1 and 2 for baseline (top) and mitigation (bottom) scenarios in AIM/CGE (A), DNE21+ (D), GCAM (G), GEM-E3 (Ge), Imaclim-R (Ic), IMAGE (Ig), POLES (P), MESSAGE (M), REMIND (R), TIAM-UCL (T) and WITCH (W). WITCH and REMIND show results at the LDV level.

3.3 Individual components: activity growth, structure, energy intensity and fuel mix

The projection of structural change due to modal shift can be seen in Figure 4, which shows the modal shares in 2010, 2050 and 2100. The figure shows some common elements:

- LDVs dominates passenger travel, both currently and far into the future in most models.
- Most models show an increasing share of aviation at similar rates. At the level of individual models, MESSAGE, IMAGE, GCAM and Imaclim-R consider speed to be a determinant of modal choice, leading to a shift towards aviation. TIAM-UCL and POLES also show increased aviation shares. Train and bus shares remain similar to the base year in most models, although MESSAGE and GCAM show a significant decrease in bus usage and IMAGE a significant decrease in train usage. POLES and Imaclim-R, which consider infrastructure constraints, show a reduction in LDV share over time.
- There are quite clear base year differences across the models, which contribute to inter-model differences in the future.

- In most models, the mitigation scenario does not lead to a significant change in the modal split of transport modes compared to baseline, reflecting its limited role in decreasing emissions in the models. AIM/CGE, DNE21+ and TIAM-UCL modal shares are exogenously set and therefore not responsive to a climate target. Imaclim-R projects more cycling and walking and MESSAGE, GCAM and IMAGE project reduced air travel compared to the baseline scenario.

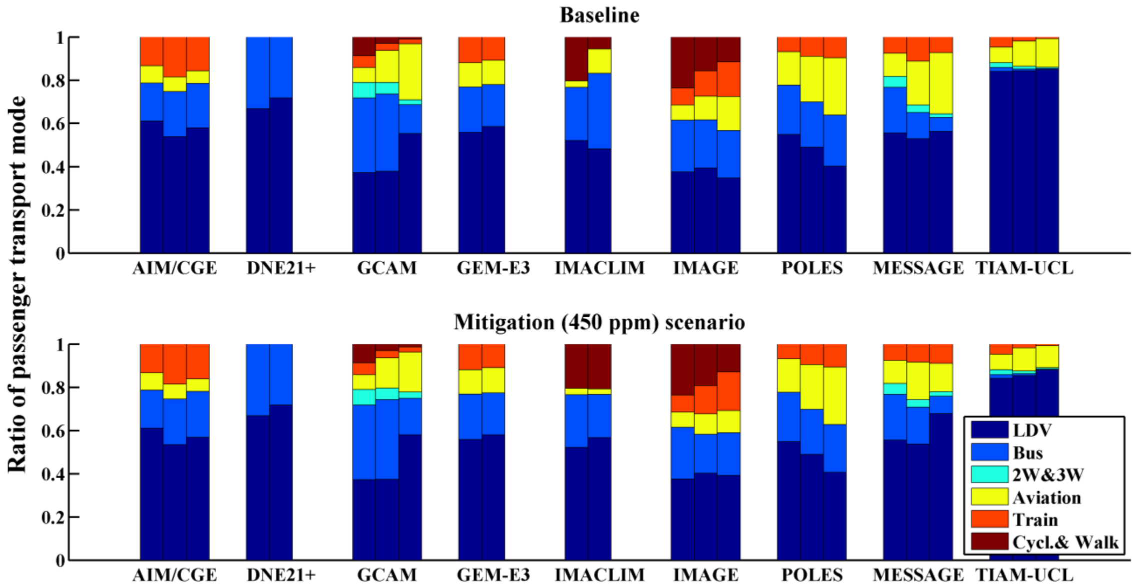


Figure 4: Passenger modal shares (structure component) in 2010, 2050 and 2100 for baseline (top) and mitigation scenario (bottom)[6].

The impact of component development on total CO_2 projections is further specified in Figure 5, which shows the global CO_2 emissions per capita (indicated by the isolines), due to activity growth plotted against CO_2 intensity, again for the baseline and mitigation scenarios[7]. The activity growth projected by the models is offset by the CO_2 intensity reduction in the baseline and most models remain at 0.6 kg CO_2/cap annually at a global level over the course of time. GCAM, MESSAGE and AIM/CGE are the exception with higher CO_2 per capita values in the second half of the century. The models move away from 0.6 CO_2 kg/cap in the mitigation scenario, mainly due to CO_2 intensity reduction, with some models reaching values lower than 0.2 CO_2 kg/cap.

[6] The Bus component for Imaclim-R also includes rail travel while the LDV component includes 2W & 3W.

[7] Only direct transport emissions are accounted for, and biofuels are treated as zero-carbon fuels

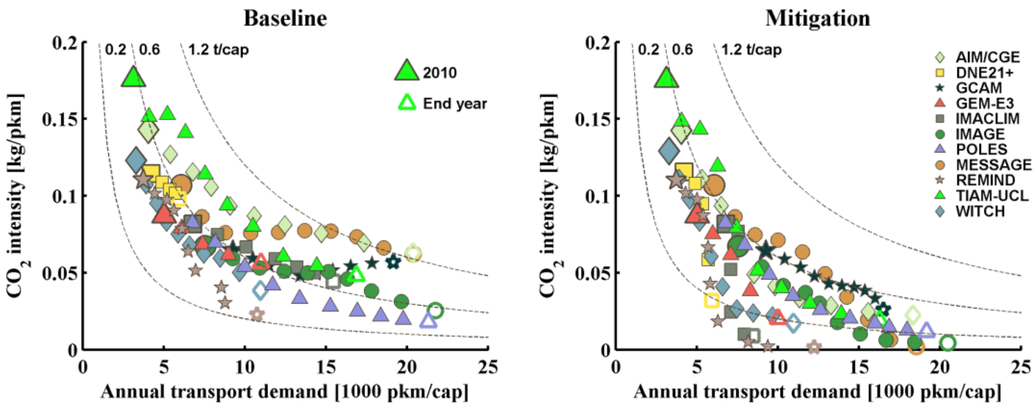


Figure 5: Global passenger transport activity per capita (x-axis) compared to CO_2 intensity (y-axis) development over time. The CO_2 emissions per capita are indicated by the plotted isolines. The left panel shows baseline and right mitigation scenario. DNE21+ and GEM-E3 model projections run to 2050, Imaclim-R to 2070 and the rest until 2100.

Figure 6 shows the carbon intensity impact of fuel mix and energy efficiency on CO_2 per passenger kilometer. For both scenarios, this is compared to the fuel mix of hydrogen/electricity, biofuels and fossil-based fuels. In the baseline scenario, in most models the reduction in CO_2 intensity is the result of energy efficiency increases, although IMAGE, REMIND, WITCH, TIAM-UCL and POLES also show fuel intensity reduction between 2050 and 2100, due to switching to a mix of hydrogen, electricity and biofuel use. This is in agreement with the Laspeyres index results in Table 2. Most models project that average global energy efficiency will decrease to 0.5–1 MJ/pkm in 2100. This is a significant decrease (46–72%) compared to 2010 values, but in line with current estimations for drivetrain fuel consumption reduction potential. Already in 2030 gasoline ICE fuel consumption could reduce with 30-50%, while switching to alternative driving mechanisms could reduce fuel consumption even further.

The higher CO_2 intensity reduction in the mitigation scenario (see also Table 2) is highly dependent on fuel switching in all models, but also on further energy efficiency improvements. IMAGE, MESSAGE (from 2090), REMIND (from 2080), and Imaclim-R (from 2060) project that more than 80% of global passenger transport fuel use will be non-fossil in a scenario stabilizing at 450 ppm CO_2eq. These models justifiably project relatively low emissions in the mitigation scenario. Both electric and hydrogen fueled vehicles, as well as biofuel use, are attractive alternative options in this scenario[8]. REMIND, Imaclim-R, IMAGE and WITCH show the trend of switching to biofuels in the first half of the century and then switching to hydrogen/electric, as found by Pietzcker et al [6], but other models do not follow this pathway. AIM-CGE and GCAM are more than 40% fueled by fossil fuels, which also explains their higher transport CO_2 emissions (Figure 2). DNE21+ is the only model that does not shift towards electricity/hydrogen.

[8] WITCH does not take into account hydrogen

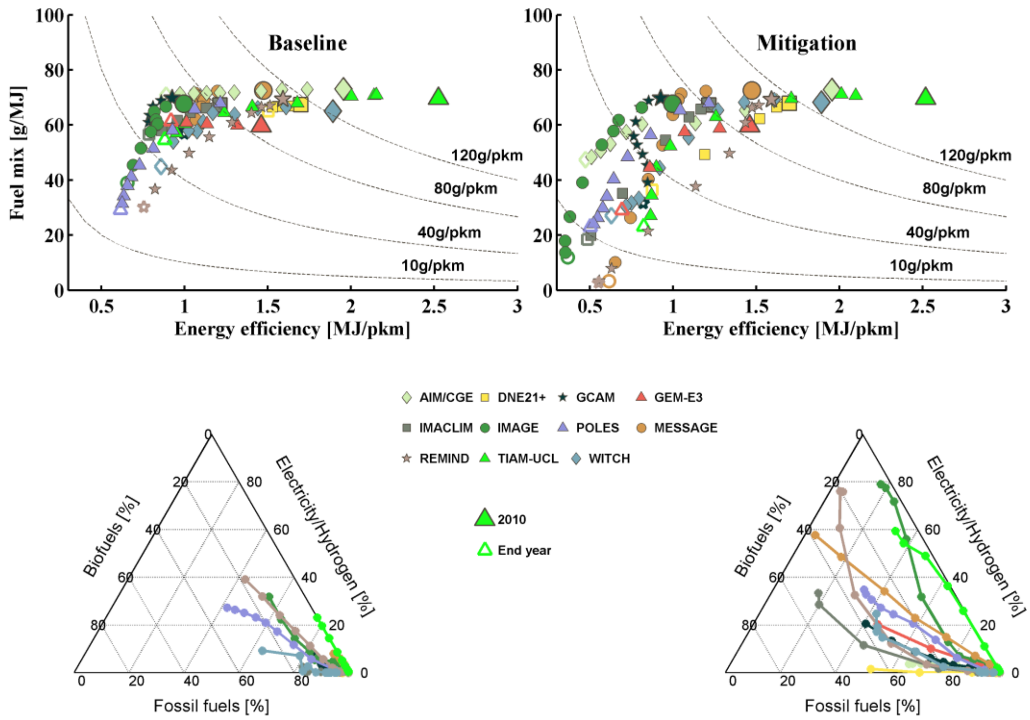


Figure 6: Global passenger transport energy intensity (x-axis) compared to fuel mix (y-axis) development in top figures. The isolines indicate emissions per passenger kilometer. The bottom panel shows passenger transport fuel shares over time, for baseline (left) and mitigation scenario (right). DNE21+ and GEM-E3 model projections run to 2050, Imaclim-R to 2070 and the rest until 2100[9].

4. Comparing model inputs to outputs for the USA: a focus on light-duty vehicles

So far, fuel switching – either to electricity/hydrogen or biofuels –, has proven to be an essential measure in IAMs to mitigate emissions from the transport sector. Models that project that the transport sector will remain relatively dependent on fossil fuels are at the high end of transport sector CO_2 emissions projections in the mitigation scenario. Similarly, models that show fuel switching in the baseline scenario are at the low end of the baseline emission range.

In an attempt to improve our understanding of differences in fuel mix projections, in this section we look specifically at LDV choice dynamics in the models. To standardize and simplify the comparison, we focus on the results for the USA region in each model. As mentioned in Section 2.1, vehicle choice in the models depends on cost of travel, which includes capital costs of the technology, efficiency, fuel prices and in some cases non-operating costs. Capital costs are related to deployment in REMIND, GEM-E3 and Imaclim-R and to R&D investments in WITCH, while in other models they are fixed in time. The distribution between vehicles is determined by either a logit or cost-optimizing algorithm.

[9] The tenary figures at the bottom show fuel mix of LDV for REMIND and WITCH.

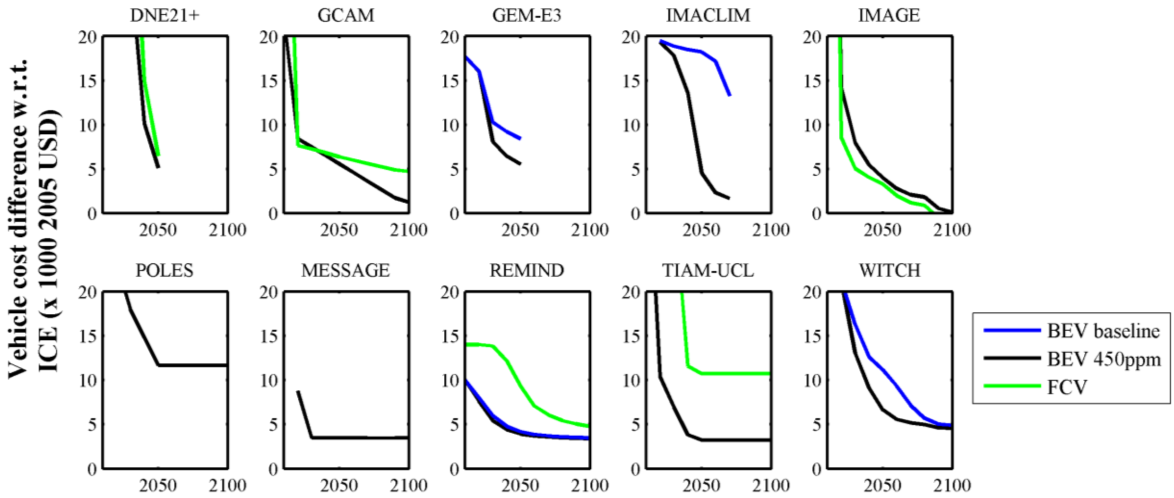


Figure 7: Difference in USA LDV fuel cell vehicle (FCV) and battery electric vehicle (BEV) investment costs compared to conventional vehicles (ICE) in the mitigation scenario. POLES and MESSAGE FCV investment cost remain to be more than 20.000 2005 USD more expenisve than conventional vehicles, i.e. outside the displayed range.

Figure 7 shows the *differences* in capital costs of alternative vehicles compared to conventional (ICE) vehicles. AIM/CGE does not consider vehicle cost. BEV prices are currently substantially higher than conventional vehicle prices, although they have decreased rapidly in recent years [35]. All models show a steep decline in BEV costs in the coming decades. POLES, MESSAGE TIAM-UCL, REMIND and WITCH reach a fairly constant value in the second half of the century for both BEV and for FCV, where FCV remaining significantly more expensive than BEV., DNE 21+, GCAM, GEM-E3, IMAGE and Imaclim-R on the other hand show a continuous decrease in alternative vehicle costs, some ultimately reaching comparable levels to conventional vehicle costs, which would lead to fuel prices combined with vehicle efficiency being more dominant in determining vehicle cost.

Comparing the techno-economic assumptions underlying the vehicle choice outcome represented by the fuel split shown in Figure 7, we see that different vehicle capital cost development assumptions do not necessarily explain different fuel distribution outcomes. For instance, GCAM with low electric vehicle cost projections also shows low-to-medium electric vehicle deployment compared with the other models. Uncertainty in the cost development of BEVs and FCVs can be seen in the variety of the model cost projections, but does not in itself explain differences in model outcomes. Consideration of non-economic factors such as behavioral considerations limiting alternative vehicle deployment in the models, optimizing vehicle choice, as well as interaction with other sectors that for example affect fuel prices, can also potentially play an important factor.

5. Discussion

In this paper, IAM passenger transport CO_2 emission scenarios from eleven global models have been compared by decomposing them into transport activity, modal structure, energy intensity and fuel mix development. The decomposition method untangles the complex model dynamics in to reduced form representation of the models, enabling us to compare the models to each other, as well as comparing them to historic trends. Some discussion on the applied method is provided.

Suitability of the decomposition method

Model comparison studies can show key model uncertainties by comparing the output of different models to their underlying model assumptions [36]. A decomposition method can be applied to identify structural changes contributing to energy consumption trends. This can also be used to validate the model baseline results by historic comparison, as shown by Marcucci et al. (2015) at the regional level [37]. Although more sophisticated methods exists, the Laspeyres decomposition analysis is an appropriate method to distinguish model dynamics underlying the projected futures. The disadvantages of the Laspeyres method index method have been discussed in literature [29] and include the fact that the method has no time and factor reversal properties, and the residual term can become large. However, the method is relatively easy to implement and interpret, which is an advantage in the large multi model study. Moreover the use of this method allows easy comparison with several studies on historical transport sector developments across global regions over a longer time [31-33], which is an important advantage.

It should be noted that also other indicators can be calculated to compare models, both across a larger set of models or with historic data, such as the intrinsic income and price elasticities [38], also discussed as part of this special issue [39]. Where price and income elasticities verify demand response to economic indicators, which are often the models key drivers, the decomposition method here focuses on the development of physical indicators such as service demand and technology change.

Discussion of the key outcomes

Interestingly, the model results presented here show a relatively small range in annual travel activity growth. Empirical activity growth data for example passenger-km/capita, spans a much wider range than that observed across the model scenarios. Still, the rates should be compared to long-term averages and relatively small differences in annual rates of change can lead to large spreads in passenger kilometer demand projections over the century. As a result, activity increases by a factor of five in some models, and in others by a factor of two. This has a large effect on the projected transport emissions pathways, and is thus a key uncertainty.

One key observation is that activity growth and mode shift hardly contribute to mitigation in the IAM transport scenarios. Earlier research has compared low carbon transport scenarios of IAMs to those of transport sector specific models and place-based research, focusing on local transport, and indicate that different scientific communities have a different perspective and find different solutions to mitigate transport emissions. Where models (IAM and transport sector models) put higher emphasize on efficiency and fuel switch potential, place-based research often show that behavioral and infrastructure policy interventions, especially in urban areas, impacting modal shift, distance travelled and technological change, can cut transport energy use and CO_2 emissions significantly [7]. These policy measures, that currently find limited application in IAM scenarios, could complement the drastic technology changes that are needed to reduce emissions [40]. Another example on modal split, is Fulton [41] who concluded that a high shift scenario with far greater urban passenger travel by low-carbon public transport and non-motorized modes could lead to a 1.7 Gt reduction in transport emissions globally by 2050 (a 40% reduction in urban transport emissions). The representation of transport infrastructure development, and in particular its costs, and the costs of transport infrastructure policies are further explained in detail in this special issue in Ó Broin et al. [13]. Further research to quantify the impact of travel reduction and modal shift either by dynamic response or scenario design in IAM transport models would be an important next step. This could improve current IAM transport scenarios and make them less reliant on technology transition, which is uncertain.

The high dependence of transport emission mitigation in the IAM scenarios on technology change (alternative vehicle adoption as well as improved efficiency) concur with previous IAM transport comparison studies [5, 6]. Diffusion of advanced vehicle technologies, however, will depend on technology development impacting costs and efficiency, as well as behavioral considerations. These processes are highly uncertain and this is reflected in the models results, which show a large range in annual fuel mix change. A comparison between the projected capital cost assumptions of LDV alternative propulsion mechanisms and the vehicle choice outcome represented by the LDV fuel split, shows that different capital cost assumptions do not necessarily explain different fuel distribution outcomes. Behavior or non-monetary considerations are often accounted for indirectly in the models by for example using a logit distribution, inertia assumptions or implicit discount rates. When taking in to account behavioral consideration a transition to advanced vehicles to mitigate GHG emissions can be more difficult (see the McCollum et al. [11] paper in this special issue). A better understanding of technology diffusion dynamics is important and, moreover, could provide the opportunity to explicitly analyze policies related to the transition to new technologies by removing these barriers to market adoption (e.g., cities installing EV chargers in urban areas).

6. Conclusion

Based on the results and the discussion, the study leads to the following conclusions.

The IAM models show similar trends in the baseline scenarios for the different factors contributing to emission changes in the transport sector: 1) continuing activity growth, 2) reduced energy intensity, 3) a limited impact of structural change to CO_2 intensive modes and 4) a fuel switch towards alternative fuels. For most factors, changes in these factors are within the historical range. However, fuel switch forms an exception. As, the transport sector has historically been dominated by oil, fuel switching did not play a role. In the future, models expect fuel mix moves away from oil in response to increasing oil prices in several models, thus pushing the impact of carbon intensity on future emissions far beyond historical rates.

In mitigation scenarios, reductions are mostly achieved through fuel switching and further enhancements in energy efficiency. In some models, activity reduction and some modal shifting also contribute to emission reduction (e.g. Imaclim-R), but energy intensity improvement and fuel switching are nevertheless much more important. The enhancement of technology efficiency as an intervention strategy for emission reduction pushes the annual efficiency change rate to the maximum of what has historically been measured in OECD regions between 1973 and 2007 by Millard-Ball and Schipper [31]. Fuel switching towards electricity, hydrogen and biofuels goes significantly beyond historical rates of change and the scenarios would imply a clear break with historical trends.

Model comparison studies allow a better understanding of future transport system behavior. At the same time, further model development is needed. The models show different pathways of technology transition, with different fuel types being deployed and different rates of deployment. Technology transition in the models is found to depend on travel cost, which is uncertain, reflected also in the range of vehicle capital cost projections in the models. Other important aspects such as fuel price and non-economic factors, (e.g. anxiety for new technologies) that are represented in various ways in the models but are not harmonized or explored in this study may also be important in projecting future shares of alternative-fueled vehicles. To improve transport modelling, further enhancement is required in the modelling of technology transition and behavioral considerations. Moreover an analysis of scenarios addressing the mitigation options that result from modal shift and from policies that impact behavior and infrastructure, especially in urban areas, could complement current results.

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Supplementary Material of *Decomposing passenger transport futures: comparing results of global integrated assessment models*

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	TIAM-UCL[1]	IMAGE[2]	Imaclim-R[3]	MESSAGE[4*]	POLES[5]
System boundaries	The fuel mix is determined endogenously. Indirect fuel use from manufacturing, upstream energy and emissions are calculated but not tied to transport.	The model determines the fuel use, which is linked to the TIMER model, hence all emissions from fuels are considered. Embodied emissions of vehicles are included in the industry sector.	As a CGE model all GHG-emitting and energy producing/ consuming sectors are included. This implies that indirect energy use and emissions from fuel production and vehicle manufacture are included, but in the energy transformation and industry sectors.	All GHG-emitting and energy producing/ consuming sectors are included. This implies that indirect energy use and emissions from fuel production and vehicle manufacture are included, but the latter is not represented by a direct linkage.	The transportation sector covers the transport of goods and passengers. Transport of energy and associated losses, which are accounted for in the own energy uses of the energy sector.
Relationship drivers and demand	GDP, population, and GDPP drive the transport demand, where energy service demand grows slower than the underlying driver. The demand is influenced through a linear relationship with the drivers. Each transport demand in each region has its own relationship driver and demand coupling factor.	GDP, IVA (for freight) population, fuel price, non-energy price, load factor, mode preferences, energy efficiency, mode speed drive service demand per mode, on the basis of Travel money budget (TMB) and Travel time budget (TTB) formulation. A fleet module determines fleet composition within each mode, affecting mode cost, energy efficiency and fuel type for each mode.	The mobility demand and modal split result endogenously from households utility maximization under constraints of revenues and time spent in transport. Each mode is characterized by a price and a speed. The price of cars mobility depends on fuel prices and the cost of car ownership, while other modes by the intermediate consumption shares and prices within the general equilibrium framework. When infrastructure use reaches congestion, the marginal speed of the mode decreases, which limits its use.	Fuel prices, vehicle costs, GDP, population, vehicle speeds, vehicle occupancy rates, passenger vehicles per capita, annual distance traveled per vehicle, etc. Travel money budget, travel time budget, income, travel prices and travel speed determine service demand for the different modes (mode choice). The optimization framework determines the fleet composition within each mode. Freight service demand is drived by population, GDP and price elasticity.	Passengers: - Cars: income increase the number of cars per capita, fuel price affects the yearly mileage - Rail and buses: income increase the mobility, fuel price increase modal shift from cars to public transport Goods: GDP growth affects the mobility per mode

	REMIND[6]	GCAM[7]	AIM-CGE[8]	DNE21+[9]	GEM-E3[10]	WITCH[11]
System boundaries	Input of final energy in different forms is required together with investments and operation and maintenance payments into the distribution infrastructure as well as into the vehicle stock. Material needs and embodied energy are not considered.	The full fuel cycle of each fuel is represented. This includes biomass from an agriculture and land use model. No other upstream inputs to the sector are considered (e.g. vehicle manufacturing, roads)	Indirect energy use is treated in energy transformation sector	Indirect energy use is not included. For example, emissions from car manufacturing process is classified into the industrial sector.	All GHG-emitting and energy producing/ consuming sectors are represented explicitly in the model	LDV and road freight are explicitly modeled, while other modes are embedded within a non-electric sector. Aspects such as infrastructure and the vehicle manufacturing are incorporated in the overall GDP and representation of final goods
Relationship drivers and demand	GDP growth, the autonomous efficiency improvements, the elasticities of substitution between capital and energy and between stationary and transport energy forms. Mobility from the different modes is input to a CES function, the output of which is combined with stationary energy	GDP, population, and services prices, derived from vehicle speeds and vehicle levelized average operating costs. GDP sets the scale of the demand, and determines the wage rate, which determines the opportunity cost of each	Transport intermediate inputs and final demand. Passenger transport is determined by GDP with elasticity. Freight transport is determined by all industrial sectors	Scenarios on service demand of road transportations are developed for passenger cars and buses separately based on per-capita GDP and the historical trends. As for road freight transport scenarios of	The mobility demand and its modal split result endogenously from households utility maximization under constraints of income and firms under maximization revenues. Each mode is characterized by a price. The price of cars mobility depends on operational cost	A linear Leontief function combines energy, O&M, vehicle capital and carbon costs to select the optimal mix of vehicle types. Vehicle ownership is a main driver which is set via a calibration based upon GDP growth. Exogenous efficiency

	in a CES function to generate a generalized energy good, which is combined with labor and capital in the main production function for GDP.	travel mode. In this way, increases in GDP will increase the per-capita demand for travel, and shift this demand towards the fastest modes.	inputs. They are formulated as input multiplying coefficient.	cargo trucks, overall cargo service per-capita is estimated by the GDP size, under assumption of modal shifts.	and the purchased cost. The price of other modes is determined in the general equilibrium framework by the intermediate consumption shares and prices.	improvements are implemented within the model.

Table A.1: Drivers of energy demand in the transport sector of eleven IAMs.

Table A.2: Technologies and final energy carriers

	TIAM-UCL	IMAGE	Imaclim-R	MESSAGE	POLES
Modes and vehicle types	Passenger : 7 modes (two wheel, three wheel international aviation, domestic aviation, road auto, road bus, rail), Freight: 7 modes (light, commercial, medium, heavy truck, rail, domestic navigation, international navigation), and hundreds of technologies.	Passenger: 7 modes (walk, bicycle, bus, train, car, high speed train and airplane), 6 freight modes (national ship freight, international ship freight, medium truck, heavy truck, rail freight, air freight) . Tens of technologies per mode.	Passenger: 4 modes (non motorized, personal vehicles, airplane, other) and 3 freight (trucks & freight rail, airplane, shipping). Technologies: ICE, efficient ICE, hybrid, plug-in hybrid and electric.	5 passenger modes and 1 freight mode. Other modes are not explicitly modeled but their energy use is accounted for via an exogenous energy demand trajectory. Tens of technologies options per mode.	Passengers: 7 modes (cars, motorbikes, bus, rail, air). Goods: 5 modes (heavy vehicles, light vehicles, rail, other (inland water), maritime). Technologies: ICE, plugin hybrid-electric, battery electric, fuel cell
Final energy carriers	Diesel, Gasoline, Ethanol, Electricity, LPG, Methanol, Natural Gas, Hydrogen, Fischer Tropsch biofuels.	The transport model only considers the secondary energy carriers: Hydrogen, Gas, Electricity, Oil, Biofuel	Liquid fuels from oil, Synthetic liquid fuels from other fossils Liquid fuels from biomass, Electricity	All fuels from the MESSAGE energy systems model are considered in the transport module	Oil products, Biofuels (energy crops and cellulosic feedstocks), Gas, Coal (for rail), Electricity and Hydrogen
Energy consumption of vehicles.	Share estimates split fuel consumption between road modes and rail modes. The model invests in technologies in order to satisfy the energy service demands in order to maximize consumer and producer surplus. Final energy consumption is endogenous to the model solution.	Different vehicle types with different energy efficiency's compete against each other (based on the multinomial logit), which allows for a change of energy efficiency of the mode.	For personal vehicles : explicit technologies with a efficiency characteristic and leaning on the cost. For other modes: efficiency improvement triggered by fuel prices.	Different vehicle types with different energy efficiencies compete against each other, which allows for an average change of energy efficiency of the mode over time. The techno-economic parameters for each technology are exogenously assumed.	Unit consumption depends on: - price: long term elasticity to account for investment and short term to account for behaviour - income for behaviour, to control the spending on fuel for transportation (maximum "budgetary coefficient")
Determinants technology costs and shares	Investment costs, O&M costs, fixed costs – are based on exogenous assumptions and change over time in response to an exogenous learning curve. Vehicle market share is outcome of the model solution.	Net present costs based on literature, decreasing exogenously in time. We assumed that the technology costs is a global variable, as the technologies tend to be traded worldwide. Vehicle share is based on a multinomial logit.	All technology characteristics are fixed in time, except costs that endogenously decrease with a learning rate. Vehicle market share is based on logit function.	The techno-economic parameters are exogenously assumed and change over time. There is also regional differentiation for certain technologies and parameter assumptions. Market shares are based on least cost optimization.	Road vehicles: Efficiency, lifetime, investment cost, fixed and variable O&M. These parameters change overtime exogenously. Vehicle competition based total user cost and infrastructure possible development.

Distribution between transport modes	Distribution is assumed exogenously, but the split between modes may slightly change due to responses to own price elasticities.	Time and costs are considered. Cost are weighted relative to time with a time-weight factor. The time-weight factor is determined by the travel money and travel time budget.	Households utility maximization under both constraints of revenues and time.	Time and costs are considered. Costs are weighted relative to time with a time-weight factor. The time-weight factor is determined by the travel money and travel time budget.	The different modes are mostly disconnected, limited by: differentiated elasticities to fuel prices and saturation effects (e.g. max. number of cars per capita, maximum air related mobility)

	REMIND	**GCAM**	**DNE21+**	**GEME3**	**AIM-CGE**	**WITCH**
Modes and vehicle types	Passenger: 4 modes, Freight: 1 mode. For passenger transport: LDV, Aviation, Bus and Electric Trains. One generic freight transport.	Passenger: 10 modes. Freight: 4 modes. Off-road vehicles, mining, or agriculture are not part of the transportation sector, except for China and India. ICE, electric, hybrid, fuel cell and compressed natural gas for bus/ passenger. For other modes two or one technology options.	Road transportation : 5 modes. The other subsectors are generated in a top-down manner. Technologies: ICEs, ICE efficienct, HEV, PHEV, electric, fuel-cell.	Passenger: 5 modes (Passenger Cars, LDV/Bus, Aviation, rail and inland navigation), Freight: 3 modes (LDV/heavy trucks, rail, inland navigation). Technologies: pure conventional, hybrid, plugin hybrid-electric, battery electric, biofuels	5 passenger modes (bus, train, car (incl 2- and 3-wheelers), train, airplane) Freight: 6 modes (national ship freight, international ship freight, medium truck, heavy truck, rail freight, air freight). Aggregated technology.	2 modes. Road passenger and freight, both featuring four vehicle types: ICE, hybrid, plug-in hybrid and battery electric.
Final energy carriers	Liquids (Coal, Gas, Oil or Biomass (only second-generation with CCS for Coal and Biomass. Electricity (only LDV).Hydrogen (only LDV) (Coal, Gas or Biomass, all combined with CCS).	Liquid fuels (includes fuels derived from oil, coal, gas, and biomass), Electricity Natural gas (mostly natural gas; also includes biogas and coal gas),Hydrogen (from many fuels), Coal (for rail in China)	Gasoline, Diesel, Bioethanol and Biodiesel, CNG, Electricity, Hydrogen from coal, gas biomass and electricity Plus CTL (coal to liquid) and CTG (coal to gas).	Road: Oil, Electricity, Gas, Biogasoline and Biodiesel (traditional and second generation). Rail: Coal, Oil, Biodiesel and electricity. Airplane: Oil, Biodiesel. Ship: Oil, biodiesel.	Road: Oil, electricity, and biofuel (bus can use gas), Railway: electricity and coal, Ship: oil, biofuel and coal, Airplane; oil and biofuel.	Liquids can come from Oil or Biomass (traditional or second-generation). Electricity can come from coal (possibly with CCS), gas, oil, biomass (possibly with CCS), wind, PV, CSP, hydro or nuclear
Energy consumption of vehicles.	The general efficiency of one transport mode improves exogenously over time in the CES function.	The energy quantity is derived from the average vehicle intensity and the load factor. The energy intensity of each technology is assumed to change over time exogenously. Endogenous changes of energy intensity are due to (a) switching from ICE to hybrid vehicles, (b) switching from smaller to larger vehicles, (c) modal shifting, or (d) switching to fuels with lower end-use energy intensity.	Energy consumption is determined based on the exogenous scenarios on service demand of road transportations in combination with technology (fuel efficiency of vehicles, costs and implicit discount rate) choice.	Different passenger cars types with different energy efficiency's compete against each other based on Weibull. The efficiency of other transport modes improves exogenously over time in the CES function	Multiplying coefficient. Fuel efficiency improvement is considered.	The efficiency of LDV and road freight transport modes improves exogenously over time based on selected efficiency improvement targets or selected forecasts.

Determinants technology costs and shares	Efficiency, lifetime, investment cost, fixed O&M. Investment cost for battery electric and fuel cell vehicles decrease endogenously following a global learning rate towards a given floor cost. The distribution of LDV vehicles follow cost optimization with different non-linear constraints	Capital costs are amortized over an exogenous lifetime, assuming a 10% discount rate. Non-fuel operating costs include insurance, registration, taxes and fees, and standard O&M expenses. These can decrease exogenously for immature technologies such as electric cars or hybrid vehicles. Vehicle market share is based on logit function.	Fuel efficiency of vehicles and costs are assumed to be improved exogenously. Lifetime does not change over time. Market shares are based on least cost optimization	Capital costs are amortized over an exogenous lifetime, assuming a 12.5% discount rate. Non-fuel operating costs include insurance, registration, taxes and fees, and standard O&M expenses. Capital cost decrease endogenously for immature technologies such as electric cars or plugin hybrid vehicles assuming a global learning rate towards a given floor cost. Vehicle market share is based on Weibull function.	Not explicitly determined.	Efficiency, lifetime, investment cost, fixed O&M. Investment cost for battery electric vehicles decreases following a global learning rate as a consequence of endogenously modeled investments in R&D. The distribution of LDV and road freight vehicles follows cost optimization with different non-linear constraints.
Distribution between transport modes	The distribution between LDV and other modes is determined via the CES production function, driven by the elasticity of substitution (1.5) and the evolution of the efficiency parameters.	The modes compete using a logit share formulation, where the costs includes both the vehicle cost and the time value cost. The time value cost is derived as the wage rate divided by the average transit speed, and modified by an exogenous time-value multiplier that is generally close to 1.	Travel demand is exogenously given for each mode. Modal shift is not endogenously evaluated.	The different type of passenger cars compete using a Weibull share formulation, where the costs includes both operational cost and purchase cost. The distribution between LDV and other modes is determined via the CES production function, driven by relative prices and the evolution of the efficiency parameters.		The distribution between modes is fixed and determined via separate demand calculations.

1)Anandarajah, Pye [24], 2)Girod, van Vuuren [16], 3)Waisman, Guivarch [21],4)Riahi, Dentener [22] , 5)Girod, van Vuuren [42],6)Luderer, Bosetti [23],7)Kyle and Kim [19],8)Sano, Wada [18] 9)Fujimori, Masui [17], 10)Karkatsoulis, Kouvaritakis [20],11)Bosetti and Longden [25],Longden [26], 1:11)EU-FP7-ADVANCE [27]

*The MESSAGE transport module used in this study is a simpler version than used in other papers of the special issue (e.g.. McCollum et al., 2016). Specifically, this version is MESSAGE-Transport V.5; yet, for the purposes of this paper, the model did not make any explicit assumptions about heterogeneous behavioral features among consumers