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Influence of travel behavior on global CO_2 emissions

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ABSTRACT

Travel demand is rising steeply and its contribution to global CO_2 emissions is increasing. Different studies have shown possible mitigation through technological options, but so far few studies have evaluated the implications of changing travel behavior on global travel demand, energy use and CO_2 emissions. For this study a newly developed detailed passenger transportation model representing technology characteristics as well as key behavioral variables is used. The model allows the reproduction of observed travel demand (1971–2005) in the different world regions and considers income and time rebound effects. Regarding future travel demand, the model allows for an evaluation of the sensitivity for future trends in travel money and time budgets, luxury level, vehicle load and modal split. The study highlights the high relevance of future development in travel behavior for climate policy. A consistent combination of different behavioral changes towards a more climate friendly travel behavior is modeled to reduce CO_2 emissions towards the end of this century by around 50% compared to the baseline.

1. Introduction

Passenger transportation is expected to account for an increasingly important fraction of future energy use and CO_2 emissions. The World Energy Outlook (IEA, 2011) for instance states that the transport sector will remain the main driver of global oil demand. Even by 2035 oil demand for transport is projected to outweigh a drop in other sectors. Various other studies show that, compared to other sectors, it is relatively expensive to mitigate emissions to low emission level in the transport sector (Girod et al., 2012; van Vuuren et al., 2011).

Studies assessing global travel demand and its CO_2 emissions focus on the influence of technology and policy (Girod et al., 2012; Grahn et al., 2009; Kyle and Kim, 2011). However, the IEA (2009) developed a scenario assuming changing modal split and a reduction in global travel demand resulting 20% lower emissions. This shows that changes in travel behavior can also contribute to climate mitigation. But, travel behavior could also increase emissions if, for instance, people increase their spending for air travel. Two important variables describing the travel behavior are the Travel Time Budget (TTB) and Travel Money Budget (TMB) proposed by Zahavi and Talvitie (1980). Based on these two anthropological invariants Schafer and Victor (2000) projected global travel demand. Still different studies show that TTB and TMB can vary over time (Mokhtarian and Chen, 2004; Toole-Holt et al., 2005). The up-date of the projections from Schafer (2010) does not include a sensitivity analysis on these two factors. Moreover, besides TMB and TTB also transport costs constrain travel demand. Transport costs do not consist of technology costs alone, but are also influenced by the luxury level chosen by the traveler (Girod and de Haan, 2010; Girod et al., 2012).

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In this study, we aim to contribute to the existing literature by looking at the question: what could be the implications of changing travel behavior for the global travel system and direct CO_2 emissions. In answering this question, we systematically focus on factors like TTB, TMB, preference for luxury level, and environmentally motivated changes like shifting preference for transport modes and increasing vehicle occupancy. For this purpose we use the newly developed passenger transport model (Girod et al., 2012) of the IMAGE/TIMER Integrated Assessment Model (Bouwman et al., 2006). This transport model takes a similar macro approach based on TTB and TMB as the model from Schafer (2010), but extends the model approach to be more responsive to changing technology costs and considers additional travel behavioral characteristics as well.

The paper is structured as follows: Section 2 describes the model, its calibration and the assumption for the projections. Section 3 presents the global travel demand, modal split, energy use and direct CO_2 emissions resulting from different assumptions about future change in important behavioral variables. Section 4 focuses on the robustness of the projections and the implications for climate policy and research. Finally we draw conclusions from the key findings of this study.

2. Method

In the method part, first the TRAVEL model is presented. Second, we focus on how travel behavior characteristics are considered. Third, we compare the simulated travel demand for the period 1971–2005 with empirical data for different world regions. Fourth, the assumption regarding changes in travel behavior for the global projections are described.

2.1. TRAVEL-model

We first discuss the main structure of the model and, next, provide a more extended description of those parts of the model that describe behavioral aspects. As depicted in Fig. 1 the TRAVEL-model consists of three main modules: (1) the travel mode module, (2) the fleet composition (technology choice) module, and (3) the vehicle (technology parameters) module. The model is specified for the 26 world regions according to the TIMER energy model (Bouwman et al., 2006). As the data is actually only available for 11 world regions, the calibration is performed at this more aggregated level. A more detailed description of the TRAVEL model, focusing on the technology side and climate policy, is provided in Girod et al. (2012).

The *travel mode module* simulates per region the travel volume in 7 different modal split categories, i.e. walking, bicycle, bus, train, car, high-speed train and airplane. It explicitly applies a TTB and TTB as travel constraints. TMB refers to the share of income and TTB to the time per day spent on transportation (more on the literature on the TTB and TMB see Sections 2.4.1 and 2.4.2). Earlier models based on the TTB/TMB approach distinguished fewer modes, combining the bus/train modes and the airplane/high speed train mode and by not explicitly including the non-motorized travel modes (Schafer et al., 2010; Schafer and Victor, 2000). We have introduced the latter category because they still account for a significant share of transport in developing countries. The distinction between airplane and high speed train is relevant for CO_2 emissions and energy use. This module is described in detail in the next section. The *fleet composition module* describes the competition of various specific technologies within each mode. For instance, within the travel mode 'cars', several different car types/technologies (default, efficient, electric, biofuel, etc.) can be chosen. The market shares of the various types are determined based on the costs and a vintage structure for the existing stock. Finally, the *vehicle module* describes efficiency, costs and speed of the different transportation technologies.

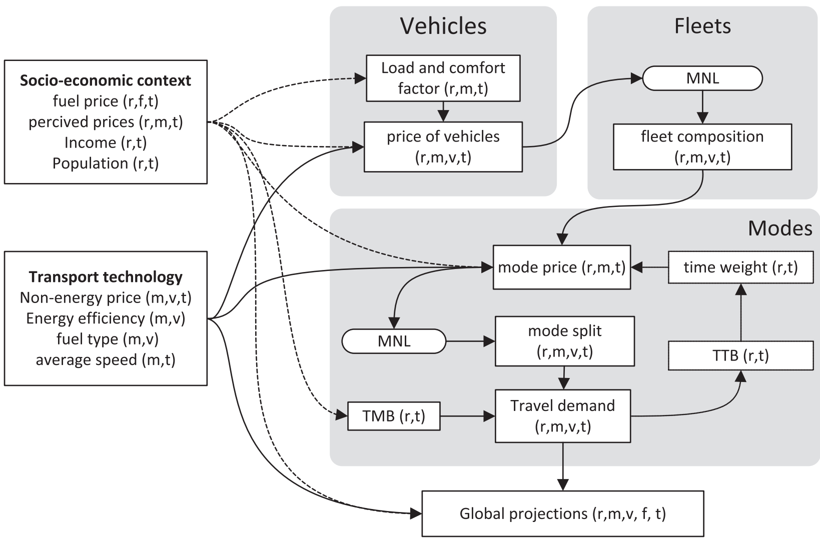

Fig. 1. Overview of the TRAVEL model. The indices *r*, *m*, *v*, *f*, *t* denote region, travel mode, vehicle type, fuel type and time, respectively.

To run the model, we introduce an exogenous time-series (1971–2100) for income, population, energy prices and technology preferences that are based on the new baseline scenario from the recent OECD Environmental Outlook (OECD, 2011). For this study, we have excluded the use of biofuels in the transport sector, because it is uncertain whether they will allow lead for net emission reduction (Sims et al., 2010). This results in higher projections for direct emissions compared to our previous publications (Girod et al., 2012). All cost data are defined in 2005 US Dollars (USD_{2005}).

2.2. Behavior in TRAVEL

The TRAVEL model includes several behavioral aspects via the explicit descriptions of the value of time, the value of money, the vehicle occupancy, the luxury level, and environmental concerns (again, for a more complete description see Girod et al, 2012).

2.2.1. Modal split and travel distance

The most important behavioral factor to consider is the *Travel Money Budget* (TMB) as the fraction of income spent on travel. The per capita travel demand (*TravelDemand*) results from dividing the expenditure for travel (USD) by the average passenger kilometer cost (USD/pkm) to the user of the different transport modes:

$$TravelDemand_{r,t} = \frac{TMB_{r,t} \cdot Income_{r,t}}{\sum_m ModeShare_{r,m,t} \cdot ModeCost_{r,m,t}} \quad (\text{pkm}) \tag{1}$$

Where the indices *r*, *m*, *t* describe the *region*, *mode* and *time*. The average cost is calculated as the sum product of shares (*ModeShare*) and cost (*ModeCosts*) for the different modes (*m*). Which travel modes are chosen by consumers is determined from the multinomial logit equation:

$$ModeShare_{r,m,t} = \frac{\exp(\lambda \cdot ModeCost_{r,m,t})}{\sum_m \exp(\lambda \cdot ModeCost_{r,m,t})} \quad (\text{fraction}) \tag{2}$$

with λ a calibration factor that reflects the sensitivity of the market share for the (relative) costs.[1] The term costs here does not only refer to the direct costs like capital costs and fuel costs: also the ‘cost of time’ and other preferences play a role (Vliet et al., 2010). The influence of the ‘cost of time’ is a driving factor behind the observed shift in transport modes from slow to faster travel modes (Schafer et al., 2010). But there are obviously more factors that influence model split than only the direct costs and the time constraints. This can be illustrated with US travel cost data: for cars, the costs amount to 16 cents per pkm for car, while for airplanes it amounts to 7 cents per pkm. In other words, if only cost and time use would determine travel choices, people would travel more by airplane than by car. However, this does not happen (Schafer et al., 2010) – related to factors such as the distance between departure and final location, availability, accessibility and preferences. To cover these aspects, we introduce the expression for costs in the following way:

$$ModeCost_{r,m,t} = Const_{r,m,t} \cdot CostPerPkm_{r,m,t} + TimeWeight_{r,t} \cdot TimeUse_{r,m,t} \quad (-) \tag{3}$$

The monetary costs (*CostPerPkm*) are corrected with a constant factor (*Const*) reflecting the role of other factors for the transport modes in the various regions such as personal and societal preferences regarding infrastructure and use of public transport. For example, the choice for dense urban centers and mass transit will lead to a higher "preference" to travel via public transports. In addition, the constant factor also reflects other factors than the ones used in this study to explain the choice for different modes, including fluctuations and errors in our price estimates. Because we believe that personal and societal preferences explain a large share of this constant factor, we refer to it simply as "preference" in the remainder of this paper. It is for instance low for cars in all world regions indicating the high preference for individual mobility, and it is lower for public transport in Europe and Japan compared to the US, indicating the historical development of and societal preference for dense cities and good public transport infrastructure (Schafer et al., 2010). The time costs are described by the time use and the time weight factor (*TimeWeight*). This factor is determined such that the TTB criterion is fulfilled, i.e. the total time travel is roughly equal to the widely found value of 1.2 hours per person and day in the year 2005 (Schafer et al., 2010):

$$TimeWeight_{t,r} = \frac{\sum_m TimeUse_{r,m,t-1} \cdot TravelDemand_{r,m,t-1}}{TTB} \cdot TimeWeight_{r,t-1,r} \quad (-) \tag{4}$$

Hence, Eq. (4) ensures that if the travel time use of the previous year ($t-1$) exceeds the TTB-criterion, the time weight increases and the travel modes with lower speed get higher aggregated cost. Both monetary and time costs are divided by the average value of all modes to obtain a dimensionless factor.

Fig. 2 illustrates the dynamics captured by Eqs. (1)–(4) by showing the development of the time weight factor. In this simplified example, we consider three transport modes similar to walking, car driving and high-speed transportation. These idealized modes are characterized by increasing costs per pkm and increasing speed (e.g. car is more expensive and faster

[1] In the model, we use the logit equation twice: first to determine modal split (as indicated in Eq. (3)) and second for the fleet composition (with vehicle types instead of transport modes).

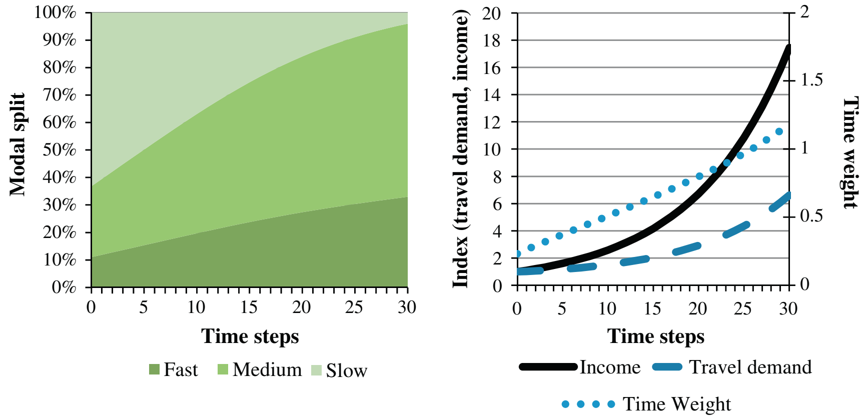

Fig. 2. Dynamics captured by the multinomial logit selection of travel modes combined with travel time budget via time use costs (Eqs. (1)–(4)). Slow describes cheap and slow, fast expensive and fast transport modes. Income is the driver and assumed to increase with 10% per time step.

than walking). The income is assumed to increase exponentially with a constant growth factor. As expected, increasing income results in raising time weight and leads to a shift to faster transport modes. But because of the increasing cost of travel modes with higher speed, travel demand increases more slowly than income.

The advantage of the TRAVEL formulation is that the TTB and TMB determine the modal split in a way that is responds to changes in the price and speed of the transport modes. For instance, when the travel costs increase because of higher fossil fuel prices or introduction of a carbon tax, the distance that can be traveled with the TMB reduces and hence time weight also reduces and the modal split shifts to slower modes. Changes in the speed of the transport modes over time can be considered as well. In this way, the model captures also rebound effects from efficiency measures that result in lower transport costs or higher speed, as suggested by various authors (Binswanger, 2001; Girod et al., 2011; Sorrell and Dimitropoulos, 2008).

The way income affects the modal split in our model is in line with the hypothesis that household optimize their consumption by allocation of time (Becker, 1965). It implies that the opportunity cost of time use increases with the wage rate. Accordingly, *TimeWeight* increases with income. However, our formulation considers the TTB budget observed across regions and time by Schafer et al. (2010). This cannot be explained by a fully rational optimization of households, but behaves similar to mental accounting, allocating expenditure to certain purposes as observed by Thaler (1999).

The assumed interchangeability of the different modes, from bike via public transport and cars to airplanes, is based on the past evolution in high income countries. As this is the basis of our model formulation and parameterization, the future growth in travel demand and the ways in which it is supplies in developing regions reflect a similar evolution. Also high income countries, one can expect a further substitution of car and public transport by high speed modes due to a change in travel behavior. For instance, people work more at home and consequently daily commuting decreases, but at the same time they might travel by fast train or airplane to their office in another city for some days each week (Schafer et al., 2010). In line with this, it is found that car-free households spend more on air travel (Ornetzeder et al., 2008).

2.2.2. Vehicle choice and costs

In addition to the costs and preferences for different travel modes discussed so far, also the penetration of different technologies within a certain mode are related to behavioral variables. One can think here of factors such as vehicle passenger load (or occupancy rate) and the preferences for more environmentally friendly vehicles. These factors characterize the different technologies within a certain mode and influence the model outcome in two ways: (1) they directly impact the fleet composition, i.e. the share of different vehicle types within the modes, which is in the model simulated through a (second) multi-nominal logit model and (2) they indirectly influence the choice of different modes because of the associated change in mode costs. The vehicle costs in passenger kilometers are formulated as follows:

$$VehPkmCost_{r,m,v,t} = \frac{NEC_m \cdot LUX_{r,t} + ATC_{r,m,v,t} + EE_{r,m,v} \cdot EP_{r,t} \cdot DF_{r,t}}{LF_{r,m,t}} \quad \text{(USD/pkm)} \tag{5}$$

With the variables differing for the different vehicle types (v), travel modes (m) and regions (r) and over time (t). The Non-Energy Costs (*NEC*) include the costs for vehicle purchase and maintenance and they are supposedly higher for higher LUxury Levels (*LUX*), which is a measure of the comfort level of travel. The Additional Technological Costs (*ATC*) account for the higher cost of more efficient vehicles. The Energy Efficiency (*EE*), Energy Price (*EP*) and the income-dependent Discount Factor (*DF*) determine the energy costs.

A detailed description of the technology data is provided in Girod et al. (2012). The non-energy costs in 2005 range from 4.8 cents (US_{2005}) per pkm for bus to 16.3 for high-speed train. The luxury level in 2005 is for instance 1.18 for USA and 0.24 for India, and increasing with income resulting in 0.9 for India in 2050 (cf. Section 2.4.3). The additional technology costs are zero for the baseline vehicle and increase for alternative vehicles, for instance by 4 cents per person kilometer for a hybrid-diesel vehicle in 2010 or by 2.6 cent for a more efficient blended wing body airplane. The efficiency varies between 0.4 MJ per pkm for trolley buses to above 3 and 2 MJ for old airplanes and cars respectively. The energy price varies regionally. The fossil fuel price in the beginning of the century is highest in Europe (around 40 USD/GJ) and lowest in the Middle East (10 USD/GJ), but it increases towards 30 USD/GJ in all regions towards the end of the century. The discount factor is determined by the vehicle life time and capital discount rates and varies between 50% and 70%.

2.3. Simulating the past

A comparison between historical and simulated data for some key statistical variables gives an impression of the quality of the model. In a rigorous analysis, one should explore such comparability throughout parameter space as part of model calibration/validation (Ruijven et al., 2010). Here, we do a more limited analysis in which we evaluate the agreement between the historical time-series data of a variable x and its simulated equivalent $\tilde{x}$ by calculating the coefficient of variation for lognormally distributed variables $CV_y = \sigma_y/\mu_y$, where μ_y and σ_y indicate the mean and the standard deviation of the relative variable $y = \ln(x/\tilde{x})$ (for mathematical details see Appendix A). The log-transformation of the data ensures that proportional differences are taken into account, which is preferable as a consequence of the multiplicative features in the simulation outcomes (Slob, 1994). The variable x chosen is *TravelDemand*. In order to get a clear picture of the value of the coefficient of variation CV_y relative to the historic travel demand, we divide it by the average demand and express the results as fraction relative to total travel demand, $RelCV_y = CV_y/\overline{\ln(x)}$.

In our assessment, we use the data on travel demand per capita as given in the official statistics for 11 world regions between 1971 and 2005 (Schafer et al., 2010). These time series provide travel distance per capita for three modes: bus/train, car, high speed modes (air flight and high speed train). We separated the data for bus and train as well as high-speed train and aeroplane using the indicated shares from Schafer and Victor (Schafer and Victor, 2000). To match the regions, we aggregate the 26 regions from the TRAVEL model to the 11 regions from Schafer et al. (2010). We then calibrated the model parameters with the aim to get the lowest possible $RelCV_y$. In this procedure, we first derive the regional TMB. Second, the substitution elasticity λ in the MNL model, is adjusted in order to reduce the deviation from the observed data. Third, the travel system inertia is determined for the different travel modes. Finally, the preference factors in 1971 and 2005 are determined. A more detailed description on the calibration is provided in Girod et al. (2012).

The results of this calibration/validation exercise are indicated with the relative coefficient of variation Table 1. For the total of 11 regions and five motorized transport modes, the deviation between historical and simulated data amount to 4% of the per capita travel demand. The correlation of historical and simulated travel demand is illustrated in Fig. 3. Overall, the model fit is good and is largely explained by the correlation with income. For Centrally Planned Asia (mainly China) the value of *RelCV* is considerably worse, but it should be noted that the quality of the historical statistical data from this region is poor. Additionally, part of the trends in this region might be heavily influenced by government policies not captured in the model. Such an explanation is supported by the fact that the model performs much better for the 1995–2005 period, during which the Chinese government introduced more market-oriented policies and the economy became more in line with those in other world regions (Fig. 3).

The range of the calibrated preference factors for the different modes is shown in Fig. 4 (cf. Eq. (3)). It is observed that cars have higher preference values than other travel modes in all world regions (the outlier in 1990 stems from China, but here again data quality plays a role). The preference factors for bus and train data show large variances, but similar deviation compared to car. The range in preference values for high-speed train are not very meaningful because only two world regions had

Table 1
Relative coefficient of variation in percent of total travel demand for simulation compared to historic data.

	Bus	Train	Car	High speed train	Air	All
North America	1.9	1.9	0.2	–	2.7	2.0
Pacific OECD	0.7	0.5	0.7	1.5	2.6	1.3
Western Europe	2.8	3.1	0.4	1.1	1.2	1.9
Eastern Europe	1.4	1.7	0.8	–	9.4	3.8
Former Soviet Union	1.4	1.3	2.0	–	5.6	3.1
Sub-Saharan Africa	0.7	5.2	1.3	–	6.1	3.5
Centrally Planned Asia	3.5	3.9	64.5	–	15.1	14.6
Latin America	2.4	1.8	1.1	–	1.7	2.0
Middle East & North Africa	1.2	3.9	0.6	–	2.5	2.2
Other Pacific Asia	1.5	1.7	2.2	–	7.0	3.7
South Asia	5.0	4.2	6.1	–	14.0	7.2
Total	2.3	2.6	4.2	3.1	5.7	4.0

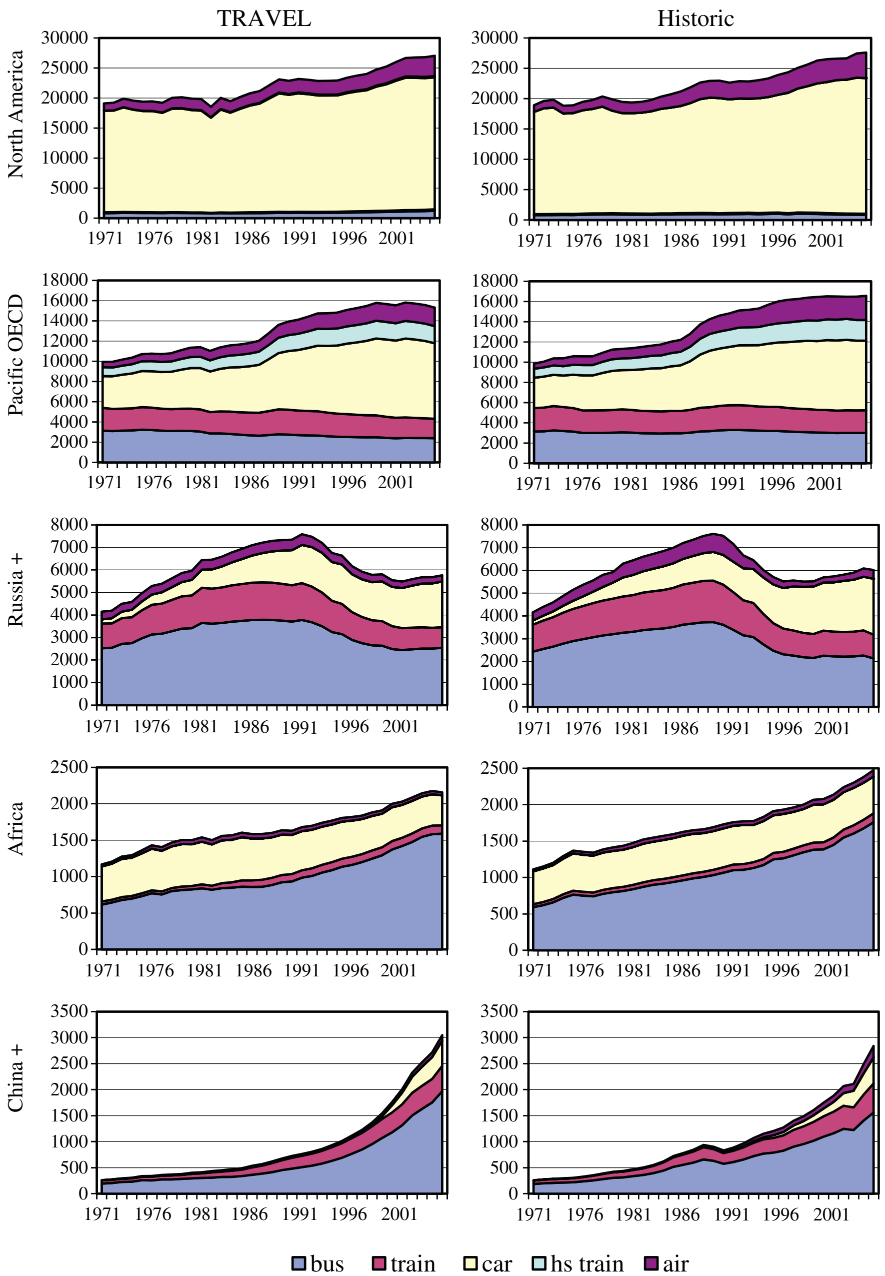

Fig. 3. Comparison of historical (Schafer et al., 2010) and simulated travel demand [pkm per capita] for five selected world regions for the years 1971–2005.

a significant amount of high-speed train travel in 2005 (Western Europe and Pacific OECD). Therefore, the preference factor for the other regions was set such that the share for high-speed train vanishes.

2.4. Travel behavior: assumption for different model runs

The key parameters in the model that determine the scenario outcomes can be divided into two sets. The first set represents and evaluates normal baseline uncertainty for travel demand (Table 2). The second set is used to define a set of parameters related to increasing environmental awareness and resultant changes in behavior (Table 3). This set relates to the avoid and shift mitigation strategy described by Dalkmann and Brannigan (2007), but we explicitly do not consider the improve strategy (e.g. more electric vehicles). For both sets, the value ranges chosen for the forward projections are discussed below. The goal is not to make a simple sensitivity analysis but to determine the importance of the travel behavior parameters by setting the input range to a range of realistic values.

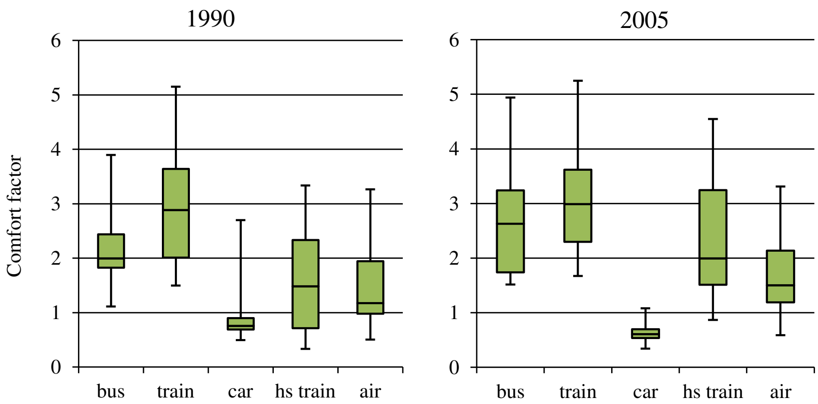

Fig. 4. Adjusted constant factors, which corrects for mode specific preferences, for main transport modes in 11 world regions. Across the different regions the constant factor for car is lower and hence the preference higher, compared to the other transport modes.

Table 2
Assumptions on parameter uncertainties in future travel behavior.

Uncertainty	Short name	Description	Model assumption			
			Measure	Low	High	Baseline
Travel time use (2.4.1)	TTB	Time scarified for traveling	Minutes per day in 2100	72	122	97
Travel money budget (2.4.2)	TMB	Part of income spend for travel	Global TMB in 2100	6%	10%	8%
Luxury level (2.4.3)	Lux	Higher price paid for higher luxury level (vehicle design, first class etc.)	Increasing price for non-energy costs with double income	30%	58%	43%

Table 3
Assumptions on parameter uncertainties regarding environmental friendly behavior.

Uncertainty	Short name	Description of possible change	Model assumptions
Vehicle passenger load (2.4.4)	Load factor	Increasing energy efficiency through slower decrease in passenger load	3.5% lower decrease in load compared to baseline with doubling of income.
Modal shift (2.4.5)	Mode-shift	Higher preference for the environmentally friendly bike and trains	Decreasing preference factors for bicycle and trains (see Table 4)

Note: Slower load decrease is only applied when the load is above US (2005) values.

2.4.1. Future Travel Time Budget (TTB)

Many studies on travel time use can be found in the literature. In fact, two opposing views can be identified. The first view concludes from empirical evidence that travel time use amounts to a constant value of around 1.2 h per day across regions and over time (Zahavi and Talvitie, 1980) (resulting in the constant travel time budget hypothesis). The alternative view is that the time budget increases with income and that TTB is only constant on a very aggregated level and differs with socio-economic circumstances (Mokhtarian and Chen, 2004). Arguments that travel time will increase in the future are, amongst others, that travel is increasingly used 'productively' as activity time and that increasing luxury levels favor longer travel times. Evidence also shows that first class travelers are more likely to spend most of their time working or studying than those in standard class – 28% compared to 15% for single/return tickets, and 22% compared to 11% for season tickets (Lyons et al., 2007). Toole-Holt et al. (2005) found that travel time increases by 1.9 minutes a year in the US during the 1983–2001 period.

We have represented both views in our analysis here. In the low travel time use case, TTB is kept constant at 1.2 h a day (Schafer et al., 2010). In the high travel time case, we assume a yearly increase of the daily TTB by 0.5 min, resulting in 122 min per day at the end of the century. The baseline scenario assumes an intermediate value of a yearly increase of the daily TTB by 0.25 min.

2.4.2. Changing Travel Money Budget (TMB)

Compared to travel time use, the Travel Money Budget (TMB) is discussed much less in the literature (Mokhtarian and Chen, 2004). Empirically, it is found that car ownership increases with income and that this corresponds with a gradual increase in TMB of about 3% to 10–11% (Schafer et al., 2010; Zahavi and Talvitie, 1980). However, a slower increase in TMB with income is also found in various studies (Mokhtarian and Chen, 2004).

We assume for the baseline scenario, a linear increase of TMB as a function of the share of car or faster transport modes, with 3% for zero share rising to 12% for 100% share of car or faster transport modes. This results in a global TMB of 10% in 2100. We assume that the TMB increases to 12% of income for the high case and decrease to 6% of income for the low case.

2.4.3. Changing luxury level

Schafer and Victor (2000) note that a certain part of the TMB is used for luxury, style, safety and engine power. The money spent for higher luxury level is no longer available for traveling and hence directly links to the resulting travel distance. In the literature, very little attention is paid to the role of luxury (or comfort) level. The income elasticity for luxury can be estimated with the time series for the US car prices from 1950 to 2005 (Schafer et al., 2010). The available evidence suggests that for every unit additional income people are willing to spend on average 0.4–0.6 unit on higher luxury level and that this number has tended to increase since the 1990s (over the full period the income elasticity is 0.52, starting from 1980 it is 0.57 and from 1990 to 2005 it is 0.7). This value is similar to a Swiss study which estimated the income elasticity of expenditure for higher quality (e.g. higher price for same physical consumption unit e.g. persons kilometer) to be around 0.5 (Girod and de Haan, 2010). But only few studies on this issue were found.

In the baseline scenario, we assume that the luxury level continues to increase with an income elasticity of 0.57, which corresponds to the value observed for car price in the US between 1980 and 2005. For the high and low case we vary this elasticity by 0.8, which represents the elasticity over longer or shorter time period for US car prices (Fig. 5). This change is applied to all modes but only when income levels raise above that of the US in 2005. Up to this point all regions are assumed to follow to US way of life and hence also their purchase behavior for higher luxury levels.

2.4.4. Increasing passenger load

The load factor indicates the number of passengers per vehicle. For the load factors in the baseline scenario, we use the estimates from IEA/WBSCD (Fulton and Eads, 2004) for the year 2000 (cf. Girod et al., 2012). Scholars and policy makers have suggested that increasing passenger loads could help to reduce emissions and policies should be formulated to promote passenger load. One such policy is the implementation of high-occupancy vehicle lanes, which can be used only by cars with more than one passenger (i.e. carpooling) (Boriboonsomsin and Barth, 2007; Minett and Pearce, 2011). Increasing or slowing down the decrease in the load factor proved difficult in the past, but the developments in information and communication technologies (ICTs) such as social media could facilitate this trend in the future in surprising and significant ways. Examples are on the spot schedule and traffic information, car sharing companies and schemes and integration of private and public transport modes. For aircraft, increasing "operational efficiency" by higher passenger load is seen as an important contribution to improving energy efficiency (Lee et al., 2010). Therefore we consider an alternative case with additional efforts to slow down the decrease in vehicle occupancy compared to the baseline by an income elasticity of 5% for all transport modes. This implies for instance that the load factor of the US decreases from 1.52 in 2005 to 1.33 towards the end of the 21st century in the baseline, while it only decreases to 1.42 in the load case.

2.4.5. Shift in travel modal split

In the baseline scenario, the preference factors are assumed to remain constant at the value derived from the calibration (cf. Section 2.3). This assumption is justified by their constant behavior over the calibration time period (1971–2005). An exception is the preference factor for air travel. Here, a difference between low- and high-income countries is found. For high-income countries, preference for planes was similar to that for buses and trains. Given the apparent relationship with income and the current low shares of air travel in low income countries, we assumed for the baseline scenario that the preference factor will increase to the level of high-income countries in all countries.

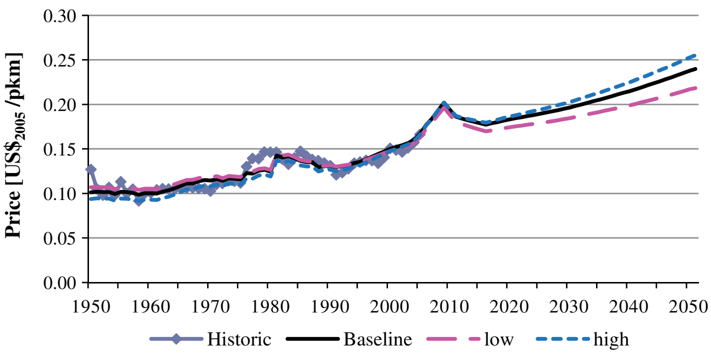

Fig. 5. Historical (Schafer et al., 2010) and simulated price trajectory for three values for the elasticity of luxury level to income (baseline scenario, high and low case).

Table 4
Average preference factor for transport modes in 2050 for the baseline and the mode-shift case. The preference factor is multiplied with the cost of the corresponding travel mode to determine the "perceived price", hence low preference factors implies higher willingness to pay.

	Walk	Bicycle	Bus	Train	Car	High speed train	Air
BaU	1.2	1.8	2.6	3.0	0.65	2.9	2.0
Mode-shift	1.2	1.4	2.6	2.0	0.65	1.8	2.0

As described in Eq. (3), the preference factor includes also personal and societal preferences. Environmentally friendly behavior can, hence lead to a shift in these preference factors. An example is the shift to public transport options to reduce CO_2 emissions per pkm (Böhler et al., 2006; Chapman, 2007). Also, high speed trains are advertised as a climate friendly alternative to airplanes (von Weizsacker and Hargroves, 2009). Such a preference shift includes also changes in infrastructure enabling public transport and (high speed) trains. The increase in preference for public transport and bicycles towards 2050 might be explained by a self-reinforcing process: when more people take public transport or the bicycle, its quality increases through the demand, triggering tighter schedules and higher density for public transport or the provision of more bicycle lanes. We consider this here by decreasing the preference factor for trains, buses and bicycles towards 2050 (see Table 4) (referred to as mode-shift case). The comparison with Fig. 4 shows that the values assumed for 2050 on global average are already observed in some regions today.

2.5. Green travel case

If people and society increase their emphasis on reducing environmental pressure, it is likely that they will not change only one aspect of travel behavior but several factors at the time. The IPCC B1 scenario for instance assumes investment in infrastructure for public transport and bicycling (de Vries et al., 2000). The IEA evaluates a scenario with decreasing travel demand and a shift in modal split towards public transports, both changes driven partly by policy measures (IEA, 2009). We therefore also evaluate a combination of behavioral changes including the following assumptions:

– Medium TTB: On one side, the shift in expenditure away from mobility also includes the time allocation, on the other side (a) the higher quality of traveling because of the higher luxury level and (b) the increasing preference for slower modes such as bicycle and normal trains increase travel time use. We therefore consider the middle case as the baseline.
– Low TMB: People shift their expenditure away from mobility towards more environmentally friendly consumption categories such as services.
– High Luxury: The trend to spend "better instead of more" is reinforced, leading to a faster increase in comfort and luxury levels. For instance, people choosing to travel first class over longer distances.
– Higher load factor: For cars, carpooling is promoted. For public transport, the higher luxury level increases as do the costs of an empty seat but at the same time this higher luxury level reduces the negative impact of higher load on travel comfort (e.g. more comfortable seats).
– Shifting modal split: Due to the higher environmental awareness, people have a higher preference for bicycle and train. Especially when such preferences are also expressed at the political level, these travel modes are promoted and become more attractive if the associated infrastructure improves accordingly.

The values chosen for the green travel scenario correspond to the high, median and low cases respectively described in the previous sections and Tables 2 and 3.

3. Results

We first present the projections for travel demand and then the changes in modal split. The resulting energy use and the associated CO_2 emissions.

3.1. Travel demand

Fig. 6 shows the different projections for world passenger travel demand. In the baseline travel demand increases from 50 to 225 tera pkm during the century. The sensitivity cases for the high and low TMB and luxury level span a broad range in the order of ±25%. The TTB shows only little sensitivity for total global travel demand. Though the decreasing travel demand with increasing TTB might seem counter-intuitive at first glance, it stems from the assumptions that (i) the monetary price of air travel per km is lower than for travel by car and (ii) the shift from car to air travel results from increasing time weight. The higher TTB results in a less importance being placed upon travel time when choosing a travel mode, hence there is a slower shift to air travel. Since the latter has a lower price per km, the average travel costs are higher resulting in an decrease in the total distance traveled within the same TMB.

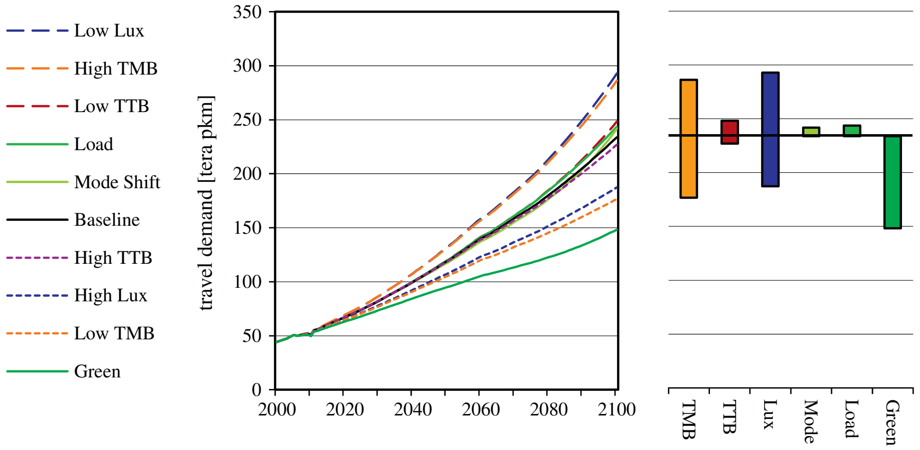

Fig. 6. Global travel demand for the different scenarios of changing travel behavior with the range for the high/low scenarios (TMB, TTB, Lux), the deviation from the baseline for the eco-variants (Mode Shift, Load) and the green traveler scenario.

Higher load factors lead to a slight increase in travel demand. This is because the higher load also decreases travel costs (cf. Eq. (5)), and as a result of the constant TMB leads to higher travel demand. In combination with the constant TTB, the increase in travel demand is only possible with a shift to faster transport modes. This rebound effect is discussed further in Section 4. The mode shift allows for higher travel demand, because train are less expensive than car. Finally, the integrated '*green travel*' scenario results in a considerable decrease of total travel demand, resulting largely from the combination of lower TMB and higher luxury level.

3.2. Modal split

In all cases, car is projected to remain the dominant passenger transportation technology (Fig. 7). Typically, the cases that project lower total travel demand also show lower shares of high speed transport modes – and vice versa. This is because only fast transport modes allow a substantial increase in the travel distance within the given TTB.

Compared to the baseline, in the modal-shift case the share of trains and bicycles is higher and the share of airplane is lower. The modal split of the *green travel* scenario is similar, but the shift to fast transport modes is even less pronounced because of the lower overall travel demand. The role of walking and cycling is largest in the case where people relax (high TTB), spend less on mobility (low TMB) or are living in a society which is ecologically aware (green) and hence promotes non-motorized transport and in general reduces the expenditure for transportation (cf. Section 2.5).

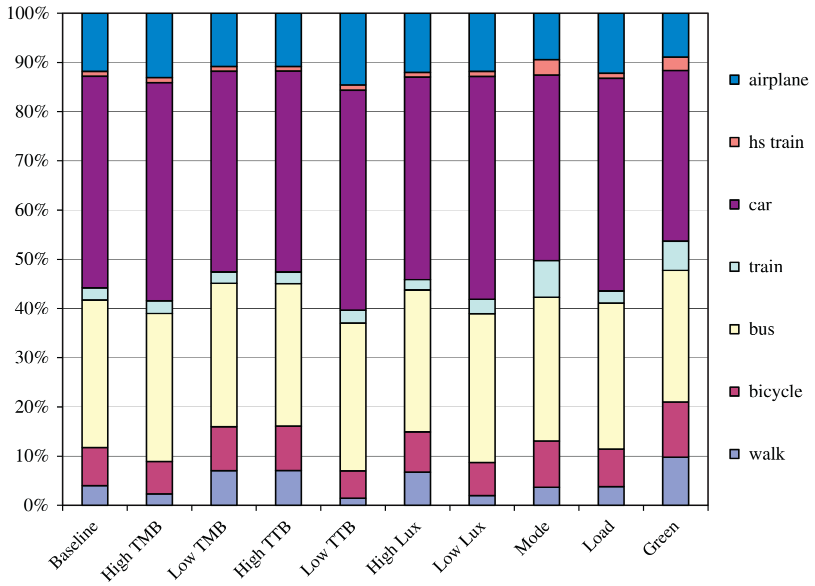

Fig. 7. Global modal split for different travel behavior scenarios in 2075 (pass-km).

3.3. Energy use

Compared to travel demand, the deviation from the baseline is amplified for energy use (Fig. 8). For *TMB*, *TTB* and *Luxury* cases, the shift towards faster transport modes in the cases with high travel demand coincides with more energy-intensive modes. The *modal-shift* case, with a shift to less energy-intensive transport modes, results in a reduction of energy use. Changes in the load factor have a small, positive impact due to the increase in transport demand and modal shift discussed in the previous section. Finally, the combined *green travel* scenario has the lowest energy use projections, since shifts in modal split coincide with a lower travel demand. Indeed, our calculations show a 50% reduction of energy use as compared to the baseline by 2100.

3.4. Direct CO_2 emissions

The direct CO_2 emissions, i.e. from fuel combustion and not from electricity generation, are directly related to the fuel mix in the energy use. In the simulations, the oil price rises over time and induces a gradual shift to natural gas, especially cars with compressed natural gas (CNG). The pattern shown in Fig. 9 therefore can be directly understood as first a clear correlation with energy use, followed by a significant decline in total CO_2 emissions as a result of a substitution from oil to gas. In the *mode-shift* case, the range in the CO_2 emission values are amplified compared to the energy use values. This reflects a shift to trains, using electricity generation, which does not lead to direct CO_2 emissions.

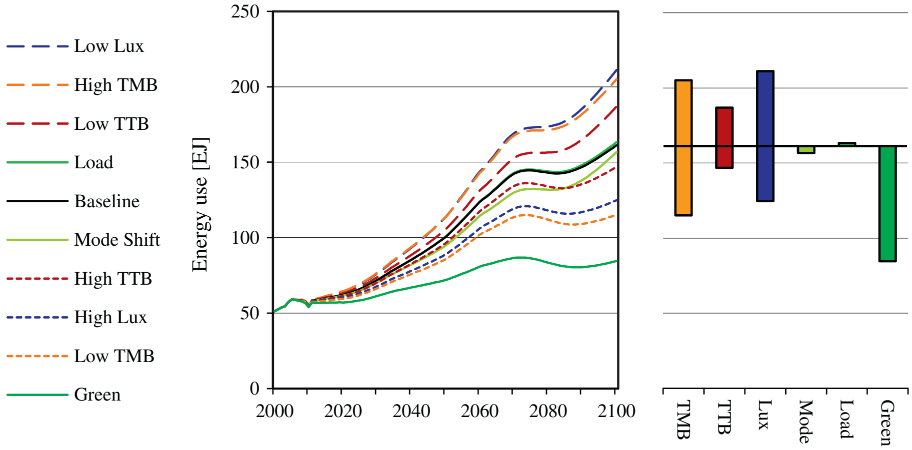

Fig. 8. Global energy use from passenger transportation for different scenarios of changing travel behavior with the range for the high/low scenarios (TMB, TTB, Lux), the deviation from the baseline for the eco-variants (Mode Shift, Load) and the green traveler scenario.

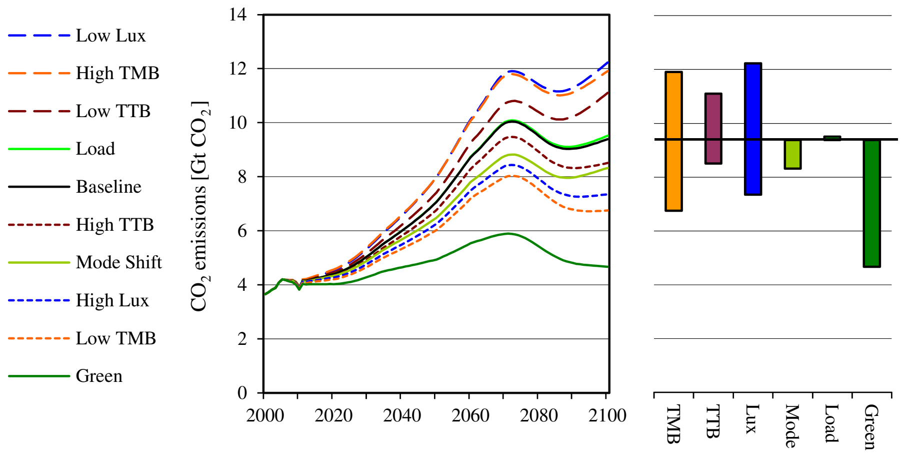

Fig. 9. Global CO_2 emission from passenger transportation for the different scenarios of changing travel behavior with the range for the high/low scenarios (TMB, TTB, Lux), the deviation from the baseline for the eco-variants (Eco-Shift, Load) and the green traveler scenario.

The CO_2 emissions in the *green travel* scenario grow very slowly, peak in 2070 and ends up 50% below the baseline in the end of the century. The net reduction is lower than the sum of the individual cases considered in the *green travel* scenario (cf. Section 2.5), however considerably higher than the single cases.

4. Discussion

We first discuss the modeling of global travel demand in general. Second, we focus on the implications of changing travel behavior. Third, we compare the *green travel* scenario with emission reductions required or obtained by climate policy. Fourth, we indicate the limitations of this study and resulting need for further research.

4.1. Modeling global travel demand

The fact that the TRAVEL model has been based on several empirically observed dynamics in travel (e.g. TTB, TMB, substitution dynamics) and the successful calibration of the simulated variables to the 1971–2005 historical data indicates that the model is able to reproduce the shift to faster transport modes and the increase in travel demand observed in the past. The values for the calibrated parameters, such as the preference factors, are plausible and in line with earlier studies that suggest higher preference for individual motorized mobility as compared to public transport. The relatively small range for car preference values across different regions also gives some confidence that the explicit factors included in the model in order to represent regional differences (income levels, discount rates) are relevant. At the same time, the rather large ranges in preference values found for the other transport modes may reflect regional differences in factors which are not explicitly considered in our model, such as population density, extent of infrastructure and urban development patterns and planning.

4.2. Uncertainties from travel behavior

The results show that plausible changes in the travel behavior as described in Section 2.4 and included in the sensitivity runs lead to large changes in future travel demand and resulting energy use and CO_2 emissions. Besides the TMB-value, the preference for higher comfort levels with higher income is found to be an important behavioral determinant and is often missed in purely technical or price/econometric studies. Its effect on travel demand is similar to a lower TMB-value, since higher luxury cost reduces the income available for traveling longer distances. Notice that we assume an impact from the aspiration for more luxury only after a region reaches the income level that the average US citizen had in 2005, that is 34,200 USD per capita. If the luxury level would change earlier and people in other lower-income regions are going to spend less on luxury but more on increasing distance than the US citizen, then a considerably higher global travel projections would result. In, addition higher luxury level lead to larger and heavier cars and thus to an increase in the energy use per vehicle kilometer (Bandivadekar et al., 2008). We have not included these effects in the model, because they are not yet fully understood. The changes in comfort levels and the implications for energy intensity is certainly an important field of further research.

The lower travel demand resulting in the model from a higher travel time budget (TTB) is might be partly artificial, since the TMB and TTB are in reality probably correlated. However, the identified mechanism is plausible: Using less time for traveling may lead to a shift towards air travel, which permits longer travel distances for the same TMB-value due to lower per kilometer costs.

Another factor that influences travel demand and CO_2 emissions is (the trend in) environmental awareness and its behavioral and societal implications. The changing modal split (*modal-shift,* cf. Section 2.4.5) leads to a significant reduction in energy use and consequently in CO_2 emissions. This is in line with the "Blue Shift" scenario from the IEA (2009) in which travel is assumed to shift to more efficient modes and to some extent eliminated via better land-use planning, greater use of information technology and other measures that reduce the need for motorized travel.

A interesting outcome from our model is the higher energy use for increasing vehicle load. This impact is a form of a rebound effect, resulting from lower costs. This kind of rebound effect is in line with theoretical and empirical studies (Girod et al., 2011; Polimeni, 2008; Sorrell and Dimitropoulos, 2008; Sorrell et al., 2009). A key question is whether the saved travel costs from the increased load are spent on other travel modes according to the constant-TMB hypothesis assumed here, or spent outside the transport sector. Empirical studies done so-far claim lower emissions due to higher load, e.g. because of high occupancy vehicle lanes or carpooling (Boriboonsomsin and Barth, 2007; Minett and Pearce, 2011). However, it might be questioned whether these studies capture the rebound effect via expenditures on other transport modes. More consistent with our model-based findings, a study evaluating total expenditure of household reported higher expenditure for air travel for households without a car (Ornetzeder et al., 2008). If an increase in the load factors occurs in combination with a reduction in TMB, then the rebound disappears. It should also be noted that because higher load factors allow traveling more at the same level of emissions, promoting higher load factors still makes sense from an economic point of view. For instance, in the *green travel* scenario the the higher load allows to travel further with the same energy use.

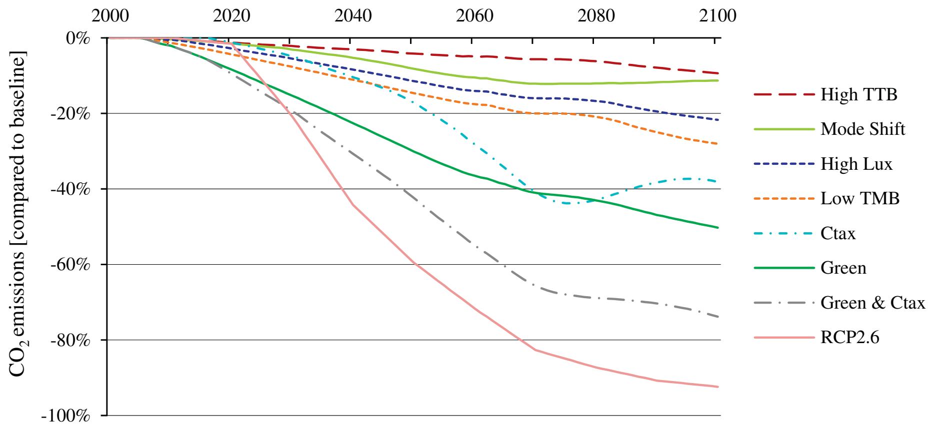

Fig. 10. Deviation of CO_2 emissions from baseline for evaluated scenarios on changing travel behavior (only outcomes resulting in lower emissions are displayed) compared to the emissions in line with the RCP2.6 and the introduction of a carbon tax.

4.3. Green travel scenario and climate policy

Are the changes in CO_2 emissions resulting from changes in travel behavior relevant for climate policy? This question can be explored by comparing the reduction in CO_2 emissions from changing behavior due to the introduction of a carbon tax. In the model, the introduction of a carbon tax accelerates the penetration of energy efficiency and natural gas. Fig. 10 shows the emission reduction relative to the baseline scenario for the period up to 2050 with a carbon tax introduced in 2015, increasing linear to of 200 USD per ton CO_2 in 2050 and then remaining at this level through the second half of this century. It reveals that the evaluated combination of changes in travel behavior (green scenario) results in a reduction of CO_2 emissions comparable to the carbon tax case. This is because the *green travel* scenario follows a different travel demand pattern. To evaluate the additionally of behavioral measures and the carbon tax we add a further scenario combining the *green travel* scenario and the carbon tax. It reveals that compared to the *green travel* scenario the tax reduces emissions over the century by 112 Gt CO_2, while the tax reduces emissions by 181 Gt CO_2 compared to the baseline. Hence, behavioral changes and carbon tax are not fully additive. This can be explained by higher share of modes that have already zero direct emissions, as well as by lower total travel demand which reduces the total impact of for instance changing vehicle efficiency.

A comparison with the so-called RCP2.6 emission pathway reference (Vuuren et al. 2011), consistent with the 2 degree climate target, can be made by looking at the sectoral distribution of the emission profiles in the corresponding study to 2.6 W/m^2 from van Vuuren et al. (2011), resulting in GHG emissions of about 1 Gt CO_2-eq. at the end of the 21st century and assuming that 20% of these emissions will be used for passenger travel. It reveals that the combination of green scenario and carbon tax gets close to the emission reduction required for the RCP2.6.

Note that biofuels are excluded because of the uncertainty regarding their future acceptance and environmental performance. Considering biofuels would allow for much stronger decarbonization of the transport system by the carbon tax (cf. Girod et al., 2012).

4.4. Limitation and further research

This study focusses on the implication of specific changes in aggregate travel behavior. Uncertainties in important drivers for the global transport system such as income or population growth, technological change or energy/climate policies are not considered. Regarding the data, the information on travel volume is uncertain even for developed regions, let alone for developing regions. However, the data from Schafer (2010) used for calibration result in estimates for the beginning of the 21st century similar to the results from other global transport models (Girod et al., 2013). Latter study shows also that the baseline projection of the TIMER model is similar to the other global transport models. However, the baseline version used in that comparison had slightly different behavioral parameter settings, resulting in somewhat lower travel demand (109 tera pkm in 2050 versus 102 tera pkm in this model).

Similar to other studies looking at the implications of changes in travel demand (IEA, 2009), we do not quantify the costs of such changes. In addition, many changes in behavior are difficult to express in monetary units, both intrinsically and because of complex interactions with other socio-economic behavior. Changes in TTB, TMB and comfort level are more a matter of preferences, which can be influenced by targeted campaign but are more likely influenced by other societal factors. Higher vehicle load factors may be difficult to achieve by political campaigns. But if it could be achieved with low or zero monetary cost, it would also result in considerable rebound effect compensating the reductions in CO_2 emissions. The shift in transport modes depends also on the development of the city and road infrastructure in the developing countries, which account for most of the global growth in travel demand. The analysis clearly shows that in order to realize the potential of changing travel behavior it must be understood how relevant variables such as TMB, luxury level, TTB and ecological preferences interact and how they can be influenced by different measures. Therefore, more information about how the changes in travel demand is of interest for climate mitigation. Especially if these changes can be achieved at lower costs compared to the alternative technological changes or are combined with co-benefits, like for instance lower space use for public transport. Ideally, the costs and effects of such measures should be determined so they can be directly compared to technology-based mitigation measures and thereby allow improvements in the effectiveness of climate policy.

Finally, we assume the same economic trends and regional income development for all scenarios. Therewith we do not consider possible implications of changing travel behavior on the wider economy. Such feedbacks might exist and would be relevant for long term projections.

5. Conclusion

The TRAVEL model can reproduce historical trends. The TRAVEL model described in this paper, using the assumption of constant travel money and time budget (TMB and TTB) as boundary conditions for behavioral change, reproduces the historical travel data from 1971 to 2005 in 11 world regions quite well at the global level and for most regions. In particular, overall travel and car use are reproduced with only modest deviations. Model results for the East Asia region before 1990 are less convincing.

Without the behavioral changes evaluated in this paper, energy use for transport increases rapidly. Using the OECD scenario (2011) as baseline, we evaluate the implications of global changes in travel behavior on model output (global travel demand, energy use and CO_2 emissions). The baseline projections of global passenger travel demand for 2100 show an increase by a factor 5 with respect to the 2000-value. Considering autonomous energy efficiency improvements, this translates into a factor 3 for energy use and, because of increasing fossil fuel price leading to higher share of gas, to a factor 2.5 for direct CO_2 emissions (without allowing for a significant share of biofuels in the transport sector).

Different possible trends in travel behavior can significantly impact future transport projections. We have evaluated several possible behavioral changes for their impact on transport energy use and emissions. Besides uncertainties in future global and regional travel demand resulting from different population and GDP growth pathways and in the pace of technological change, changes in behavioral travel parameters can significantly impact the projections for travel demand and the associated energy use and CO_2 emissions. The largest influence is found from changes in expenditure for travel distance, which is influence by the travel money budget (TMB – the share of income used for mobility) as well as by the luxury level (the expenditure used to increase comfort but not travel distance of mobility).

Combining different behavioral factors may reduce transport direct CO_2 emissions by around 50% in the end of the century compared to the baseline.

The reduction from behavioral changes is comparable to the reduction resulting from a carbon tax of 200 USD per ton of CO_2. Combining behavioral changes and a carbon tax (of 200 USD per ton of CO_2) results in emission reductions close to the reduction required in the transport sector for the 2 degree climate target respectively RCP2.6 pathway. Hence, changing travel behavior is relevant for climate policy and could either facilitate or complicate climate change mitigation. Changes in travel behavior and carbon tax are, however, not additive, because the "green travel" scenario has lower climate mitigation potential.

Further research on the impact of travel behavior is required. This study indicates the relevance of travel behavior for the passenger transportation system and its climate impact. However, to compare changing travel behavior with techno-economic climate mitigation options, further research is needed into the possibilities to influence travel behavior. A further research goal is a better understanding of the different travel behavior variables (especially luxury level) as well as their interrelation with each other and with important variables of the transport system (such as the energy efficiency of vehicles). Finally, for such long term projections also the relation of passenger transportation to the economic system and possible feedbacks with economic growth need to be understood.

Acknowledgement

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Appendix A

The coefficient of variation for lognormal distributed variable x can be denoted as:

$$CV_y = \sigma_y/\mu_y = \sqrt{(e^{\sigma_y^2} - 1)} \tag{A.1}$$

where μ_y and σ_y indicate the mean and standard deviation of $y = \ln(x)$. An unbiased estimate for the variance σ_y^2 of the (normally distributed) variable y is:

$$s_y^2 = \frac{\sum_{k=1}^{N}(y_k - \bar{y})^2}{N-1} \tag{A.2}$$

were $\bar{y}$ denotes the population mean of y over the N measurements y_k for $k = 1, \ldots, N$. We apply this formula to the relative variable $y = \ln(x/\bar{x})$ where x are the historical data, while $\bar{x}$ are the simulated counterparts, assuming that y is normally distributed (approximately).

Notice namely that the natural logarithm of the proportional values $x/\bar{x}$ is equal to the differences of the logarithms: $\ln(x/\bar{x}) = \ln(x) - \ln(\bar{x}) = u - \bar{u}$. The average value of y is therefore $\bar{y} = \bar{u} - \bar{\tilde{u}}$. In case that u and $\tilde{u}$ have not the same average value, we can establish an expression for the estimator of the variance σ_y^2 according to:

$$s_y^2 = \frac{\sum_{k=1}^{N}\left((u_k - \bar{u}) - \left(\tilde{u}_k - \bar{\tilde{u}}\right)\right)^2}{N-1} = \frac{\sum_{k=1}^{N}(u_k - \tilde{u}_k)^2}{N-1} - \frac{N}{N-1}\left(\bar{u} - \bar{\tilde{u}}\right)^2 \tag{A.3}$$

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