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Model-based analysis of future global transport demand

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ABSTRACT

Transport models are utilized to analyze the transition towards a low-carbon and sustainable future of transportation. Within these analyses, trends in transport demand serve as a crucial parameter. To address this, a cluster-based transport model was developed to estimate future global transport demand on a national level, encompassing both domestic and international transportation, extending until the year 2050. The transport demand was divided into passenger and freight, which were further split into road, rail, marine, and aviation sectors. According to the available transport-related data, the most influential factors on transport demand are gross domestic product per capita and urban population. Model results show an increase in the total passenger and freight transport demand to 183 trillion passenger-km and 395 trillion ton-km in 2050, respectively. This corresponds to a tripling of transport demand compared to 2020, primarily driven by the more significant rise in developing countries compared to developed ones.

Introduction

Transportation is one of the most significant activities in human life, by which productivity and human reach are ever increasing (Profillidis and Botzoris, 2019a). Both passenger and freight transportation are intertwined with the economic, socioeconomic, environmental, and health domains (IPCC, 2022; Lamb et al., 2021). Prior to the COVID-19 pandemic, the International Transport Forum (ITF) predicted global transport demand would triple from 2015 to 2050 (2019). In 2021, the global transport sector consumed approximately 31,500 TWh of energy (IEA, 2022). 90 % of this energy was provided by oil-based fuels, 4 % by biofuels, 5 % by natural gas, and 1 % by electricity. Since 1990, global transportation greenhouse gas emissions have steadily increased at a rate of about 2 % per year (Lamb et al., 2021). These tendencies make transport one of the most challenging sectors with respect to climate change mitigation (Gota et al., 2019). As the economy and population grow, so too will the demand for passenger and freight transport (ITF, 2021). Amongst other objectives, an analysis of the future impact of the transport sector on greenhouse gas (GHG) emissions in the context of transport demand modeling is needed (Kraus et al., 2022; Yeh et al., 2022). Transport demand data can be subsequently integrated with energy demand models (Khan Ankur et al., 2022) to analyze the transition to a low-carbon and sustainable transport future.

However, despite existing global estimations on the evolution of transport demand, there is a noticeable gap at the national scale, with limited coverage of transport modes. High-quality transport demand data is not readily available. Therefore, this paper seeks to review existing transport demand data, leveraging available socio-economic information to generate a global transport demand model at the national level. The results of this modeling exercise will be analyzed based on regions and transport modes. The objectives of the paper are:

1. To develop a comprehensive model that estimates future global transportation demands, encompassing four distinct modes for both passenger and freight—namely, road, rail, marine, and aviation. The model aims to provide a national resolution focus.
2. To analyze the future global transport demand development, utilizing the generated transport demand data.

This paper is structured as follows. The main studies on global transport demand modeling and the available transport demand data are reviewed in Section 2. Section 3 describes the methodology of the developed transport demand model. The analysis of the model results, ranging from global, to cluster, to country-specific developments, is

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conducted in Section 4. The main findings are summarized in Section 5.

Literature review

Profillidis and Botzoris (2019b) classify the transport demand modeling into two methods, namely qualitative and quantitative. Executive judgment, the Delphi method, and scenario writing are examples of qualitative methods. Quantitative approaches include, for instance, time series (Dantas et al., 2017; Khan and Khan, 2020; Marazzo et al., 2010), econometric (Carmona-Benítez et al., 2017), and activity-based methods (Hafezi et al., 2019; Reul et al., 2021). Choosing a transport demand modeling method depends on the accuracy, data, time, and cost entailed (Profillidis and Botzoris, 2019b). Available studies on global transport demand models vary by method, model structure, and input variables (Façanha et al., 2012; Fulton et al., 2009; Khalili et al., 2019; Kyle and Kim, 2011; Mittal et al., 2017; Nkiriki et al., 2022; Riahi et al., 2012; Schafer and Victor, 2000), as will be elaborated in the following section.

Models

Schafer and Victor (2000) employ so-called travel time and travel money budgets to determine future passenger transport demand. The Global Change Assessment Model (GCAM) (Kyle and Kim, 2011) and MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact)-Transport (Riahi et al., 2012) models use cross-sectoral endogenous functions to project future development (Yeh et al., 2017). Meanwhile, the Mobility Model (MoMo) (Fulton et al., 2009) and International Council on Clean Transportation (ICCT) Roadmap model (Façanha et al., 2012) rely on expert judgment and detailed, country-specific research and expertise (Yeh et al., 2017). In turn, the AIM (Asia-pacific Integrated Model) transport model incorporates behavioral parameters and transportation technologies details as its variables (Mittal et al., 2017). The challenge of using a bottom-up approach is to obtain the data for the variables (e.g., transport cost, vehicle cost, etc.) for each country. While the manufacturing cost of new vehicles can be determined globally (Grube et al., 2021), other cost factors differ from country to country.

Khalili et al. (2019) draw on continental-level transport demand data and disaggregate it to the national level using gross domestic product (GDP) per capita and population. The model has four transport modes, namely road, rail, marine, and aviation. For road, rail, and aviation transport, they use the ICCT roadmap regional data (Façanha et al., 2012). For marine transport, data is drawn from the third International Marine Organization (IMO) greenhouse gas study (Smith et al., 2015).

Nkiriki et al. (2022) use GDP, population, and urban population as input variables. Historical transport demand data available from the ITF (2021) is utilized, which consists of freight transport data for 38 countries and passenger transport demand data for 43 countries between 1990 and 2018. The GDP, population, and urban population elasticity are calculated using a regression method. With this approach, it is assumed that, on a global level, each country will have the same level of development as indicated by the available historical data of countries, which are mostly developed ones. Therefore, the considered elasticities for each variable used in the previous studies are the same globally (Fulton et al., 2009; Kyle and Kim, 2011; Mittal et al., 2017; and Nkiriki et al., 2022). Thus, it is assumed that the influence of the considered parameters on transport demand is similar for all countries, ranging from developed to the least developed countries.

Building upon the existing body of literature, previous studies have primarily focused on modeling global transport demand without adequately considering the regional nuances and developmental disparities among countries. In this study, the novelty lies in the development of a cluster-based model that considers the regional aspects and development status of each country individually. This approach calculates elasticities for each cluster, taking into account the unique characteristics of each region. By doing so, this study provides a better estimation of future global transport demand on a national level. Therefore, the study constitutes an advancement in the field of transportation demand modeling by accounting for the regional differences and characteristics that affect it, which were previously overlooked in other studies.

Data

One of the main challenges in global transport demand modeling is the lack of access to high-quality data on current and historical transport demand (Yeh et al., 2022). Furthermore, the significance of future trends cannot be understated, as relying solely on historical data is inadequate, particularly in the context of developing countries. The datasets on passenger and freight transport demand (*passenger-km and ton-km*) on a global scale and at a national level are not publicly available. There are several datasets available for some countries, but these are often incomplete and inconsistent due to the differences in data collection and processing methods. As a result, it is difficult to interpret and analyze the data.

The ITF (2021) report provides historical statistical data from 2012 to 2019 for some countries and projected data on a global scale through 2050. Passenger transport demand is distinguished between road and rail. The road passenger demand is divided into light duty vehicles (LDVs) and buses. The freight transport demand is distinguished between road, rail, and marine.

The International Council on Clean Transportation (Façanha et al., 2012) provides historical and projected passenger and freight transport activity data from 2000 until 2030 in five-year intervals. The data are available on regional and global scales. The regional scale is divided into Eurasia, Middle east, and North Africa (MENA), Sub-Saharan Africa, Northeast Asia, Southeast Asia, North America, and South America. The transport modes are split into road, rail, and aviation. Road transport demand is in turn divided into LDVs, buses, motorcycles, and trucks.

Statista (2022) provides national level data derived from the International Monetary Fund, World Bank, United Nations, and Eurostat, which collect their data from ministries of transport, national statistical offices, and other institutions that serve as official data sources (OECD. Stat, 2022). The available historical and projected data are passenger transport demand for road, rail, and aviation. The data are available at a yearly resolution from 2000 to 2040 for 49 countries' road passenger transport, 94 countries' rail passenger transport, and 151 countries' aviation passenger transport (in millions of passengers, not passenger-kilometers). The Statista data are licensed and not publicly available.

Khalili et al. (2019) provide transport demand data on a national level. Passenger and freight transport demand data are divided into road, rail, marine, and aviation. Furthermore, this dataset encompasses international transportation as well. The road passenger transport demands are split into LDVs, two- and three-wheelers (2 W/3W), and buses. The road freight transport demands are split into light heavy-duty vehicles (LHDTs), medium heavy-duty vehicles (MHDTs), and heavy-heavy duty vehicles (HHDTs). The historical and projected data are available from 2000 to 2050 in five-year intervals. Data is available for a total of 209 countries. The dataset includes territories that are not listed as member states of the United Nations, such as Anguilla, Bermuda, Cayman Islands, Cook Islands, and others.

Nkiriki et al. (2022) provide historical and projected road transport demand from 2010 to 2050 in five-year intervals. Using the shared socioeconomic pathways (SSPs) scenarios of projected GDP, population, and urban population, they project road transportation demand in 179 countries. Table 2 in the Appendix provides a summary of the available transport demand historical and projected data.

Methodology

The transport model presented in this paper was developed to

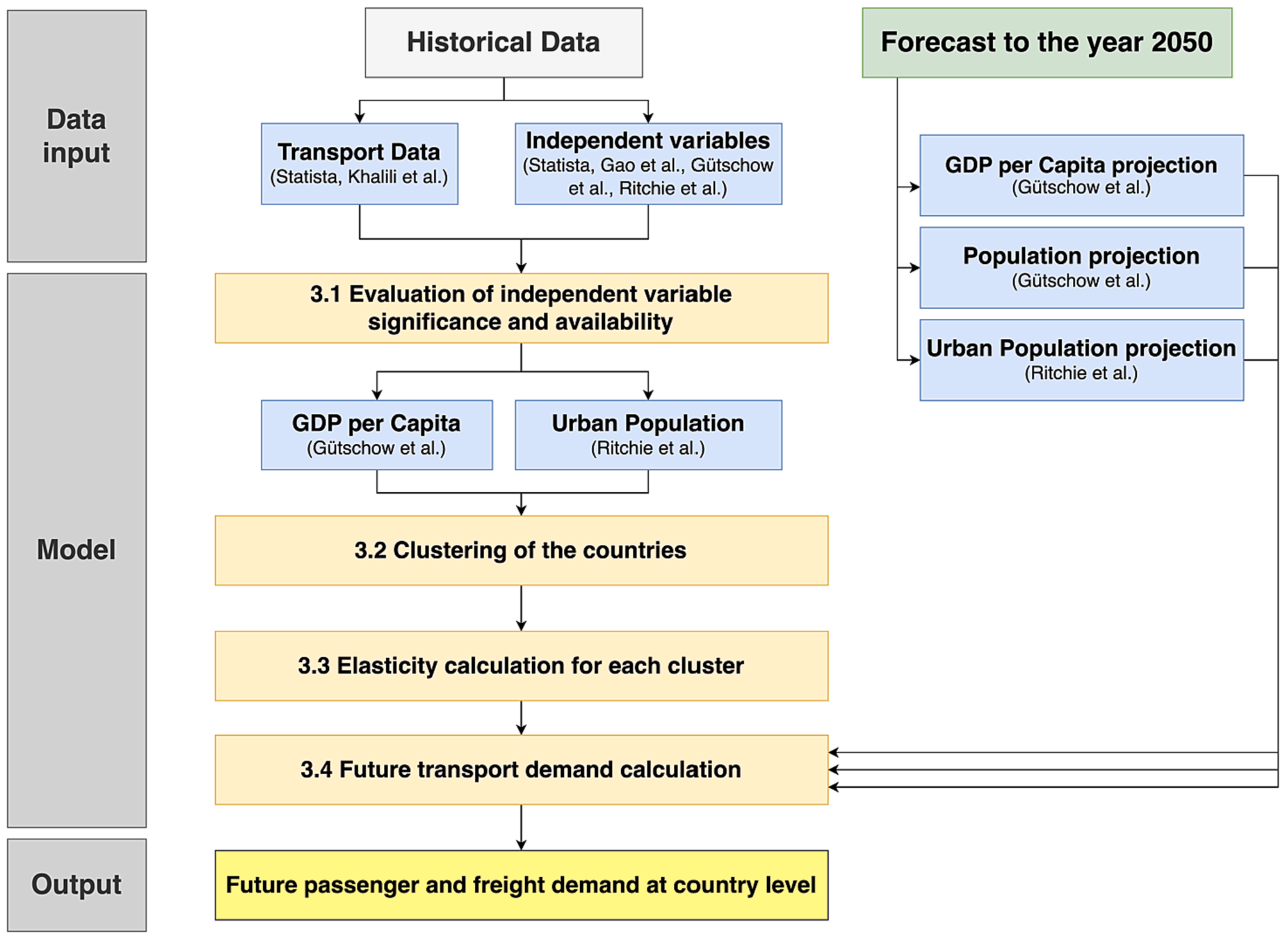

Fig. 1. Model overview (data input: Gao and O'Neill, 2020; Gütschow et al., 2021; Khalili et al., 2019; Ritchie and Roser, 2018; Statista, 2022).

Table 1
Datasets used for the significance evaluation.

Data	Time range	Resolution	Unit	Available data(n countries)	Reference
Road passenger per capita	2000–2019	Yearly	Passenger-km	49	(Statista, 2022)
Rail passenger per capita	2000–2019	Yearly	Passenger-km	94	(Statista, 2022)
Marine passenger per capita	2000–2020	Five-year	Passenger-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
Aviation passenger per capita	2000–2020	Five-year	Passenger-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
Road freight per capita	2000–2020	Five-year	Ton-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
Rail freight per capita	2000–2020	Five-year	Ton-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
Marine freight per capita	2000–2020	Five-year	Ton-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
Aviation freight per capita	2000–2020	Five-year	Ton-km	163	(Gütschow et al., 2021; Khalili et al., 2019)
GDP per capita	2000–2020	Yearly	Constant 2011 international dollars	163	(Gütschow et al., 2021)
Population	2000–2020	Yearly	Thousands	163	(Gütschow et al., 2021)
Urban population	2000–2020	Yearly	Percentage of population	163	(Ritchie and Roser, 2018)
Urban area per capita	2000–2020	Ten-year	m^2	163	(Gao and O'Neill, 2020)
Consumer transportation spending per capita	2000–2019	Yearly	Thousand USD	152	(Statista, 2022)
Consumer vehicle spending per capita	2000–2019	Yearly	Thousand USD	152	(Statista, 2022)
Road investment	2000–2019	Yearly	Percentage of GDP	51	(Statista, 2022)
Car stock per capita	2000–2019	Yearly	Thousand	45	(Statista, 2022)
Rail investment	2000–2019	Yearly	Percentage of GDP	46	(Statista, 2022)
Rail line	2000–2019	Yearly	Thousand meters	46	(Statista, 2022)

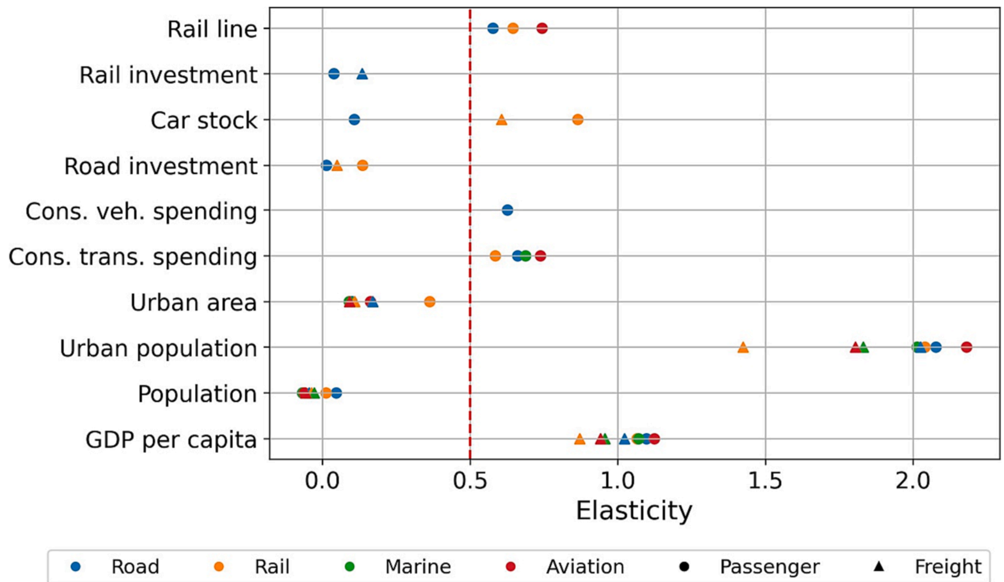

Fig. 2. Elasticity of the independent variable from the available transport-related datasets. For independent variables, see Table 1.

estimate and analyze future global transport demand at the national level, taking into account international transportation. The range of the projection is determined to be until 2050 because many GHG emission reduction targets refer to that time horizon (Gota et al., 2019; IEA, 2022; IPCC, 2022; ITF, 2021). This study operates under the assumption that the COVID-19 pandemic has been neglected in many studies due to the lack of high-quality datasets for 2020 that take the COVID-19 crisis into consideration. Despite the potential impact of the pandemic on transportation demand, this study omits it in order to maintain the consistency and reliability of the dataset.

An overview of the methodology is displayed in Fig. 1, demonstrating the detailed process that was used to develop the cluster-based model, calculate elasticities for each cluster, and project future global transport demand on a national level.

The model is divided into four parts. In the first, the available independent variables' significance is evaluated (Section 3.1). In the second, the countries are clustered based on the selected variables (Section 3.2). In the third, the cluster elasticities are calculated and discussed (Section 3.3). Lastly, yearly future transport demand at the national level is calculated based on cluster-specific elasticities (Section 3.4). These four steps are described in more detail in the following subsections.

Evaluation of the independent variables' significance

An evaluation of the significance level of the independent variables was performed by determining the elasticity. Elasticity is a fundamental concept in economics that describes the degree of responsiveness of a good or service to changes in its determinants. It represents the ratio of the percentage change in the dependent variable to that in the independent variable. More specifically, it measures the sensitivity of the dependent variable to changes in the independent variable and provides a quantitative estimate of the magnitude of this relationship. Therefore, elasticity constitutes a valuable tool for analyzing the effects of various factors on the demand for a particular good or service (Litman, 2021). The elasticity of countries for which data is available is calculated using the log–log linear regression model. This approach involves taking the natural logarithm of both the dependent and independent variables, thereby transforming them into a linear relationship. By employing this model, the elasticity of the dependent variable (transport demand) with respect to the independent variable (transport-related variables) remains constant along the entire curve. Additionally, log–log models exhibit symmetry, meaning that the elasticity of the dependent variable with respect to the independent variable remains the same regardless of the direction of change. The log transformation of both variables allows for a regression analysis to be conducted, effectively highlighting the relationship between these variables. The coefficient of log-transformed data is interpreted as the elasticity (Litman, 2021; Nkiriki et al., 2022). The dependent variables, namely the transport demand data, are always given per capita to account for population size and facilitate better comparisons with other available studies. Road and rail passenger data from Statista (2022) are already presented per capita. Passenger and freight transport demand data from Khalili et al. (2019) are divided with population data from Gütschow et al. (2021), and so per capita transport demand data are obtained. Further information on the datasets used is shown in Table 1.

The calculated elasticities of the independent variables are shown in Fig. 2. There are eight dependent variables, namely the transport demands of the road, rail, marine, and aviation sectors in both passenger and freight transport and ten independent variables, namely GDP per capita, population, urban population, urban area per capita, consumer transportation spending per capita, consumer vehicle spending per capita, road investment, car stock per capita, rail investment, and rail line. The condition of being a significant independent variable (elasticity above 0.5) is true for six variables (Profillidis and Botzoris, 2019a). The highest elasticity is determined for urban populations ranging from 1.42 to 2.18 million. The second highest is calculated for GDP per capita. The elasticity of consumer spending on transportation is slightly above 0.5 for all modes. The car stock elasticity for road, rail, and aviation passengers also has the same range of values. Another significant variable for rail passenger and freight transport is rail line length.

Based on the discussed elasticity comparison, GDP per capita and urban population are the most significant independent variables. The definition of "urban" is established according to the criteria set by the UN World Urbanization Prospects, and it is adjusted accordingly for each individual country (Ritchie and Roser, 2018). Furthermore, for these two parameters, the projected data for 163 countries is publicly available (see Table 1) (Gütschow et al., 2021; Ritchie and Roser, 2018). For the other significant independent variables, the projected data are not available for all countries globally. Therefore, GDP per capita and urban population are the two independent variables considered for the transport demand model.

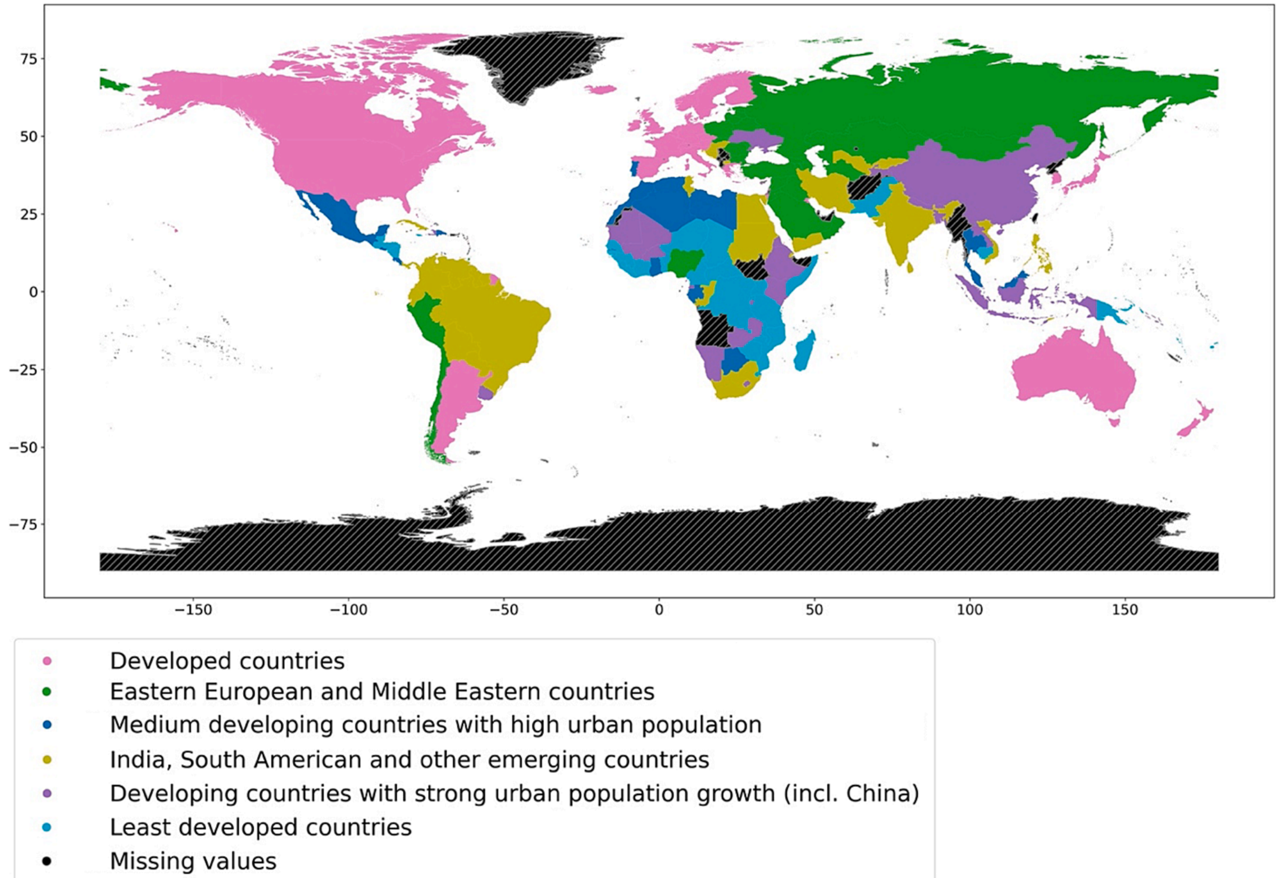

Fig. 3. World map of the six clusters using six features: GDP per capita (2020), urban population (2020), GDP per capita growth rates (2000–2010 and 2000–2019), and urban population growth rates (2000–2010 and 2000–2019).

Clustering of countries

After evaluating the independent variables' significance, the clustering of countries was undertaken using the selected variables, namely GDP per capita and urban population. The primary reasons for clustering are twofold. First, it allows for the easy filling of missing data. Second, it enables analysis of the evolution of transport demand between clusters.

Parameters used for the clustering are as follows:

- Status quo GDP per capita (2020)
- Status quo urban population (2020)
- Growth rates of GDP per capita from 2000 to 2010
- Growth rates of GDP per capita from 2000 to 2019
- Growth rates of urban population from 2000 to 2010
- Growth rates of urban population from 2000 to 2019

The growth rates of the variables are also considered in the clustering to take into account their development. Two long-term growth rates were used, namely from 2000 until 2010 and from 2000 until 2019. The growth rates after 2020 were not considered because of the COVID-19 pandemic. Initially, the six parameters used were scaled (Pedregosa et al., 2011). Hence, centroid-based clustering was performed using the *k-Medoids* algorithm (Aggarwal and Reddy, 2014). The optimal number of clusters was obtained by using the elbow and silhouette methods (Yuan and Yang, 2019). Both methods resulted in six clusters being the optimal number (Fig. 3 and see Appendix for elbow and silhouette score result). Cluster 1 consists of *Developed countries*, which have the highest status quo GDP per capita and urban population in 2020. Their urban population growth was the slowest from both 2000–2010 and 2000–2019. Cluster 2 consists of countries like the cluster name, which is *Eastern European and Middle Eastern countries*. This cluster had the highest growing GDP per capita from 2000 to 2010 and 2000–2019. These countries also exhibited the second-highest status quo GDP per capita in 2020. The countries that belong to cluster 3 are Mexico, some African, and some Southeast Asian countries. The cluster consists of countries with high status quo urban populations that corresponds to our terming them *Medium developing countries with high urban populations*. They also have the second fastest growing urban population. India, South American, and some of the African countries are in cluster 4, which is named *India, South American, and other emerging countries*. China, Indonesia, and some of the African countries form cluster 5, which is named *developing countries with strong urban population growth (incl. China)*. They had the fastest growing urban populations from 2000 to 2010 and 2000–2019. The last cluster is the *Least developed countries*, which primarily consists of African countries, which had the lowest status quo GDP per capita and urban population in 2020. Fig. 3 displays a summarizing map of the described clusters.

After defining the clusters, the GDP per capita and urban population elasticities of each cluster were calculated using available historical data from Statista (2022) and Khalili et al. (2019) (see Table 1). The elasticities of each cluster were then used to calculate future transport demand at the national level, which is explained in the next sub-section.

Cluster elasticity

The transport demand elasticities of GDP per capita and urban population were calculated for each mode and cluster. In order to calculate the cluster elasticity for passenger and freight transport demand, historical transport demand data from the dataset collected by Statista (2022) and Khalili et al. (2019) were used. The available

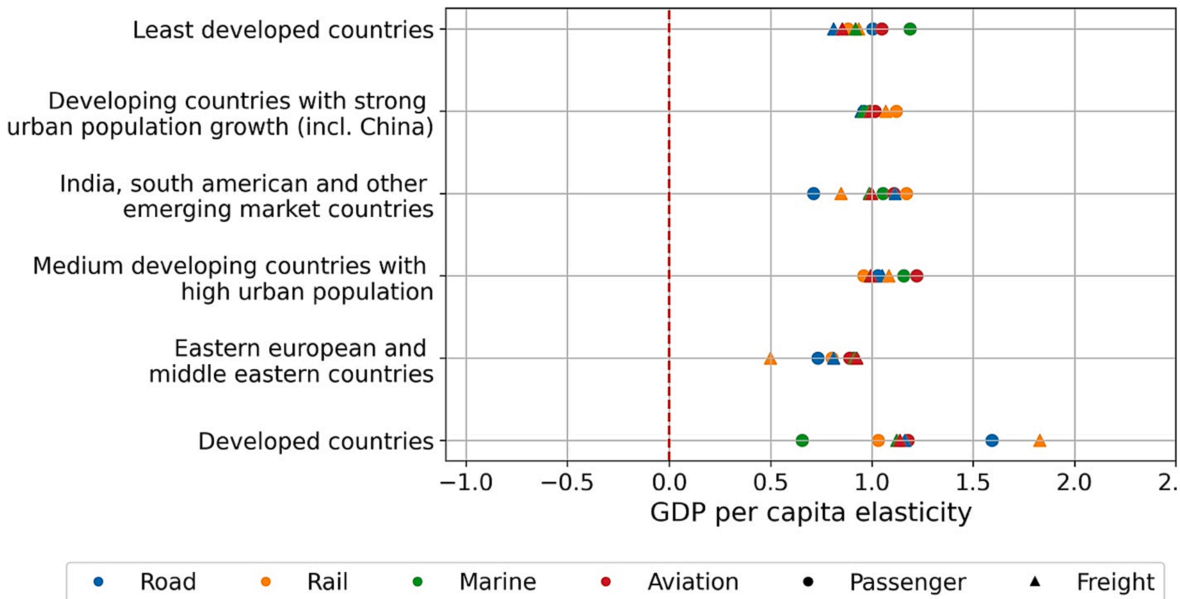

Fig. 4. GDP per capita elasticity of road, rail, marine, and aviation passenger and freight transport demand for six clusters.

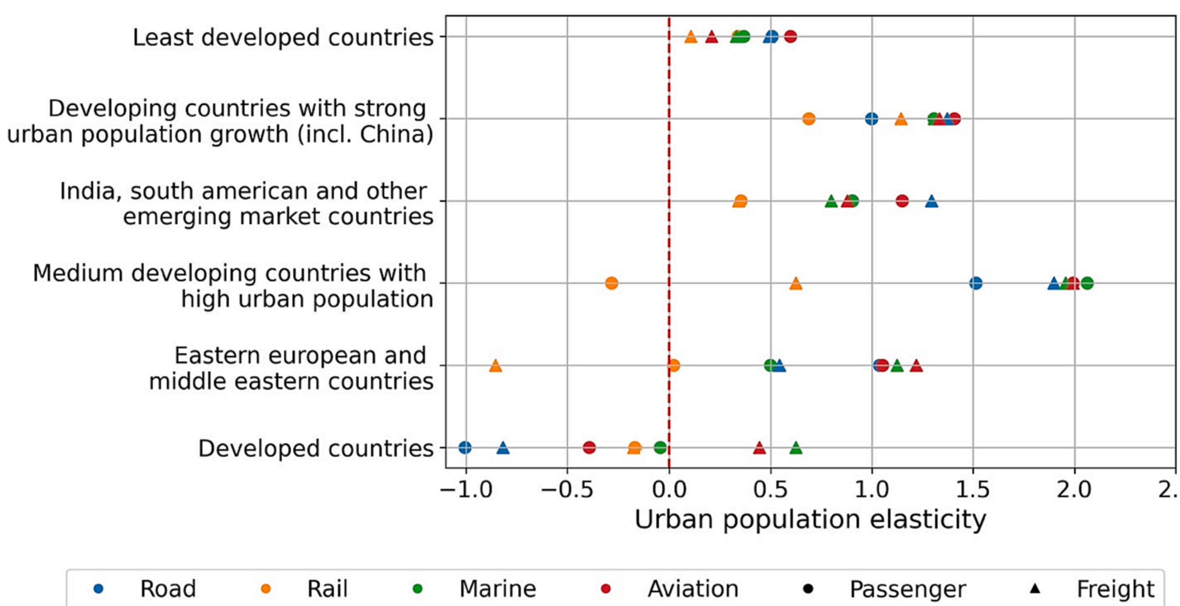

Fig. 5. Urban population elasticities of road, rail, marine, and aviation passenger and freight transport demand for six clusters.

transport data was first validated by comparing the transport demand datasets from the different sources. The available transport demand datasets for all transport modes were then plotted with GDP per capita. Extreme outliers in transport demand data were also corrected. The value was replaced by the country with the nearest current GDP per capita and urban population share. Socioeconomic data like GDP per capita and population were adopted from Gütschow et al. (2021) and provide national-level socioeconomic data, which was downscaled from Shared Socioeconomic Pathway (SSP) scenario databases. Urban population data was drawn from Ritchie and Roser (2018), which based their data on UN world urbanization prospects from 2018 (United Nations, 2018). The projected socioeconomic data was used to estimate future global transport demand. In this subsection, the elasticities between each mode and cluster are compared to identify significant differences. The details of the elasticity, its statistical significance, and the number of data points can be seen in Table 3.

The GDP per capita elasticities of road, rail, marine, and aviation passenger and freight transport for each cluster is shown in Fig. 4. The passenger transport elasticities range between 0.71 and 1.59 for road, 0.80 and 1.17 for rail, 0.66 and 1.19 for marine, and 0.89 to 1.22 for aviation. The elasticities of freight transport range between 0.81 and 1.16 for road, 0.5 and 1.83 for rail, 0.92 and 1.12 for marine, and 0.85 to 1.14 for aviation. The positive elasticities indicate that as the GDP per capita increases, the demand for passenger and freight transport also grows.

In the cluster *developed countries*, the GDP per capita elasticities of rail freight and road passenger transport are higher compared to other modes, which means that with the increasing GDP per capita, rail freight and road passenger transport will see the highest growth in demand. Compared to the other modes, rail passenger transport has the highest GDP per capita elasticity in the clusters *developing countries with strong urban population growth (incl. China)* and *India, South American, and other*

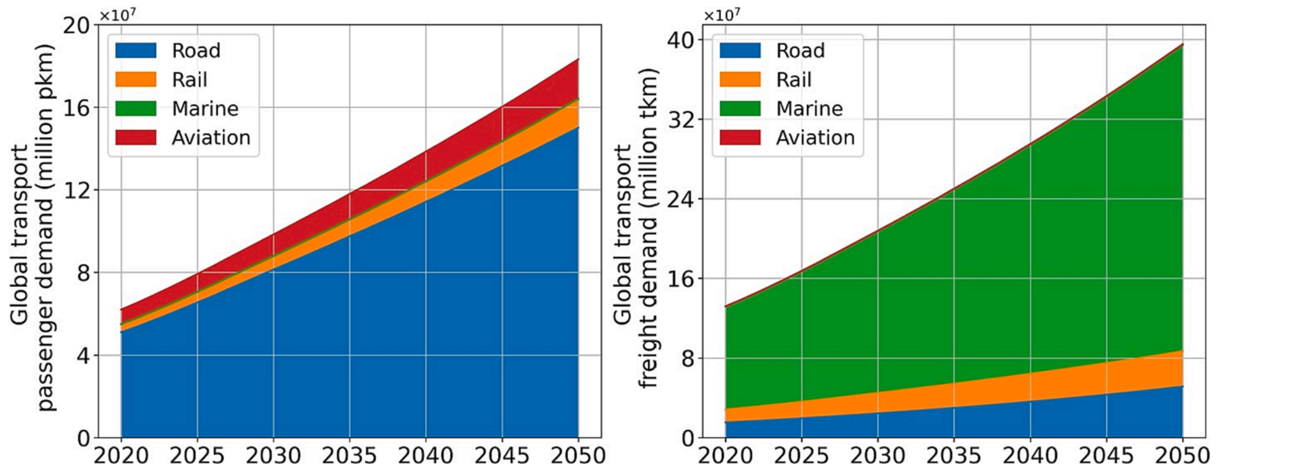

Fig. 6. Global passenger (left) and freight (right) transport demands, encompassing international transportation divided into road, rail, marine, and aviation, observed from 2020 to 2050.

emerging market countries. This means that in these two clusters, rail passenger transport is subject to the highest growth with increasing GDP per capita. Aside from rail freight mode in the cluster *eastern European and middle eastern countries*, in other clusters, the range of elasticities does not significantly differ, and ranges from 0.8 to 1.2. In these clusters, a one percent increase in GDP per capita results in increases of 0.8 % to 1.2 % in freight transport demand. Therefore, the growth rates of GDP per capita and freight transport demand are similar in these clusters.

The urban population elasticities of road, rail, marine, and aviation for both passenger and freight transport for each cluster are displayed in Fig. 5. The elasticities for road passenger range between −1 and 1.51, −0.28 and 0.69 for rail passenger, −0.05 and 2.06 for marine passenger, and −0.39 to 1.99 for aviation passenger. The elasticities range between −0.82 and 1.9 for road freight, −0.85 and 1.14 for rail freight, 0.33 and 1.96 for marine freight, and 0.21 to 1.99 for aviation freight. The negative elasticity means that as the urban population grows, the demand for transportation decreases. The difference in the range of elasticities between clusters compared to the GDP per capita elasticity is noticeable here.

In the cluster *developed countries*, most of the urban population elasticities are negative, with road passenger having the highest negative value. This shows that the need for road passenger transport is decreasing as the urban population grows, consistent with the findings and interpretation presented in the study by Noussan et al. (2020). This is also the case for rail passenger in the cluster *medium developing countries with high urban populations* and rail freight in the cluster *eastern European and middle eastern countries*. However, the positive urban population elasticities do not depict the urban density but rather indicate economic growth. This finding aligns with the conclusions drawn in the study conducted by Zhang and Xie (2019). Thus, as the urban population grows, so too does the transport demand. In all clusters, the urban population elasticities of marine and aviation freight have positive values.

The calculated GDP per capita and urban population cluster elasticities for each cluster are used in equation (3.1), and will be discussed in the next sub-section.

Transport demand

The global transport demand model was developed for 163 countries, using an econometric method. The method employs causal relationships as the basis for forecasts (Profillidis and Botzoris, 2019c). It is assumed that the change in the causes will have similar effects on transport demand in the future as in the past. The historical and projected GDP per capita and urban population were used to calculate transport demand. The elasticity determines the evolution of transport demand, which in this study will differ from one cluster to another. The elasticities of GDP per capita and urban population were calculated for each cluster based on the historical data from 2000 to 2019. Future transport demand is modeled with the following equation:

$$\boldsymbol{TD_{i,k} = \eta_i \bullet GDP_{i,k}{}^{\alpha_j} \bullet Urbpop_{i,k}{}^{\beta_j}} \qquad 3.1$$

where:

TD	passenger or freight transport demand per capita [pkm/capita or tkm/capita],
η	The scaling factor based on 2019 [pkm/(constant 2011 international dollars * percentage share of population)],
GDP	GDP per capita [constant 2011 international dollars/capita],
Urbpop	the urban population share [%],
α	elasticity of GDP per capita
β	elasticity of urban population
i	Country
j	Cluster
k	Year

The scaling factor was calculated for each country based on historical transport demand, GDP per capita, and urban population in 2019.

To validate the model, a comparison between the available historical data and the model results was performed. The validation was performed by calculating the mean absolute percentage error (MAPE) between the historical transport demand (passenger and freight) and calculated historical transport demand from the model. For global passenger and freight transport demand, the MAPE values were 10.2 % and 13.4 %, respectively. Historical datasets for marine and aviation freight transport demand are not available for the years 2000, 2005, and 2010. Consequently, the total global freight transport demand in those years consists only of road and rail freight demand.

Results and discussion

Temporal, regional, and modal analyses were performed to evaluate the results. The scope of the temporal analysis was from 2020 to 2050. For regional analyses, the six clusters discussed in sub-section 3.2 were used. Four modes, namely, road, rail, marine, and aviation, both in passenger and freight transport demand, were compared for the modal analysis. The section is divided into four sections. The first presents an analysis of future global transport demand from 2020 to 2050, including the modal split. The second is the analysis of cluster-specific future transport demand. In the third, the future development of passenger transport demand on a national level is compared. The last section

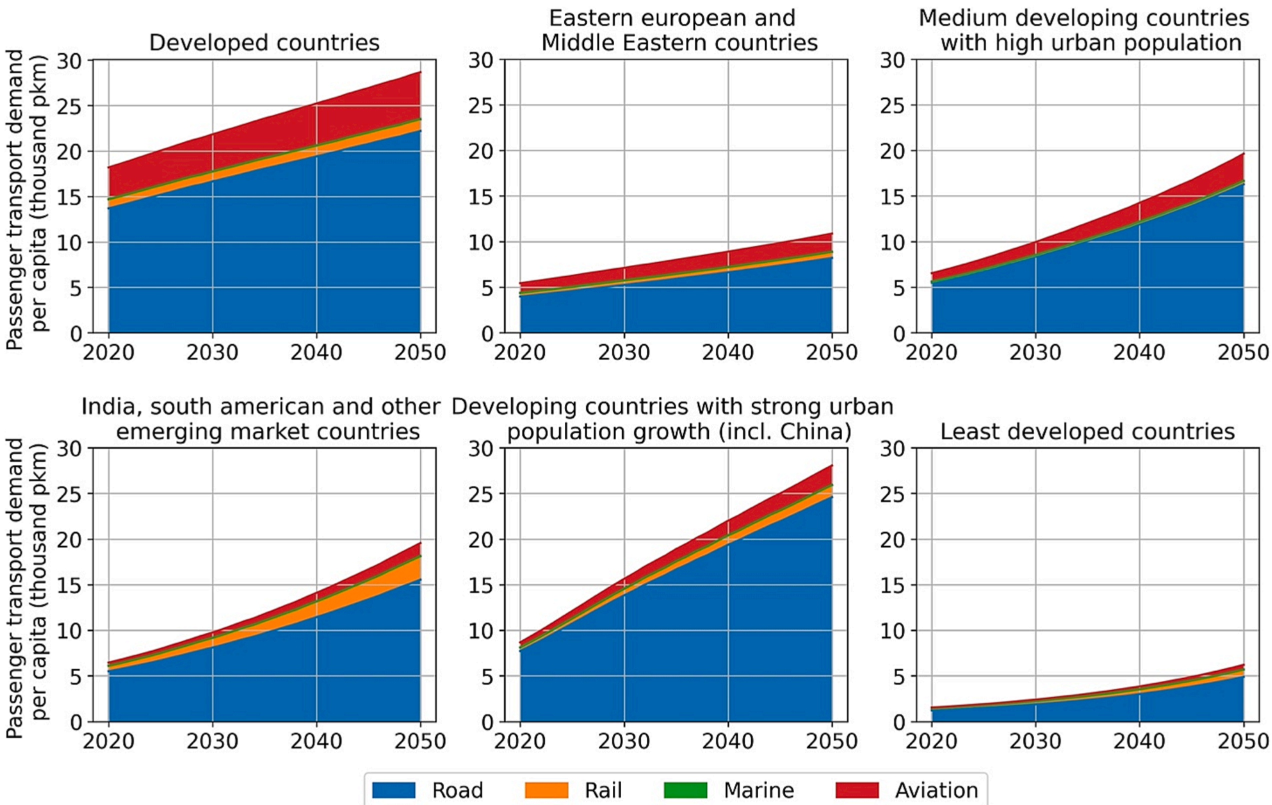

Fig. 7. Passenger transport demand per capita by cluster, encompassing international transportation divided into road, rail, marine, and aviation, observed from 2020 to 2050.

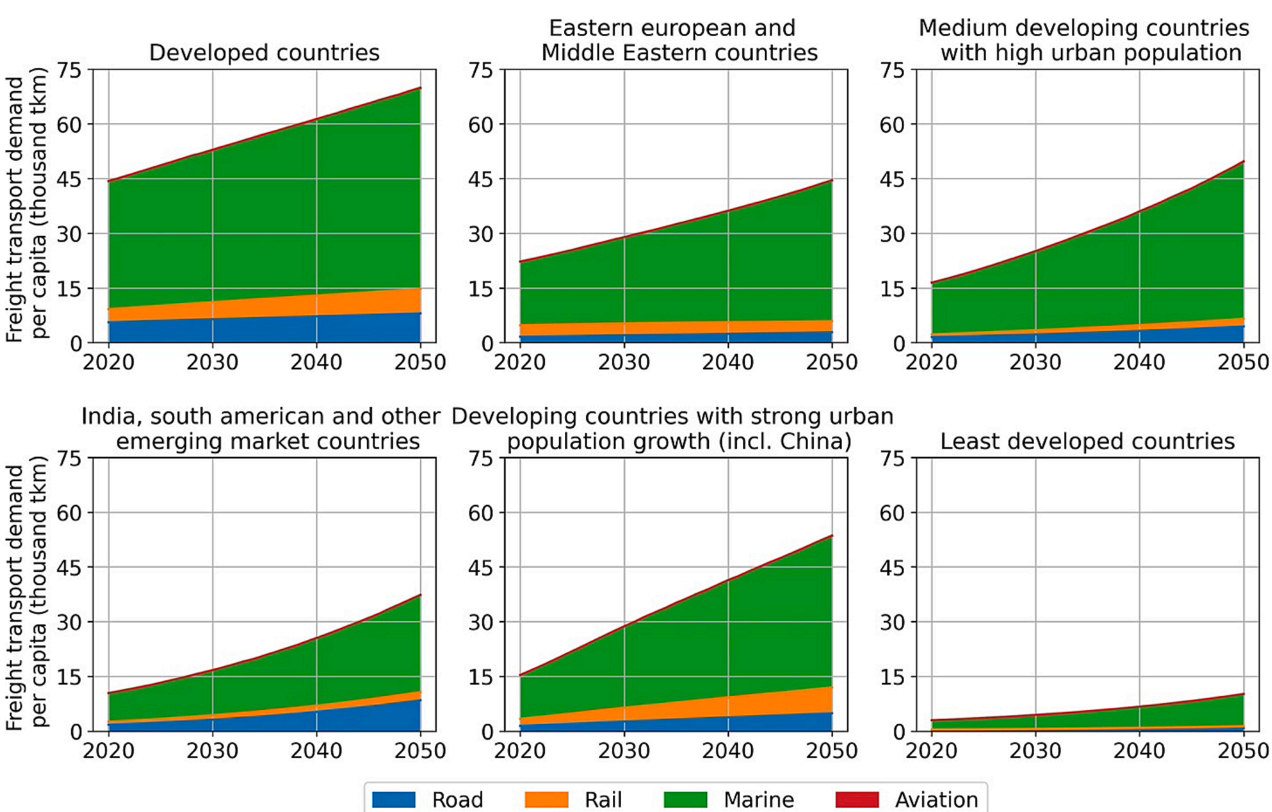

Fig. 8. Freight transport demand per capita by cluster, encompassing international transportation divided into road, rail, marine, and aviation, observed from 2020 to 2050.

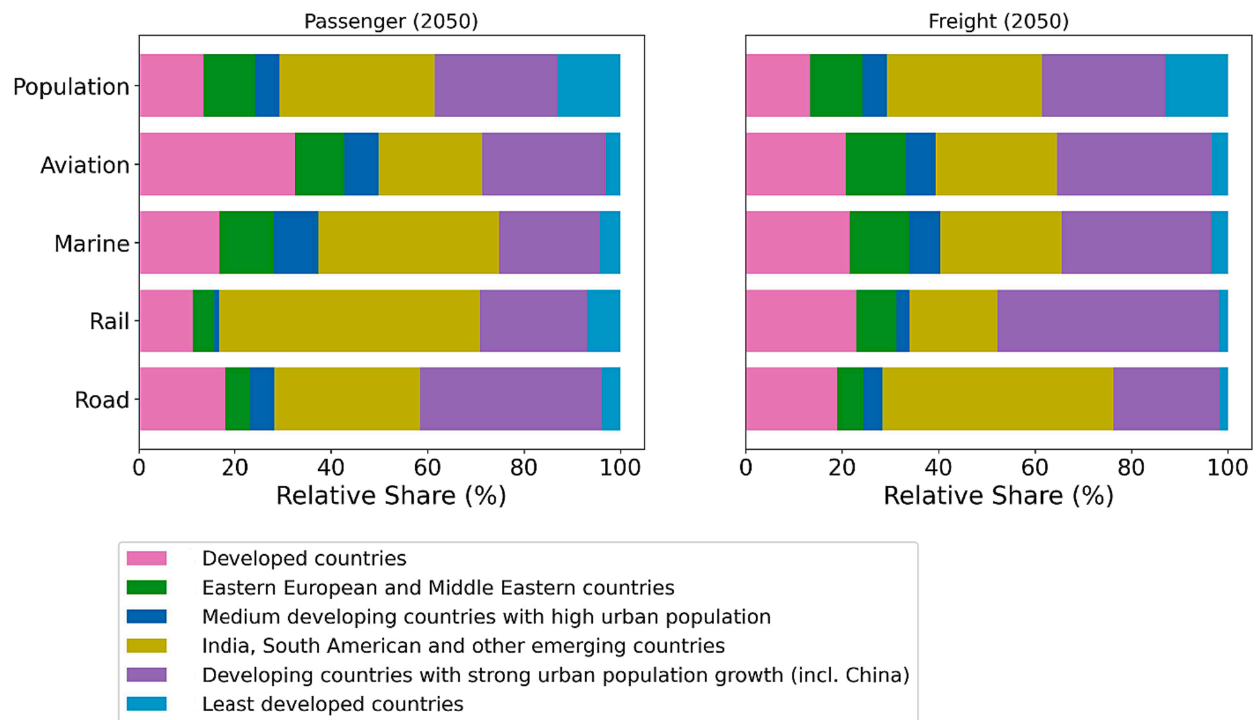

Fig. 9. Six clusters' relative shares of population, passenger, and freight transport demand (road, rail, marine, and aviation) encompassing international transportation in 2050.

presents a comparison of the model results with other studies. Detailed results of the yearly mode-specific transport demand on a national level from 2020 to 2050 can be found in the supplementary material.

Global development

The cumulative global passenger and freight transport demand, which includes international transportation, are shown in Fig. 6. The passenger transport demand increases from 2020 to 2050 by 196 % and freight transport demand by 200 %. Global passenger transport demand is dominated by the road sector and freight transport demand by the marine. According to the model, in 2050, the total global passenger and freight demand will be equal to 183 trillion passenger-km (pkm) and 395 trillion ton-km (tkm), respectively. The increase in global transport demand is due to socioeconomic development. The growth is especially significant in the developing and least developed countries because their current transport demand is comparably low.

Cluster-specific transport demand analysis

Development of future global transport demand differs between each cluster. Passenger transport demand per capita for the six clusters from 2020 to 2050 is shown in Fig. 7. From 2020 to 2050, the cluster *developed countries* had the slowest increase and the cluster *least developed countries* the highest. The cluster *Eastern European and Middle Eastern countries* does not demonstrate a substantial increase due to its relatively lower elasticities compared to the others. In 2050, the per capita passenger transport demand of cluster *developing countries with strong urban population growth (incl. China)* will be in the same range as the cluster *developed countries*. With the high population, especially in China and Indonesia, the absolute transport demand of the cluster will reach almost 65 trillion pkm in 2050. Road passenger transport demand generally has the highest transport demand per capita compared to other modes. According to the model, by 2040 the road passenger transport demand per capita of the cluster *developing countries with strong urban population growth (incl. China)* will surpass the cluster *developed countries*. Rail passenger transport demand will significantly increase in the cluster *India, South American and other emerging countries,* with per capita values reaching about 2500 pkm in 2050. In this cluster, India has a significant influence because of its high population and high share of rail transport. By 2037, marine passenger transport demand per capita of the cluster *medium developing countries with high urban population* will exceed the cluster *developed countries*. In the aviation sector, the cluster *developed countries* has the highest per capita values, with a difference of 2000–4000 pkm compared to other clusters.

Fig. 8 shows the six clusters' freight transport demands per capita from 2020 to 2050. The highest freight transport per capita is in the marine sector. The cluster *developed countries* surpasses the others with per capita values ranging from 35,000 tkm in 2020 to 55,000 tkm in 2050. By 2048, the road freight transport demand per capita of the cluster *India, South American, and other emerging market countries* will exceed the cluster *developed countries*, due to its high increase in GDP per capita. The rail freight transport demand per capita of the cluster *developing countries with strong urban populations (incl. China)* will surpass the cluster *developed countries* by 2045. In the cluster *eastern European and Middle Eastern countries*, rail freight transport demand per capita slightly decreases through 2050 due to negative urban population elasticity.

The following compares the four modes (road, rail, marine, and aviation) of passenger and freight transport demand in 2050. The six clusters' relative share of population and transport demand in 2050 is presented in Fig. 9. In the passenger transport sector, the cluster *India, South American and other emerging countries* has the highest share of rail and marine passenger transport demand. The cluster *developing countries with strong urban population growth (incl. China)* dominates the road passenger transport demand share. The cluster of *developed countries* has the highest share in aviation passenger transport demand, although it has a small share of global population. In the freight sector, aviation, marine, and rail transport demand are dominated by the cluster *developing countries with strong urban population growth (incl. China)*. The most significant share is in rail freight transport demand, amounting to 46 %. The cluster *India, South American and other emerging countries* has the

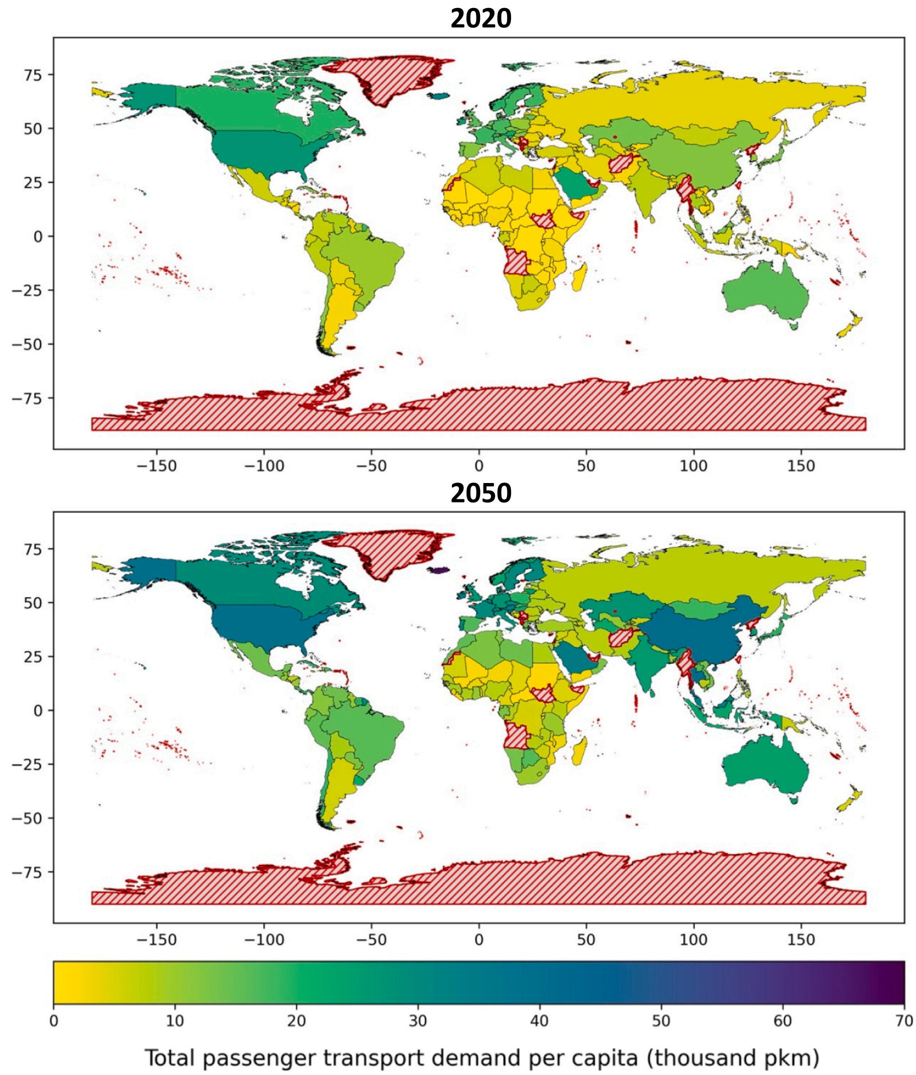

Fig. 10. Total passenger transport demand per capita by country, encompassing international transportation in 2020 (top) and 2050 (bottom). Countries with missing data are shaded in gray and crossed red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

highest share of road freight transport demand, with 48 %.

Transport demand development at the national level

Following the cluster-level analysis, transport demand is discussed in this sub-section on a national level. As the absolute transport demand correlates strongly with population, transport demand is again analyzed per capita, as is shown in Fig. 10. The difference in the passenger transport demand per capita between the developed, developing, and least developed countries is visible on the map. In developed countries, such as the USA, Germany, and France, passenger transport demand per capita in 2020 is equal to 26,528 pkm, 17,261 pkm, and 18,217 pkm, respectively. The demand will increase to 38,336 pkm, 27,209 pkm, and 29,771 pkm in 2050. As was discussed previously, with a small share of the total population, developed countries have a significant share of the total transport demand. In this study, the elasticity is assumed to be constant, implying that the development from 2020 to 2050 remains consistent. Incorporating the time variability of elasticity could potentially enhance the model, particularly in developed countries that experience a strong increase (Fouquet, 2012). In developing countries such as Brazil, South Africa, and Indonesia, passenger transport demand per capita in 2020 was equal to 9,576 pkm, 4,575 pkm, and 5,724 pkm, respectively. In 2050, the demand in these countries will increase to 15,717 pkm, 9,657 pkm, and 23,131 pkm, respectively. The increase in demand in developing countries varies depending on their projected socioeconomic development. Of these three developing countries, for example, Indonesia is projected to see a significant increase in its GDP per capita and urban population from 2020 to 2050. Thus, transport demand will grow significantly compared to the other two developing countries, namely Brazil and South Africa. This is also the case for the two countries with the highest current population share, namely China and India, whose total passenger transport demand per capita increases from 11,831 pkm and 7,291 pkm, respectively, in 2020, to 40,631 pkm and 25,493 pkm in 2050. The high transport demand per capita in China is due to the significant increase in socioeconomic development. In the least developed countries, such as Bangladesh, Chad, and Zambia, passenger transport demand in 2020 was equal to 1881 pkm, 822 pkm, and 1489 pkm, respectively. The demand will increase by 2050 to 9,727

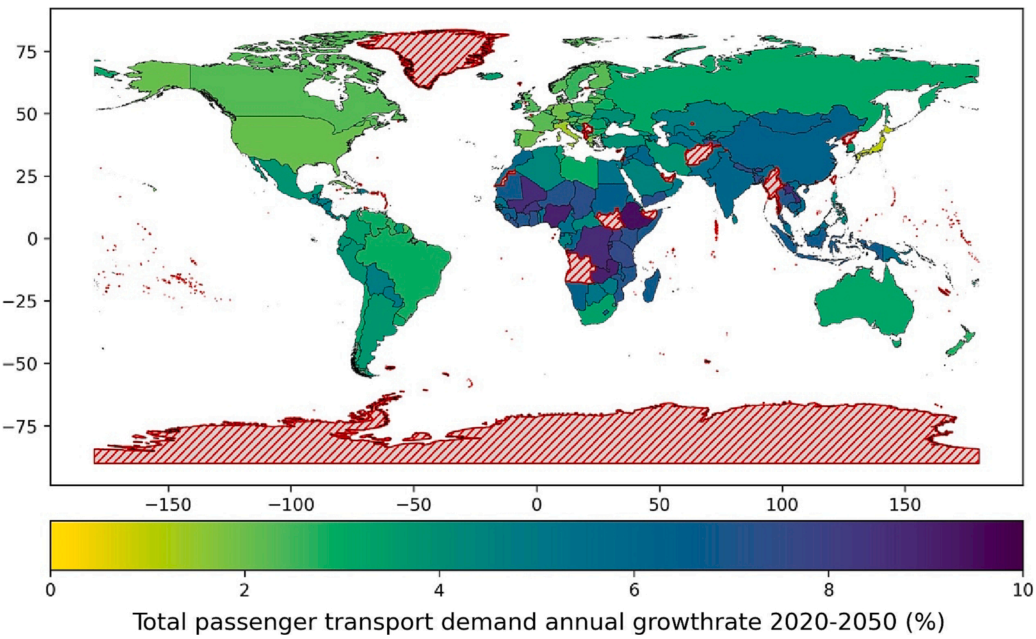

Fig. 11. Total passenger transport demand average annual growth rate by country, encompassing international transportation from 2020 to 2050. Countries with missing data are shaded in gray and crossed red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

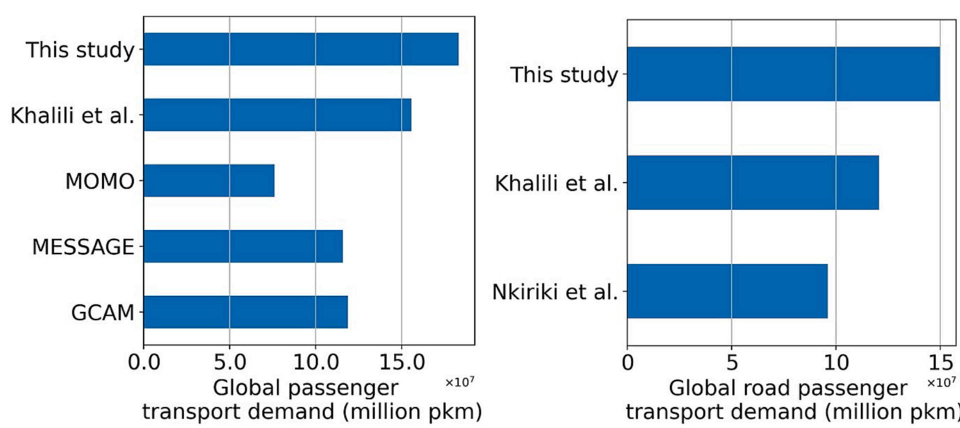

Fig. 12. Comparison of global passenger (left) and road passenger (right) transport demand in 2050 (Khalili et al., 2019; Nkiriki et al., 2022; Yeh et al., 2017). 'This study' indicates the results from the developed model.

pkm, 3858 pkm, and 7,737 pkm, respectively.

Fig. 11 shows the annual growth rate of global total passenger transport demand from 2020 to 2050 at the national level. The results suggest that most of the countries in sub-Saharan African and Asia will have the highest annual growth rates. For instance, Ethiopia, Zambia, and Nigeria will have a passenger transport demand annual growth rate equal to 9.5 %, 9 %, and 9 %, respectively. China and India will have an annual growth rate equal to 6.4 % and 6 %, respectively. Developed countries like the USA, Germany, and France will have an annual growth rate equal to 2 %, 2 %, and 2.3 %, respectively. The developed countries have lower annual growth rates due to declines in population growth.

The rapid growth in transportation demand in developing countries could translate to high demand for transport energy and GHG emissions. Therefore, research on decarbonizing the transport sector, especially in the global context, is needed to achieve a low-carbon and sustainable global transport future (Emodi et al., 2022).

Comparison with the literature and outlook

Finally, the global transport demand results from this study are compared with the available literature. The four main global passenger transport demand projections for 2050 by Khalili et al. (2019) and the three models, MoMo, MESSAGE, and GCAM (Yeh et al., 2017), are included in the comparison (Fig. 12). Passenger transport demand in the year 2050 is the highest in this study. Khalili et al., MoMo, MESSAGE, and GCAM predict the global passenger transport demand in 2050 to 156 trillion pkm, 76 trillion pkm, 116 trillion pkm, and 119 trillion pkm. In this study, demand is projected to grow to 183 trillion pkm in 2050. The difference primarily arises due to two differences in the methodological approach: first, the divergent independent variables used to calculate future transport demand; and second, the level at which the elasticities were determined.

In MoMo, six exogenous variables are used to calculate transport demand, namely vehicle kilometers traveled, vehicle survival rates, load factor, GDP, and population. Gompertz curves are applied to calculate the vehicle ownership rate, which is a main parameter in the model. In MESSAGE and GCAM, the parameters GDP, population, technology costs, and time costs are used for the calculation of global passenger transport demand. Technology and time costs are calculated endogenously, as no data for the future exists. Khalili et al. (2019) used the available global transport demand data given by the ICCT (Façanha et al., 2012) and disaggregated it to each country. In this study, development is divided into different clusters. In other studies, however, different levels of development in the countries are neglected. This effect can also be seen in the comparison of global road passenger transport demand in 2050.

This is compared with the results from Nkiriki et al. (2022) and Khalili et al. (2019) in the right-hand diagram of Fig. 12. The highest transport demand occurs again in this study. The difference compared to Nkiriki et al. results from that in the elasticity approaches. Nkiriki et al. used the same elasticity for all countries, which indicates that the development of the transport demand for all countries was identical. In the present study, the elasticities were determined individually for the six defined clusters. From the elasticity comparison of each cluster (see Section 3.3), it can be observed that the development of each cluster differs.

For future improvement of the model developed in this study, a better quality of historical data would be desirable. Thereby, the input of the historical transport data could be updated. The developed model utilizes a constant GDP per capita and urban population elasticity, indicating that the development of transport demand from 2020 to 2050 is linear with the development of GDP per capita and urban population. For future development of the model, changing elasticities based on the development of each cluster or country can be applied (Fouquet, 2012). How the elasticities change must be analyzed. It is to be tested whether the changing elasticity will have a realistic and better prediction of future transport demand. It is also important to highlight that the developed model exclusively focuses on socio-economic independent variables, specifically GDP per capita and urban population share. This selection was made after conducting a thorough evaluation of elasticity and data availability, as discussed in Section 3. It should be acknowledged that there exist other significant parameters that have the potential to influence transport demand, such as infrastructure or the political situation of the country. However, due to unavailability of data, these parameters have not been included in the model.

Conclusions

This study provides an answer to the research question regarding the evolution of future global transport demand, including international transportation. To achieve this, a model utilizing a cluster-based econometric method was developed. The available transport-related data is collected, and the elasticity of each variable calculated. The highest significance and best data availability occurred for the independent variables of GDP per capita and urban population. The status quo data and growth rate of the two variables were used to cluster countries globally with the centroid-based clustering k-Medoids method. This results in the following six clusters:

- *Developed countries*
- *Eastern European and middle eastern countries*
- *Medium developing countries with high urban populations*
- *India, South American and other emerging countries*
- *Developing countries with strong urban population growth (incl. China)*
- *Least developed countries*

The cluster-specific elasticities determined demonstrate the differences between the countries' transport systems. Based on the calculations in this study, the total passenger and freight transport demand increase to 183 trillion passenger-km and 395 trillion ton-km in 2050, respectively. The passenger transport demand is dominated by road, with a share of 82 % in 2050. Marine freight transport demand makes up the highest share of the total freight demand, totaling 78 % in 2050. From 2020 to 2050, passenger and freight transport demand grow significantly by 196 % and 200 %, respectively. Although passenger and freight transport demand will keep increasing until 2050, the decadal growth rate is decreasing. Developing countries will see a more substantial increase in all transport modes compared to developed ones. Still, developed countries generally exhibit higher transport demand per capita in 2050, whereas countries in the African region will see the highest annual transport demand growth from 2020 to 2050.

Overall, the model's results underline the expected continued growth of global transport demand in almost all areas. Reducing transport, implementing modal shift, and adopting technological advancements are approaches to achieve GHG reduction targets. The analysis indicates that transport demand, particularly road transport demand, continues to increase, necessitating a technological shift to meet GHG targets. On one hand, this entails the development of infrastructure that can accommodate such changes. On the other hand, achieving global goals for GHG emission reductions necessitates technological advancements in drivetrains due to the persistent rise in transport demand.

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CRediT authorship contribution statement

Steffen Tjandra: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft. **Stefan Kraus:** Conceptualization, Supervision, Writing – review & editing. **Shitab Ishmam:** Conceptualization, Supervision, Writing – review & editing. **Thomas Grube:** Conceptualization, Funding acquisition, Project administration, Writing – review & editing, Supervision. **Jochen Linßen:** Funding acquisition, Project administration, Supervision, Writing – review & editing. **Johanna May:** Project administration, Supervision, Writing – review & editing. **Detlef Stolten:** Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared results as supplementary material.

A. Appendix

Available transport demand data

Table 2
Available historical and projected transport demand data. LDVs: light duty vehicles; 2 W: two-wheelers; 3 W: three-wheelers; LHDT: light-heavy duty trucks; MHDT: medium-heavy duty trucks; HHDT: heavy-heavy duty trucks.

Data	Time range	Resolution	Unit	Available data(n countries)	Reference
Road passengers	2012–2019	Yearly	Passenger-km	45	(ITF, 2021)
Rail passengers	2012–2019	Yearly	Passenger-km	54	(ITF, 2021)
Road freight	2012–2019	Yearly	Ton-km	53	(ITF, 2021)
Rail freight	2012–2019	Yearly	Ton-km	53	(ITF, 2021)
Marine freight	2012–2019	Yearly	Ton-km	52	(ITF, 2021)
Total passengers	2015–2050	Five-year	Passenger-km	Global	(ITF, 2021)
Total freight	2015–2050	Five-year	Ton-km	Global	(ITF, 2021)
LDV Activity	2000–2030	Five-year	Vehicle-km	Global and regional	(Façanha et al., 2012)
Bus Activity	2000–2030	Five-year	Vehicle-km	Global and regional	(Façanha et al., 2012)
Motorcycle Activity	2000–2030	Five-year	Vehicle-km	Global and regional	(Façanha et al., 2012)
Truck Activity	2000–2030	Five-year	Vehicle-km	Global and regional	(Façanha et al., 2012)
Rail passengers	2000–2030	Five-year	Passenger-km	Global and regional	(Façanha et al., 2012)
Rail freight	2000–2030	Five-year	Ton-km	Global and regional	(Façanha et al., 2012)
Aviation passengers	2000–2030	Five-year	Passenger-km	Global	(Façanha et al., 2012)
Road passengers per capita	2000–2040	Yearly	Passenger-km	49	(Statista, 2022)
Rail passengers per capita	2000–2040	Yearly	Passenger-km	94	(Statista, 2022)
Aviation passengers	2000–2040	Yearly	Passengers	151	(Statista, 2022)
Road passengers	2000–2050	Five-year	Passenger-km	209	(Khalili et al., 2019)
Rail passengers	2000–2050	Five-year	Passenger-km	209	(Khalili et al., 2019)
Marine passengers	2000–2050	Five-year	Passenger-km	209	(Khalili et al., 2019)
Aviation passengers	2000–2050	Five-year	Passenger-km	209	(Khalili et al., 2019)
Road freight	2000–2050	Five-year	Ton-km	209	(Khalili et al., 2019)
Rail freight	2000–2050	Five-year	Ton-km	209	(Khalili et al., 2019)
Marine freight	2000–2050	Five-year	Ton-km	209	(Khalili et al., 2019)
Aviation freight	2000–2050	Five-year	Ton-km	209	(Khalili et al., 2019)
Road Share (LDV, 2 W, 3 W, Bus, LHDT, MHDT, HHDT)	2000–2050	Five-year	Passenger-km and ton-km	209	(Khalili et al., 2019)
Road passengers	2010–2050	Five-year	Passenger-km	179	(Nkiriki et al., 2022)
Road freight	2010–2050	Five-year	Ton-km	179	(Nkiriki et al., 2022)

Elbow and silhouette method result

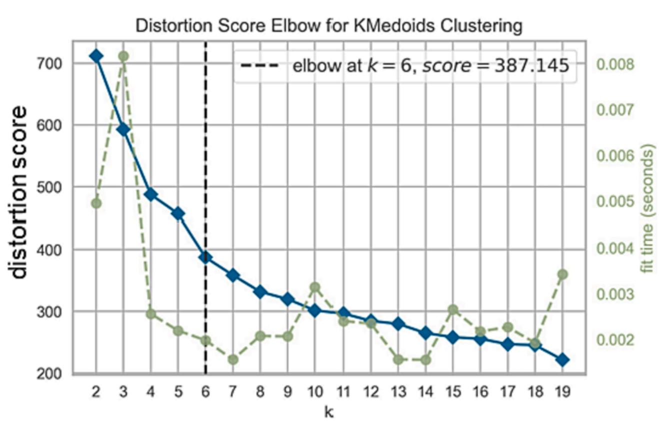

Fig. 13. Elbow method using six features. GDP per capita (2020), urban population (2020), GDP per capita growth rates (2000–2010 and 2000–2019), and urban population growth rates (2000—2010 and 2000–2019). k: number of cluster.

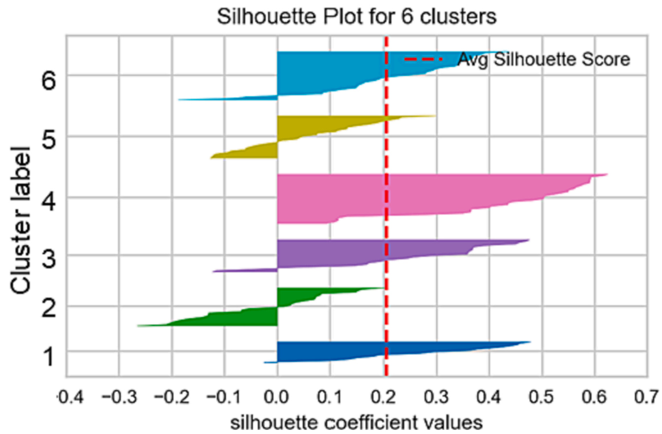

Fig. 14. Silhouette method score using six features. GDP per capita (2020), urban population (2020), GDP per capita growth rates (2000–2010 and 2000–2019), and urban population growth rates (2000—2010 and 2000–2019).

Table 3
Transport demand cluster GDP per capita and urban population elasticity, as well as the number of data points derived from historical data for elasticity calculation. The asterisks relate to the statistical significance (*p < 0.05, ** p < 0.01, *** p < 0.001).

Transport mode	Cluster	GDP per capita elasticity	Urban population elascity	GDP per capita data point	Urban population data point
Road	Developed countries	1.59***	−1.01*	170	170
Road	Eastern European and Middle Eastern countries	0.73***	1.04***	135	135
Road	Medium developing countries with high urban population	1.03***	1.51***	75	75
Road	India, South American and other emerging countries	0.71***	0.90***	150	150
Road	Developing countries with strong urban population growth (incl. China)	0.96***	1.00***	105	115
Road	Least developed countries	1.00***	0.51**	170	170
Rail	Developed countries	1.03***	−0.17*	170	170
Rail	Eastern European and Middle Eastern countries	0.80***	0.02*	135	135
Rail	Medium developing countries with high urban population	0.96***	−0.28***	75	75
Rail	India, South American and other emerging countries	1.17***	0.35*	150	150
Rail	Developing countries with strong urban population growth (incl. China)	1.12***	0.69*	80	115
Rail	Least developed countries	0.88***	0.34***	170	170
Marine	Developed countries	0.66***	−0.05***	170	170
Marine	Eastern European and Middle Eastern countries	0.91***	0.50***	135	135
Marine	Medium developing countries with high urban population	1.16***	2.06*	75	75
Marine	India, South American and other emerging countries	1.05***	0.90***	150	150
Marine	Developing countries with strong urban population growth (incl. China)	0.99***	1.31***	115	115
Marine	Least developed countries	1.19***	0.37*	170	170
Aviation	Developed countries	1.18***	−0.39*	170	170
Aviation	Eastern European and Middle Eastern countries	0.89***	1.05**	135	135
Aviation	Medium developing countries with high urban population	1.22***	1.99***	75	75
Aviation	India, South American and other emerging countries	1.11***	1.15***	150	150
Aviation	Developing countries with strong urban population growth (incl. China)	1.01***	1.41***	115	115
Aviation	Least developed countries	1.05***	0.60**	170	170
Road freight	Developed countries	1.16***	−0.82*	170	170
Road freight	Eastern European and Middle Eastern countries	0.81***	0.54*	135	135
Road freight	Medium developing countries with high urban population	1.05***	1.90***	75	75
Road freight	India, South American and other emerging countries	1.12***	1.29***	150	150
Road freight	Developing countries with strong urban population growth (incl. China)	0.95***	1.37***	115	115
Road freight	Least developed countries	0.81***	0.49**	170	170
Rail freight	Developed countries	1.83***	−0.17***	170	170
Rail freight	Eastern European and Middle Eastern countries	0.50***	−0.85*	135	135
Rail freight	Medium developing countries with high urban population	1.08***	0.62**	75	75
Rail freight	India, South American and other emerging countries	0.85***	0.34*	150	150
Rail freight	Developing countries with strong urban population growth (incl. China)	1.07***	1.14***	115	115
Rail freight	Least developed countries	0.93***	0.11***	170	170

(*continued on next page*)

Table 3 (*continued*)

Transport mode	Cluster	GDP per capita elasticity	Urban population elascity	GDP per capita data point	Urban population data point
Marine freight	Developed countries	1.12***	0.63*	170	170
Marine freight	Eastern European and Middle Eastern countries	0.92***	1.12**	135	135
Marine freight	Medium developing countries with high urban population	0.99***	1.96*	75	75
Marine freight	India, South American and other emerging countries	0.99***	0.80***	150	150
Marine freight	Developing countries with strong urban population growth (incl. China)	0.95***	1.31***	115	115
Marine freight	Least developed countries	0.92***	0.33***	170	170
Aviation freight	Developed countries	1.14***	0.44***	170	170
Aviation freight	Eastern European and Middle Eastern countries	0.93***	1.22***	135	135
Aviation freight	Medium developing countries with high urban population	1.00***	1.99*	75	75
Aviation freight	India, South American and other emerging countries	1.00***	0.88***	150	150
Aviation freight	Developing countries with strong urban population growth (incl. China)	0.99***	1.33***	115	115
Aviation freight	Least developed countries	0.85***	0.21***	170	170

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trip.2024.101016.

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