Estimating global demand for land-based transportation services using the shared socioeconomic pathways scenario framework

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Abstract
The global demand for transportation is growing owing to accelerated socioeconomic development worldwide. If the current modes of transportation, consisting mostly of personal internal combustion engine vehicles, dominate this growth, greenhouse gas emissions will rise and worsen the climate crisis. A key empirical challenge in understanding the barriers and opportunities for low-carbon transportation systems in developing countries is the lack of demand data. Because existing country-specific transport demand models focus on countries with robust historical datasets, it has been difficult to estimate the service demand for developing countries. To address this limitation, we develop a log–log regression model linking socioeconomic variables with demand for land-based passenger and freight transport services. Using socioeconomic data from the shared socioeconomic pathways (SSPs) developed for climate analysis, we then produce scenario-based estimates for land-based transportation services for 179 countries around the world. The global average annual land-based passenger demand growth rate ranges between 1.3% and 4.1%, while the annual growth rate for land-based freight demand ranges between 3.1% and 3.6% across the 30 years between 2020 and 2050. Middle-income countries in Asia such as India and China, show the highest expected transport demand. Meanwhile, the results suggest that low-income countries in the sub-Saharan African region are likely to experience the largest growth in demand for passenger and freight transport services. These two trends come together at an inflection point around the year 2030. Prior to 2030, the transport demand was the highest in East Asia. After 2030, there is an ascendency in transport demand in South Asia and sub-Saharan Africa, whereby the cumulative demand share of these two regions reaches near parity with that of East Asia by 2050. Sustainably meeting this growing demand will require the adoption of data-driven transport planning tools and leveraging cross-linkages across other energy sectors such as electricity.

1. Introduction
Globally, transportation is the fourth largest source of greenhouse gas (GHG) emissions (Lamb et al 2021). In 2018, the transportation sector accounted for 30% of the total final energy consumed and 14% of global direct carbon dioxide (CO₂) emissions (IEA 2019, 2020, Lamb et al 2021). The transportation sector is also experiencing a 2% annual growth rate in emissions, which poses a challenge for meeting the climate stabilization
goals set forth in the Paris agreement (Lamb et al 2021). Under this agreement, countries committed to limiting temperature change compared to pre-industrial temperature to 'well below 2 °C' (United Nations 2015). Since the agreement’s ratification, there is a growing consensus on the need to limit temperature changes to 1.5 °C to limit catastrophic climate change. Meeting these temperature goals would require the world to reach net-zero CO2 emissions by 2050 (IPCC 2018). In turn, achieving net-zero CO2 emissions would likely require avoiding any significant growth in new emissions sources.

According to the United Nations (UN), the global population will continue to grow exponentially in the coming decades (UN Population Division 2019). Therefore, there is a need to consider how to sustainably meet the growing population’s demand for goods and services while improving living standards and simultaneously mitigating and avoiding CO2 emissions. Due to surging economic activity, past population growth has led to increased demand for transportation services, a pattern that is likely to continue in the coming decades. Indeed, the International Transportation Forum ITF (2019, 2021a) reports that global passenger demand for transportation will triple by 2050, while demand for freight transportation will increase two-fold in the same time frame. The ITF projects that this growth in transportation demand will primarily occur in developing countries in East Asia, South Asia, West Asia, Latin America, and the Caribbean (ITF 2021a). This increased need for transportation services will likely lead to an increasing demand for energy used in the transportation sector, which could in turn increase global CO2 emissions. Simultaneously meeting the growing demand for transportation services and reaching a net-zero CO2 emissions target will require the deployment of mitigation strategies in both developed and developing countries. While there has been significant research about the barriers and opportunities for low-carbon transport systems in developed countries, there is still a need for a more detailed analysis of low-carbon transportation pathways in developing countries (Daggash and Mac Dowell 2021).

The CO2 emissions from the transportation sector are a function of travel demand, travel mode, transport technology, CO2 intensity of fuels, and energy efficiency. Thus, a crucial input to the models used for evaluating low-carbon transportation pathways is the future demand for transportation services. Statistical models use historical data to predict the relationship between socioeconomic variables and aggregate demand for services (Ajanovic et al 2006, Peña-Guzmán and Rey 2020, Wolde-Rufael 2004). Statistical models have also been used to estimate demand for residential electricity, industrial energy consumption, and energy use in agriculture (Karkacier et al 2012, Tsekeris and Tsekeris 2011). Researchers have used regression models to estimate the demand for residential electricity, industrial energy consumption, and energy use in agriculture (Karkacier et al 2006, Peña-Guzmán and Rey 2020, Wolde-Rufael 2004). Statistical models have also been used to estimate service and energy demand in the transportation sector (Ajanovic et al 2012, Daldoul et al 2016, Limanond et al 2011, Singh 2006, Varjan et al 2017). For developing countries, the sporadic nature of transport data and lack of statistics across countries constitute a barrier to estimating future energy demand for the transportation sector (Ajanovic et al 2012). Using data on transportation-related energy consumption in developed countries to estimate energy use in the transportation sector in developing countries creates internal validity concerns. For example, the efficiency of vehicle fleets in developing countries is likely different from that in developed countries, which affects the validity of the energy demand estimated using data from developed countries. Thus, Ajanovic et al (2012) suggested an alternative approach that models demand for transport services (in passenger-kilometers and tonne-kilometers) instead of the vehicle and fuel demand.

On a global scale, the ITF (2019, 2021a) and the World Economic Council (2011) rely on historical data and scenario frameworks to project transportation services demand on a global and regional scale to 2050. The IEA’s mobility model (MoMo) for global transport was published in the energy technology perspectives (ETP) report, covering 22 regions and countries (IEA 2017, 2020). Unfortunately, country-level estimates from these modeling efforts are not freely available. Other researchers have estimated the demand for transportation services using case studies. In India, Singh (2006) used a log–log model to estimate the demand for passenger transport services by 2031, based on historical population and income data. Khalili et al (2019) recently used an income-and-population-dependent econometric model to examine global demand for transport services by 2050. This study builds on prior work by presenting a regression-based model for estimating country-level passenger and freight transport demand. Our log–log linear model relies on publicly available historical land-based transportation demand and socioeconomic data. We then use the model to develop future scenario-based demand projections for transportation services in 179 countries. We rely on socio-economic data from the shared socioeconomic pathways (SSPs) previously developed by the international community to support climate-related research, ensuring that we develop internally consistent demand scenarios that other researchers can use to evaluate low-carbon transportation futures.

2. Methods

In this study, we rely on a two-stage process to develop scenarios for land-based passenger and freight transport demand worldwide up to 2050. Figure 1 describes the modeling approach for combining a double log model
with a scenario-based framework. At the baseline, we trained the log–log model on historical land-based transportation consumption trends. We then added the SSP projections to fit the land-based passenger and freight transport demand from 2020 to 2050 at the global, regional, and national levels.

2.1. Regression model

In selecting the variables for the transportation model, we consider two factors: elasticity of transport demand and data availability. The income elasticity of demand represents the relationship between changes in income and demand for given services, whereas the price elasticity of demand describes the relationship between prices and demand. Empirically, in a study spanning over 100 years, Fouquet (2012) reported income elasticities of transport demand between 0.8 and 3.1. In comparison, Fouquet (2012) estimates that price elasticities of transport demand are negative but have a lower magnitude ranging between $-1.5$ and $-0.6$ across the study period.

In line with these findings, Dunkerley et al. (2014) suggest that income elasticities are more substantial than price elasticities when evaluating long-term trends in demand for transport services. Similarly, Dunkerley et al. (2014) suggest higher and positive income elasticities of freight demand. Specifically, Dunkerley et al. (2014) find income elasticity ranges between 0.5 and 1.4 for passenger transport and between 0.5 and 1.5 for freight transport. Van Dender and Clever (2013) argue that the price elasticity of transport demand does not sufficiently influence to be included in transport vehicle demand forecasting. According to the literature, income elasticity is not only positively correlated to demand but is also 1.5 to 3 times higher than price elasticity (Litman 2013).

In this study, we aim to estimate possible scenarios for transport demand in countries around the world. Given the unavailability of long-term, region-specific prices for transport services and the higher values of income elasticity of demand, we rely on income data to build a regression-based model. Note that our study does not aim to identify the causal relationship between the dependent and independent variables. Instead, we aim to develop a model that accounts for the correlation among the variables to create future demand scenarios. Our future demand scenarios are not predictions of the future but instead provide a range of possible futures. Specifically, we rely on the gross domestic product (GDP) as a proxy for income (Cuaresma 2017, The World Bank Group 2020). The model also included total population as an explanatory variable. Dunkerley et al. (2014) also suggest that urbanization rates affect demand for transport services, so we include an urbanization variable in the model. The choice to use population and urbanization as model variables was also a result of our cross-validation to evaluate the log–log model performance that we trained on historical data. The cross-validation exercise, shown in more detail in the supporting information (SI) (https://stacks.iop.org/ERIS/2/035009/mmedia) (tables S7 and S8), confirms that GDP, population, and urbanization improve model performance compared to the GDP per capita measure.

We relied on the World Bank’s historical income and population data for 217 countries and territories from the World development indicators dataset (The World Bank Group 2020). We use country-level GDP, population, and urban population data, where the absolute urban population is a product of the urban share and total population. We calculated population density by dividing the total population by land area. We use GDP and GDP per capita purchasing power parity data from the World Bank databank in constant 2017 USD.
We also collect demand data for the land-based passenger (in passenger-kilometers (km)) for 38 countries and freight transport (in tonne-km) for 43 countries between 1990 and 2018 from the transport outlook of the International Transport Forum (ITF 2019, 2021b). These demand data for passenger and freight transport are an aggregate for each country across all modes (cars, buses, trucks, rail, etc). Thus, the model in this paper does not disaggregate transportation demand by mode. Furthermore, an implicit assumption in this study is that historical correlations between population, GDP, and transportation demand for sample countries represent the future relationship between the variables in all countries. A wide range of economic development levels is represented across the historic panel data which includes 911 observations for passenger transport and 1351 data points for freight transport. Across the countries and years in the historical dataset, many of the countries transitioned through different income groups; therefore, the data points covered a range of broader economic development levels delivering a reliable benchmark to develop consistent scenarios for global analysis.

For our analysis, we used a log–log linear regression model. This statistical analysis technique uses multiple regression analysis to explore the relationship between the log-transformed dependent and independent variables (Limanond et al 2011). The coefficients of a log-transformed data can be interpreted as their elasticity. These models are common in transportation modeling (Wadud 2011). For example, Souche (2010) used a log–log linear model to estimate daily car and transport trips in urban areas, noting the logarithmic model reduces the risk of heteroskedasticity. Recently, log-transformed models have also been used to estimate demand for freight and passenger air transport (Carmona-Benítez et al 2017, Tabassum and Khan 2020). Finally, log-transformed models have been used to estimate demand for public transit (Alam et al 2018), micro-mobility (Lee et al 2021) and active transport (Singhvi et al 2015).

Based on our exploratory analysis (shown in SI—figures S1 and S2), the independent and dependent variables have skewed distributions, therefore, we log-transformed the variables and addressed outliers while checking for any zero values. Equation (1) describes the general form of our log–log linear model, which was trained on historical transport demand data. The independent variables in equation (1) are GDP in 2020 US dollars (US$), population (POP), and urbanization (URB) as a share of the population in urban areas. We used the United States Bureau of Labor Statistics Consumer Price Index conversion rates to compute the 2020 US$ equivalent for all economic data (U.S. Bureau of Labor Statistics 2021). We estimate the demand for passenger and freight services in passenger-km traveled ($p_{km}$) and tonne-km ($tkm$) traveled, respectively.

\[
\ln \ln (p_{km} \text{ or } tkm) = \beta_0 + \beta_1 \ln(\text{GDP}) + \beta_2 \ln(\text{POP}) + \beta_3 \ln(\text{URB}) + \varepsilon. \tag{1}
\]

The regression in equation (1) shows a statistically significant relationship between population, GDP, and transportation demand. The adjusted coefficient of determination ($R^2$) measures how well the regression line fits the data and how well the predictions are correlate with the actual values. The results in table 1 indicate that the log–log linear model fits the data well.

Based on the coefficients, land-based passenger and freight transport demands are positively correlated with income and population levels. The scatterplot for passenger travel against urbanization, as well as freight transport demand against urbanization, show a strong positive correlation (figure 2). Urbanization is positively related to demand in figure 2, which could indicate an increase in short trips. However, urbanization also

### Table 1. Model fit results in comparison with selected model highlighted yellow. The asterisks relate to the statistical significance ($^* p < 0.05, ^{**} p < 0.01, ^{** *} p < 0.001$), while the bracketed ranges represent 95% confidence intervals clustered at the country level.

| (a) Passenger | Model 1 | Model 2 | Model 3 | Model 4 |
|----------------|---------|---------|---------|---------|
| Intercept, $\beta_0$ | $-3.69^{**}(---4.45---2.93)$ | $0.31(---0.34---0.95)$ | $-0.45(---1.18---0.27)$ | 7.52*** (6.85--8.19) |
| log(GDP), $\beta_1$ | $1.00^{**}(1.00--1.12)$ | $0.68^{**}(0.64--0.72)$ | $0.97^{**}(0.94--0.99)$ | 1.07*** (1.03--1.11) |
| log(POP), $\beta_2$ | $2.29^{**}(2.05--2.53)$ | $0.41^{**}(0.36--0.46)$ |  |  |
| log(URB), $\beta_3$ | $-2.30^{**}(---2.59---2.01)$ |  |  |  |
| Observations | 911 | 911 | 911 | 929 |
| Countries | 40 | 40 | 40 | 40 |
| Years | 28 | 28 | 28 | 28 |
| Adjusted $R^2$ | 0.90 | 0.88 | 0.84 | 0.75 |

| (b) Freight | Model 1 | Model 2 | Model 3 | Model 4 |
|----------------|---------|---------|---------|---------|
| Intercept, $\beta_0$ | $-0.01(-0.70--0.68)$ | $0.07(-0.48--0.62)$ | $-0.86^{**}(-1.18--0.24)$ | 7.62*** (7.09--8.15) |
| log(GDP), $\beta_1$ | $0.66^{**}(0.61--0.71)$ | $0.65^{**}(0.62--0.69)$ | $0.95^{**}(0.92--0.97)$ | 1.00*** (0.97--1.03) |
| log(POP), $\beta_2$ | $0.45^{**}(0.25--0.66)$ | $0.42^{**}(0.38--0.46)$ |  |  |
| log(URB), $\beta_3$ | $-0.04^{**}(-0.28--0.20)$ |  |  |  |
| Observations | 1351 | 1351 | 1351 | 1390 |
| Countries | 50 | 50 | 50 | 50 |
| Years | 28 | 28 | 28 | 28 |
| Adjusted $R^2$ | 0.87 | 0.86 | 0.82 | 0.73 |
suggests a dense population for which less travel may be required to perform economic activities (Dunkerley et al 2014). The sign change for urbanization coefficients in the regression may be attributed to the severe correlation between population and urbanization, resulting in a suppressor variable effect (Ludlow and Klein 2014). Therefore, taking into account income and population, a one percent increase in urbanization results in reductions of 2.3% in passenger-km and 0.04% in freight tonne-km for land-based transport demand.

It is worth noting, however, that multicollinearity poses challenges to the interpretation of the coefficients. The correlation matrix in (SI table S5) shows the correlation coefficients among the independent and dependent variables which were indeed high. Kutner et al (2004) suggests that the need to correct the model to address multicollinearity depends on the purpose of the study noting that ‘the fact that some or all predictor variables are correlated among themselves does not, in general, inhibit our ability to obtain a good fit nor does it tend to affect inferences about mean responses or predictions of new observations’. The purpose of our study is not to evaluate the causal relationship between the independent and dependent variables. Instead, our goal is to develop scenario-based estimates of future transportation demand consistent with the narratives of the SSPs so they can be used in future transportation, energy, and climate systems research.

Additionally, we explore the model performance by examining the residuals of the predicted values against the actual historical data in the models by varying the variables included (as shown in figure 2). The model underestimates the demand for outliers, such as India, with a high income and population at the country level. Meanwhile, in the historical data, Montenegro has the lowest income and population across all years, and the model overestimates the demand in similar countries such as Albania and Armenia. These observations speak to the limitations of the linear regression model and global averages, which cannot accurately capture patterns for countries that deviate from the historical demand trends. Using a broad scenario analysis framework helps to address reduce some of the uncertainties in forecasting demand using the historical dataset.

Cross-validation is a statistical method used to evaluate model performance by dividing data into training and testing sub-sets, with the latter being used to validate the model (Refaeilzadeh et al 2009). Cross-validation can be done in a couple of ways: (1) leave observations out randomly, (2) leave whole countries out randomly, and (3) leave future time periods out. We use five-fold cross-validation, grouping the panel data by...
Table 2. Summary of SSP storylines and assumptions for quantification of the socioeconomic projections with ratios provided by IIASA (Cuaresma 2017, Jiang and O’Neill 2017, KC and Lutz 2017, Riahi et al 2017).

| Scenario | Name (description)                                                                 | GDP [ratio 2050:2010] | Population [ratio 2050:2010] | Urban share [ratio 2050:2010] |
|----------|-----------------------------------------------------------------------------------|-----------------------|-------------------------------|-------------------------------|
| SSP1     | Sustainable—taking the green road (inclusive and sustainable pathway)             | High economic growth  | Low population growth        | High urbanization [1.9]       |
| SSP2     | Middle-of-the-road (path follows historical patterns)                              | Uneven income growth  | Moderate population growth   | Moderate urbanization [1.8]   |
| SSP3     | Regional rivalry—a rocky road (low international priority and regional cooperation) | Slow income growth    | High population growth in developing countries [1.5] | Low urbanization [1.6]       |
| SSP4     | Inequality—a road divided (increasing regional inequalities within and across countries) | Unequal GDP growth    | Moderate population growth   | High urbanization [2.0]       |
| SSP5     | Fossil-fuelled development (rapid global technological progress and heavy fossil-fuel deployment) | High economic growth  | Global population peaks      | High urbanization [1.9]       |

country guided by the ‘groupdata2’ R package (Olsen 2021). The method is used to estimate the generalization performance (ability to handle out-of-sample data) and compare the performance of two or more models to support selection. The log–log model we select in our analysis, has the lowest average errors for passenger travel, and we conclude it is the best predictor of out-of-sample data compared to the other models (SI table S8).

2.2. Future demand scenarios

Using the demand function for transportation described in equation (1), we developed five scenarios for future transportation demand in countries around the world. For this purpose, we rely on data from the SSPs database maintained by the International Institute for Applied System Analysis (IIASA). These SSPs characterize future socioeconomic scenarios that would influence GHG emissions and drive climate impacts (Bauer et al 2017, Ebi et al 2014, IPCC 2021, Riahi et al 2017). Researchers have used these SSP scenarios to explore challenges
Figure 4. Passenger and freight demand projections by SSP scenarios. Our results for the annual land-based passenger demand in billion pkm and land-based freight transport in billion tkm on a global scale aggregated across each of the SSP scenarios.

Figure 5. Scenario-based projections of land-based transportation demand by (a) region and (b) income group. The panels in each plot represent the land-based passenger scenario-based projections on the right and the land-based freight demand on the left, with the results grouped and faceted by scenario. Panel (a) shows that South Asia and East Asia & Pacific regions will have the highest absolute demand for land-based transport by 2050. In panel (b), we observe the most considerable demand in middle-income countries.

and response options to climate change (Bauer et al 2017, Chen et al 2020, Dellink et al 2017, O’Neill et al 2017, Rao et al 2019).

The SSP storylines are not predictions of the future but exploratory narratives of plausible ‘what ifs’, though they cannot cover every possible scenario. Table 2 presents the characteristics of the five SSPs. The IIASA provides quantitative GDP, population, and urbanization data for each SSP for 232 countries and territories via the SSP database (IIASA 2018). Figure 3 shows the global estimates of the primary key drivers used in our regression model until 2050 for each SSP.

In addition to reporting absolute values for the demand for passenger and freight transport in each SSP, we estimated passenger and freight demand growth rates across each country and scenario for these demands
between 2020 and 2050 using the nonparametric smoothing spline regression from the R ‘growthrates’ package in equation (2) (Petzoldt 2020). $\beta_0$ is the estimated coefficient corresponding to the intercept, $\beta_1$ is the coefficient of the exponential time component on demand, $K$ is the demand saturation level to ensure that forecasts are within the plausible range of the forecasted population, $\varepsilon$ represents the error term, and $t$ is the time in years from 2020 to 2050 in five years increments.

$$\text{annual growth rate} = \frac{K \times \beta_0}{\beta_0 + (K - \beta_0)e^{\beta_1t}} + \varepsilon. \quad (2)$$

Figure 6. Land-based passenger (a) and freight (b) transport demand by country in 2050 across each scenario. The coloring represents absolute demand in 2050 for each country. Countries with missing data are shaded gray.

3. Results

3.1. Global demand for land-based passenger and freight transportation services

Using the log–log linear model and SSP projections, we projected the demand for land-based passenger and freight services over a 30 years time horizon from 2020 to 2050 under different socioeconomic scenarios. These results are not predictions of the future but exploratory narratives of possible futures, and throughout the rest of the paper, we refer to them as scenario-based projections. Figure 4 shows the scenario-based projections of global demand for land-based passenger and freight transport. We also compared the results with the existing global projections from the ITF to validate the model. ITF (2019) uses more complex independent variables, which makes for a useful validation with our representative model. The global results were within the range of the ITF model (shown in figure S6 in the SI). Our results go a step further to provide more granular data on a country-level data for 179 countries.

The results show that the global land-based passenger services demand will increase by a ratio of between 1.2 and 2.2 across all the SSPs, while global land-based freight transport demand will increase by a factor of between 1.6 and 2.6 over the 30 year period (figure 4). The reference demand in 2020 across all scenarios ranges from 50 500 billion passenger-km (pkm) in SSP1 to 69 400 billion pkm in SSP3, and between 16 100 billion tonne-km (tkm) in SSP4 and 16 300 billion tkm in SSP5. Across the scenarios, the absolute passenger mobility by 2050 ranges between 64 600 billion pkm (SSP4) and 119 000 billion pkm (SSP3). The global annual growth rate of land-based passenger demand scenario-based projections ranges between 1.3% (in SSP4) and 4.1% (in SSP3), whereas the annual growth rate for land-based freight demand ranges between 3.1% (in SSP3) and 3.6% (in SSP5) over the 30 years.

The global land-based passenger demand is the highest in SSP3, with the highest population growth across all scenarios. Land-based freight transport is the highest in the SSP5 scenario, with the highest economic activity growth. The rapid growth in passenger transport demand in SSP5 after 2030 (figure 4) may be attributed to the sharp growth in income around 2030 in SSP income projections.

3.2. Demand for land-based passenger and freight transportation services by region and income group

Comparing income group and region classifications, as described in the SI (tables S1 and S2), the results suggest that lower and upper-middle-income countries and countries in Asia will have the highest global demand for land-based transportation services by 2050. Figure 5 plots the results across each SSP and shows the transport demand by region and income groups. We used the income levels and regional classifications from the World Bank (Serajuddin and Hamadeh 2020, The World Bank 2021). The results suggest that low-income countries,
Figure 8. Annual growth rates in land-based passenger (a) and freight (b) transport demand by country. The color sharing of the countries represents the annual growth rate over the 30 years between 2020 and 2050.

particularly in sub-Saharan Africa, have the lowest absolute values of total demand for land-based transportation services across the period of analysis, whereas Asian and middle-income countries have the highest overall demand for land-based transportation services by 2050. Accounting for 24% of the global population and 34% of global GDP, the East Asia and Pacific region passenger demand projections are approximately 36% of the global passenger transport service demand. The freight transport demand of the region ranges from 8600 billion tkm (SSP3) to 14 000 billion tkm (SSP5) by 2050, accounting for approximately 33% of the global freight transport share.

Figure 6 shows country-level estimates of land-based transport demand. The detailed data underlying this figure are available via a Zenodo repository. Figure 6 highlights that India, China, the United States, and Indonesia will remain the countries with the highest absolute demand for land-based passenger and freight
transportation. However, the share of global land-based transport demand start shifting after 2030, as shown in figure 7. This figure shows that after 2030, the share of global demand from East Asia, North America, Europe, and Central Asia starts decreasing while South Asia and sub-Saharan Africa account for an increasing share of global land-based transport demand. By 2050, the demand in South Asia and sub-Saharan Africa is projected to reach near parity with demand from East Asia. Figure 7 also shows that middle-income countries account for between 50% and 70% of the global land-based passenger and freight transportation demand across all the scenarios and all periods.

3.3. Demand growth rates

Our scenario-based analysis shows that low-income countries and countries in sub-Saharan Africa could experience the highest percentage changes in transportation demand over the 30 years. Figure 8 quantifies the annual growth rate of the land-based transportation demand between 2020 and 2050 by country. The rapid growth in the demand for transportation services could translate into a rise in transportation-related demand for energy and GHG emissions in these countries unless cost-effective mitigation options are deployed. These trends suggest that while countries with higher initial baselines will continue to see high absolute demand, developing countries currently experiencing rapid population growth and economic activity are likely to experience accelerated growth.

4. Discussion and conclusions

We develop a statistical model to evaluate the potential demand for land-based transportation services worldwide. Our log–log linear model relies on publicly available historical land-based transportation demand and socioeconomic data. We then use the model to develop country-specific future demand scenario-based projections for land-based transportation services worldwide by relying on different SSPs. Using a model that depends only on three variables, we can include estimates for low-income countries for which detailed empirical data is not readily available and advanced demand estimation methods are difficult to deploy. This study identified internally consistent demand estimates for land-based transportation services across 179 countries under five socioeconomic SSP scenarios. Thus, this study is forecasting anchored in five agreed-upon and oft-used scenario-based narratives of energy transitions and decarbonization efforts throughout the world without probability assignment.

Globally, the results indicate that passenger mobility and freight transportation are expected to double by 2050. The results of this study suggest that the highest transportation demand occurs in East Asia and the Pacific. On the other hand, low-income developing countries or sub-Saharan African nations would experience the highest growth rates in demand for transportation services. These two trends come together at an inflection point around 2030. East Asia and the Pacific account for the greatest demand share before 2030. However, after 2030, there is an increase in demand for South Asia and sub-Saharan Africa, reaching near parity with East Asia by 2050.

Much attention has been paid to decarbonizing the transport sector in Europe, North America, and East Asia, as these regions have the largest absolute demand values, resulting in larger energy use and emissions from the transportation sector. However, the larger growth rates in land-based transport demand in developing countries in South Asia and sub-Saharan Africa could pose challenges for their climate mitigation and adaptation targets. Countries in these regions have relatively lower GHG emissions but they still have developed emission reduction targets under the Paris agreement. The rapid growth in the demand for land-based transportation services could limit the ability of these countries to reduce emissions, as detailed by their national determined contributions to the Paris agreement. Indeed, the growing demand for land-based transportation services could lead to growing GHG emissions from these regions unless appropriate strategies are deployed to decouple demand and emissions. For example, low-income African countries constitute a 40% share of used vehicle sales globally, and the lack of regulation leads to an influx of highly polluting vehicles (UN Environment Programme 2020). The results indicate higher demand growth rates for transportation services in low-income countries that are already the most vulnerable to climate change impacts. Continuing to meet this rising demand with high-polluting second-hand vehicles with low fuel-economy ratings is concerning. Some countries such as Rwanda, have imposed restrictions on the import of used vehicles (Ayetor et al 2021). These countries need to consider policies to expand the availability of more efficient low-carbon transport options.

Rapid growth in demand for land-based transportation services has implications on the need for new infrastructure. Road infrastructure in emerging economies is inadequate and characterized by traffic congestion. Which would worsen with increased demand if population growth outpaces the rate of infrastructure expansion (Meijer et al 2018). For example, the results indicate the democratic republic of Congo (DRC) could have one of the highest growth rates in land-based transport demand up to 2050, but the country does not have
sufficient road infrastructure for its current population. According to Meijer et al (2018), the road network in the DRC will need to increase by 81% by 2050 under the SSP scenarios. Furthermore, an increase in land-based freight demand could impose additional requirements on the quality of roads that need to be constructed. Similarly, meeting the growing demand for transportation services in places where the electricity infrastructure is still underdeveloped offers opportunities for co-optimizing power and transport infrastructure to support low-carbon technologies. Consumer behavior is a key driver of useful energy demand. Encouraging consumers to purchase more efficient and low carbon alternatives must go hand in hand with meeting human needs at a low cost.

While the use of personal vehicles will likely increase in developing countries where demand for transport services is expected to increase rapidly, these countries also have the opportunity to design and invest in low-carbon public transit (e.g., rapid bus systems) and active transport (e.g., protected bike lanes) infrastructure. Investing in such infrastructure, while transport demand is still relatively low, could help establish more sustainable behavioral patterns. While more people will continue to ‘move around’, providing affordable public transportation can reduce the energy intensity and resulting emissions from meeting the passenger transport demand globally. With the rising rate of urbanization, city planners have the opportunity to leverage urban form strategies to reduce the emissions implications of increased mobility (Creutzig et al 2015).

Similarly, governments will need to provide affordable and less energy-intensive modal options in sparsely populated rural areas where residents may travel longer distances. Finally, the expansion of rail transportation infrastructure could reduce the burden of road freight and minimize the use of carbon-intensive passenger vehicles. The demand estimates reported in this study can serve as inputs for future analyses of these infrastructure options.

An underlying assumption in our model is that all countries follow the same trends that link GDP and population to transportation demand. While the data points used in the regression include a large range of GDP, population, and urbanization values that cover some of the characteristics of developing countries, unpredictable systemic changes can affect the relationships between these variables. For instance, in 2020, the COVID-19 pandemic decreased passenger mobility as people worked from home (ITF 2021a). Although we do not explore these effects, additional improvements in digitalization could further decouple GDP and travel demand (IEA 2020, ITF 2019). Similarly, other systemic changes like shared and smart mobility, teleworking, dematerialization of the economy, vehicle automation, and supply chain management could affect the relationship between the dependent and independent variables used in this paper (Mouratidis et al 2021). These impacts are highly uncertain, and there is not sufficient empirical data to include them in a statistical model (Jaramillo et al 2022). Despite this caveat, this study sheds light on important data gaps and our results provide a starting point for understanding demand patterns in developing countries. For example, our results could serve as inputs for macro-energy system models to evaluate opportunities for providing low-carbon energy to the transportation sector.

In conclusion, the global transition to low-carbon infrastructure systems is crucial for simultaneously meeting the growing demand for transport services identified in this study and climate stabilization goals. Thus, there is a growing need to evaluate the barriers to and opportunities for the deployment of these low-carbon systems. Although significant efforts have been made to model decarbonization pathways in developed countries using energy system models, these evaluations are lacking for developing countries. In the context of the least developed countries, current energy modeling research has traditionally focused on providing minimum energy access. However, the results of this study suggest that such models should also include the energy needs of the transportation sector, which will be driven by the demand for transportation services analyzed in this paper.

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Conflict of interest statement

The authors declare no conflicts of interest.
**Ethics statement**

This work does not include live subjects (human or animals).

**Funding statement**

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**Data availability statement**

The data generated and/or analyzed to support the findings of this study are openly available (Nkiriki et al. 2021).

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