SOCIAL AND GEOGRAPHICAL DISTRIBUTION OF MOBILITY-RELATED GREENHOUSE GAS EMISSIONS IN POZNAŃ AND TRI-CITY FUNCTIONAL URBAN AREAS

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Abstract: Mobility is an important source of greenhouse gas (GHG) emissions and a major contributor to human-induced climate change. Much of these emissions result from urban residents' travel within urban areas (i.e. short-distance travel [SDT]) and away from them (i.e. long-distance travel [LDT]). In this study, we focus on the distribution of mobility-related GHG emissions in two functional urban areas in Poland: Poznań and the Tri-city. Using data from a representative survey (N ~2000 in each area), we investigate the emission distribution and associations between emission levels and the socio-economic characteristics and residential locations of study participants. Emission levels are unequally distributed: the top 10% of emitters contribute >50% of SDT and LDT emissions. People with high education and income levels tend to travel and emit more within and away from the cities. People of retirement age travel and emit much less than the younger people. SDT emission levels are clustered spatially and increase with the increasing distance from the main city centres and decreasing density. LDT emissions have only very weak or no association with residential location.

Key words: travel behaviour, greenhouse gas emissions, residential location, spatial analysis, long-distance travel, short-distance travel

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Introduction

Mobility is an important part of human life, from daily work commutes to shopping trips to holidays on different continents. It is also an important source of greenhouse gas (GHG) emissions and significantly contributes to human-induced climate change. Transport is estimated to have contributed 14% of all GHG emissions from anthropogenic sources (Lamb et al. 2021) and 24% of CO_2 emissions from energy sources (Ritchie 2020) in 2018. Road passenger transport makes up around half of these emissions, mostly from private car use. The share of rail in transport

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emissions is small (~1%) due to its relatively low travel volume and high energy efficiency. Passenger aviation contributes 9% of transport emissions and 2% of total CO_2 emissions (Ritchie 2020). If non-CO_2 effects, including nitrogen oxide emissions and contrail formation, are included, aviation's contribution to human-induced global warming amounts to 4% of the total (Klöwer et al. 2021). However, in some wealthy countries of Northern and Western Europe, aviation has become the largest source of transport emissions (Aamaas et al. 2013, Aamaas, Peters 2017, Czepkiewicz et al. 2019, Kamb, Larsson 2019), which brought the attention of researchers, politicians, and the public.

The relatively small share of aviation emissions in all sources results from highly unequal participation in air travel. Only about 11% of humanity travelled by plane in 2018, and 2–4% did so internationally (Gössling, Humpe 2020). Despite much higher average levels of air travel, the unequal distribution persists in wealthy European societies. About 20% of UK households are responsible for 75% of flights (Büchs, Mattioli 2021). Several studies conducted in European urban regions report that 20% of residents generate around 60% of emissions from flying (Brand, Preston 2010, Czepkiewicz et al. 2019). There are also high differences between European countries. While 84% of Iceland's residents travelled abroad in 2018, mostly by plane (Schmidt et al. 2023), only about 24% of Poland's residents spent holidays abroad in 2022 (CBOS 2023), and about half of the trips abroad were by plane in 2018 (GUS 2019). Among all consumption categories, air travel contributes most to the high inequalities in carbon footprints globally and Europe (Ivanova, Wood 2020).

The highly unequal distribution also applies to emissions resulting from car travel, even though it is more evenly distributed between the income groups than flying (Ivanova, Wood 2020). Even in highly car-dependent societies with high car ownership rates, differences in distances travelled by car may result in emission inequalities similar to those in flying (Czepkiewicz et al. 2019). For example, 20% of top emitters in the Paris metropolitan area contribute 75% (Leroutier, Quirion 2022), and in Barcelona, 74% (Bel, Rosell 2017) of CO_2 emissions. Even though car ownership is prevalent across income groups, income levels still strongly differentiate land travel's carbon and energy footprints in Europe (Ivanova, Wood 2020) and its wealthy countries (Baltruszewicz et al. 2023).

Despite efforts to decarbonise the sector, global transport GHG emissions continue rising (Lamb et al. 2021). It is the only sector in the European Union whose emissions have grown since 1990 (by 33%; see European Environment Agency 2022). Poland, where this study is conducted, has strongly contributed to this growth – its transport emissions in 2019 were three times higher than those in 1990 (European Commission 2021). International aviation is the fastest-growing sector in all geographical contexts. COVID-19 travel restrictions temporarily reverted its rapid growth, but it is predicted to soon rebound to pre-pandemic levels (IATA 2023).

Passenger transport is thus an important aspect of climate change mitigation, and sustainable mobility is an important paradigm in research and policy (Banister 2008, Naess 2020). Transport's reliance on fossil fuels and relatively marginal share of alternative fuels and electric engines makes it a 'hard-to-decarbonise' sector. There is a growing realisation that besides changes in fuels and their efficiency, a reduction in travel demand and a shift in travel modes is necessary to reach climate change mitigation targets (Holden et al. 2020). Cities, their built environment (BE) and transport infrastructures have a high potential for such shifts and reductions and thus have been an important focus of research and policy.

Social and geographical factors shaping short-distance travel (SDT, travel within the urban area of residence, also described as 'daily travel' or 'local travel') are relatively well-known and described. A vast body of research (Ewing, Cervero 2010, Barla et al. 2011, Ko et al. 2011, Naess 2012, Buchs, Sylke 2013, Stevens 2017, Leroutier, Quirion 2022) shows that distances travelled, the share of travel by car and the resulting GHG emissions all tend to be higher in locations further away from main city centres, with lower population density and poorer public transport provision, while higher income and labour market status, and being a male have a positive correlation with emissions (Zhao et al. 2013, Brand et al. 2021). Being an employed and motorised man from the far suburbs is also associated with a higher likelihood of being a top emitter who travels longer distances (Leroutier, Quirion 2022). Some studies also highlight the important role of an individual's level of education (Wu et al. 2019), although its contribution to emissions is often non-linear, with lower emission levels of those with tertiary education (Bel, Rosell 2017, Brand, Preston 2010). As income is also positively correlated with the number of kilometres travelled by car in different urban contexts (Delbosc et al. 2019), it should be expected to correlate with SDT emissions. On average, people also tend to travel longer distances, use cars more as they age, and reduce their travel activity around retirement age. However, in Western countries, older adults have started to be more mobile than before, while the younger generations seem to be less car-oriented (Buehler, Nobis 2010, Hjorthol et al. 2010, Siren, Haustein 2012).

Although there is some disagreement as to how strong the effect of the BE on local travel activity is compared to people's attitudes and preferences (Bohte et al. 2009, Cao et al. 2009, Ewing, Cervero 2017, Handy 2017, Stevens 2017), there is strong quantitative and qualitative evidence of both statistical association and causal effects (Naess et al. 2019). The BE, preferences for certain residential conditions and mobility behaviour are intertwined in a dynamic relationship (Lu 2023). For example, the life stage partly determines housing choices (Booi, Boterman 2020). As a result, suburbs tend to be inhabited by middle-class families with children who travel longer distances and thus emit more. In turn, lower-income and non-family households, who tend to travel and emit less, often inhabit downtown areas. In the last few decades, however, these relationships have been subject to change and have become less obvious. For example, central parts of cities are becoming increasingly popular among higher-income people looking for better local access to various amenities. But, if inner city residents use a car, they tend to choose high-emission models, which might cancel out the emission-reducing effects of living in the centre (Leroutier, Quirion 2022). On the other hand, increasing housing prices in the inner parts of the cities make lower-income citizens more likely to migrate to the suburbs (Hochstenbach, Musterd 2018). Although economically disadvantaged people often emit less and travel shorter distances, living in suburban areas increases these emissions due to car dependence and the poor accessibility of peripheral parts of agglomerations (Xiao et al. 2017).

Most recently, researchers have devoted increasingly more attention to previously understudied long-distance travel (LDT), its climate impacts and its association with socio-demographic characteristics and residential location (Mattioli, Adeel 2021). LDT is defined in multiple ways, most commonly as travel away from one's everyday environment, usually with a specific distance threshold (ibidem). Individual and household characteristics associated with high LDT activity include higher incomes, education levels, and travel-related skills (e.g. speaking foreign languages) (Christensen 2015, Czepkiewicz et al. 2020a). Some studies also highlight the important role of occupation, particularly emphasising the contribution of individuals in leadership positions who frequently engage in business trips (Larsen et al. 2023).

Multiple studies have documented differences in LDT activity between the residents of large cities, smaller towns, and rural areas (Czepkiewicz et al. 2018a). High LDT activity might cluster in space due to the residential sorting of people with varying cultural and economic capital levels. As a result, at the city-region scale, the spatial patterns in LDT are mostly explained by differences in how people with certain characteristics are distributed and less so by the direct influence of the BE. Urbanites tend to have higher education levels and incomes and benefit from better access to airports and train connections than those who live in more peripheral locations (Bruderer Enzler 2017). Residents of major cities are also more likely to have migration backgrounds and internationally spread social networks, which further contribute to travel activity (Mattioli et al. 2021). There are also differences in LDT activity and emissions between people living in various parts of major urban areas, which are not as easily explained. Several studies suggest that residents of central districts of Nordic capitals tend to travel by air much more than residents of less central locations (Czepkiewicz et al. 2018c, 2019).

Moreover, in previously studied urban areas, attitudes and norms that correlate with high air travel activity, such as cosmopolitan orientation, were higher among city centre residents and largely explained the spatial distribution of LDT emissions (Czepkiewicz et al. 2020b). However, available studies have mostly been conducted in wealthy countries and their major cities. There is little evidence from other regions, including Central and Eastern Europe.

This article contributes to this literature by presenting a study from Poznań and the Tri-city (Gdańsk, Sopot, and Gdynia) functional urban areas (FUAs) in Poland. The article covers SDT (i.e. travel within the urban area) and LDT (i.e. travel away from the urban area). We estimate the GHG emission levels associated with each scope of travel based on a survey conducted among the residents of Poznań and Tri-city FUAs. We explore and statistically describe the composition of travel-related GHG emissions and their statistical (i.e. in terms of inequality) and geographical distribution patterns. We also explore and describe the bivariate relationships between the BE characteristics of residential locations, socio-demographic characteristics, and travel-related GHG emissions.

Study areas

The study is conducted in Poznań and the Tri-city's FUAs. The areas are similar in size as both have around 800 thousand inhabitants within the study area and more than 500 thousand inhabitants in the core cities (Gdańsk and Gdynia in the case of the Tri-city). The areas differ in urban form. Poznań is more monocentric, with suburban towns distributed concentrically from the core city. The Tri-city is more polycentric and has a more linear structure, with spatial development restricted by the Baltic Sea in the east and north and the Tri-city Landscape Park in the West. Differences in urban form dictated the choice of the study areas.

The extent of FUAs was based on the criterion of 10% of the working-age population commuting to the core city (or cities) in 2016. The resulting FUAs include 17 municipalities in the Poznań area and 11 municipalities in the Tri-city area.

The Poznań FUA is located in Western Poland in Greater Poland Voivodeship. It is connected to Warsaw and Berlin by the A2 highway and E20 railway and to Wroclaw and Bydgoszcz by the S5 express road. It has one major train station that served ca 15 million passengers [Mp] in 2021, with direct connections to 64 destinations in Poland and Germany (including Berlin). Poznań-Ławica Airport served 2.25 Mp in 2022.

The Tri-city FUA is in North Poland in Pomeranian Voivodeship by the Baltic Sea. It is connected to Torun and Lodz by the A1 highway and to Warsaw by the S7 express road. It has several high-service train stations, including Gdynia Główna (8.35 Mp in 2021), Gdańsk Główny (7.96 Mp), Gdańsk Wrzeszcz (6.9 Mp) and Sopot (5.5 Mp). Urban rail operator Szybka Kolej Miejska (SKM) makes up a high share of train passengers served in these stations. Gdańsk Lech Wałęsa Airport served 4.57 Mp in 2022. The region is connected to Sweden by direct ferry connections.

Materials and methods

Survey data collection

The data used in the article are from a survey conducted primarily from November 2022 to February 2023 in the two areas, with complementary data collection in March–April 2023. The digital geo-questionnaire included conventional survey questions and an interview map that allowed participants to mark locations on maps and answer questions about the locations (Czepkiewicz et al. 2018b). The survey included a variety of mobility-related topics, of which socio-demographic characteristics, residential location, travel activity, and vehicle characteristics are used in this article. Its content was available in Polish, English, and Ukrainian. The survey was administered by professional pollsters, who visited households using a random route procedure with starting points distributed proportionally to residential distribution in census areas and filled out in a computer-assisted personal interview (CAPI) setting using tablet computers. Only one person from each drawn household could take part in the survey. The socio-demographic characteristics of the sample were controlled to obtain a representative structure in terms of age, gender, education level, and residential location (i.e.

the proportion between the core municipalities and the rest of the region). The initial sample size was 2075 in Poznań and 2075 in the Tri-city. After data cleaning, deleting erroneous and fraudulent answers, and including answers from complementary data collection, the sample size was 1845 in Poznań and 2004 in Tri-city. Some parts of the questionnaire were presented only to randomly selected participants. Hence, the sample size (N) for particular analyses is smaller.

Travel activity

The travel activity of study participants is divided into two geographical scopes: SDT and LDT. SDT includes trips made within the core city of each FUA and its surroundings. LDT includes trips made away from the core city of the FUA or its surroundings, at least 50 km from the residential location.

Data about SDT were collected in the geo-questionnaire using an interactive map tool. The pollsters marked locations most frequently visited by the study participants during the last 3 months in four categories: 'Working, studying, picking up children', 'Shopping, services, errands', 'Culture, entertainment, religion, meetings' and 'Sport, rest, recreation'. After marking a location, study participants answered questions about details of activities done at the location, visiting frequency, usual trip origin (i.e. visited from home, from work, on the way between home or work), the frequency of using travel modes, typical travel time and the number of people who usually travel in the car (if a location is visited by car). The pollsters were instructed to mark at least five of the most frequently visited locations. The average number of marked locations was 4.9 in Poznań and 4.3 in the Tri-city. The residential locations of study participants were collected similarly.

Data about LDT were collected using a series of matrix questions about the number of trips made by car, plane, train, bus, or ferry away from the study area in the last 12 months within distance bands: 50–200 km, 201–500 km, 501–1000 km, 1001–3000 km and >3000 km. Examples of destinations within the distance bands from the study area were provided next to each question. The LDT measurement did not distinguish between private and business trips.

Travel distances

In the case of SDT, yearly travel distances were estimated in several steps. Firstly, road distances between home and visited locations were modelled using a Route tool in ArcMap. The Network Dataset was based on OpenStreetMap data, and routing was done with the assumption of car driving using hierarchy attributes and one-way restrictions, optimising travel time. The road data were screened manually for completeness by comparing it with other data sources (Google Maps and orthoimages) and were sufficiently complete in both study areas. Only road segments accessible for cars were used in routing. Secondly, a yearly distance was estimated for each visited location based on answers about travel frequency, coded to numeric values (Table A1 in Appendix). Finally, a proportion of distance by each travel mode was estimated using coded answers to a question about the frequency of using travel modes when travelling to a location. In the case of LDT, yearly travel distances were estimated by multiplying a numeric value for the number of trips in the last 12 months and a numeric value for the distance band for each answer in the matrix questions and travel mode (Table A2 in Appendix).

Greenhouse gas emissions

Yearly travel-related GHG emissions of study participants were estimated by multiplying yearly travel distances and emission coefficients. The coefficients were estimated using secondary sources for travel modes other than private cars in SDT. Table A3 in the Appendix contains the resulting coefficients, assumptions behind them, and data sources. All emission coefficients are estimated using a Well-to-Wheel (in case of ground transport, [WTW]) and Well-to-Wake (in case of aviation, [WTW]) approach, meaning that GHG emissions associated with fuel extraction, production and transport, and emissions from electricity production and transport are included along with emissions resulting from combustion in a vehicle. The analysis does not include emissions associated with vehicle and infrastructure production and maintenance (i.e. indirect emissions). Two emission coefficients are provided for air travel: CO_2 emissions and non-CO_2 effects.

The latter includes contrail formation, cirrus cloudiness, NO_X emissions, sulphate aerosols, and other effects resulting from planes' operation at high altitudes, which result in net positive anthropogenic radiative forcing (Lee et al. 2021). Estimating non-CO_2 effects on global warming is much less certain than CO_2 (ibidem); hence, the values are reported separately, and bivariate analyses only use CO_2 values. To avoid overestimation, we adopt a conservative estimation of these effects (Table A4 in Appendix). As non-CO_2 effects occur only at high altitudes, they are not included for short-haul flights (up to 500 km), which do not reach such altitudes and are the highest for long-haul flights.

For private cars in SDT, emission coefficients were partly calculated using data provided by study participants: fuel consumption of the car primarily used by the person (in $l \cdot 100\ km^{-1}$, or, in the case of electric vehicles, electric energy consumption in $kWh \cdot 100\ km^{-1}$), its drive and fuel type (diesel, gasoline and liquefied petroleum gas [LPG] internal combustion engine vehicles [ICEV], plug-in hybrid electric vehicles [PHEV], hybrid electric vehicle [HEV], and battery electric vehicle [BEV]) and the number of people who usually travel in the car to a visited location. In case of missing data, average fuel or energy consumption in each category was used.

The general formula for calculating the GHG emissions from travel activity is (adapted from Dillman et al. (2021))

$$E_{WTW} = \sum_i TD \times MS_i \times EF_i \quad (1)$$

where:
- E_{WTW} is the sum of Well-to-Wheel emissions from the travel activity of a person within the period (here, 1 year),
- TD is the distance travelled by all modes,
- MS is the share of distance travelled by mode i (such as private car, bicycle, train, bus, tram, plane, or ferry),
- EF is an emission factor of a mode i expressed in CO_2 equivalent per passenger kilometre ($kg\ CO_2eq \cdot pkm^{-1}$).

The general formula for calculating the emission factors for each mode is:

$$EF_i = \sum_j VS_j \times \frac{FU_j \times FC_j}{AL_i} \quad (2)$$

where:
- EF is an emission factor of a travel mode i,
- VS is a share of each vehicle type j in transport performance of the travel mode (e.g. the share of passenger kilometres transported by bus or tram),
- FU is the average fuel or energy use in a vehicle type j per vehicle kilometre,
- FC is the carbon intensity of a fuel or energy source (in this case, calculated with the Well-to-Wheel method) per unit of mass or volume, and
- AL is the average load of a vehicle type j expressed in the number of passengers.

In the case of air travel, the fuel use is expressed per seat kilometre, and the average load is replaced with a utility factor (UF, an average percentage of occupied seats) in the following equation:

$$EF_i = \sum_j VS_j \times FU_j \times FC_j \times UF_j \quad (3)$$

Emission coefficients in aviation are distinguished between distance bands used in the survey (50–200 km, 201–500 km, 501–1000 km, 1001–3000 km, and >3000 km). Table A4 in the Appendix contains emission factors for LDT modes.

The statistical distribution of resulting per capita emission levels is highly skewed with many zeroes (a zero-modified lognormal distribution). We treat all zeroes as true values, signifying that a person did not travel with motorised modes in the 12 months preceding the survey. In LDT emissions, five extreme outliers with values >30 tCO_2e were excluded from statistical analyses.

Built environment characteristics

Analyses presented in the article use variables describing the residential locations of study participants and BE characteristics around these locations calculated using geospatial methods. The variables relate to the BE characteristics used in previous studies. The variables include the following:
1. Distance to the closest first-order centre in the FUA
2. Local population density
3. Local basic services density
4. Local street intersection density

Distance to the closest first-order centre describes the residential location relative to the main concentrations of workplaces and services. It has been used in multiple previous studies on travel (Naess 2012). Here, it was calculated using the Closest Facility tool in ArcMap, with a Network Dataset based on OpenStreetMap data and routing with the assumption of car driving, using hierarchy attributes and one-way restrictions. The centres were delineated based on an aggregate value of three density measures:

1. The density of services and workplaces derived from the REGON (National Business Registry) database
2. The density of services derived from the OpenStreetMap database
3. The density of visited locations derived from the survey

Poznań's centres are located in Stare Miasto, Jeżyce and Św. Łazarz neighbourhoods. In the Tri-city, they are located in Gdańsk Śródmieście, Gdańsk Wrzeszcz and Gdynia.

Local population density is the number of residents in a 1-km grid cell, derived from the National Census 2021 (GUS 2022). The distribution of population density values and location of the first-order centres is also shown in Fig. 1.

Local basic service density was calculated in 1-km-radius circles around residential locations using points of interest data from the OpenStreetMap database. Basic service categories include ATMs, post boxes and offices, stores, beauty and hairdresser salons, laundry and cleaning services, churches, social centres, healthcare and childcare facilities, and sports and recreation facilities. Street intersection density was calculated in 1 km radius circles around residential locations using street data from the Topographic Objects Database (BDOT10k).

All BE characteristics are strongly correlated with each other with absolute ρ values in the range from 0.63 to 0.79. Distance to the closest city centre is negatively correlated with the other three variables: population density, basic service density, and street intersection density, all decrease with the increasing distance from the closest city centre.

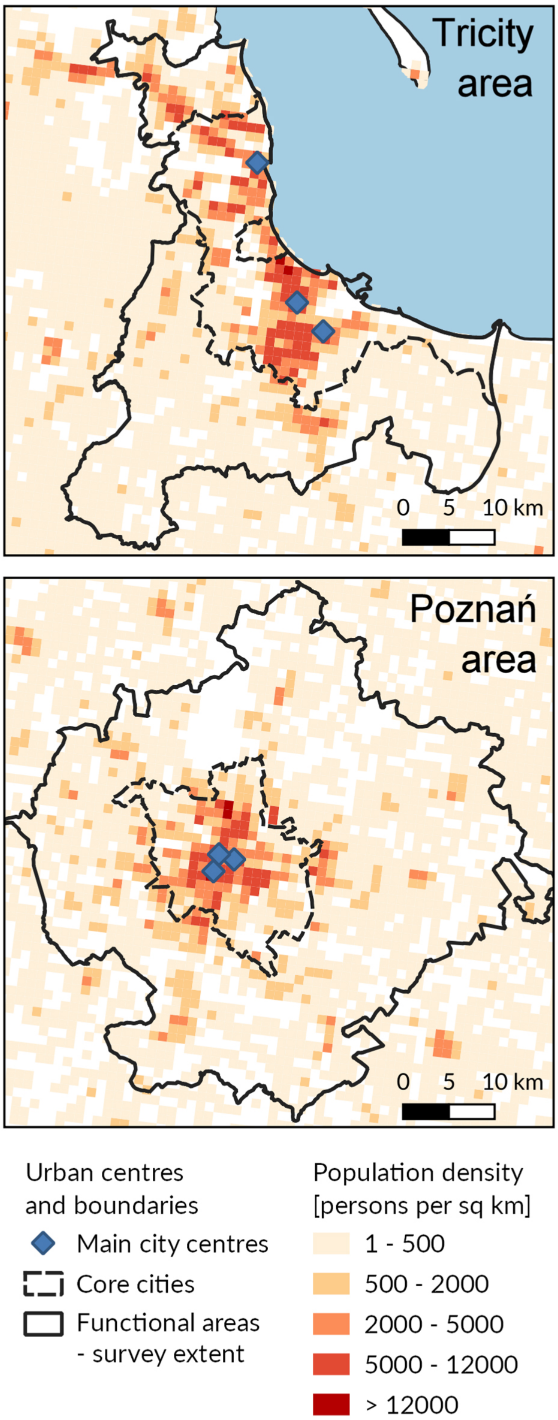

Fig. 1. Spatial extent of the study areas: the Tri-city and Poznań functional areas and their core cities, population density distribution, and locations of the main city centres.

Socio-demographic and economic characteristics

The analyses use four basic socio-demographic variables: age (employed as a continuous variable for correlation calculations and presented with 5-year ranges in figures), gender (a nominal variable with three possible answers), educational level (an ordinal variable with six possible answers: primary school, vocational school, secondary school, bachelor degree, master's degree, and doctor) and personal income (employed as a continuous variable for correlation calculations and presented with eight ranges in figures).

We also used parents' education level (the one with the higher education among the two, measured on an ordinal scale identical to the one measuring respondent's age) as a proxy for cultural capital. The variable was utilised based on the findings of other studies, indicating a significant impact of parental educational status on the travel patterns of their descendants through socialisation effects. The results of these studies suggest that individuals with graduated parents tend to have their first international travel earlier in life than others (Mattioli et al. 2022).

At the household level, we measured declared household income (measured on a continuous scale using eight ranges), household size (by number of members), and number of cars. Household income was equivalised to consumption unit by a modified OECD equivalence scale, which assigns a value of 1 to the first adult in the household, 0.5 to each additional adult member, and 0.3 to each child under 18 (Eurostat 2021). The analyses also include five categories of households (single-person households, multi-person households without children, multi-person households with children aged under 6 years, multi-person households with children aged 7–18 years, and multi-person households with children representing both age categories).

Statistical methods

At the preliminary stage of the analysis, we used methods of univariate statistical analysis. We screened the distributions of explained variables with distribution measures such as mean, median, quartile, and interquartile range. We visualised them using histograms – both in the original and logarithmic scales. We analysed distribution inequality using Lorenz curves. High inequality of emission values, skewed distribution towards high values, and a significant number of true zeros (i.e. no emissions) were reasons to use non-parametric statistical methods throughout the further analyses.

We analysed emission levels and selected socio-economic variables with spatial statistics in GeoDa software (Center for Spatial Data Science at the University of Chicago, 2023). We used a global Moran's *I* statistic (Anselin 2020a) to assess the degree of spatial association in the whole region and Getis-Ord Gi^* to identify areas with local clusters of high or low values (Anselin 2020b). Both methods use weight matrices, which link pairs of values from adjacent observations or neighbours. Our analysis used a uniform 2000-m distance band to create the weight matrices. As a result, some observations have no neighbours, and those in densely populated areas may have higher numbers of neighbours and thus higher statistical significance than observations in less densely populated areas. Moran's *I* may sometimes be insensitive to the local spatial association, and the Gi^* maps were computed even when Moran's *I* did not show a significant association level. We used untransformed emission values in the calculations and assessed the statistical significance using pseudo-p-values based on 999 permutations.

We used Spearman's of rank correlation to capture the direction and strength of the relationships between ordinal and continuous variables and Kruskal–Wallis tests to assess multiple group comparisons within nominal and ordinal variables. In both cases, we used $p < 0.05$ as a threshold for statistical significance.

We visualised the relationships between continuous explained variables (emissions in SDT and LDT) and categorical or ordinal explaining variables with boxplots. We use the following symbols in the charts:

- rectangle ('box') represents the interquartile range,
- the width of the rectangle represents the number of observations in a category,
- the vertical line inside of the box represents the median value,
- a dot represents the mean,
- horizontal lines extending from the boxes ('whiskers') mark a range of up to 1.5 of the interquartile range below the 1st quartile and above the 3rd quartile
- observations outside the ranges of boxes and whiskers are treated as outliers and visualised as circles.

Due to highly skewed distributions and the existence of outliers, the y-variable (horizontal) axis was cut at 5000 kg CO_2eq.

Results

Education and financial situation significantly differentiate SDT and LDT. The associations are stronger in the case of LDT but remain significant in SDT. Individuals with higher education and income emit more GHGs in both travel scopes than those with lower educational levels and less favourable economic conditions. The similarity in these relationships likely contributes to a relatively strong correlation between LDT and SDT emissions ($\rho = 0.40$).

However, the relationship between emissions and residential location is markedly different in these travel scopes. SDT emission levels are much more strongly clustered in space and associated with BE characteristics than LDT emissions. Nevertheless, LDT emissions have some level of spatial association and variability.

Share of travel modes in distances and GHG emissions

Cars dominate the share of GHG emissions and distances in the SDT scope in both urban areas (Fig. 2). It makes up 68% of distances and 89% of emissions in the Poznań area and 57% of distances and 85% of emissions in the Tri-city. The Tri-city area has a higher share of public transport modes in distances and emissions (18% of distances and 11% of emissions by bus or tram, and 5% of distances and 2% of emissions by train) than Poznań does (15% of distances and 8% of emissions by bus or tram, and 1% of both distances and emissions by train). Shares of distances and emissions by e-bikes or e-scooters and motorcycles are negligible (<1%) in our sample.

The car accounts for the highest share of distances in LDT (Fig. 3) made by the residents of the Poznań area (55%) and a lower share of emissions (39%) than the plane does (57%) due to a much higher emission factor of air travel when non-CO_2 effects are included. In the Tri-city area, the highest share of LDT distances and emissions comes from air travel (49% of distances and 74% of emissions). Other notable differences are the higher share of ferry and bus travel in the Tri-city and the higher share of train travel in Poznań. Notably, our sample's average yearly LDT distances are higher in Poznań than in the Tri-city (6692 km and 4001 km, respectively). Distances travelled by plane are similar among residents of both urban areas (2134 km in Poznań and 1941 km in the Tri-city).

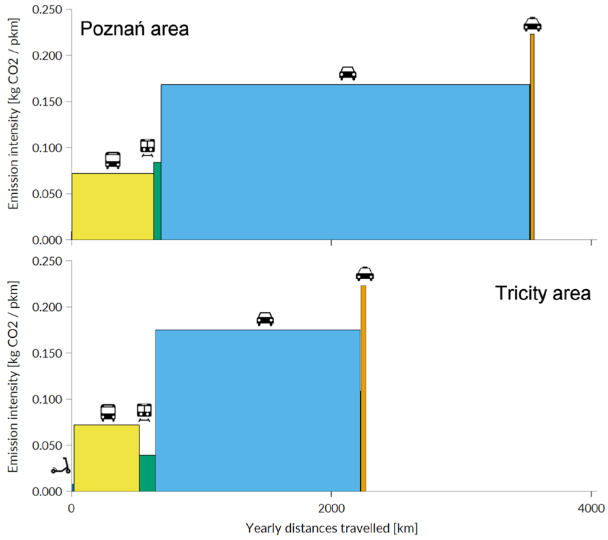

Fig. 2. Short-distance travel CO_2 emissions in Poznań and the Tri-city areas by travel mode. The box area represents the average yearly emission level.

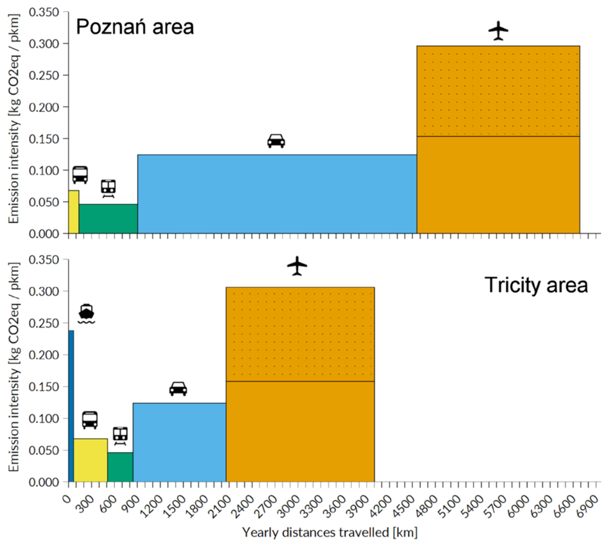

Fig. 3. Long-distance travel GHG emissions in Poznań and the Tri-city area by mode. Box area represents average yearly emission levels. Non-CO_2 effects of air travel are marked with dotted areas.

Distribution of greenhouse gas emissions

SDT and LDT emission levels are unequally distributed (Fig. 4). The top 10% of emitters generate 50% of emissions in SDT and 54% of emissions in LDT. The top 20% generate 71% of emissions in SDT and 78% of emissions in LDT. The top 1% is responsible for 12% of emissions in SDT

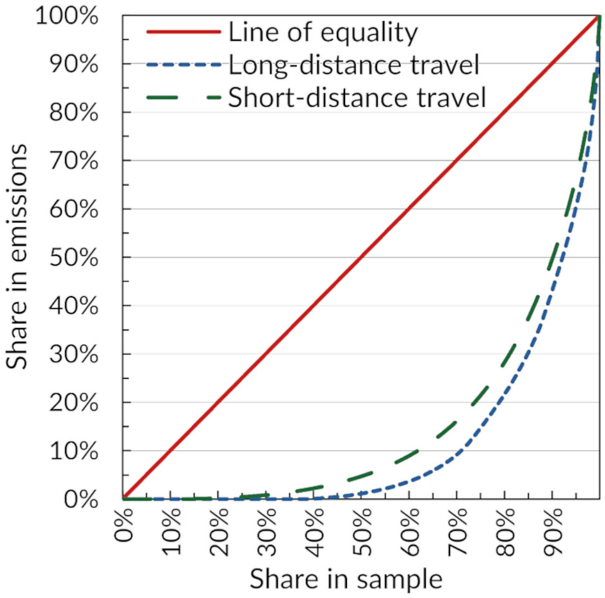

Fig. 4. Lorenz curve of emission levels in long-distance travel and short-distance travel.

and 17% in LDT, while the bottom 50% generates merely 5% of emissions in SDT and 1% in LDT.

Greenhouse gas emissions and socio-demographic categories

Both SDT and LDT are differentiated by respondents' age. The relationship is moderately negative (ρ = −0.41 in SDT and −0.34 in LDT) but non-linear (Fig. 5). The means and medians of emissions from both travel scopes are the highest in the middle-age categories (around 40–44) and lower among younger and older groups. People of retirement age (over 60 years and 65 years) have much lower emissions than younger groups. Gender significantly differentiates SDT emissions, with men emitting more than women (Fig. A1 in the Appendix) but it has no association with LDT emissions (Fig. A2 in the Appendix).

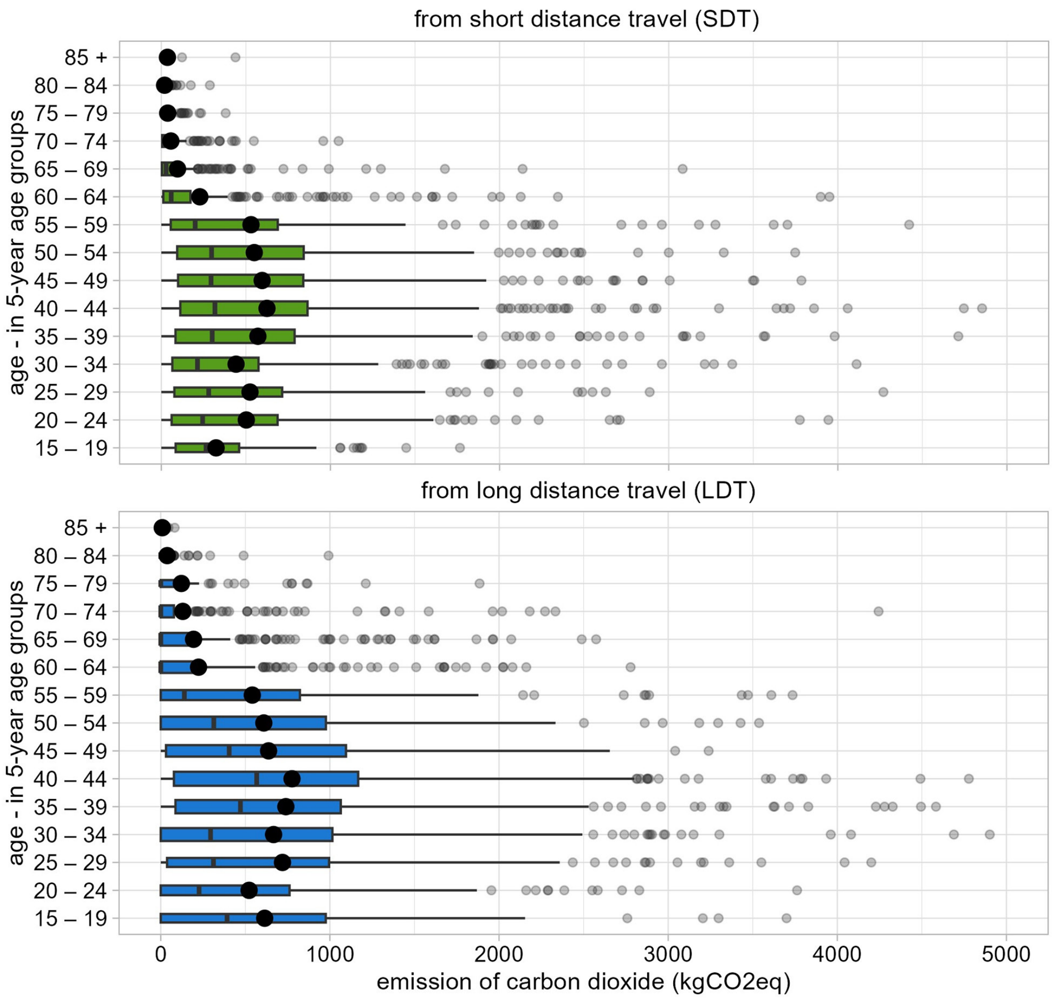

Fig. 5. CO_2 emissions from short-distance (top, green, N = 3699, ρ = −0.41, $p < 0.001$) and long-distance travel (bottom, blue, N = 3746, ρ = −0.34, $p < 0.001$) in 5-year age groups in the whole sample.

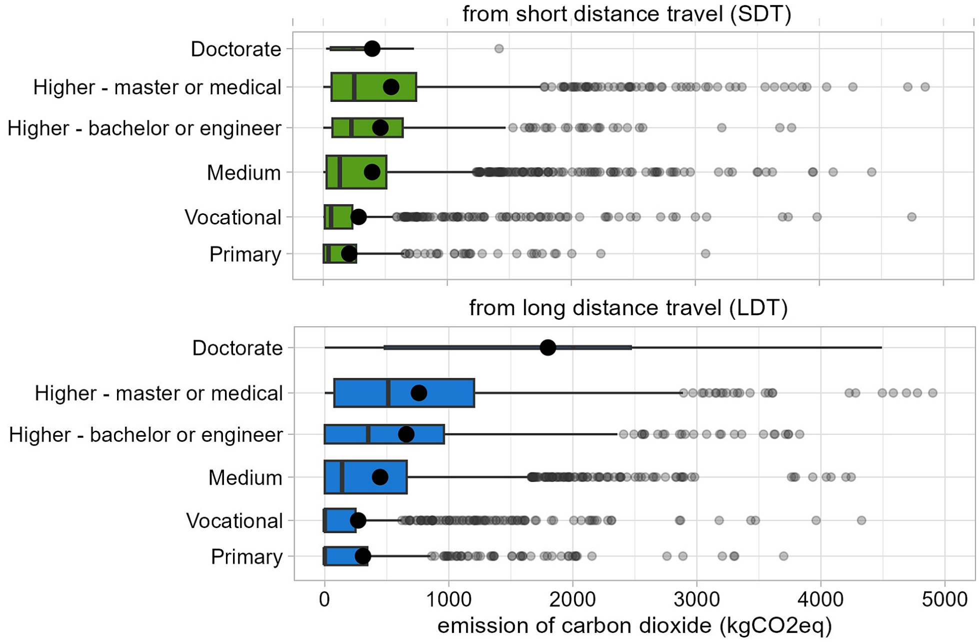

Fig. 6. CO_2 emissions from short-distance travel (top, green, N = 3703, ρ = 0.26, $p < 0.001$) and ling-distance travel (bottom, blue, N = 3750, ρ = 0.30, $p < 0.001$) in respondents' education level in the whole sample.

Education differentiates emissions from both travel scopes – they rise as the respondent's education increases (ρ = 0.30 for LDT and 0.26 for SDT). The relationship is monotonic in LDT (people with doctoral degrees have the highest emission levels). It is also mostly monotonic in SDT, except for the highest level of education, which is relatively scarce in the dataset (Fig. 6). Importantly, the moderate relationship also holds for the education level of respondents' parents (ρ = 0.31 for LDT and 0.27 for SDT) with a similar association shape.

Income also differentiates emissions from both SDT and LDT. The relationship holds for personal income (ρ = 0.26 for LDT and 0.28 for SDT) and equivalised household income (ρ = 0.30 for LDT and 0.26 for SDT). The relationship between income and SDT is not monotonic – the median is highest in the upper-middle categories. In LDT, increasing income leads to higher emissions. Perceiving one's economic situation as difficult predicts low emissions in both travel scopes. Once the evaluation improves, the LDT emissions rise sharply (ρ = 0.36). The effect is less pronounced in SDT (ρ = 0.28). People who have difficulties making ends meet have average emissions close to zero in both travel scopes.

Household size and composition differentiate emissions in both scopes. Respondents in larger households tend to have higher SDT emissions (ρ = 0.22). For LDT, the effect of this variable is weaker (ρ = 0.18), and emissions rise in household sizes from 1 to 4 people but decrease for larger sizes. The highest categories (five or more household members) should be interpreted cautiously due to few observations.

Residential location and greenhouse gas emissions

In line with previous studies, the residential location differentiates SDT emissions. They exhibit significant spatial autocorrelation in both urban areas (Table 1) and a positive monotonic relationship with the distance from the residential

Table 1. Global Moran's *I* of emission levels.

Study area	Travel scope	Moran's *I*	Pseudo p-value	N
Tri-city	Short-distance	0.064	0.001	1978
	Long-distance (all)	0.010	0.039	1917
	Long-distance (air)	0.014	0.016	1917
Poznań	Short-distance	0.126	0.001	1824
	Long-distance (all)	0.092	0.001	1800
	Long-distance (air)	0.065	0.001	1800

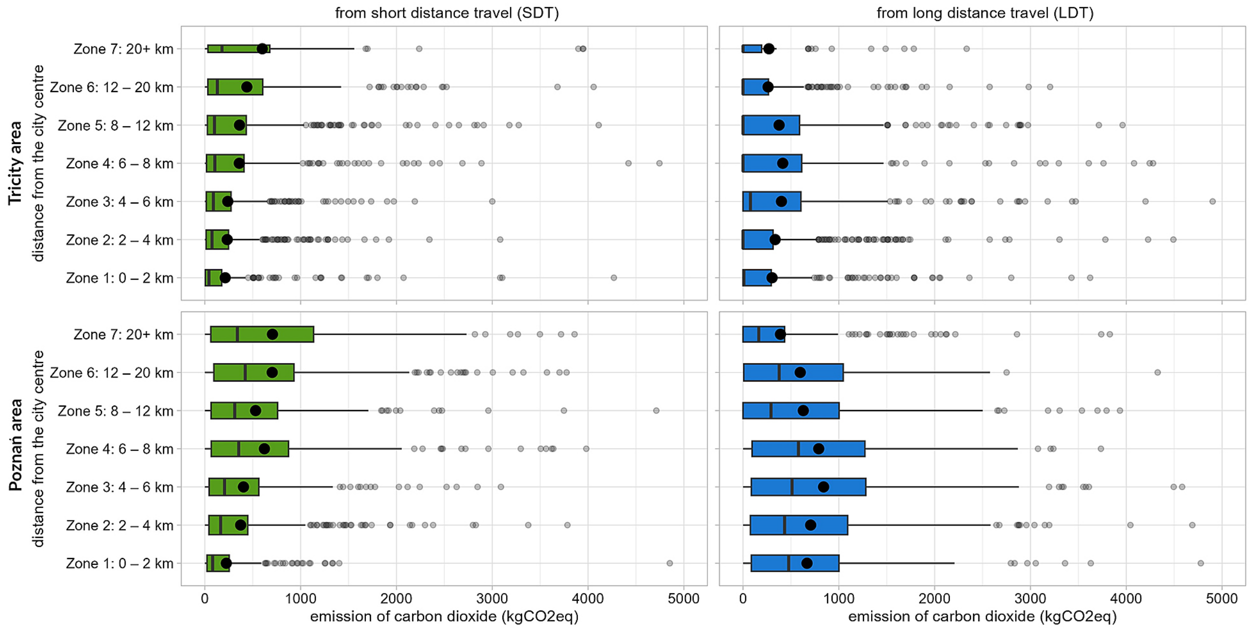

Fig. 7. SDT and LDT emissions and distance from the residential location to the closest city centre in the Tri-city (SDT: N = 1897, ρ = 0.17, $p < 0.001$ and LDT: N = 1914, ρ insignificant, $p > 0.05$) and Poznań (SDT: N = 1799, ρ = 0.23, $p < 0.001$ and LDT: N = 1800, ρ = −0.11, $p < 0.001$) areas.

location to the closest city centre (Fig. 7, ρ = 0.23 in Poznań and 0.17 in Tri-city). In general, the further one lives from the main centres, the higher emissions from local travel tend to be. The spatial autocorrelation of SDT emissions (Table 1) and their correlations with BE al variables (Table 2) are stronger in the Poznań area than in the Tri-city, possibly due to the monocentric structure of the former.

In Poznań, clusters of low SDT emission values are centrally located (up to ~5 km from the main city centre) and densely populated areas in the core city. Clusters of high values are located in the suburban areas, both within the core city limits and in municipalities of Tarnowo Podgórne, Suchy Las, Murowana Goślina, and others (Fig. 8).

In the Tri-city, clusters of low SDT emissions are located primarily in Gdańsk and Gdynia, with smaller clusters in Sopot, Rumia, and Reda along the main urban railroad. Another cluster of low values is located in Żukowo town, ca 19 km from Gdańsk centre. Clusters of high emission values are mostly located in suburban parts of Gdańsk and neighbouring Pruszcz Gdański (Fig. 8).

The residential location has a weaker effect on LDT emissions than the SDT. There is a significant spatial autocorrelation of LDT emissions in the Poznań area but not in the Tri-city (Table 1). Notably, the LDT emissions are the highest in the medium range of distances from the centres (ca 4–8 km in Poznań and 4–12 km in the Tri-city) and appear to decrease in areas both farther from and closer to main city centres (Fig. 7).

In the Poznań area, there are some clusters of high levels of LDT emissions in the Poznań city (Rataje, Ławica, and Szczepankowo) and the suburban town of Pobiedziska (Fig. 8). There is a cluster of low LDT emission values in the central part of Gdańsk (Wrzeszcz neighbourhood) and clusters of high values in Rumia and parts of Gdańsk (Brzeźno and Nowy Port) and Gdynia (Orłowo) (Fig. 8). Note that the clusters of high LDT values are sensitive to even small numbers of outliers and should be interpreted cautiously. There are clusters of low LDT values in other suburban towns (e.g., Murowana Goślina, Tarnowo Podgórne, Puszczykowo, and Swarzędz) and the southern part of Poznań.

SDT emissions are moderately associated with BE characteristics in Poznań and weakly associated with the Tri-city (Table 2). The correlations between LDT emissions and BE characteristics are very weak but significant ($p < 0.001$) in Poznań and not significant in the Tri-city. Correlation signs are opposite in SDT and LDT (Table 2).

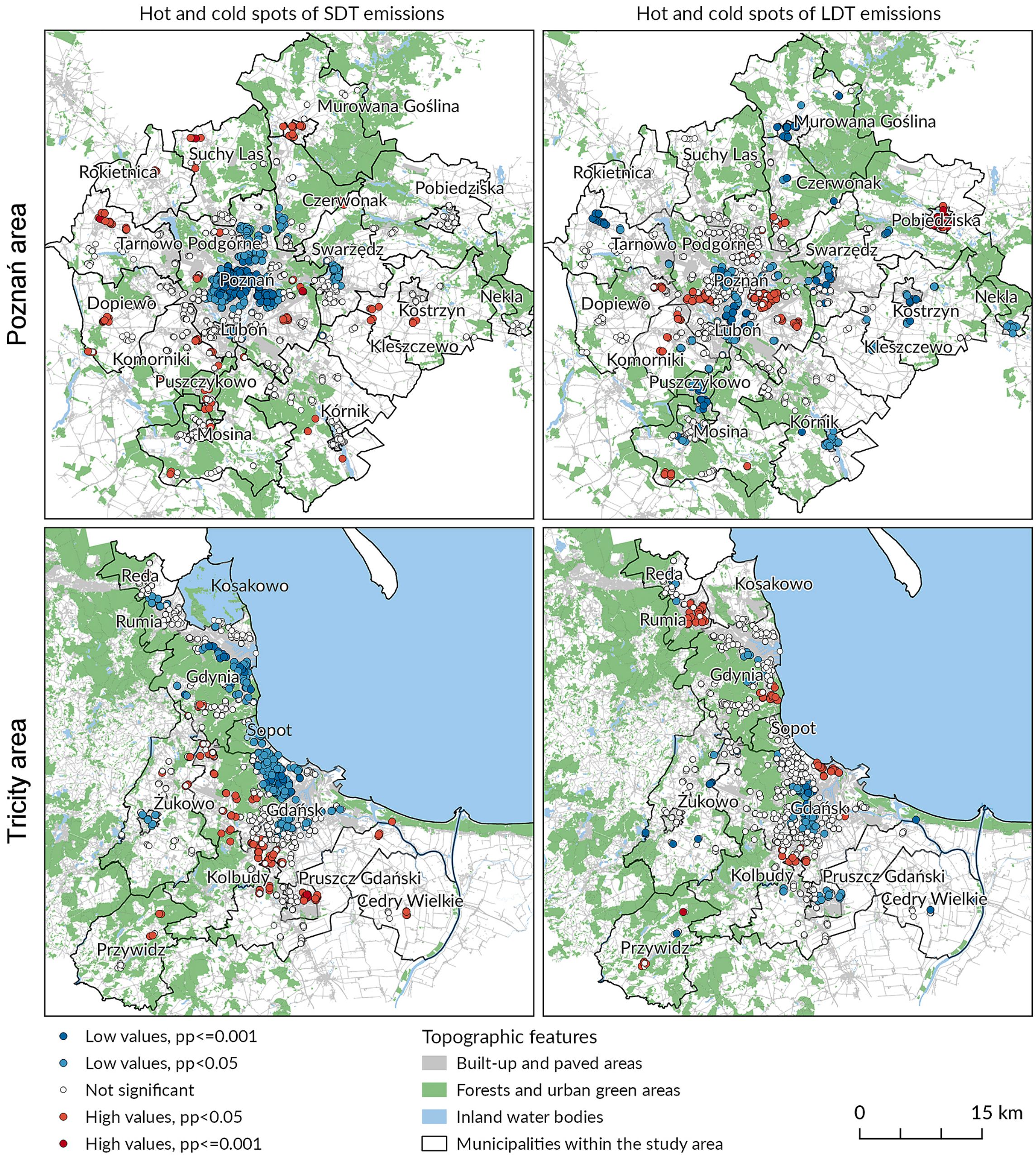

Fig. 8. Hot and cold spots of SDT and LDT emissions in the Poznań area and Tricity area were calculated with Getis-Ord Gi* method with a 2000 m distance band.

Table 2. Spearman correlation coefficients (ρ) between built environment characteristics and emissions from long- and short-distance travel.

Travel scope	Area	Distance to the closest city centre	Population density	Basic service density	Street intersection density
Short-distance travel emissions	Poznań	0.23	−0.25	−0.28	−0.24
	Tri-city	0.17	−0.10	−0.20	−0.17
Long-distance travel emissions	Poznań	−0.10	0.09	0.07	0.09
	Tri-city	−0.03	0.03	0.01	0.02

Discussion

Main findings

Our study highlights the high level and share of LDT emissions in travel emissions among the residents of two large urban areas in Poland. A high share of these emissions comes from air travel, which has the highest emission intensity of all modes and enables travel over very long distances. The high level of LDT emissions compared to SDT ones puts Poznań and Tri-city areas in line with other relatively wealthy cities and countries, where such patterns have also been reported (e.g. Aamaas, Peters 2017). In line with previous studies (Brand, Preston 2010, Czepkiewicz et al. 2019, Büchs, Mattioli 2021), we find a very high level of inequality in generating LDT emissions. The level of inequality in our sample is higher than that in the studies conducted in wealthier cities or countries and similar to the global inequalities reported by Oswald et al. (2020) for energy use. Importantly, the high carbon inequality also applies to SDT, including daily car use, which is also in line with previous research (Bel, Rosell 2017, Czepkiewicz et al. 2019, Ivanova, Wood 2020, Leroutier, Quirion 2022, Baltruszewicz et al. 2023).

Age significantly differentiates emission levels in both travel scopes. The highest difference is between people in the retirement age (above 60 years or 65 years) and the younger groups. Younger respondents emit significantly more than their counterparts in the retirement age group. In the case of SDT, the difference might be explained by a lack of daily commuting among retirees. Another possible explanation is the dominating biographical pattern, according to which people tend to buy a car when they become adults and return to public transport upon retirement. In the case of LDT, it might be due to generational differences in levels of travel-related skills (e.g. languages), financial resources, physical abilities, and dispositions. The pattern is markedly different than in, for example, the Nordic countries, where people over 60 years tend to travel abroad more frequently than younger groups (Larsen et al. 2023).

Education and income differentiate SDT and LDT emission levels, although the effect is stronger for LDT. Parents' education level affects both travel scopes but more strongly the LDT. It suggests that long-distance mobility patterns are reproduced between generations through primary socialisation, for instance, by developing travel-related skills and dispositions early in life (Mattioli 2020).

The study also indicates the important role of respondents' education level. In both SDT and LDT, better-educated people emit more than less-educated people, except for people with doctoral degrees whose SDT emissions are lower than among respondents with other higher education levels. This conclusion goes in line with other studies showing that in general, highly educated people emit more, but their SDT emissions often follow an inverted *U*-shaped curve due to a higher association with low-emitting transport modes (Santos et al., 2013, Bel, Rosell 2017). It may suggest that highly educated people are often more familiar with pro-environmental transport modes while representing a cosmopolitan profile of life activities that contributes to the higher LDT emissions. It also strengthens our previous conclusion that underlines the important role of cultural capital in affecting both travel scopes and leisure or professional activities, including international travel.

We also found significant differences in SDT and LDT emissions according to household size. In both cases, single-person households emit less than the larger households. In SDT, it is probably influenced by the increasing complexity of mobility needs in multi-person households, especially those living in the suburbs. Previous studies report similar results (Zhao et al. 2013, Xiao et al. 2017, Wu et al. 2019), although some indicate that a positive link between household size and emissions omits the effects of the economy of scale. For instance, Barla et al. (2011) found that each additional adult in the household reduces the respondents' emissions by 20% due to the shared use of household vehicles.

Contrary to some previous studies (e.g. Czepkiewicz et al. 2019), we did not find a strong spatial association of LDT emissions. There is only a very weak spatial association in Poznań. The difference between this study and the previous studies might result from differences in study design (e.g. the inclusion of all age groups, the lack of distinction between leisure and work-related travel) and study area characteristics, including different patterns of spatial sorting of people with different levels of capitals and dispositions. As for SDT, we found concentrations of people with relatively low emissions in centrally located, densely built areas with good public transport provision, such as Poznań city centre and along the fast-urban rail in Tri-city. Conversely, suburban parts of both areas registered a higher concentration of citizens with relatively high emissions levels, supposedly due to longer distances to main centres and other destinations, pro-car preferences of suburbanites, poor access to alternative means of transport, and in some cases good accessibility of ring roads. A similar spatial structure of emissions was identified in previous studies (Zhao et al., 2013, Bel, Rosell 2017, Leroutier, Quirion 2022).

Limitations and future studies

As an exploratory analysis, this study cannot conclude about associations between multiple variables. The next steps should involve partial correlations and regression analyses to assess multivariate relationships.

Furthermore, errors and uncertainties are inevitable in data collection and analysis. Several factors might have introduced uncertainty to travel distance measurement, which is the basis for our emission calculation. Firstly, using a geo-questionnaire to collect travel activity data might underestimate travel distances by omitting trips. The pollsters were instructed to collect from study participants around the five most frequently visited locations, and they captured, on average, <5 points for a participant. Less-frequent trips are thus not captured, and total distances and emission values in SDT are likely underestimated. The method may also underestimate the share of occasionally used travel modes (e.g. e-scooters and shared bikes). Future studies should consider combining geo-questionnaires with traditional travel diaries that capture all trips over a certain period (e.g. a week) or activity tracking methods (e.g. smartphones or GPS receivers) to validate the measurements.

Secondly, SDT and LDT distances were captured using different methods, and their direct comparison is uncertain. The time frame for reporting LDT was long (last 12 months), an improvement over studies that use shorter recall periods and underreport such trips. Still, the time frame might introduce recall bias and increase respondent burden, potentially leading to underestimated numbers (Mattioli, Adeel 2021). Trip distances are also based on a rough estimation from the distance band, which introduces some uncertainties (e.g. trips to locations 75 km away receive a 150 km value, and trips to locations 8000 km away receive a 4000 km value).

Thirdly, we measure SDT by capturing the *most-frequent* trips within the urban area and LDT by capturing *all trips* away from the urban area at least 50 km from home. Such a setting might have led to the omission of some infrequent trips within the urban area or close to it but <50 km from home (e.g. weekend trips to a nearby forest or a lake for leisure purposes), captured neither by SDT nor LDT measure. Furthermore, trip frequencies are also prone to over- or underestimation. For example, if someone visits a place two times a week, it translates to 72 trips per year, and if they visit it three times a week, it translates to 168 trips per year. Nevertheless, these uncertainties should not significantly influence the analyses presented in this study.

Fourthly, the question about LDT was preceded by a yes/no filter question about travelling away from the urban area. The negative answer allowed pollsters to skip questions about trip frequency and shortened the time required to complete the questionnaire. Some pollsters chose this option when respondents did, in fact, travel and created false zeros in trip frequencies and distances. We have screened the database for this fraud and deleted suspicious answers, but there still might be some errors in the data, and the share of people with zero LDT emissions is likely overestimated. Because of these reasons, the total emission levels are likely underestimated. Direct comparisons between SDT and LDT emission levels should also be taken cautiously. Analyses presented in this article did not distinguish between private and business travel, reducing their comparability with similar studies.

There are also uncertainties in estimating emission factors. Unlike CO_2, estimating the non-CO_2 effects on global warming potential is highly uncertain (Lee et al. 2021), and the results are reported separately. Emission factors are strongly influenced by load factors (i.e. the average number of passengers). The average load of private cars (1.64) was likely overestimated by survey participants (other travel surveys typically report an average load of 1.5), and SDT emissions are likely underestimated. There are also inevitable uncertainties and simplifying assumptions in other emission factors, including the load factor of buses, trains, and planes.

Takeaways for policy

LDT comprises a high share of total travel emissions in Poznań and Tri-city areas. Even though a direct comparison between SDT and LDT is uncertain in our dataset, the results suggest that climate change mitigation policies should devote more attention to LDT. Urban sustainability and mobility policies focus on SDT, and aviation is often considered out of scope, even though cities are important sources of both incoming and outgoing traffic (Heinonen, Czepkiewicz 2021). The high inequality of LDT emission levels and their correlation with economic and cultural capital suggests that introducing taxes on air travel might be progressive (i.e. they would put the fiscal burden on the privileged and not on the disadvantaged). Still, the influence of potential policies on vulnerable groups, such as migrants, should be carefully considered.

Regarding SDT, our results confirm earlier studies that connect residential location relative to main centres and neighbourhood characteristics with daily travel activity and emissions (Ewing, Cervero 2010, Naess 2012, Stevens 2017). In our sample, SDT emission levels are markedly lower in centrally located, densely populated locations with good local accessibility of services and dense street networks. Even though our study design did not allow us to account for the role of attitudes in the relationships, the results add to the vast literature on the importance of compact city policies to emission reduction policies. Importantly for the public debate on urban transportation policies, people with high economic and education status generate higher SDT emission levels than other groups. It suggests that policies restricting car use in large urban areas like Poznań and the Tri-city would primarily burden high-status groups. However, it is uncertain how such policies may impact people with low levels of resources who still require a car for daily work and errands, and it should be the subject of future research on the topic.

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Author's contribution

M.C. supervised the project, conceptualised the study, carried out spatial statistical analyses, prepared maps, and contributed to the literature review, data preparation, and writing and editing of all sections. C.B. carried out bivariate statistical analyses, prepared charts, and contributed to data preparation and writing the results section. D.K. and F.S. contributed to the literature review, data preparation, and writing introduction and discussion sections. All authors contributed to questionnaire design, study design, and article writing.

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Appendix

Table A1. Estimation of yearly travel frequency based on survey answers.

Answer options	Yearly trip number
Less than once a month	10
1–3 times a month	24
1–2 times a week	72
3–4 times a week	168
5 times a week or more	240

Table A2. Estimation of trip distance based on distance bands.

Distance band [km]	Numeric value
50–200	125
201–500	350
501–1000	750
1001–3000	2000
>3000	4000

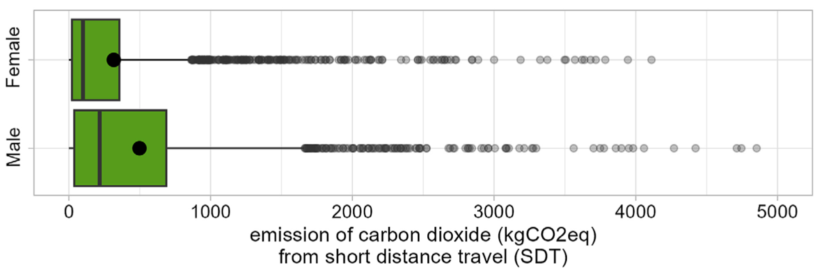

Fig. A1. CO_2 emissions from short-distance travel in main gender groups (N = 3699, $\rho = -0.15$, $p < 0.001$).

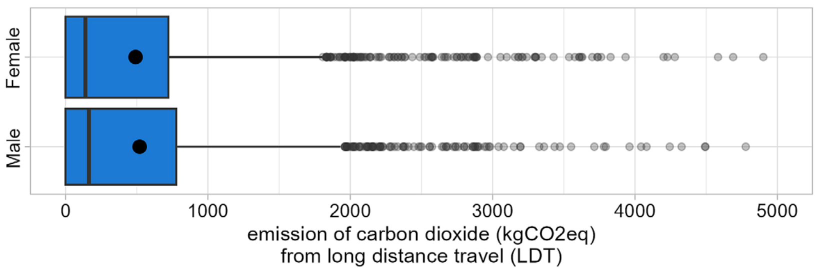

Fig. A2. CO_2 emissions from long-distance travel in main gender groups (N = 3746, ρ insignificant, $p > 0.05$).

Table A3. Emission factors for short-distance travel modes.

Travel mode	Vehicle type	Emission coefficient	Fuel use		Fuel WTW carbon intensity		Electric energy use		Electric energy carbon intensity		Average load		
		[kg CO_2 · pkm^{-1}]	[l · 100 km^{-1}]	Source	[kg CO_2 · l^{-1}]	Source	[kWh · 100 km^{-1}]	Source	[kg CO_2 · kWh^{-1}]	Source	[pax]	Source	Assumptions
Private car	Gasoline ICEV	0.164	7.16	Survey average weighted by travel distance	3.016	(Prussi et al. 2020)					1.64	Survey answers	
	Diesel ICEV	0.197	7.08		3.484								
	LPG ICEV	0.116	7.64		1.876								
	HEV	0.145	6.65		3.016								
	PHEV	0.142	6.68		3.016		18.2	Survey average weighted by travel distance	0.792	(KOBiZE 2022), adjusted using Scarlat et al. (2022) method			Share of electric drive: 50%
	BEV	0.092					17.3		0.792				
	Weighted average	0.169										Weighted by travel distance	
Tram or bus	Diesel bus	0.081	42	MPK	3.484	(Prussi et al. 2020)					18	MPK	Share of electric buses in bus performance: 8% Share of buses in transport performance: 50%
	Electric bus	0.067					152	MPK	0.792			MPK	
	Tram	0.064					289	(Krych 2019)	0.792		36	(Krych 2019)	
	Weighted average	0.072											
Urban train	Urban train (Poznań)	0.084					740	(Jakubowski et al. 2018, 2016)	0.792		70	UTK	EN57 train Average load from KW and Polregio
	Urban train (Tricity)	0.039					740		0.792		150	UTK	EN57 train average load in SKM and PKM
E-bike or e-scooter	E-bike	0.005					0.6	(Weiss et al. 2020)	0.792		1		Share of e-bikes: 50%
	E-scooter	0.011					1.4		0.792		1		
	Weighted average	0.008											

MPK – own calculations based on 2021 operational data provided by Miejskie Przedsiębiorstwo Komunikacyjne w Poznaniu (unpublished).
UTK - own calculations based on 2022 operational data published by Urząd Transportu Kolejowego (UTK, 2023).
KW – Koleje Wielkopolskie.
SKM – Szybka Kolej Miejska w Trójmieście.
PKM – Pomorska Kolej Metropolitalna.

Table A4. Emission factors for long-distance travel modes (data of the UTK 2023 for Polregio and PKP Intercity railway carriers).

Travel mode	Vehicle type	Distance band(s)	CO_2 emission coefficient [kg $CO_2 \cdot$ pkm^{-1}]	CO_2 emission coefficient [kg $CO_2 \cdot$ vkm^{-1}]	CO_2 emission coefficient Source	non-CO_2 emission coefficient [kg CO_2eq $\cdot$ pkm^{-1}]	non-CO_2 emission coefficient RFI factor	Average load or utility factor [pax]	Average load or utility factor [%]	Average load or utility factor Source	Other assumptions and sources
Car		All	0.124	0.223	(IEA 2023)	NA		1.8	NA		
Train	Average	50–200 km	0.068		Own estimation based on fuel and energy consumption in commonly used trains			73		UTK – Polregio	75% share in performance, EN57
	Diesel		0.031	5.859							25% share in performance; railcar – 65.8 l/100 km of diesel fuel
	Electric		0.080	2.294							Polish electricity, KOBiZE (2022) adjusted with Scarlat et al. (2022) method
	Electric	201–1000 km	0.053	11.084				209		UTK – PKP Intercity	
	Electric	>1001 km	0.022	4.676							European electricity (Scarlat et al., 2022)
Ferry		50–200 km	0.415		(Czepkiewicz et al. 2018c)						
		>200 km	0.238								
Bus		50–1000 km	0.073		(Mantzos et al. 2018)						
		>1001 km	0.067		(Doll et al. 2020)						
Plane		50–200 km	0.699		Own estimations based on Knörr and Hüttermann (2016)	0.000	1.0		71		Fuel use per seat-km from Knörr and Hüttermann (2016) Kerosene WTW emissions from Jing et al. (2022)
		201–500 km	0.348			0.000	1.0		71		
		501–1000 km	0.209			0.119	1.6		75		
		1001–3000 km	0.151			0.143	2.0		75		
		>3000 km	0.133			0.213	2.8		80		