Cities 160 (2025) 105818

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Crime-associated inequality in geographical access to education: Insights from the municipality of Rio de Janeiro

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ARTICLE INFO

Keywords:
Inequality
Crime
Simulation
OpenRouteService
Educational access
GeoAI
Rio de Janeiro

ABSTRACT

Education is a fundamental right, supported by initiatives like Education for All (EFA) and the Millennium Development Goals (MDGs). Despite progress, full educational access remains challenging, particularly in highly criminal areas.

This paper examines the impact of crime on school access in the municipality of Rio de Janeiro. Using ancillary data and geospatial artificial intelligence (GeoAI), we downscaled official police crime records to street level. By considering different levels of crime tolerance in school path choices, we simulated how crime can force students to walk longer distances to avoid violence.

Our findings indicate a 48.60 % average increase in travel time to the closest school for students whose shortest routes intersect with high-crime areas. This adjustment reduces mean crime exposure by 44.10 % and maximum exposure by 81.94 %. Both individual crime risk aversion and no-go areas of criminal disputes significantly ($p \leq 0.05$) impacted educational access. Estimating street-level crime exposure was challenging due to spatial bias in official and crowdsourced crime reporting.

These methods and insights are crucial for improving educational access in high-crime areas, providing a better understanding of barriers to equitable education, and being applicable to other cities and accessibility studies for various societal needs.

1. Introduction

Education is recognized globally as a fundamental human right and a key to fostering equality, eradicating poverty, reducing crime, and supporting sustainable development (United Nations, 2015; United Nations Educational, Scientific and Cultural Organization, 2014).

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https://doi.org/10.1016/j.cities.2025.105818
Received 1 August 2024; Received in revised form 16 January 2025; Accepted 11 February 2025

Article 26 of the Universal Declaration on Human Rights underscores the inalienable right to education for all (United Nations, 1948). Despite significant global strides, 244 million children and youth still face barriers to education access due to persistent social, economic, cultural, and security-related obstacles (UNESCO, 2022). Education can serve as a transformative force, offering individuals a pathway to social mobility and labor market access by increasing legitimate employment opportunities and wages, thereby diverting youth from criminal activity (Lochner, 2020). However, social disparities often create barriers to accessing quality education, resulting in a cyclical effect where these disparities are perpetuated, as high crime rates and socioeconomic inequalities limit educational opportunities, which in turn contribute to further social inequality and crime (UNESCO, 2022).

Among OECD countries, Brazil ranks 38th out of 44 in educational participation for children under 14 years old (OECD, 2024), contradicting the rights ensured by Brazil's Federal Constitution, which guarantees free education from early childhood to tertiary education (OECD, 2021). Brazil has made significant strides in reducing its Gini index from 63 in 1989 to 52 in 2022 through expansions in educational attainment (OECD, 2021; World Bank, 2024a). This improvement is partly due to initiatives like the Bolsa Família, a conditional cash transfer program that reduced poverty by 15 % and extreme poverty by 25 % (de Souza et al., 2019) and has had a significant effect on school attendance, reducing dropout and abandonment rates (Santos et al., 2019). The Bolsa Família program has also contributed to significant crime reductions (Chioda et al., 2016), addressing inequalities worsened by drug trafficking and urban gang violence. However, high crime rates in urban areas still pose a significant barrier to school attendance and access, impacting students' safety and their ability to engage in educational activities. Therefore, creating opportunities for education in such environments remains essential to breaking this cycle and further reducing social inequality and crime in Brazil.

Most Brazilians (88 %) live in urban areas (World Bank, 2024b), where access to education can vary significantly, resulting in educational disparities between regions and schools (Rodrigues et al., 2020). Socioeconomic status significantly affects educational opportunities, sometimes compelling children from impoverished families to forgo schooling in favor of contributing labor to the household (Fast, 2020; Ferrão & Alves, 2023). Additionally, settlement patterns and structures, including the uneven distribution of schools and educational resources, often disadvantage certain neighborhoods (Curtis et al., 2015). Numerous studies have reported disparities in geographical access to education due to inadequate public transportation, infrastructure deficiencies, cultural barriers that discourage certain groups, such as girls, from attending school, and safety concerns (Afoakwah & Koomson, 2021; Andersson et al., 2012; Bautista-Hernández, 2023; Ermagun & Samimi, 2018; Lee et al., 2013; Mandic et al., 2023; Mitra & Buliung, 2015). High crime rates in urban areas can further exacerbate educational access issues, deterring students from attending school and influencing their transportation choices (Appleyard & Ferrell, 2017; Chen et al., 2018; Mitra & Buliung, 2014; Patil et al., 2024; Wiebe et al., 2013). Dangerous and disruptive violence incidents, including street gun battles, may force students to seek safer modes of transportation, which not all can afford, leading to social exclusion and curtailed academic goals. There is evidence that exposure to violence on the school path leads to absenteeism, particularly when the routes traveled require walking through streets with higher rates of violent crimes (Burdick-Will et al., 2019; Burdick-Will et al., 2021). In the 2019 National Survey of School Health (PeNSE), which interviewed 11.8 million students from the 7th grade of primary education to the 3rd grade of secondary education, 11.6 % of students reported discontinuing school attendance due to safety concerns during their commute. The percentage was twice as high for public school students compared to their private school counterparts. This issue was most pronounced in the state of Rio de Janeiro, where 17.6 % of respondents - the highest percentage recorded in the survey - missed at least one day of school in the last 30 days due to concerns about their commute (Instituto Brasileiro de Geografia e Estatística (Ed.), 2022). Moreover, most studies on access to education, employment opportunities, and public services use traditional routing models that focus solely on finding the shortest path routes, ignoring key local context information such as the spatial distribution of urban crime (Ermagun & Samimi, 2018; Pereira, 2018). Despite advances in routing-based simulations to analyze cumulative access to opportunities, a research gap remains in studying crime-associated inequalities in urban accessibility.

This study aims to address the gap by analyzing the extent to which crime in the municipality of Rio de Janeiro influences inequalities in geographical access to education. Initially, official crime statistics (Instituto de Segurança Pública, 2024; Ministério Público do Estado do Rio de Janeiro, 2024) and the locations of past shootings registered by the crowdsourced data platform "Fogo Cruzado" (Cruzado, 2024a) were downscaled to the street level. In this process, ancillary data, including street view imagery and GeoAI, was employed to derive perceptual crime-safety scores at the street level, which were then used to refine and spatially disaggregate police crime records. The refined data were incorporated into routing-based simulations using OpenRouteService (ORS) (HeiGIT gGmbh, 2024a; HeiGIT gGmbh, 2024b) to model school routes that avoid high-crime areas and quantify cumulative travel time differences to the closest schools in relation to crime patterns. Various crime weight factors were implemented in routing to analyze variations across different individual crime aversion levels. The study focused on pedestrian walking, as many low-income children use active transportation on their way to school and not all have access to motorized transportation options like private automobiles or public transport. By conducting these analyses, we seek to inform urban planners about critical intervention points, thereby facilitating steps towards equal access to education and its associated sustainable socioeconomic benefits (Bell et al., 2022; Lochner, 2020). Specifically, we seek to answer the research question: "To what extent does crime potentially inhibit geographical access to schools, measured by cumulative average travel time?" Answering this question can inform policies aimed at achieving the United Nations Sustainable Development Goals (SDGs), particularly Goal 10: Reduced Inequalities, and Goal 4: Quality Education. More broadly, it can promote more inclusive cities and reduce inequalities in access to opportunity.

2. Related work

This study builds on two primary research areas: street-level crime modeling and the integration of crime patterns into routing and educational accessibility analyses.

2.1. Street-level crime modeling

High-resolution crime modeling has become essential in criminology, as research increasingly seeks to capture and predict crime patterns at finer spatial scales. However, data protection policies and privacy constraints often restrict crime data to anonymized, aggregated forms, limiting their effectiveness for localized analyses in urban planning, public safety, and targeted resource allocation (Herrmann, 2013). Consequently, much of the existing literature has focused on modeling crime at administrative levels, such as police units, employing a range of datasets and computational techniques (He & Zheng, 2021; Jing et al., 2024; Kang & Kang, 2017). In contrast, few studies have attempted to downscale crime data to the street level, where analysis is often constrained by the lack of high-resolution, ground-truth data.

The emerging availability of high-resolution geospatial data, offers new opportunities to refine crime modeling at finer scales. Instead of relying solely on crime incident interpolation (Chen et al., 2024; Kim et al., 2023) or spatiotemporal probability estimates based on historical data (Garcia-Zanabria et al., 2022), recent studies have integrated detailed street-level features. Such contextually enriched models can better account for the factors underlying crime distribution and may provide more robust, forward-looking insights into potential hotspots, particularly as urban environments evolve. For instance, Musah et al. (Musah et al., 2020) developed a predictive model for residential burglary risk by integrating factors such as street accessibility, road segment length, and business density within a negative binomial Poisson regression framework, producing a spatially explicit map of burglary risk predictions at the street level. Andersson et al. (Andersson et al., 2017) leveraged street-level imagery and a 4-Cardinal Siamese Convolutional Neural Network (4-CSCNN) to classify areas into high- and low-crime clusters, illustrating the potential of CNNs in crime prediction. Expanding on this, Kang et al. (Kang et al., 2023) employed deep learning to produce a numerical safety score for each street segment based on perceptual cues from street view imagery. While these approaches offer valuable insights reflecting survey data, they have not yet been applied to downscale official crime records to the street level, highlighting a research gap in utilizing such street-level features to enhance crime risk predictions.

2.2. Crime-conscious routing for accessibility studies

Pedestrian routing applications typically prioritize distance or travel time when generating route suggestions (Siriaraya et al., 2020). However, growing evidence highlights the value of incorporating additional factors into routing algorithms, such as greenery along routes (Ludwig et al., 2021), preferences for quieter (Novack et al., 2018) or less polluted pathways (Luo et al., 2018; Sharker & Karimi, 2014), safer routes (Garvey et al., 2016; Goel et al., 2017), and paths through socially active areas (Nishimura et al., 2016; Novack et al., 2018). Research consistently shows that individuals are often willing to take longer routes to satisfy various personal preferences and needs (Salazar Miranda et al., 2021; Shatu et al., 2019).

The integration of crime risk into routing analysis has garnered substantial attention in urban studies, particularly in high-crime environments. Numerous studies have examined how crime levels influence individual routing decisions (Alpkoçak & Cetin, 2020; Byon et al., 2010; Galbrun et al., 2016; Kaur et al., 2021; Levy et al., 2020; Mata et al., 2016), with additional research emphasizing the necessity of modeling realistic route-choice behaviors rather than relying solely on optimal, shortest-path assumptions when evaluating accessibility (Lima et al., 2016). For instance, Sullivan et al. (Sullivan et al., 2017) have demonstrated that individuals navigating insecure environments often prioritize personal safety over travel efficiency, highlighting the critical role of perceived security in route selection. Similarly, Kaur et al. (Kaur et al., 2021) found that individuals with higher crime risk aversion are more willing to accept longer detours to minimize exposure to crime. However, while longer detours may enhance perceived safety, they can also become burdensome, particularly when they significantly extend travel time or distance. Therefore, an effective crime-conscious routing algorithm must balance crime exposure reduction with route efficiency to ensure a practical and user-friendly experience. Incorporating adjustable detour limits based on individual crime risk aversion could enhance the system's flexibility, making it more appealing not only to vulnerable populations but also to a broader range of users.

To the best of our knowledge, this study is the first to integrate street-level crime data into a routing-based accessibility analysis that explicitly accounts for varying levels of crime risk aversion. Although prior research has explored the relationship between urban crime and accessibility at broader administrative scales (Setiawan et al., 2019; Tung et al., 2018), few studies have utilized advanced routing engines to incorporate crime-conscious decision-making into street-level accessibility models. While this research specifically addresses educational access for adolescents, the proposed framework offers a scalable and adaptable approach for broader accessibility studies centered on crime safety considerations.

3. Materials and methods

Here we propose a novel method to quantify the impact of urban violence on access to opportunities and demonstrate the proposed workflow in a case study of access to education in the municipality of Rio de Janeiro (cf. Fig. 1). The first step involved downscaling official police crime statistics to a 200 m grid using ancillary data on social inequality, perceptual safety, and armed groups, with a priori expectations of influencing urban crime patterns. Second, this data, along with the locations of past shootings and the road network, was used to estimate a crime index at the street level. Third, the estimated street-level crime index and the locations of dispute areas were utilized to perform crime-conscious pedestrian routing, thereby quantifying geographical accessibility to schools, measured by cumulative average travel time, and addressing the research question. Before we present each methodological step in detail, we present the context of the case study region and our data sources in the next subsections.

3.1. Case study region

The municipality of Rio de Janeiro was chosen as our study area because it remains one of the most dangerous megacities in South America (Hirata et al., 2022) (cf. Appendix B). Researchers have described crime in the municipality of Rio de Janeiro as akin to an armed conflict or war (Muggah, 2017), featuring a high degree of armed violence that often draws in the police and uninvolved locals, and is often discussed in conflict-evoking terms, particularly regarding drug trafficking (Grillo, 2019; Hirata & Grillo, 2019). Experts cite poor conditions and inequality in state institutions such as schools as contributors to the cycle of crime and violence (Camargo et al., 2021) as well as Brazil's population of young men, generally rampant inequality, drug use, weapon access (Murray et al., 2013), and economic woes (Britto et al., 2022).

Not only is crime an issue, but police responses may exacerbate the problem through an "outrageous" number of civilian deaths (Ford, 2022), especially for racial minorities, in official statistics. Injunctions to limit the number of police raids even reduced civilian and police deaths (Hirata et al., 2021), as most raids target stolen goods and respond to robberies rather than address Rio's violent drug trafficking enterprises (Grillo & Martins, 2020). Police special operations routinely result in "unpredictable urban battles against armed criminals", halting normal life functions such as schools, work, and even hospital operations (Hirata et al., 2022). In this context, Brazil has experienced an expansion of milícias, which are armed criminal groups known for drug trafficking and extortion rackets (Fahlberg & Vicino, 2016). These groups are sometimes praised for maintaining some level of tranquility in otherwise routinely violent neighborhoods (Hirata, 2022). Unlike gangs, they tend to be partially composed of former or off-duty policemen and politicians (Riccio & Skogan, 2017), blurring the distinction between the enforcers and contravenors of law and order. Due to these unique features of Rio's urban crime, the city represents a compelling case study region for simulating and analyzing how crime shapes access to public services like education. Further insights into the facets of crime in the municipality of Rio de Janeiro are provided in Appendix C.

3.2. Crime statistics

Our data on crime statistics come from three inputs: (i) official crime statistics collected at the police unit level, (ii) crowd sourced data on locations of reported shootings, and (iii) the areas of current dispute between armed groups.

The official police statistics, collected at 21 police units between January 2003 and October 2023 (Instituto de Segurança Pública, 2024; Ministério Público do Estado do Rio de Janeiro, 2024), contained data on various types of crimes, including homicides, theft, robberies, and drug trafficking (cf. Appendix D). This crime data was compiled from

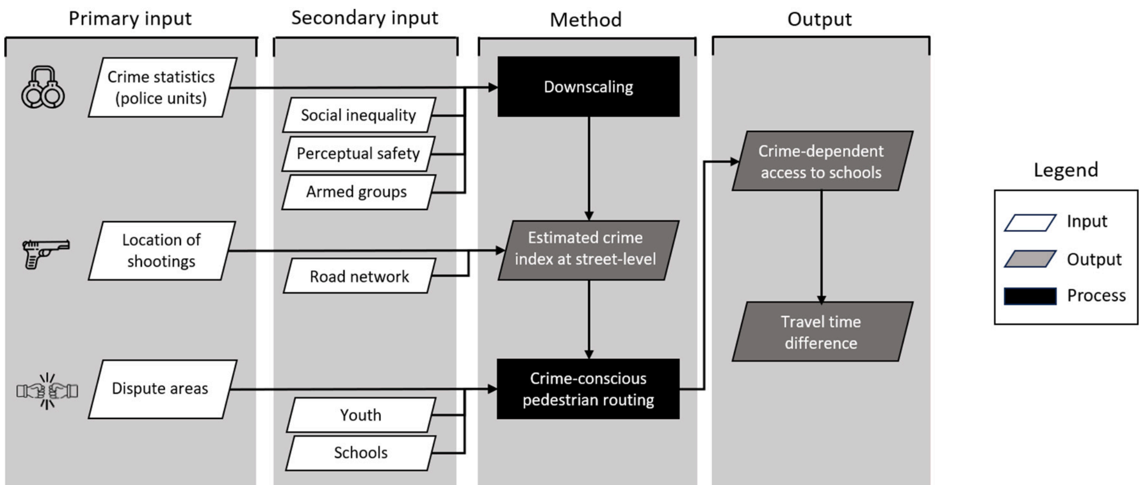

Fig. 1. Methodology for assessing how urban crime impacts travel time to schools. A schematic workflow illustrating the downscaling process of crime statistics to a 200 m grid using ancillary data is given in Appendix A.

police reports filed at Rio de Janeiro State Civil Police Secretariat (SEPOL) stations and complemented with State Military Police (SEPM) information. Data quality control was provided by the General Police Inspectorate (CGPOL) of the State Civil Police Secretariat. Due to the infrequency of some types of crimes, not all crime types were considered equally in our analysis, recognizing their potential to influence the sense of street-crime safety among pupils in urban areas in various ways.

The location of past shootings registered by the crowdsourced data platform “Fogo Cruzado”, spanning from May 7th, 2016, to October 1st, 2023, were gathered from the openly accessible Fogo Cruzado API (Cruzado, 2024a). This dataset comprised 24,215 point coordinates on armed violence, averaging 9.2 daily records. The downloaded data contained attributes detailing crime types, gender, and age distribution of victims. Among the included crime types were: “attempted robbery”, “homicide”, “dispute”, “execution”, “attack on civilians”, “cargo robbery”, “fight”, “street robbery”, and “police operation”. However, 64.01 % of the records remained unclassified. In total, 7681 fatalities were reported (cf. Appendix E).

Areas of dispute between armed groups, identified by research institutes of local crime investigation in the municipality of Rio de Janeiro (Grupo de Estudos dos Novos Ilegalismos Universidade Federal Fluminense, 2024; Defensoria Pública do Estado do Rio de Janeiro, 2024; FAU-UPS, 2024; Instituto Nacional de Ciencia e Tecnologia - UFRJ, 2024; NEVCU-UFRJ, 2024; NEV-USP, 2024; Núcleo de Pesquisas em Cultura e Economia, 2024; Redes da mare, 2024), were made available upon request by Fogo cruzado for the year 2019 (Cruzado, 2024b; Hirata et al., 2022) (cf. Appendix F.9). These areas are characterized by a high potential for sudden violent eruptions involving either criminal actors or confrontations between organized criminal groups and law enforcement agencies. Such incidents pose significant risks to civilians residing in or transiting through these neighborhoods. In disputed areas, the threat of crossfire compels residents to remain indoors, resulting in a cessation of public activities. Armed groups, including police forces, engage in conflicts over territorial dominance, governance, and control within these regions (Fig. 2).

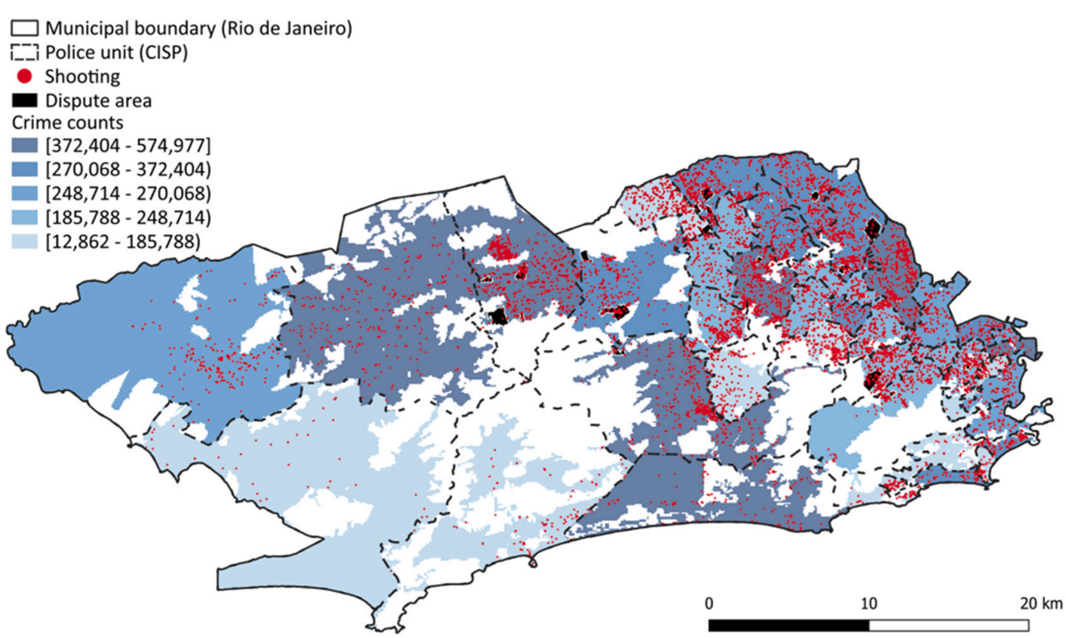

Fig. 2. Official crime statistics, location of shootings, and dispute areas. Areas with no population, including steep regions of rainforest, are shown in white.

3.3. Methods

3.3.1. Street-level crime index

To downscale the collected crime statistics from police unit to street level, we employed a downscaling approach similar to dasymetric mapping (Eicher & Brewer, 2001), a geospatial technique aimed at enhancing the accuracy of thematic maps by using higher resolution auxiliary data - such as land-use information - to downscale aggregated population data. In our study, we assumed that crime incidents do not occur uniformly within each police unit and that ancillary data on social inequality, perceptual crime-safety, and location of armed groups are associated with the spatial occurrence of crime in urban settings.

Based on these assumptions, we first downscaled official crime statistics to a 200 m grid utilizing the ancillary data. The hyperparameter of 200 m was chosen for the experiment because it balances the need for detailed spatial resolution necessary for routing with the practicality of data management, allowing for more granular analysis of crime patterns while maintaining a manageable dataset size. To achieve this downscaling, crime data was spatially disaggregated using ancillary datasets, ensuring alignment with official records at the administrative level. During this process, all crime types and each ancillary indicator were given equal consideration. The downscaling formula for allocating crime counts from each police unit j to individual grid cells A_i, indexed by i, is defined as follows:

$$T_{i,j} = w_{i,j} \cdot \frac{1}{n_j} \cdot T_j \quad \forall j \in J \tag{1}$$

$$\sum_{i=1}^{n_j} w_{i,j} = 1 \quad \forall j \in J \tag{2}$$

where:

- $T_{i,j}$ represents the estimated crime count for grid cell $A_{i,j}$ within police unit j,
- $w_{i,j}$ denotes the weight applied to grid cell $A_{i,j}$, derived from ancillary data to capture the relative likelihood of crime occurrence,
- n_j is the total number of grid cells allocated to police unit j, with each grid cell assigned to the police unit containing the majority of its area,
- T_j represents the total recorded crime incidents within police unit j.

Subsequently, we applied zonal statistics utilizing the 200 m downscaled official crime numbers and 10 m OpenStreetMap (OSM) road segment buffers to estimate the crime index at street level (cf. Fig. 3). The number of shootings within OSM road segments was added as an additional indicator of the crime. Shootings and the crime statistics collected for police administration units were weighted equally to model a street-level crime index. The formulas for street-level crime index C_k is given by:

$$C_k = \frac{1}{2} \times \mathcal{N}\left(\sum_{i \in G_k} T_{i,j} \right) + \frac{1}{2} \times \mathcal{N}(S_k) \quad \forall k \in K \tag{3}$$

where:

- C_k denotes the street-level crime index for street segment k,
- $\sum_{i \in G_k} T_{i,j}$ represents the aggregate of downscaled crime totals for all grid cells in the set G_k, comprising those cells intersecting the buffered area of road segment k,
- S_k indicates the total count of shooting incidents recorded within the 10 m buffer surrounding street segment k,
- $\mathcal{N}(\cdot)$ denotes min-max normalization, applied to scale values between zero and one.

The resulting street-level crime index C_k was normalized between zero and one using min-max scaling, as required by the routing engine, where a value of one represents high crime and a value of zero represents low crime. A detailed description of applied ancillary data for the downscaling of the official police records to the 200 m grid is provided in Appendix F. For simplicity, the islands within the municipality of Rio

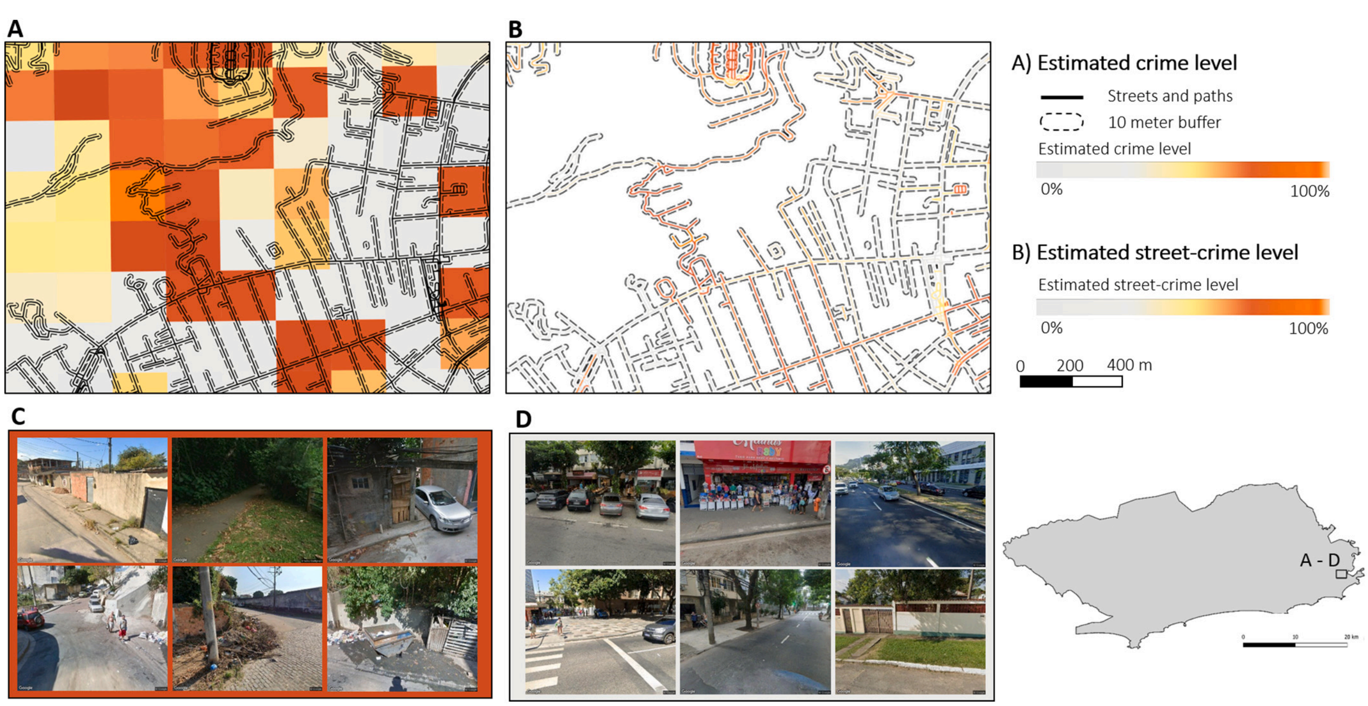

Fig. 3. Panel A and B illustrate an example of the downscaling process of the estimated crime index from a 200 m grid to street level. Zonal statistics were applied using a 10 m buffer for each OSM road segment. A perceptual crime-safety score derived from street view imagery was utilized to refine official police records. This involved employing a deep neural network to extract perceptual crime-safety features from street view images, including elements such as safety fences, street lights, busy areas, and trash, which influence perceived crime safety. A perceptual crime-safety score was calculated for each image. Panel C displays images where individuals might feel more unsafe compared to the street view images in Panel D. ©2023 Google.

de Janeiro were excluded from the study area.

A crucial component of our street-level crime index refers to safety perceptions derived from street view images. Beyond purely measuring physical dimensions of crime-related activities, incorporating human subjective safety perceptions comprehensively incorporates the human dimensions into our crime indices. To accomplish this, we downloaded over 400, 000 street view images using the Google Street View Static API. To measure safety perceptions of these images, we utilize a pre-trained deep convolutional neural network that has been trained on the expansive Place Pulse dataset. This global dataset has collected more than one million ratings regarding perceptions on street view images worldwide, and has been widely used for understanding human perceptions of environment. With advanced deep learning methods, we derive safety perception scores on a scale from 1 to 9, with 9 representing the highest level of safety perceptions. This allows us to quantitatively assess and compare the human safety perceptions of different urban environments within the street view imagery. This methodology has been widely in several prior studies such as Dubey et al. (Dubey et al., 2016) and Zhang et al. (Zhang et al., 2018). For a more detailed discussion of the technical aspects of this approach, including the specific algorithms and validation processes used, please refer to Appendix F.2.

3.3.2. Crime-conscious pedestrian routing

For the crime-conscious pedestrian routing, we utilized the ORS, an open-source routing engine that operates on OSM road network data (HeiGIT gGmbh, 2024a; HeiGIT gGmbh, 2024b). The ORS offers various services, including the calculation of shortest and fastest origin-destination paths for different transportation modes, such as biking, walking and driving. To find the optimal route between two points efficiently, different routing algorithms are implemented in ORS. This optimization problem is solved by the classical Dijkstra algorithm (Dijkstra, 1959) or by speed-up alternatives such as A* (Hart et al., 1968) or Contraction Hierarchies (Geisberger et al., 2008) - depending on the constraints of the routing problem the best algorithm is automatically selected by the ORS. In this study, we use the walking profile for routing, which considers OSM-tagged road attribute features, such as road type, access restriction, and obstacles, such as barriers or traffic signals. Transportation via ferries was avoided for simplicity. We chose walking as it is a form of active travel mode that does not exclude certain groups, acknowledging that not all people have access to motorized transportation modes like public transport or cars (Kotoula et al., 2021). In addition, this approach seemed particularly relevant when modeling the mobility of students. For the heuristic calculation of the shortest path for pedestrians, the cost function of the ORS is expressed as follows:

$$C(P) = \sum_{s \in P} l_s \tag{4}$$

where:

- P is a path consisting of a sequence of OSM road segments $(s_1, s_2, \ldots, s_n)$,
- s represents an OSM road segment along the path P,
- l_s represents the length in meters of the OSM road segment s.

In our case study, we adapted the default cost function for shortest-path pedestrian routing with a penalty function that captures the crime risk to model more realistic routing choices in the urban crime context. We modified the cost function of crime routing C_{crime} for the path P as follows:

$$C_{crime}(P) = \sum_{s \in P} (\alpha \cdot c_s{}' + l_s{}') \tag{5}$$

where:

- c_s' is the scaled crime index of the road segment s, where 1 represents high crime and 0 represents low crime,
- l_s' is the scaled length of the road segment s, scaled to a range of [0,1] where the longest segment in the dataset is scaled to 1 and the shortest to 0,
- α is a crime weight factor controlling the influence of the crime index on the routing choice, with possible values $\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$.

This cost function considers both the scaled length of OSM road segments and the scaled estimated crime index, with the weighting factor α ranging between 0.1 and 1 and adjusting for the trade-off between minimizing road length and avoiding high-crime streets. A higher weighting factor potentially results in a safer but also longer path. A lower weighting factor potentially leads to smaller detours but higher crime exposure. Of course, the actual route depends on the available alternatives: if all road segments are similar with respect to crime exposure, the weighting factor will have no influence on the route optimization. A multiplication-based cost function approach was chosen because the crime index represents an intensity value. An illustrative example of a short walking route compared to a crime-conscious walking route to the closest school is visualized in Appendix G.

In addition, to incorporate the estimated street-level crime index as a soft routing constraint into the ORS, we excluded road segments that intersect with dispute areas - identified as zones of high criminal exposure (cf. Fig. 2) - from our routing graph, applying these exclusions as hard constraints in routing decisions. Consequently, youth living within these conflict areas were not considered in the routing analysis, as it is assumed that residents in these areas prefer to stay at home for safety reasons. As a result, these individuals were assigned a NaN (not a number) value for school accessibility, reflecting their exclusion from the routing model. This affected 44,117 students, which represents 3.76 % of all youth in the municipality of Rio de Janeiro.

3.3.3. Crime-conscious access to closest school

To address our research question regarding the extent to which crime impacts access to schools, as measured by average travel time, we considered 1412 private and public schools geolocated in OSM, spanning levels one to three according to the International Standard Classification of Education (ISCED). To model different levels of risk aversion towards crime, we simulated ten different crime weight factors for our estimated crime index within the adapted cost function for routing (cf. Formula 6). The higher the crime weight factor, the safer and potentially longer the school path is expected to be, assuming there are significant variations in crime levels across different routes. However, if crime is uniformly distributed within a region, the crime weight factor will have minimal impact on routing decisions. For the routing, we sampled 20,943 origin locations, represented by the centroids of our 200 m crime index grid. Each origin was weighted by the number of children and adolescents (aged 5–19 years) residing in the corresponding grid cell. These population counts, retrieved from the WorldPop database (Tatem, 2017), summed to a total of 1,172,758 for the entire municipality of Rio de Janeiro. For each origin, the shortest path and ten crime-conscious paths - for different crime weight factors - to the closest school were calculated. This resulted in 230,373 ($11^{*}20,943$) simulated school trips for the municipality of Rio de Janeiro. In doing so, we assumed that all pupils attend the closest school to their home location. To quantify crime-associated inequality in geographical access to education, we calculated the cumulative travel time difference between school trip simulations that considered crime and those that did not. Here, “cumulative travel times” refers to travel times weighted by the youth population, specifically the 1,128,640 out of 1,172,758 youth population traveling.. Visualizing these differences enabled us to map residential areas with varying levels of crime impact on access to the closest school.

3.3.4. Road network analysis

To create a product applicable to urban planning, we generated a classified road network that indicates avoidable, unavoidable, ideal, and preferable routes. Avoidable street segments were identified by extracting the route segments of the shortest route, which were not identical to the crime-conscious route. Preferable street segments were identified by extracting the route segments of the crime-conscious route, which were not identical to the shortest route. Unavoidable route segments were defined as streets or paths which were contained in both the shortest and crime-conscious routes and showed a crime index higher than 0.5. Streets where the shortest and crime-conscious routes were identical and which had a crime index lower than 0.2 were considered ideal route segments, i.e. the route is simultaneously short and safe. The extracted route segments were classified for each simulated school path. Finally, the predominant classification for each OSM street segment across all population-weighted simulated school paths was visualized.

4. Results

4.1. Street-level crime index

Fig. 4 illustrates the estimated crime index for each OSM street segment in the municipality of Rio de Janeiro. The estimated crime distribution follows an east-west gradient, with a higher crime index observed in the northeastern districts of the municipality. This pattern aligns with the shootings data presented in Fig. 2.

4.2. Crime-conscious access to closest school

Panel A of Fig. 5 illustrates the simulated trip distribution based on travel time to the closest school. Notably, 73.49 % of the population-weighted simulated trips fell within the 0–10 min travel time class, indicating that approximately three-quarters of the population had relatively quick access to schools. 94.21 % of the population can access a school within 20 min of walking. This highlights that the majority of the population had reasonable access to schools in the municipality of Rio de Janeiro. However, 5.79 % of the population had estimated travel times longer than 20 min, indicating the portion of the population with longer simulated travel times to school. Panel B of Fig. 5 depicts the spatial distribution of crime-conscious travel times to the closest school, illustrating the influence of school density and urban infrastructure on educational access. Central urban zones, characterized by high human activity, exhibited higher school densities, resulting in shorter population-averaged travel times. In contrast, peripheral urban areas, characterized by marginal settlements, high rural-urban migration, and lower average incomes (cf. Appendix F.5), exhibited longer travel times. These findings align with the broader understanding that the causes of disparities in educational access within urban areas are multifaceted and linked to socioeconomic factors and settlement structures, which often disadvantage certain population groups (Curtis et al., 2015; Fast, 2020).

4.3. Cumulative travel time difference to closest school

Panel A of Fig. 6 illustrates the spatial distribution of the cumulative travel time difference to the closest school, comparing the shortest route with a crime-conscious route using a crime weight factor of 1.0. Areas with high crime rates, particularly near dispute areas, exhibited high positive cumulative travel time differences. Conversely, regions with lower crime exposure demonstrated shorter travel times, indicating that students in these areas supposedly face fewer detours to avoid crime, thereby reflecting higher educational accessibility. This spatial variation highlights the impact of local crime on educational accessibility, identifying critical areas where enhancing safety could improve school access for affected populations. By applying a crime weight factor of 1.0, indicating high personal risk aversion to avoid crime on the way to school, 1765 (8.4 %) out of 20,943 simulated school paths involved a detour. Analyzing whether the increase in travel time due to crime-consciousness (for all school paths with detours) depended on the travel times to the closest school (without considering crime) revealed no significant ($p > 0.05$) change, suggesting that the increase in travel time due to crime-conscious routing was independent of the shortest travel distance to the school (cf. Fig. 6, Panel B).

4.4. Mean vs. maximum crime exposure

The proposed routing approach balances the trade-off between travel time and crime exposure by incorporating both hard constraints (avoidance of dispute areas) and soft constraints (balancing travel time with crime exposure) (cf. Fig. 7). Fig. 8 demonstrates that out of the 1765 school paths with crime-conscious detours, 7.99 % have a lower

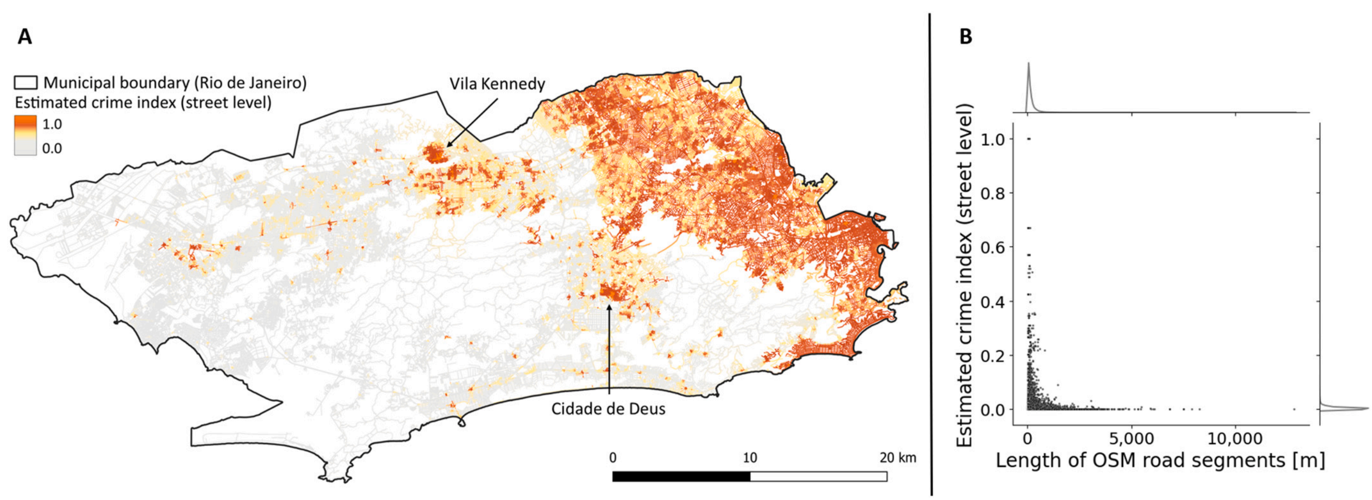

Fig. 4. Panel A illustrates the urban crime index at the street level for the municipality of Rio de Janeiro, following an east-west gradient, with high crime estimates in the east. Two smaller crime clusters were estimated in Vila Kennedy and Cidade de Deus, neighborhoods known for high crime rates (Fahlberg et al., 2020). Areas without roads are shown in white. Panel B demonstrates the distribution of OSM road segment lengths in the municipality of Rio de Janeiro over estimated crime levels, highlighting that the method of zonal statistics buffering (cf. Fig. 3) led to a small number of long road segments with high average crime levels. It also illustrates the skewness in the distribution of street crime levels across all road segments and the distribution of OSM road lengths. The plots at the margin shows kernel density representations of the distribution of values across the two axes.

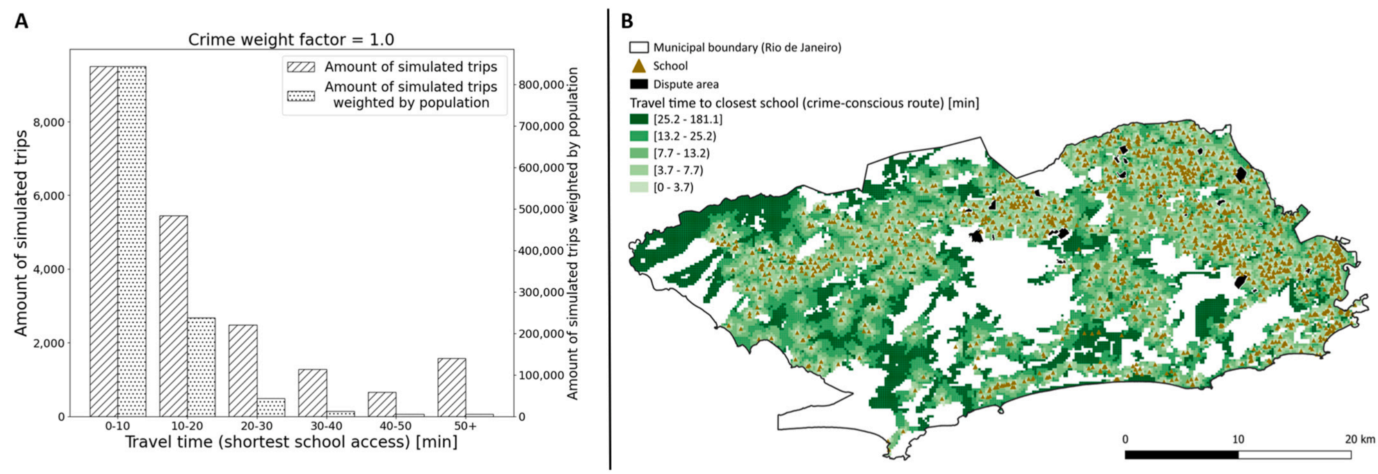

Fig. 5. Panel A illustrates the amount of simulated trips ($n = 20{,}943$) and population-weighted simulated trips ($n = 1{,}146{,}690$) per travel time to the closest school. Panel B highlights the spatial distribution of crime-dependent travel time to closest schools. Travel times are displayed at the level of 200 m cells using a quantile color scheme. Areas with no population, including steep regions of rainforest, are shown in white. Both result plots are shown for a crime weight factor of 1.0, which ranks crime avoidance very high.

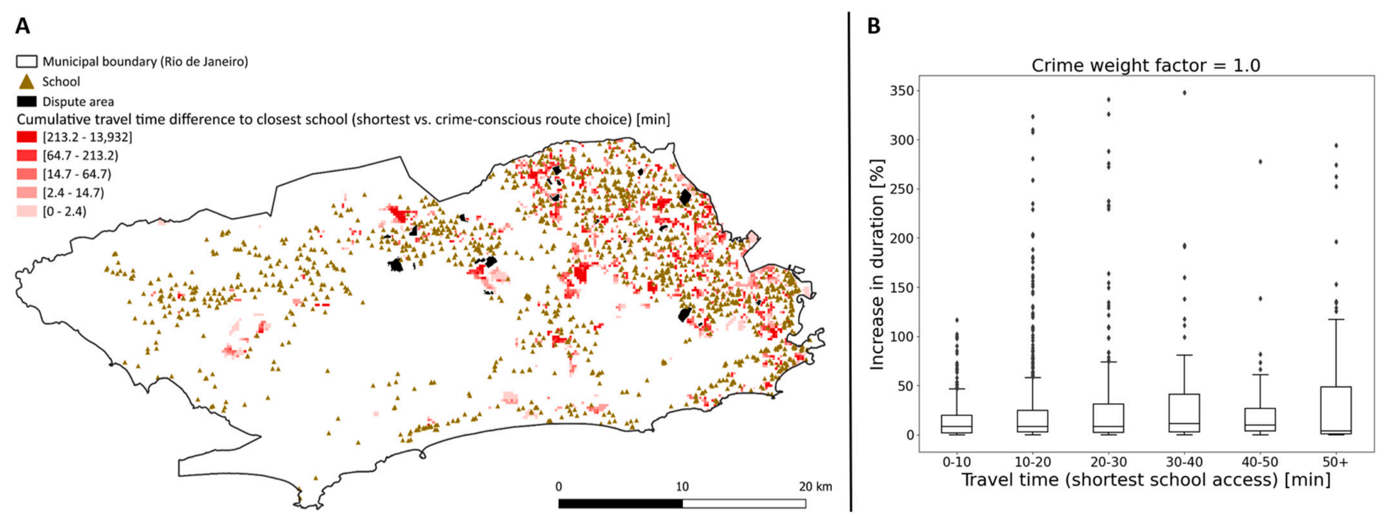

Fig. 6. Panel A visualizes the impact of crime on commute duration to the closest school. Panel B shows the increase in duration of safer routes compared to shortest routes, grouped by 10-min intervals of the shortest school access duration. Illustrated results of Panel B are shown for 1765 school paths with crime-conscious detours, with a crime weight factor of 1.0, reflecting high individual risk aversion to avoiding crime during the journey to school.

average crime exposure, and 3.80 % have a lower maximum crime exposure than shortest school paths. Here, the average crime exposure is the mean crime rate along the route, and the maximum crime exposure is the highest crime rate encountered along the route. The scatterplots illustrate that the relative decrease in crime exposure was more pronounced on school paths that have high levels of crime exposure. The clear majority (91.76 %, $n = 19{,}213$) of simulated crime-conscious detours showed no change in mean crime exposure, 7.99 % ($n = 1672$) showed a reduction in mean crime exposure and only 0.25 % ($n = 53$) showed an increase in mean crime exposure. Even more (96.07 %, $n = 20{,}115$) simulated crime-conscious detours showed no change in maximum crime exposure, only 3.80 % ($n = 795$) showed a reduction in max crime exposure, and 0.13 % ($n = 28$) an increase in maximum crime exposure. These single occurrences of minor increases in mean or maximum crime exposure presumably occurred because the trade-off function sometimes prioritized routes with lower maximum crime exposure, even at the cost of a slight increase in mean exposure, to avoid paths with high crime spots and vice versa.

Considering all school paths with an increase in travel time and a reduction in either mean or maximum crime exposure, the left panel of Fig. 9 demonstrates that the absolute decrease in mean crime exposure was, on average, 20.32 % higher for school paths that did not cross dispute areas ($n = 418$) compared to those that do ($n = 1347$). Similarly, the right panel of Fig. 9 shows that the mean relative increase in maximum crime exposure was, on average, 2.74 % higher for school paths not crossing dispute areas compared to those that did. The relative increase in travel time to the closest school was 19.79 % higher for school paths that cross dispute areas than for those that do not. While the decrease in mean crime exposure appeared to consistently increase with larger relative increases in travel time, the highest decrease in maximum crime exposure occured at around a 100 % relative increase in travel time to the closest school, as indicated by locally weighted scatterplot smoothing (LOWESS) (Cleveland, 1981).

4.5. *Crime weight factor*

The simulation process is highly influenced by the selected individual crime risk aversion factor (cf. Fig. 10, Panels A to D). Panel A

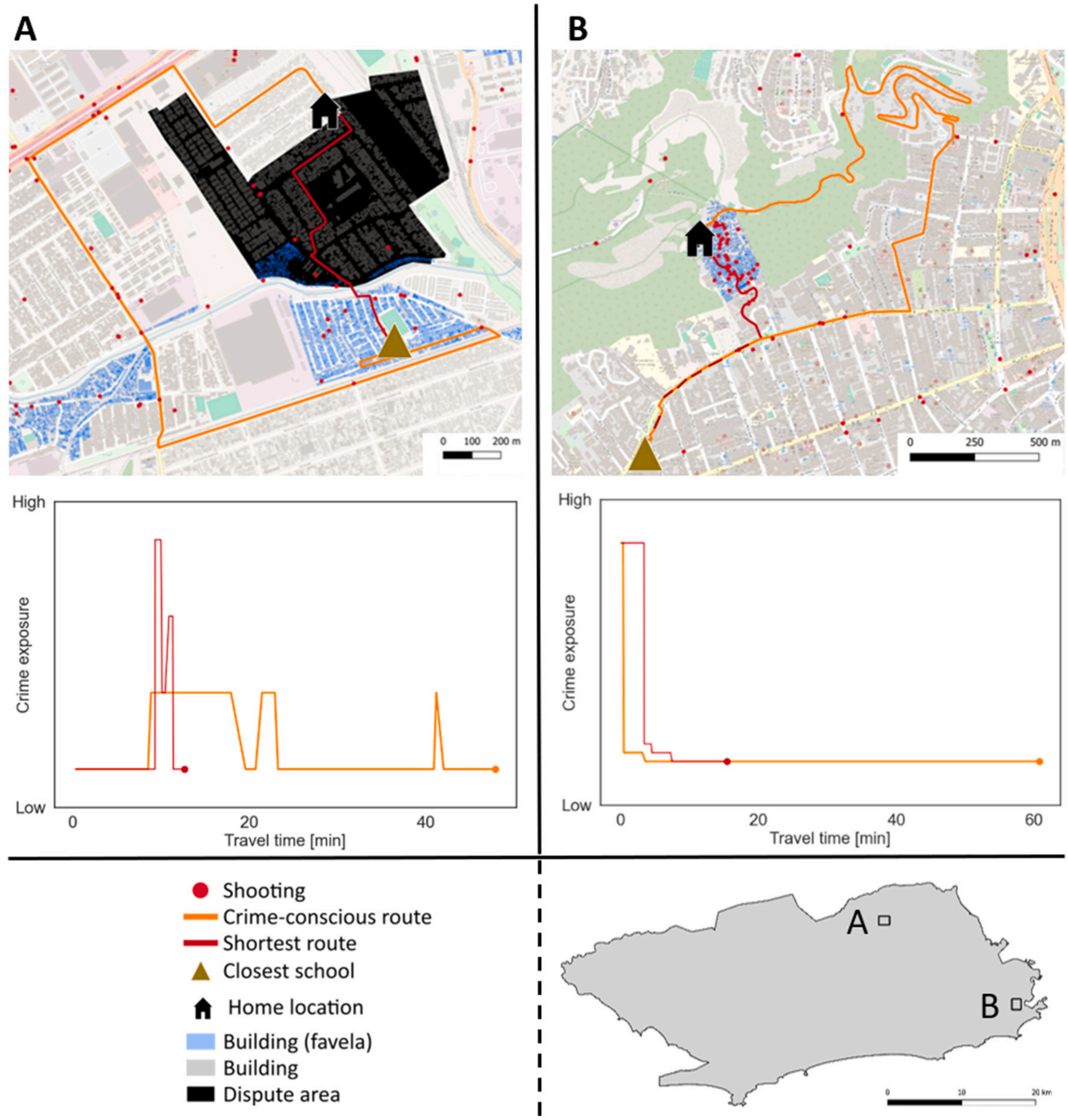

Fig. 7. Exemplary visualization, based on two extremely long detours due to crime avoidance. Left panels (A) illustrate an example where both hard and soft crime constraints influence the school path choice, while the right panels (B) show an example where only soft crime constraints affect educational access. In the left panels (A), the crime-conscious route avoids the disputed area (black), resulting in a 277.71 % longer travel time (35:09 min) but achieving an average crime index value nearly 3 times lower (63.04 % reduction) compared to the shortest path to the closest school. In the right panels (B), the crime-conscious detour results in a 293.94 % longer travel time (45:18 min) but achieves an average crime index value nearly 17 times lower (94.21 % reduction) compared to the shortest route to the closest school. Line segments shared by both routes are marked by dashed colors. In other scenarios, crime-conscious detours can render the second nearest school more accessible than the closest school due to modifications in the travel route.

illustrates the percentage increase in travel time to the closest school as the crime weight factor is adjusted from 0.1 (low crime risk aversion) to 1.0 (high crime risk aversion), highlighting particularly that the maximum percentage increase in duration becomes larger between 0.1 and 0.7. The mean increase in duration for a crime weight factor of 0.1 was measured to be 12 %, while the average increase in travel time to the closest school is twice as high for a crime weight factor of 1.0 (cf. Panel B). This trend follows a saturation pattern, as we observe a slight leveling off in the increase of the mean increase in duration. A similar saturation pattern in the sensitivity analysis was observed for the number of simulated detours (cf. Panel C). Panel D highlights the decrease in shared route fractions between the shortest school access routes and crime-conscious school access routes as a function of the crime weight factor. While a crime weight factor of 0.1 results in an average shared route fraction of 65.13 %, a crime weight factor of 1.0 results in a shared route fraction of 54.85 %.

4.6. Road network analysis

Fig. 11 illustrates the predominant classification (avoidable, preferable, unavoidable, and ideal) of each OSM road segment based on all population-weighted school trip simulations. Due to the low share of crime-conscious detours (8.4 %) in all simulated school paths, most road segments were classified as ideal. Ideal route segments are both part of the shortest and crime-conscious path to the closest school with a crime index below 0.2, offering a safe and short route. Especially interesting for intervention planning are the unavoidable routes. Unavoidable route segments were defined as common to both the shortest and crime-

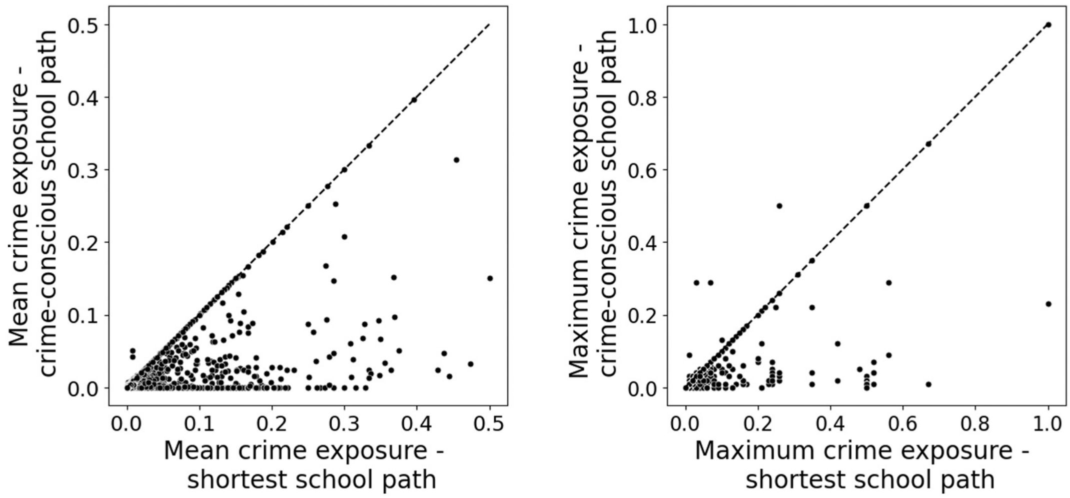

Fig. 8. Mean (left panel) and maximum (right panel) absolute crime exposure on a path to closest school compared between shortest and crime-conscious route choice, with a crime weight factor of 1.0 applied in the simulations.

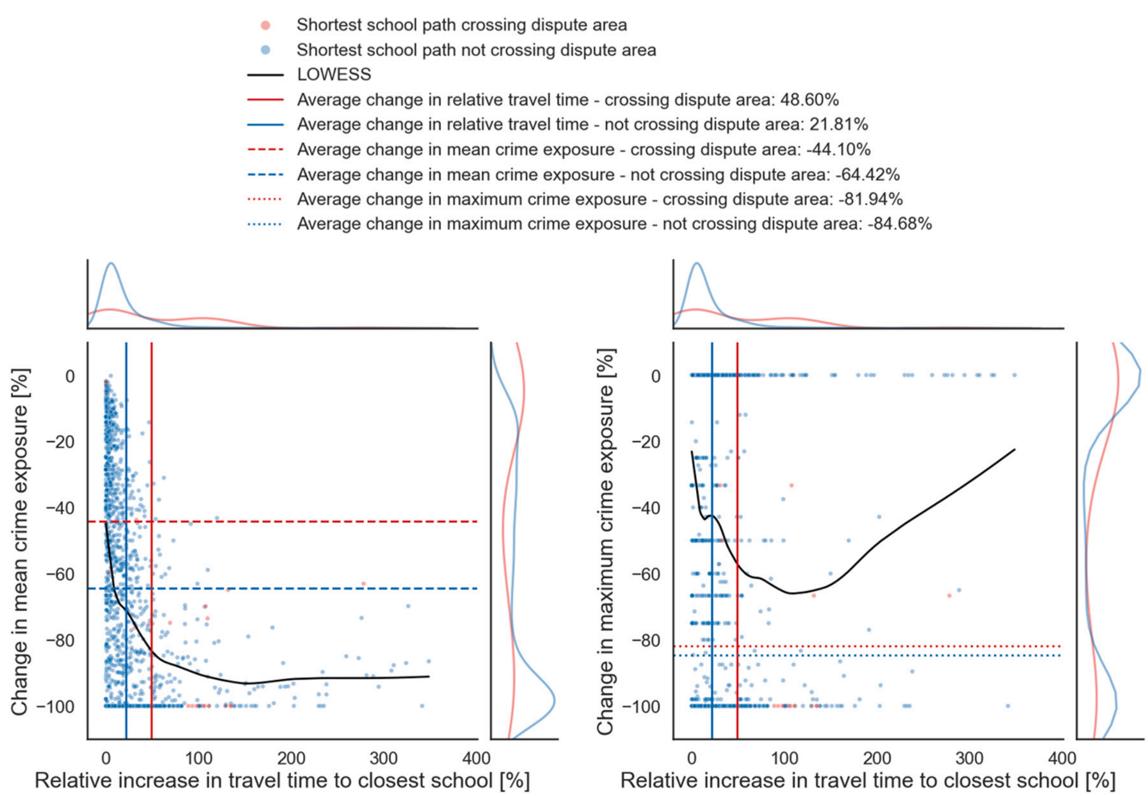

Fig. 9. Decrease in mean (left panel) and maximum (right panel) crime exposure compared to the increase in travel time of simulated crime-conscious walking routes with detours (distance shortest < distance crime-conscious route) to closest school in the municipality of Rio de Janeiro, with a crime weight factor of 1.0 applied in the simulations. All points at $y = -100$ indicate crime-conscious routes for which the mean or maximum crime exposure dropped completely to zero. All points at $y = 0$ indicate crime-conscious routes for which there was either no change in mean or maximum crime exposure, with more routes showing changes in mean crime exposure than maximum exposure. The black line represents the locally-weighted scatterplot smoothing (LOWESS). The plots at the margin shows kernel density representations of the distribution of values across the two axes.

conscious routes but with a crime index above 0.5, pinpointing road segments where high-risk pedestrian commute to the closest school was inevitable in the conducted simulations. In the scenario using a crime weight factor of 1.0, 41,010 students (3.63 % of the young population) had to travel through these unavoidable routes.

5. Discussion

This study quantified the critical role of urban violence in shaping educational access in the municipality of Rio de Janeiro. It thereby advocates for a comprehensive approach to understanding social disparities beyond traditional metrics such as census statistics. By incorporating individual crime risk aversion factors and simulating no-go areas into routing models, the study revealed significant barriers to

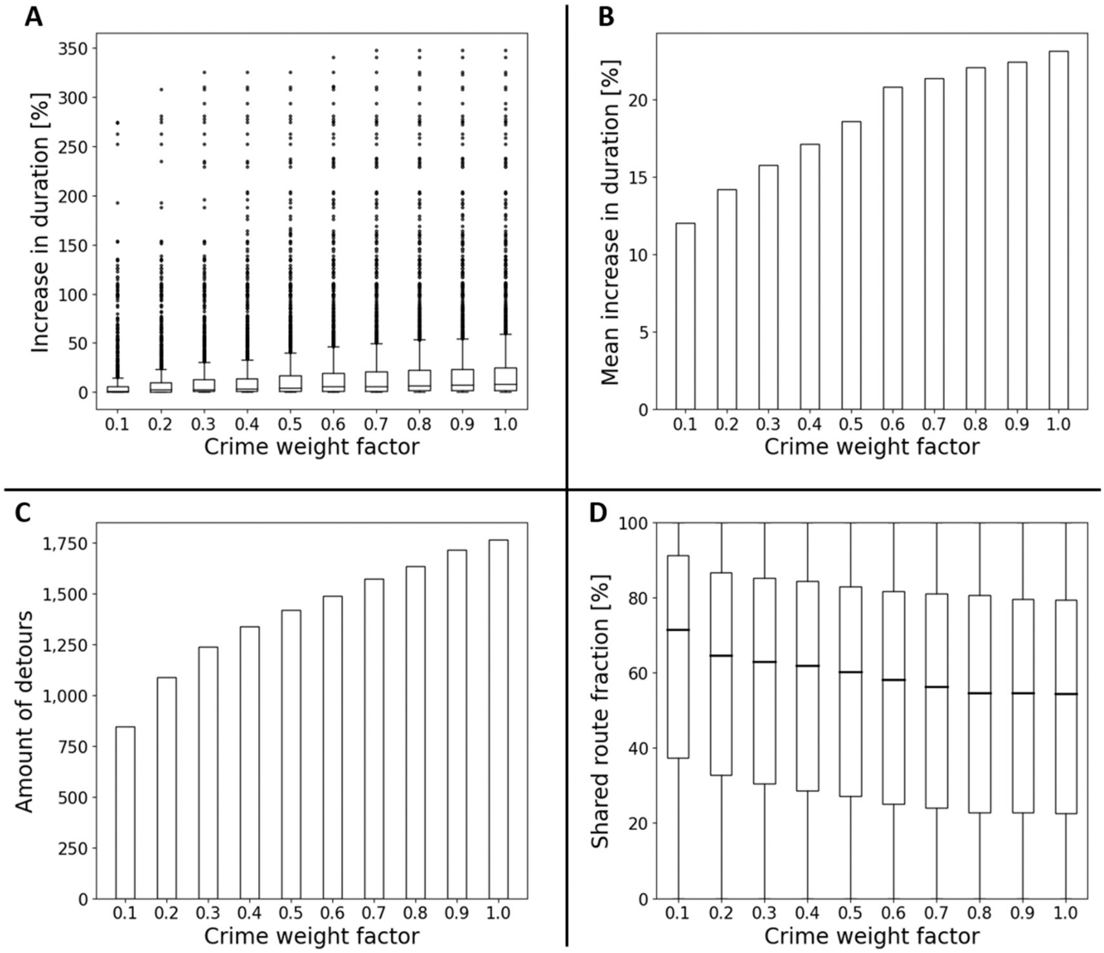

Fig. 10. Detour sensitivity towards the crime weight factor. Panel A visualizes the distribution of the change in duration over all simulated crime weight factors. Panel B shows the progression with slight saturation of the mean positive change in duration with increasing crime weight factors. Panel C highlights the number of school paths with detours due to crime-conscious routing for each crime weight factor. Panel D illustrates the fraction of the route shared between the shortest and safest routes to the closest schools, indicating a lower fraction of shared routes with an increasing crime weight factor.

equitable education linked to urban crime patterns. While the analysis provides valuable insights, several limitations regarding (i) the estimation of the crime index at street level and (ii) the simulations for analyzing crime-conscious access to education should be acknowledged.

5.1. Limitations of the street-level crime index

Estimating a crime index at the street level remains a challenge primarily due to the limited spatio-temporal resolution of available crime reports. This study employed a downscaling mapping approach to redistribute official crime statistics at the street scale, ensuring consistent aggregation results. However, in the absence of ground truth data at street scale, the accuracy of this disaggregation remains uncertain. While our approach of downscaling with ancillary data aims to provide a more realistic representation compared to a random distribution of events, it is important to recognize that this method is based on certain assumptions which we believe better reflect real-world conditions. We acknowledge that the selection of a 200 m grid and 10 m road buffer as the primary spatial units for downscaling crime records to street-level introduces certain dependencies in our results, which may vary with alternative resolutions. This selection also involves potential impacts from the Modifiable Areal Unit Problem (MAUP), where results can be sensitive to the chosen spatial unit, potentially affecting the interpretation of crime patterns. While our approach seeks to balance spatial granularity with computational feasibility, a sensitivity analysis of grid and buffer sizes could yield insights into how variations in spatial resolution might impact the accuracy and interpretability of the crime index. However, even with sensitivity analyses, challenges will persist as long as crime records remain available only at highly aggregated levels. Although high-resolution crime data are often collected, they are generally not shared due to data protection policies, ethical considerations, and security protocols. Implementing anonymized data-sharing practices could greatly enhance methodological precision. Collaborating with local authorities to explore ethical avenues for sharing anonymized, high-resolution records may offer a promising direction for future research.

Besides the limited resolution of the available crime data, it is important to note that crime statistics may be subject to underreporting, particularly for less visible crimes such as assault and robbery. These biases can affect the accuracy of the estimated street-level crime index, especially in deprived neighborhoods which experience underpolicing and lesser law enforcement (Hirata, 2022). Consequently, the results of our approach may not fully capture the true distribution of urban crime in the municipality of Rio de Janeiro, underscoring the necessity of integrating additional data sources (cf. Appendix F), such as social media e.g. information from Telegram groups on shootings, to enhance the robustness of crime estimates.

Another limitation arises from the equal weighting of various types of crime statistics and ancillary data during the downscaling process for simplification. This uniform weighting does not account for the differing impacts and reporting frequencies of various crime types, which could skew the resulting crime index. Future work should consider differential

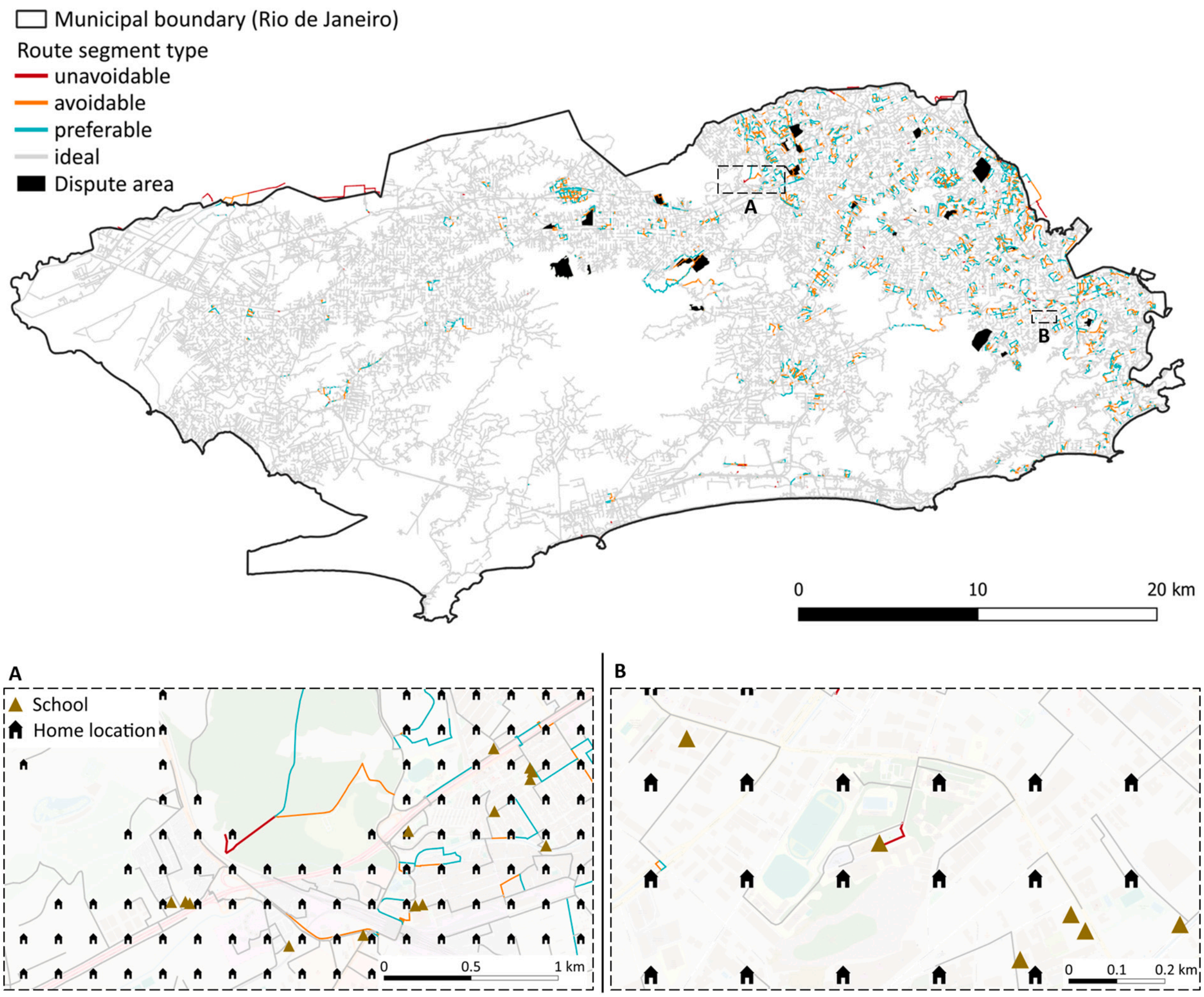

Fig. 11. OSM road network classification of road segments as avoidable (5.69 %), preferable (6.59 %), unavoidable (0.38 %), and ideal (87.32 %) on routes to the closest school. The visualization reflects the predominant classification across all population-weighted simulated school paths. The visualized road segments do not represent the entire OSM road network, only the segments selected in our simulated student routes. A major proportion of the unavoidable route segments were either the initial or final segments of the school path, where alternative routes are often not given.

weighting schemes based on the severity and prevalence of different crimes to improve the accuracy of the street-level crime index and potentially test different weightings of ancillary data using regression models to determine their optimal weighting.

The observed east-west gradient in official crime statistics and our crime estimates (cf. Figs. 2 and 4) - with higher estimated crime rates in eastern districts of the municipality of Rio de Janeiro and lower estimates in the west - can be attributed to several factors. One factor is the similar east-west socioeconomic gradient across the municipality of Rio de Janeiro (cf. Appendix F.5), with lower average household income in western districts and higher income in the eastern parts. Regions with lower average household income are hypothesized to exhibit lower crime reporting rates relative to the actual occurrence of crimes, potentially due to diminished perceptibility or tolerance of such incidents. Another explanation for the bias in official crime statistics is that the western districts of the municipality of Rio de Janeiro are predominantly controlled by milícias (cf. Appendix F.9). Milícias, composed primarily of former police officers, politicians, and soldiers, have taken over areas previously dominated by drug gangs. While they have mitigated violence associated with drug trafficking, residents are now subjected to extortion by the milícias for essential services such as gas, water, and transportation (Hirata et al., 2022). The threat of severe repercussions for speaking out against milícias leads to underreporting of crimes to official authorities, which we observe (cf. Figs. 2). Despite their initial goal of enhancing security, there is evidence that these areas continue to experience high levels of criminal activity due to the absence of formal law enforcement (Hirata et al., 2022).

5.2. *Constraints of crime-conscious routing and educational access simulation*

Considering the aforementioned limitations in estimating a crime index at the street level, the crime-conscious routing developed in this study also has its constraints. It inherently depends on the location of urban violence and the spatial distribution of dispute areas. Additionally, the fluid and evolving nature of crime hotspots necessitates adaptive and responsive modeling techniques, which were not considered in this study. Therefore, prioritizing methodologies to estimate disputed areas and adapt intervention maps in a timely manner is essential for future research aimed at enhancing the accuracy of crime impact analysis. Leveraging additional data sources, such as local news, could yield a more comprehensive and timely understanding of urban crime dynamics, potentially facilitating more effective and proactive interventions.

In addition, does the simulation of crime-conscious access to schools encounter major limitations. Firstly, the simplification of all students walking to school does not account for alternative modes of transportation such as school buses, cars or transit. Secondly, the assumption that all students attend the closest school, regardless of the type of school or the students' age, oversimplifies the actual school selection process. This approach neglects variations in school types and the potential for students to attend schools based on parental work locations or personal preferences. These assumptions were made to simplify the analysis but should be carefully considered when interpreting the results and their implications for policy and urban planning. Future studies could benefit from incorporating more complex models that account for different transportation modes and more realistic school selection behaviors to provide a more comprehensive understanding of educational accessibility in the context of urban crime.

The quality of OSM data significantly impacts our analysis of how crime affects educational access in the municipality of Rio de Janeiro. The level of completeness of OSM roads affects the quality of the accessibility analysis (Barron et al., 2014; Wang et al., 2013), as incomplete data can create gaps in the network, leading to inaccurate routing analysis and a misrepresentation of true accessibility to schools. In our study, we found that 96.6 % of Microsoft roads (Microsoft, 2024) (as of February 27, 2023) were matched by OSM (as of July 2, 2024) for the municipality of Rio de Janeiro, indicating a high level of completeness in the OSM dataset, assuming that the Microsoft road dataset is sufficiently complete. For our study, this figure suggests that OSM data is sufficiently reliable, especially considering that roads and particularly major roads are usually the first features to be mapped in OSM (Barrington-Leigh & Millard-Ball, 2017). Smaller roads and footpaths are mapped later in most places, which could introduce some bias, especially in favela areas in the municipality of Rio de Janeiro. Thematic accuracy is also crucial, as accurate and complete road attributes, such as road type, are essential for precise modeling of which paths can actually be used by pedestrians. In this study, we applied pedestrian routing based on OSM data, which generally considers almost all paths walkable except for roads limited to cars such as highways.

Additionally, accurate mapping of school locations is essential for determining accessibility measures; incorrect or missing school data can lead to overestimating or underestimating the impact of crime on educational access. Estimating the completeness of school data is more challenging than for roads due to the lack of recent local ground truth datasets with precise school locations. However, the ohsome quality API (OQAPI) tool (Heidelberg Institute for Geoinformation Technology, 2024) helped us to estimate completeness for the schools in the municipality of Rio de Janeiro based on a saturation curve approach (Brückner et al., 2021). The tool indicated that school mapping reached saturation, a typical pattern in OSM mapping when reaching a higher state of completeness. However, the absence of school-level classification data in OSM for some schools prevented the differentiation between various school types in this analysis. These OSM data quality issues introduce potential biases. The results in Fig. 6 suggest that urban violence only affects school access locally. However, this impression arises because the analysis includes all types of schools. While the municipality of Rio de Janeiro has a substantial number of primary schools, the availability of childcare and high schools is much more limited (Saraiva et al., 2022). This discrepancy introduces bias in our crime-related findings. Future research should focus on validating OSM data against official sources and incorporating community feedback to improve the accuracy and relevance of mapped information. An additional check for the completeness of OSM school data could be conducted by calculating the number of students per school to ensure plausibility.

5.3. Customization and adaptation of crime-conscious routing

The proposed approach of crime-conscious routing allows for analyzing educational access within heterogeneous urban landscapes by simulating various crime aversion factors, which can be customized to reflect the intensity of local crime conditions and individual risk perceptions. When transferring this approach to different settings, it is crucial to adjust the parameters to ensure they are salient for the new context. Such customization ensures the model's relevance and sensitivity to crime dynamics across different regions and addresses community-specific safety concerns. Additionally, cross-cultural considerations can be incorporated, making the model adaptable to diverse cultural differences in risk perception and crime-reporting behaviors.

The proposed method was designed with the potential to facilitate the integration of frequently updated urban crime data, if available, to develop dynamic routing solutions that can respond to emerging crime threats. This capability can be developed and integrated in future iterations of the approach. Recognizing that crime is a highly dynamic phenomenon, this feature is particularly beneficial for practical applications. For instance, in the municipality of Rio de Janeiro, data streams from the near real-time shooting alert apps "Fogo Cruzado" (Cruzado, 2024a) and "Onde tem tiroteio" (Onde tem tiroteio, 2024) could enhance the model's responsiveness to near real-time crime incidents, thereby improving its efficacy in selecting safer routes to school. The proposed concept can additionally be adapted to analyze crime-conscious access to other public facilities beyond schools, such as hospitals, parks, and community centers. This scalability extends its applicability across multiple domains, addressing a wide range of public safety and accessibility issues.

5.4. Community engagement and validation

Engaging local communities in providing feedback on crime hotspots and perceived safety could further enhance the model's accuracy and acceptance. Developing citizen science initiatives, where community members contribute data and insights, can result in more nuanced and locally informed crime mapping and routing decisions. Additionally, it is important to involve local communities in validating the model to ensure its usefulness and relevance. This process would help verify that the model meets the actual needs and perceptions of the community rather than being solely based on assumptions by researchers.

An example of the necessity for community validation can be illustrated using Panel B of Fig. 9. This figure depicts a school route for a hypothetical student living in Favela Santa Marta (Botafogo) and traveling to a school in the Humaitá neighborhood. Our simulations suggest that the safer route would be much longer than the shortest path to school, crossing Corcovado Mountain and passing through Laranjeiras and Botafogo to avoid the lanes, stairs, and streets of the favela. However, ethnographic evidence indicates that residents of favelas generally do not perceive their own neighborhoods as risky (Mano, 2021; Menezes, 2018). This perception of safety changes mainly during special police operations and conflicts, which are not common everywhere (Cavalcanti, 2024; Silva & Menezes, 2020). Specifically, Santa Marta is not frequently affected by such disputes and operations (Grupo de Estudos dos Novos Ilegalismos, 2020; Grupo de Estudos dos Novos Ilegalismos, 2021a; Grupo de Estudos dos Novos Ilegalismos, 2021b; Grupo de Estudos dos Novos Ilegalismos, 2021c; Grupo de Estudos dos Novos Ilegalismos, 2022). Consequently, a typical student would likely not choose such an extensive detour to reach school, except possibly during extreme events. This highlights that while our simulations provide valuable proof of concept, they may not fully capture real-world complexities. The perceptual crime-safety classification of street view images, using the neural network pre-trained with the Place Pulse dataset and applied for downscaling, might require contextual adaptation, as perceptions of violence are locally embedded. Therefore, integrating local knowledge is crucial for refining the model and enhancing its practical relevance. Further refinement with local expertise is essential to improve the accuracy and applicability of crime impact analyses.

5.5. Implications for urban planning and policy

The classified road network map (cf. Fig. 11) reveals important implications for urban planning and policy decisions aimed at improving safety and access to essential services. By illustrating the spatial distribution of safe versus high-risk routes and the interplay between educational access and urban crime, this approach offers detailed insights into the impact of crime on educational access. It can inform targeted interventions and resource allocation to enhance public safety, such as strategically placing street lights or CCTV cameras, or providing school buses as a safe commuting option (Burdick-Will et al., 2019; Burdick-Will et al., 2021). However, the specific findings for the municipality of Rio de Janeiro are highly dependent on official crime statistics, which inherently exhibit biases due to underreporting. Underreporting can vary across different areas, influenced by crime prevalence, gang control, individual differences in perceptions of crime, and varying levels of trust in law enforcement, thereby affecting the spatial accuracy of the data.

Insights from this study can be utilized to develop educational programs and awareness campaigns that enhance public understanding of safety-related issues in urban environments. Educating residents about safer routes and the importance of reporting crime can foster a more proactive community and improve safety. A limitation to the generalizability and transferability of the proposed methods is their reliance on openly available crime data and geospatial ancillary data for downscaling, which were manually obtained among other sources from local law enforcement agencies and municipal data repositories. Increased open-source sharing of anonymized police statistics, particularly at a granular level below police ward units and at the scale of individual crime incidents, could significantly benefit further studies and applications.

6. Conclusion and outlook

This study reveals the profound impact of urban violence on educational access in the municipality of Rio de Janeiro by modeling crime-conscious school path choices. It highlights the potential of routing-based accessibility analysis to understand social disparities beyond conventional metrics like census statistics. The analysis shows that urban crime patterns create significant ($p \leq 0.05$) obstacles for students, disproportionately affecting their access to education. This crime-associated inequality in geographical access to education underscores the importance of integrating crime risk into urban planning and education policy. Policymakers can leverage these insights, e.g. on unavoidable school path segments featuring high crime estimates, to design interventions that mitigate the adverse effects of urban violence on educational access. For instance, enhancing security in critical areas and improving transportation options for at-risk students can directly address these barriers.

The developed method is not only applicable to educational access but can also be extended to other opportunities such as employment and healthcare. It is adaptable to different locations and can incorporate various modes of transportation and more accurate crime data as they become available. This versatility allows for the analysis of access to diverse urban opportunities beyond education, considering additional hypothesized factors influencing access. Future research could integrate near real-time routing workflows and personalized risk profiles based on sociodemographic backgrounds, enhancing the study's utility for near real-time applications, particularly in the municipality of Rio de Janeiro with the availability of the near real-time crowdsourced data platform for urban violence. Additionally, modeling educational access more realistically by considering different levels of schools could further enhance the applicability of this method. Exploring crime exposure at different times of the day and considering motorized transportation options, given affordability, could provide deeper insights into urban violence dynamics and access to essential social services. Enhancing street-level crime estimates and refining the identification of no-go areas remain critical challenges. Addressing these issues will improve the accuracy and applicability of the method, providing more detailed insights for urban planners and policymakers.

In summary, this study not only quantifies the impact of urban violence on educational access but also offers a flexible tool adaptable to various urban planning challenges. By providing actionable insights, this research supports the design of policies that promote equitable opportunities and resource allocation, contributing to the broader goals of sustainable urban development, social equity, and improved quality of life in both developed and developing contexts.

CRediT authorship contribution statement

Steffen Knoblauch: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ram Kumar Muthusamy:** Software. **Maya Moritz:** Writing – review & editing, Writing – original draft. **Yuhao Kang:** Software. **Hao Li:** Writing – review & editing, Conceptualization. **Sven Lautenbach:** Writing – review & editing. **Rafael H.M. Pereira:** Writing – review & editing. **Filip Biljecki:** Writing – review & editing. **Marta C. Gonzalez:** Writing – review & editing. **Rogerio Barbosa:** Writing – review & editing. **Daniel Veloso Hirata:** Writing – review & editing. **Christina Ludwig:** Writing – review & editing. **Maciej Adamiak:** Writing – review & editing. **Antônio A. de A. Rocha:** Writing – review & editing. **Alexander Zipf:** Supervision.

Declaration of competing interest

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

Acknowledgements

Not applicable.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.105818.

Data availability

All digitally shareable materials necessary to reproduce the reported methodology have been made available in a public, open-access repository (https://doi.org/10.5281/zenodo.14887036).

References

Afoakwah, C., & Koomson, I. (2021). How does school travel time impact children's learning outcomes in a developing country? *Review of Economics of the Household, 19*, 1077–1097.

A. Alpkoçak, A. Cetin, Safe map routing using heuristic algorithm based on regional crime rates, in: D. J. Hemanth, U. Kose (Eds.), Artificial intelligence and applied mathematics in engineering problems, volume 43 of *Lecture Notes on Data Engineering and Communications Technologies,* Springer International Publishing, Cham, 2020, pp. 335–346. doi: https://doi.org/10.1007/978-3-030-36178-5\textunderscore}25.

Andersson, E., Malmberg, B., & Östh, J. (2012). Travel-to-school distances in Sweden 2000–2006: Changing school geography with equality implications. *Journal of Transport Geography, 23*, 35–43.

V. O. Andersson, M. A. F. Birck, R. M. Araujo, Investigating crime rate prediction using street-level images and siamese convolutional neural networks, in: D. A. C. Barone, E. O. Teles, C. P. Brackmann (Eds.), Computational neuroscience, volume 720 of *Communications in Computer and Information Science,* Springer International Publishing, Cham, 2017, pp. 81–93. doi: https://doi.org/10.1007/978-3-319-71011-2\textunderscore}7.

Appleyard, B. S., & Ferrell, C. E. (2017). The influence of crime on active & sustainable travel: New geo-statistical methods and theories for understanding crime and mode choice. *Journal of Transport & Health, 6*, 516–529.

Barrington-Leigh, C., & Millard-Ball, A. (2017). The world's user-generated road map is more than 80% complete. *PLoS One, 12*, Article e0180698.

Barron, C., Neis, P., & Zipf, A. (2014). A comprehensive framework for intrinsic openstreetmap quality analysis. *Transactions in GIS, 18*, 877–895.

Bautista-Hernández, D. A. (2023). Determinants and metropolitan patterns of school travel time. Is location associated with average years of schooling?: The case of mexico City. *Cities, 139*, Article 104408.
Bell, B., Costa, R., & Machin, S. (2022). Why does education reduce crime? *Journal of Political Economy, 130*, 732–765.
Britto, D. G. C., Pinotti, P., & Sampaio, B. (2022). The effect of job loss and unemployment insurance on crime in Brazil. *Econometrica, 90*, 1393–1423.
Brückner, J., Schott, M., Zipf, A., & Lautenbach, S. (2021). Assessing shop completeness in openstreetmap for two federal states in Germany. *AGILE: GIScience Series, 2*, 1–7.
Burdick-Will, J., Nerenberg, K. M., Grigg, J. A., & Connolly, F. (2021). Student mobility and violent crime exposure at Baltimore city public elementary schools. *American Educational Research Journal, 58*, 602–634.
Burdick-Will, J., Stein, M., & Grigg, J. (2019). Danger on the way to school: Exposure to violent crime, public transportation, and absenteeism, sociological. *Science, 6*, 118–142.
Byon, Y.-J., Abdulhai, B., & Shalaby, A. (2010). Incorporating scenic view, slope, and crime rate into route choices. *Transportation Research Record: Journal of the Transportation Research Board, 2183*, 94–102.
Camargo, A.d. P. R., de Lima, R. S., & Hirata, D. V. (2021). Quantificação, estado e participação social: potenciais heurísticos de um campo emergente. *Sociologias, 23*, 20–40.
Cavalcanti, M. (2024). For a war yet to end: Shootouts and the production of tranquillity in massive Rio de Janeiro. *The Geographical Journal, 190*, Article e12565.
Chen, H., Gao, X., Li, H., & Yang, Z. (2024). A framework for the optimal deployment of police drones based on street-level crime risk. *Applied geography (Sevenoaks, England), 162*, Article 103178.
Chen, P., Jiao, J., Xu, M., Gao, X., & Bischak, C. (2018). Promoting active student travel: A longitudinal study. *Journal of Transport Geography, 70*, 265–274.
Chioda, L., de Mello, J. M., & Soares, R. R. (2016). Spillovers from conditional cash transfer programs: Bolsa família and crime in urban Brazil. *Economics of Education Review, 54*, 306–320.
Cleveland, W. S. (1981). Lowess: A program for smoothing scatterplots by robust locally weighted regression. *The American Statistician, 35*, 54.
Cruzado, F. (2024a). Fogo cruzado api. *URL*. https://fogocruzado.org.br/API.
Cruzado, F. (2024b). Mapa historico dos grupos armados do rio de janeiro. *URL*. https://fogocruz.github.io/mapafc/.
Curtis, C., Babb, C., & Olaru, D. (2015). Built environment and children's travel to school. *Transport Policy, 42*, 21–33.
Defensoria Pública do Estado do Rio de Janeiro, Defensoria pública do estado do rio de janeiro, 2024. URL: https://defensoria.rj.def.br/.
Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik, 1*, 269–271.
A. Dubey, N. Naik, D. Parikh, R. Raskar, C. A. Hidalgo, Deep learning the city: Quantifying urban perception at a global scale, in: B. Leibe, J. Matas, N. Sebe, M. Welling (Eds.), Computer vision – ECCV 2016, volume 9905 of *Lecture Notes in Computer Science,* Springer International Publishing, Cham, 2016, pp. 196–212. doi: https://doi.org/10.1007/978-3-319-46448-0\textunderscore}12.
Eicher, C. L., & Brewer, C. A. (2001). Dasymetric mapping and areal interpolation: Implementation and evaluation. *Cartography and Geographic Information Science, 28*, 125–138.
Ermagun, A., & Samimi, A. (2018). Mode choice and travel distance joint models in school trips. *Transportation, 45*, 1755–1781.
Fahlberg, A., & Vicino, T. J. (2016). Breaking the city: Militarization and segregation in Rio de Janeiro. *Habitat International, 54*, 10–17.
Fahlberg, A., Vicino, T. J., Fernandes, R., & Potiguara, V. (2020). Confronting chronic shocks: Social resilience in Rio de janeiro's poor neighborhoods. *Cities, 99*, Article 102623.
Fast, I. (2020). Unequal traveling: How school district and family characteristics shape the duration of students' commute to school. *Travel Behaviour and Society, 20*, 165–173.
FAU-UPS, Fau-ups, 2024. URL: http://www.labcidade.fau.usp.br/.
Ferrão, M. E., & Alves, M. T. G. (2023). The relationship between students' socio-demographics and the probability of grade repetition in brazilian primary education: Is it decreasing over time? *Large-scale Assessments in Education, 11*.
Ford, A. (2022). How religious militias and warrior mentalities mix in Rio de Janeiro. *URL*. https://insightcrime.org/news/religious-militias-warrior-masculinities-mix-rio-de-janeiro/.
Galbrun, E., Pelechrinis, K., & Terzi, E. (2016). Urban navigation beyond shortest route: The case of safe paths. *Information Systems, 57*, 160–171.
Garcia-Zanabria, G., Raimundo, M. M., Poco, J., Nery, M. B., Silva, C. T., Adorno, S., & Nonato, L. G. (2022). Cripav: Street-level crime patterns analysis and visualization. *IEEE Transactions on Visualization and Computer Graphics, 28*, 4000–4015.
M. Garvey, N. Das, J. Su, M. Natraj, B. Verma, Passage, in: J. Nichols, J. Mahmud, J. O'Donovan, C. Conati, M. Zancanaro (Eds.), Companion publication of the 21st international conference on intelligent user interfaces, ACM, New York, NY, USA, 2016, pp. 84–87. doi: https://doi.org/10.1145/2876456.2879470.
R. Geisberger, P. Sanders, D. Schultes, D. Delling, Contraction hierarchies: Faster and simpler hierarchical routing in road networks, in: C. C. McGeoch (Ed.), Experimental algorithms, volume 5038 of *Lecture Notes in Computer Science,* Springer Berlin Heidelberg, Berlin, Heidelberg, 2008, pp. 319–333. doi: https://doi.org/10.1007/978-3-540-68552-4\textunderscore}24.
N. Goel, R. Sharma, N. Nikhil, S. D. Mahanoor, M. Saini, A crowd-sourced adaptive safe navigation for smart cities, in: 2017 IEEE international symposium on multimedia (ISM), IEEE, 2017, pp. 382–387. doi: https://doi.org/10.1109/ISM.2017.77.
Grillo, C. C. (2019). *Da violência Urbana à guerra: Repensando a sociabilidade violenta.* DILEMAS: Revista de Estudos de Conflito e Controle Social – Rio de Janeiro (pp. 62–92).
Grillo, C. C., & Martins, L. A. (2020). Indo até o problema: Roubo e circulação na cidade do rio de janeiro. *Dilemas - Revista de Estudos de Conflito e Controle Social, 13*, 565–590.
Grupo de Estudos dos Novos Ilegalismos, Aumento das operações policiais: Caracterização e impactos, 2020. URL: https://geni.uff.br/wp-content/uploads/sites/357/2021/02/2020_11_Relatorio-Geni_ADPF-635_aumento-das-operacoes_FINAL.pdf.
Grupo de Estudos dos Novos Ilegalismos, 11 meses de restrição às operações policiais no rio de janeiro, 2021a. URL: https://geni.uff.br/wp-content/uploads/sites/357/2022/05/2021_Um-ano-de-ADPF-das-favelas_GENI.pdf.
Grupo de Estudos dos Novos Ilegalismos, Medindo a eficiência das operações policiais: Avaliação e monitoramento, 2021b. URL: https://geni.uff.br/2021/04/19/medindo-a-eficiencia-das-operacoes-policiais-avaliacao-e-monitoramento/.
Grupo de Estudos dos Novos Ilegalismos, Operações policiais e violência letal no rio de janeiro: Os impactos da adpf 635 na defesa da vida, 2021c. URL: https://geni.uff.br/2021/04/05/operac%CC%A7o%CC%83es-policiais-e-viole%CC%82ncia-letal-no-rio-de-janeiro-os-impactos-da-adpf-635-na-defesa-da-vida/.
Grupo de Estudos dos Novos Ilegalismos, Chacinas policiais, 2022. URL: https://geni.uff.br/2022/05/06/chacinas-policiais/.
Grupo de Estudos dos Novos Ilegalismos Universidade Federal Fluminense. (2024). Grupo de estudos dos novos ilegalismos universidade federal fluminense (geni-uff). *URL*. https://geni.uff.br/institucional/.
Hart, P., Nilsson, N., & Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. *IEEE Transactions on Systems Science and Cybernetics, 4*, 100–107.
He, J., & Zheng, H. (2021). Prediction of crime rate in urban neighborhoods based on machine learning. *Engineering Applications of Artificial Intelligence, 106*, Article 104460.
Heidelberg Institute for Geoinformation Technology, ohsome quality api (oqapi), 2024. URL: https://heigit.org/big-spatial-data-analytics-en/ohsome/ohsome-quality-analyst-oqt/.
HeiGIT gGmbh, Openrouteservice, 2024a. URL: https://openrouteservice.org/.
HeiGIT gGmbh, Openrouteservice backend documentation, 2024b. URL: https://giscience.github.io/openrouteservice/.
Herrmann, C. R. (2013). Street-level spatiotemporal crime analysis: Examples from bronx county, ny (2006–2010). In M. Leitner (Ed.), *Crime modeling and mapping using geospatial technologies* (pp. 73–104). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-007-4997-9{\textunderscore}4.
Hirata, D. V. (2022). M. I. Couto. *Mapa histórico dos grupos armados do rio de janeiro*. https://geni.uff.br/2022/09/13/mapa-historico-dos-grupos-armados-no-rio-de-janeiro/.
Hirata, D. V., Cardoso, A., Grillo, C. C., dos Santos Junior, O. A., Lyra, D. A., & Dirk, R. C. (2022). The expansion of milícias in Rio de Janeiro. Political and economic advantages. *Journal of Illicit Economies and Development, 4*, 257–271.
Hirata, D. V., & Grillo, C. C. (2019). Movement and death: Illicit drug markets in the cities of são Paulo and Rio de Janeiro. *Journal of Illicit Economies and Development, 1*, 122.
Hirata, D. V., Grillo, C. C., & Dirk, R. C. (2021). Operações policiais no rio de janeiro (2006-2020): Da lacuna estatística ao ativismo de dados. *RUNA, archivo para las ciencias del hombre, 41*.
Instituto Brasileiro de Geografia e Estatística (Ed.). (2022). Pesquisa nacional de saúde do escolar : análise de indicadores comparáveis dos escolares do 9° ano do ensino fundamental : municípios das capitais : 2009/2019 / IBGE, Coordenação de População e Indicadores Sociais. URL https://biblioteca.ibge.gov.br/visualizacao/livros/liv101955.pdf.
Instituto de Segurança Pública, Isp dados abertos, 2024. URL: http://www.ispdados.rj.gov.br/.
Instituto Nacional de Ciencia e Tecnologia - UFRJ, Observatório das metrópoles, 2024. URL: https://www.observatoriodasmetropoles.net.br/.
Jing, C., Lv, X., Wang, Y., Qin, M., Jin, S., Wu, S., & Xu, G. (2024). A deep multi-scale neural networks for crime hotspot mapping prediction. *Computers, Environment and Urban Systems, 109*, Article 102089.
Kang, H.-W., & Kang, H.-B. (2017). Prediction of crime occurrence from multi-modal data using deep learning. *PLoS One, 12*, Article e0176244.
Kang, Y., Abraham, J., Ceccato, V., Duarte, F., Gao, S., Ljungqvist, L., … Ratti, C. (2023). Assessing differences in safety perceptions using geoai and survey across neighbourhoods in Stockholm, Sweden. *Landscape and Urban Planning, 236*, Article 104768.
Kaur, R., Goyal, V., Guntur, V. M. V., Saini, A., Sanadhya, K., Gupta, R., & Ratra, S. (2021). A navigation system for safe routing. In *In: 2021 22nd IEEE international conference on Mobile data management (MDM)* (pp. 240–243). IEEE. https://doi.org/10.1109/MDM52706.2021.00047.
Kim, D., Baek, J., Yang, J., Roh, H., Jeong, H., Ruiz, B., … Matson, E. T. (2023). Safe route recommendation based on crime risk prediction with urban and crime data. In *In: 2023 IEEE ninth international conference on big data computing service and applications (BigDataService)* (pp. 111–118). IEEE. https://doi.org/10.1109/BigDataService58306.2023.00022.
K. M. Kotoula, G. Botzoris, G. Ayfantopoulou, V. Profillidis, Urban school travel – Understanding the critical factors affecting parent's choices, in: E. G. Nathanail, G. Adamos, I. Karakikes (Eds.), Advances in mobility-as-a-service systems, volume 1278 of *advances in intelligent systems and computing,* Springer International Publishing,

Cham, 2021, pp. 912–922. doi: https://doi.org/10.1007/978-3-030-61075-3\textunderscore}88.
Lee, C., Zhu, X., Yoon, J., & Varni, J. W. (2013). Beyond distance: children's school travel mode choice. *Annals of behavioral medicine : a publication of the Society of Behavioral Medicine, 45*(Suppl. 1), S55–S67.
Levy, S., Xiong, W., Belding, E., & Wang, W. Y. (2020). Saferoute. *ACM Transactions on Intelligent Systems and Technology, 11*, 1–17.
Lima, A., Stanojevic, R., Papagiannaki, D., Rodriguez, P., & González, M. C. (2016). Understanding individual routing behaviour, journal of the Royal Society. *Interface, 13*.
Lochner, L. (2020). *Education and crime* (pp. 109–117). in: The Economics of Education, Elsevier. https://doi.org/10.1016/B978-0-12-815391-8.00009-4
Ludwig, C., Lautenbach, S., Schömann, E.-M., & Zipf, A. (2021). Comparison of simulated fast and green routes for cyclists and pedestrians: Schloss dagstuhl – Leibniz-zentrum für informatik, LIPIcs, volume 208. *GIScience, 2021*, 208.
Luo, J., Boriboonsomsin, K., & Barth, M. (2018). Reducing pedestrians' inhalation of traffic-related air pollution through route choices: Case study in California suburb. *Journal of Transport & Health, 10*, 111–123.
Mandic, S., Sandretto, S., Hopkins, D., Wilson, G., Kidd, G., & García Bengoechea, E. (2023). School choice, distance to school and travel to school patterns among adolescents. *Journal of Transport & Health, 33*, Article 101704.
Mano, A. D. (2021). *Morro de medo: Regimes de mobilidades após uma década de unidades de policia pacificadora em favelas do Rio de Janeiro*. Revista do núcleo de antropologia urbana da USP: Ponto Urbe.
Mata, F., Torres-Ruiz, M., Guzmán, G., Quintero, R., Zagal-Flores, R., Moreno-Ibarra, M., & Loza, E. (2016). A mobile information system based on crowd-sensed and official crime data for finding safe routes: A case study of mexico City. *Mobile Information Systems, 2016*, 1–11.
Menezes, P. V. (2018). Monitorar, negociar e confrontar: as (re) definições na gestão dos ilegalismos em favelas "pacificadas". *Tempo Social, 30*, 191–216.
Microsoft, Road detections from microsoft maps aerial imagery, 2024. URL: https://github.com/microsoft/RoadDetections.
Ministério Público do Estado do Rio de Janeiro, In loco, 2024. URL: http://apps.mprj.mp.br/sistema/inloco/.
Mitra, R., & Buliung, R. N. (2014). The influence of neighborhood environment and household travel interactions on school travel behavior: An exploration using geographically-weighted models. *Journal of Transport Geography, 36*, 69–78.
Mitra, R., & Buliung, R. N. (2015). Exploring differences in school travel mode choice behaviour between children and youth. *Transport Policy, 42*, 4–11.
Muggah, R. (2017). Rio de janeiro: A war by any other name. *URL*. https://smallwarsjournal.com/jrnl/art/rio-de-janeiro-a-war-by-any-other-name.
Murray, J., Cerqueira, D. R.d. C., & Kahn, T. (2013). Crime and violence in Brazil: Systematic review of time trends, prevalence rates and risk factors. *Aggression and Violent Behavior, 18*, 471–483.
Musah, A., Umar, F., Yakubu, K. N., Ahmad, M., Babagana, A., Ahmed, A., … Cheshire, J. A. (2020). Assessing the impacts of various street-level characteristics on the burden of urban burglary in Kaduna, Nigeria. *Applied geography (Sevenoaks, England), 114*, Article 102126.
NEVCU-UFRJ, Nevcu-ufrj, 2024. URL: http://necvu.com.br/.
NEV-USP, Center for study of violence (nev-usp), 2024. URL: https://nev.prp.usp.br/en/.
Nishimura, T., Nishida, K., Toda, H., & Sawada, H. (2016). How fashionable is each street?: Quantifying road characteristics using social media. In *In: 2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)* (pp. 429–436). IEEE. https://doi.org/10.1109/ASONAM.2016.7752270.
T. Novack, Z. Wang, A. Zipf, A system for generating customized pleasant pedestrian routes based on openstreetmap data, sensors (Basel, Switzerland) Vol. 18 (2018).
Núcleo de Pesquisas em Cultura e Economia. (2024). Núcleo de pesquisas em cultura e economia (nucec). *website*. https://www.nucec.com.br/.
OECD. (2021). *Education in Brazil*. OECD. https://doi.org/10.1787/60a667f7-en
OECD. (2024). Brazil: Overview of the education system (eag 2023). URL https://gpseducation.oecd.org/CountryProfile?primaryCountry=BRA&treshold=10&topic=EO.
Onde tem tiroteio, Onde tem tiroteio website, 2024. URL: https://www.ondetemtiroteio.com.br/.
Patil, D. S., Bailey, A., George, S., Ashok, L., & Ettema, D. (2024). Perceptions of safety during everyday travel shaping older adults' mobility in bengaluru, India. *BMC Public Health, 24*, 1940.
Pereira, R. H. (2018). Transport legacy of mega-events and the redistribution of accessibility to urban destinations. *Cities, 81*, 45–60.
Redes da mare, Redes da mare, 2024. URL: https://www.redesdamare.org.br/.
Riccio, V., & Skogan, W. (2017). Police and Society in Brazil. *CRC Press*. https://doi.org/10.4324/9781315154114
Rodrigues, L.d. O., Costa, E. M., Silva, V. H. M. C., Mariano, F. Z., & de Jesus Filho, J. (2020). Nota sobre diferenças de desempenho entre escolas urbanas e rurais no brasil. *Revista Brasileira de Economia, 74*.
Salazar Miranda, A., Fan, Z., Duarte, F., & Ratti, C. (2021). Desirable streets: Using deviations in pedestrian trajectories to measure the value of the built environment. *Computers, Environment and Urban Systems, 86*, Article 101563.
Santos, M. C. S., Delatorre, L. R., Ceccato, das Graças Braga, M., & Bonolo, P.d. F. (2019). Programa bolsa familia e indicadores educacionais em crianças, adolescentes e escolas no brasil: revisão sistemática. *Ciência & Saúde Coletiva, 24*, 2233–2247.
Saraiva, M., Silva, L. P., Braga, K., & Pereira, R. H. M. (2022). Transporte urbano e insuficiência de acesso a escolas no brasil. *Texto para Discussao IPEA*. https://repositorio.ipea.gov.br/bitstream/11058/11810/7/TD_2854_web.pdf, 2024.
Setiawan, I., Dede, M., Sugandi, D., & Agung Widiawaty, M. (2019). Investigating urban crime pattern and accessibility using geographic information system in Bandung city. *KnE Social Sciences*. https://doi.org/10.18502/kss.v3i21.4993
Sharker, M. H., & Karimi, H. A. (2014). Computing least air pollution exposure routes. *International Journal of Geographical Information Science, 28*, 343–362.
Shatu, F., Yigitcanlar, T., & Bunker, J. (2019). Shortest path distance vs. least directional change: Empirical testing of space syntax and geographic theories concerning pedestrian route choice behaviour. *Journal of Transport Geography, 74*, 37–52.
Silva, L. A., & Menezes, P. V. (2020). (des) continuidades na experiência de "vida sob cerco" e na "sociabilidade violenta". *Novos estudos CEBRAP, 38*, 529–551.
Siriaraya, P., Wang, Y., Zhang, Y., Wakamiya, S., Jeszenszky, P., Kawai, Y., & Jatowt, A. (2020). Beyond the shortest route: A survey on quality-aware route navigation for pedestrians. *IEEE Access, 8*, 135569–135590.
de Souza, P. H. G., Osorio, R. G., Paiva, L. H., & Soares, S. (2019). Os efeitos do programa bolsa familia sobre a pobreza e a desigualdade: um balanço dos primeiros quinze anos. *IPEA Texto para discussão, 2499*.
D. Sullivan, C. Caminha, H. P. M. Melo, V. Furtado, Towards understanding the impact of crime on the choice of route by a bus passenger, in: E. Oliveira, J. Gama, Z. Vale, H. Lopes Cardoso (Eds.), Progress in Artificial Intelligence, volume 10423 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2017, pp. 41–50. doi: https://doi.org/10.1007/978-3-319-65340-2\textunderscore}4.
Tatem, A. J. (2017). Worldpop, open data for spatial demography. *Scientific Data, 4*, Article 170004.
Tung, E. L., Boyd, K., Lindau, S. T., & Peek, M. E. (2018). Neighborhood crime and access to health-enabling resources in Chicago. *Preventive Medicine Reports, 9*, 153–156.
UNESCO. (2022). 244m children won't start the new school year. https://www.unesco.org/en/articles/244m-children-wont-start-new-school-year-unesco.
United Nations. (1948). *Universal declaration of human rights (Paris)*.
United Nations. (2015). Global education first initiative. *URL*. https://www.gcedclearinghouse.org/sites/default/files/resources/%5BENG%5D%20Global%20Education%20First%20Initiative_0.pdf.
United Nations Educational, Scientific and Cultural Organization, Sustainable development begins with education, 2014. URL: https://sdgs.un.org/sites/default/files/publications/2275sdbeginswitheducation.pdf.
Wang, M., Li, Q., Hu, Q., & Zhou, M. (2013). Quality analysis of open street map data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-2*(W1), 155–158.
Wiebe, D. J., Guo, W., Allison, P. D., Anderson, E., Richmond, T. S., & Branas, C. C. (2013). Fears of violence during morning travel to school, the journal of adolescent health : Official publication of the society for. *Adolescent Medicine, 53*, 54–61.
World Bank, Urban population (% of total population) - brazil, 2024a. URL: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=BR.
World Bank, Gini index -, brazil, 2024b. URL: https://data.worldbank.org/indicator/SI.POV.GINI?locations=ZA%26most_recent_value_desc%3Dtrue-BR&most_recent_value_desc=false.
Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning, 180*, 148–160.