The Nexus of Urbanisation and Risk Exposure: Assessing vulnerability and adaptation to health and climate hazards in Brazil

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ABSTRACT

Cities in the Anthropocene are increasingly affected by multiple, concurrent and interacting hazards that lead to deaths, economic losses, and suffering for millions of people every year. These hazards may trigger crises that impact urban areas across their economic, social, political, institutional, infrastructural and technological systems. In a vulnerability gap, an unequal development legacy combines with an unequal attribution of risks. Developed countries with high adaptation capacities built upon past emissions are on one side of the gap. On the other side, developing countries lack infrastructure, are socially unequal and have limited adaptation capability. This vulnerability gap could widen in the coming decades, since ongoing unequal development may couple with health and climate crises and their political, social, health and environmental risks, as the COVID-19 pandemic pointedly demonstrated. Past and future urban adaptation in the Anthropocene thus converge on environmental justice, making it a central problem for decision-making and policy development.

This research addresses the problem of environmental justice in health and climate hazards by focusing on urban systems in Brazil. To this end, I investigate the relationship between socio-environmental vulnerability and urban development through a mixed-methods, interdisciplinary research design. Three main topics delineate this design. The first is the interconnected character of the impact of multiple stressors on urban systems. The second is the unequal character of vulnerability, where urban development shows intense interaction with inequality, especially in informal, low-income settlements in the Global South. The third is the potential to study and manage inequalities and crises in the Anthropocene with interdisciplinary and open scientific methods in geography towards a more sustainable and socially just world.

In this context, I pose the following research question: How do hazards interact with the unequal features of urban development in the Global South, considering the nexus between urbanisation and risk exposure? To answer this question, this dissertation presents five studies investigating health and climate vulnerability, urban development and the hazards of the Anthropocene. I focus on Brazil as a relevant example of contemporary urban development and high socio-environmental vulnerability in the Global South. This research presents a data-intensive use of traditional geographic analysis combined with health geography and behavioural research techniques to investigate spatio-temporal dynamics at multiple scales. The goal is to reinforce an integrative approach to the research question in the name of a more robust scientific understanding of the research problems.

Informal settlements in urban deltas from the Global South exemplify the chain of deprivations that create an unequal distribution of risks in cities in the Anthropocene. The first contribution of this dissertation explores this issue in the Jacuí River Delta where the unequal urban development processes of Porto Alegre (Brazil) present low-income families with a difficult choice

between settling at risk close to the city centre or in the peripheries. By examining the risk responses of households in two landscapes of risk in the delta, this contribution seeks to understand the factors that condition risk responses against a significant flood event in 2015. The analysis showed that poorer households suffered more intense impacts and had a lower response capacity despite the abundant perception of imminent flood risk. These findings are central to adaptation policies and environmental justice.

The second contribution investigates the association between socioeconomic deprivation and COVID-19 fatalities. That chapter examines cities across the social vulnerability spectrum found in Brazil using health research methods. It innovates by depicting the spatio-temporal progression of deaths at different vulnerability levels. The results indicated consistent associations between long-term social vulnerability and COVID-19 fatalities, as more vulnerable cities presented lower survival probabilities across the period. These results highlight the importance of promoting multidimensional sustainable development and reducing structural vulnerability to prevent excess deaths.

However, structural socioeconomic vulnerability does not explain all the variability in COVID-19 fatalities. The third contribution of this research is the implementation of an agent-based model to assess mobility behaviour during the COVID-19 pandemic in Brazil. The model implements groups of agents with different demographic profiles and scenarios to determine the decision-making in mobility choices including well-being and exposure. The results showed that agents moved away from public transportation modes whenever financially possible, preferring individual modes instead. Agents with lower incomes could not make the same choices as affluent agents, resulting in segregation that signals that it is possible to buy their way out of exposure.

The fourth contribution of this dissertation seeks a common denominator between climate change and COVID-19 in the form of socio-environmental vulnerability. This contribution relies on mixing qualitative and quantitative methods across multiple scales and using varied samples. The results show that the adverse social outcomes of health and climate hazards may compound. These combined effects are especially prominent for high-vulnerability populations and territories. Lower adaptive and resistive capacities mean that adverse effects reverberate longer and across such varied dimensions as personal health, family life and livelihoods.

The fifth contribution investigates the relationship between geography research and vulnerable informal settlements. It assesses citizen empowerment and verifies the potential of volunteered graphic information (VGI) methods to provide much-needed data on informal settlements in the Global South. It uses a qualitative framework to classify two VGI practices in Mexico City and São Paulo. This classification exposed the agents involved in the VGI, decoupling the volunteers who produced data from the subjects represented in the data. Therefore, it brings to light the potential conflicts between these agents and limitations on technological literacy, available resources, agency and involvement of research subjects.

The main conclusion of this dissertation is that health and climate crises interact between themselves and with unequal urbanisation in the Global South through factors of exposure and socio-environmental vulnerability. Adaptation policies also take shape over unequally developed cities and should counter social inequality, as it provides synergies across multiple vulnerability factors. As climate change deepens in the Anthropocene, research and policy should explore the synergies between unequal development and adaptation. Ultimately, this research seeks to promote environmental justice towards more effective, efficient and just implementation of global transformation and sustainable development policies.

ZUSAMMENFASSUNG

Städte im Anthropozän sind zunehmend von verschiedenen zeitgleichen und sich gegenseitig beeinflussenden Gefahren betroffen, die jedes Jahr für Tausende Menschen zu Todesfällen, wirtschaftlichen Verlusten und Leid führen. Diese Gefahrenmomente können Krisen auslösen, welche die Ballungsgebiete in ihren wirtschaftlichen, sozialen, politischen, institutionellen, infrastrukturellen und technologischen Systemen beeinträchtigen. Ein ungleiches Entwicklungsvermächtnis in Kombination mit einer ungleichen Risikoverteilung führt zu einer Vulnerabilitätskluft. Auf der einen Seite stehen Industrieländer mit hoher Anpassungskapazität, die auf früheren Emissionen aufbaut. Auf der anderen Seite fehlt es den Entwicklungsländern an Infrastruktur, sie sind ungleich und verfügen über begrenzte Anpassungsfähigkeiten. Diese Vulnerabilitätskluft könnte sich in den kommenden Jahrzehnten vergrößern, da eine fortlaufende ungleiche Entwicklung mit politischen, sozialen und ökologischen Krisen zusammentreffen kann, wie die COVID-19-Pandemie deutlich gezeigt hat. Die Anpassungen von Städten im Anthropozän sowohl in der Vergangenheit als auch in der Zukunft konvergieren somit in Umweltgerechtigkeit und machen diese zu einem zentralen Problem für Entscheidungsfindung und Politikgestaltung.

Diese Forschungsarbeit befasst sich mit dem Problem der Umweltgerechtigkeit bei Gesundheits- und Klimagefahren, indem sie den Fokus auf die urbanen Systeme in Brasilien legt. Zu diesem Zweck untersuche ich die Beziehung zwischen Vulnerabilität und Stadtentwicklung mittels interdisziplinärer Mixed-Method-Forschung. Drei zentrale Themen gestalten diesen Forschungsansatz. Das erste ist die Tatsache, dass die Auswirkungen verschiedener Stressoren in städtischen Systemen miteinander verknüpft sind. Das zweite ist der ungleiche Charakter von Vulnerabilität, dort wo Stadtentwicklung eine intensive Wechselwirkung mit Ungleichheiten zeigt, insbesondere in den informellen Siedlungen im Globalen Süden. Das dritte ist das Potenzial, Ungleichheiten und Krisen im Anthropozän mit interdisziplinären und offenen wissenschaftlichen Methoden in der Geografie zu untersuchen und zu bewältigen, um eine nachhaltigere und sozial gerechtere Welt zu schaffen.

In diesem Zusammenhang frage ich: Wie interagieren Gefahren mit den ungleichen Merkmalen der Stadtentwicklung im Globalen Süden unter Berücksichtigung eines Zusammenhangs zwischen Urbanisierung und Risikoexposition? In dieser Dissertation werden zur Beantwortung dieser Frage fünf Studien vorgestellt, die die Vulnerabilität, die Stadtentwicklung und die Krisen des Anthropozäns untersuchen. Ich konzentriere mich auf Brasilien als relevantes Beispiel für zeitgenössische Stadtentwicklung und hohe Vulnerabilität im Globalen Süden. Diese Forschungsarbeit präsentiert eine datenintensive Nutzung traditioneller geografischer Analysen in Kombination mit Techniken der Gesundheitsgeografie und der Verhaltensforschung, um räumlich-zeitliche Dynamiken auf verschiedenen Ebenen zu untersuchen. Das Ziel ist die Stärkung einer

integrativen Herangehensweise an die Forschungsfrage im Sinne eines solideren wissenschaftlichen Verständnisses der Forschungsprobleme.

Informelle Siedlungen in Flussdeltas von Städten des Globalen Südens verdeutlichen die Verkettung von Deprivationen, die im Anthropozän zu einer ungleichen Risikoverteilung in Städten führen. Im ersten Beitrag dieser Dissertation geht es um diese Problematik im Jacuí-Flussdelta. In dem Flussdelta stellen die ungleichen Stadtentwicklungsprozesse von Porto Alegre (Brasilien) einkommensschwache Familien vor eine schwierige Wahl zwischen der Ansiedlung im exponierten Zentrum oder dem Stadtrand. Über die Untersuchung der Risikobewältigung von Haushalten in zwei exponierten Landschaften im Flussdelta wird in diesem Beitrag versucht, die Faktoren zu verstehen, die die Risikobewältigung bestimmen. Die Analyse zeigt, dass die ärmeren Haushalte trotz der ausgeprägten Wahrnehmung der Überschwemmungsgefahr stärker unter den Auswirkungen litten und eine geringere Reaktionsfähigkeit aufwiesen. Diese Erkenntnisse sind zentral für Anpassungsstrategien und Umweltgerechtigkeit.

Im zweiten Beitrag wird der Zusammenhang zwischen sozioökonomischer Deprivation und COVID-19-Todesfällen untersucht. In diesem Kapitel werden brasilianische Städte aus dem gesamten Spektrum der sozialen Vulnerabilität unter Verwendung gesundheitswissenschaftlicher Methoden betrachtet. Das Innovative daran ist die Darstellung des räumlich-zeitlichen Verlaufs von Todesfällen auf verschiedenen Vulnerabilitätsstufen. Die Ergebnisse weisen auf feste Zusammenhänge zwischen langfristiger sozialer Vulnerabilität und COVID-19-Todesfällen hin, da in risikoreicheren Städten im gesamten Zeitraum geringere Überlebenswahrscheinlichkeiten bestanden. Diese Ergebnisse unterstreichen, wie wichtig es ist, eine mehrdimensionale, nachhaltige Entwicklung zu fördern und die strukturelle Vulnerabilität zu verringern, um zusätzliche Todesfälle zu verhindern.

Die strukturelle Vulnerabilität erklärt allerdings nicht die gesamte Variabilität bei COVID-19-Todesfällen. Im dritten Beitrag dieser Forschungsarbeit wird ein agenten-basiertes Modell zur Bewertung des Mobilitätsverhaltens während der COVID-19-Pandemie in Brasilien umgesetzt. Das Modell beinhaltet Gruppen von Agenten mit unterschiedlichen demografischen Profilen und Szenarien. Es soll herausgefunden werden, wie sie unter Abwägung zwischen dem Streben nach Wohlbefinden und der Vermeidung von Exposition ihre Entscheidungen treffen. Die Ergebnisse zeigen, dass wann immer es finanziell möglich war, die Agenten auf öffentliche Verkehrsmittel verzichteten und stattdessen private Verkehrsmittel nutzten. Agenten mit geringerem Einkommen konnten sich eine solche Entscheidung nicht leisten, was zu einer Segregation der Gesellschaft führte und aufzeigt, dass es möglich war, sich von der Exposition freizukaufen.

Der vierte Beitrag in dieser Dissertation sucht nach einem gemeinsamen Nenner zwischen Klimawandel und COVID-19 in Form von Vulnerabilität. Er stützt sich auf eine Vermischung qualitativer und quantitativer Methoden auf verschiedenen Ebenen und unter Verwendung unterschiedlicher Stichproben. Die Ergebnisse zeigen, dass die negativen sozialen Folgen von Gesundheits- und Klimakrisen miteinander interagieren und sich verstärken können. Diese kombinierten Effekte sind besonders ausgeprägt bei vulnerablen Bevölkerungsgruppen in Gebieten, wo aufgrund geringerer Anpassungs- und Widerstandsfähigkeiten negative Auswirkungen länger und über unterschiedliche Dimensionen wie persönliche Gesundheit, Familienleben und Lebensunterhalt nachhallen.

Im fünften Beitrag wird die Beziehung zwischen geografischer Forschung und vulnerablen, informellen Siedlungen reflektiert. Es wird die Ermächtigung der Bürgerinnen und Bürger beurteilt und das Potenzial für volunteered geographic Information (VGI) Methoden zur Erhebung dringend benötigter Daten zu informellen Siedlungen im Globalen Süden überprüft. Dabei wird ein qualitativer Forschungsrahmen verwendet, um zwei VGI-Praktiken in Mexiko-Stadt und São Paulo zu klassifizieren. In dieser Klassifizierung wurden die in den VGI involvierten Agenten, offengelegt, wodurch die Freiwilligen, die die Daten produzierten, von den in den Daten dargestellten Subjekten entkoppelt wurden. Dadurch werden die potenziellen Konflikte zwischen diesen Agenten und den Einschränkungen hinsichtlich der technologischen Kompetenz, der verfügbaren Ressourcen, der Handlungsfähigkeit und der Beteiligung der Forschungssubjekte deutlich.

Die wichtigsten Schlussfolgerungen aus dieser Dissertation sind, dass Gesundheits- und Klimakrisen über die Faktoren der Exposition und Vulnerabilität untereinander sowie mit der ungleichen Urbanisierung im Globalen Süden interagieren. Auch nehmen Anpassungsstrategien konkrete Formen an und sollten der Ungleichheit entgegenwirken, da dies Synergien über verschiedene Vulnerabilitätsfaktoren hinweg produziert. Während der Klimawandel und das Anthropozän immer weiter voranschreiten, sollten sowohl die wichtigen Forschungsarbeiten als auch die Politik die Synergien zwischen ungleicher Entwicklung und Anpassung untersuchen. Letztendlich zielt diese Forschungsarbeit darauf ab, Umweltgerechtigkeit zu fördern, um eine effektivere, effizientere und gerechtere Umsetzung weltweiter Transformations- und nachhaltiger Entwicklungsstrategien zu erreichen.

CONTENTS

LIST OF PUBLICATIONS

1. Santos, A. P., Rodriguez Lopez, J. M., Chiarel, C., & Scheffran, J. (2022). Unequal Landscapes: Vulnerability Traps in Informal Settlements of the Jacuí River Delta (Brazil). *Urban Science*, *6*(4), 76. https://doi.org/10.3390/urbansci6040076.

As the lead author, Alexandre P Santos contributed approx. 80 % of the article's content. In collaboration with his co-authors, he developed the research idea, conducted the literature review, performed formal analysis, developed the software, curated data, prepared the first draft and led the review process.

2. Santos, A. P., Rodriguez Lopez, J. M., Heider, K., Steinwärder, L., Scheffran, J., & Vargas, J. C. B. (2022). One year of the COVID-19 pandemic in the Global South: Uneven vulnerabilities in Brazilian cities. *Erdkunde*, 76(2), 75–91. https://doi.org/10.3112/erdkunde.2022.02.02.

As the lead author, Alexandre P Santos contributed approx. 70 % of the article's content. In collaboration with his co-authors, he developed the research idea, conducted the literature review, performed formal analysis, developed the software, curated data, prepared the first draft and led the review process.

3. Peng, Y., Rodriguez Lopez, J. M., Santos, A. P., Mobeen, M., & Scheffran, J. (2023). Simulating exposure-related human mobility behavior at the neighborhood-level under COVID-19 in Porto Alegre, Brazil. *Cities*, 134(104161). https://doi.org/10.1016/j.cities.2022.104161.

As a contributing author, Alexandre P Santos contributed approx. 20 % of the article's content. Yechennan Peng led the model development. Alexandre P Santos provided central support in developing the model concept, designing the model scenarios, selecting, and preparing the data, implementing the model, analysing the results, and drafting the manuscript.

4. Santos, A. P., Pessoa Colombo, V., Heider, K., & Rodriguez-Lopez, J. M. (2023). Comparing Volunteered Data Acquisition Methods on Informal Settlements in Mexico City and São Paulo: A Citizen Participation Ladder for VGI. In S. Rodríguez López (Ed.), *Interdisciplinarity, GIScience, and socio-environmental research in Latin America* (pp. 255–280). Springer. https://doi.org/10.1007/978-3-031-22680-9_12.

As the lead author, Alexandre P Santos contributed approx. 60 % of the article's content. In collaboration with his co-authors, he developed the research idea, conducted the literature review, performed the formal analysis, prepared the first draft, and led the review process.

LIST OF ACRONYMS

ABM	Agent-based model
CNDs	Chronic non-communicable diseases
COVID-19	Corona virus disease 2019
COVIDGI	“Volunteered geographic information on the COVID-19 pandemic in the Global South” research project
ECLAC	Economic Commission for Latin America and the Caribbean
FIA	Federation Internationale de l'Automobile
GI	Geographic information
GIS	Geographic information system
GPS	Global positioning system
HDI	Human development index
IBGE	Brazilian Institute of Geography and Statistics
ICU	Intensive care unit
ILISs	Informal, low-income settlements
IPCC	Intergovernmental Panel on Climate Change
IPEA	Instituto de Pesquisa Econômica Aplicada
ITDP	Institute for Transportation and Development Policy
KME	Kaplan-Meier estimator
LDCs	least developed countries
NPIs	Non-pharmaceutical interventions
OSHA	Occupational Safety and Health Administration
OSM	OpenStreet Map
PAOT	Procuraduria Ambiental y del Ordenamiento Territorial del DF (Mexico)
PMT	Protection motivation theory
PNUD	United Nations Development Programme
PPGIS	Public participatory geographic information systems
SDOH	Social determinants of health
SP CSA1	São Paulo case study area 1 – expanded centre
SP CSA2	São Paulo case study area 2 – Benfica
SVI	Social Vulnerability Index
UFRGS	Federal University of Rio Grande do Sul
VIABLE	Values and Investments for Agent-Based Interaction and Learning for Environmental Systems model
VGI	Volunteered geographic information
VHR	Very high-resolution imagery

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1 INTRODUCTION

Cities are central components of the Anthropocene. On the one hand, global urbanisation demonstrates the intensity of the changes that humanity produces in the planet's biophysical environment (Frank et al., 2017; McPhearson et al., 2016). Society has produced urban areas to adapt the underlying environment to human needs (Alberti et al., 2018). In doing so, humanity has increased opportunities for social interaction (Bettencourt & West, 2010) that support the current global and predominantly urban civilisation (Paresi et al., 2016). On the other hand, humanity has pushed the Earth's climate beyond its natural variability (IPCC, 2022). Under climate change, cities have suffered losses and damage from extreme weather events and health crises, such as floods and the COVID-19 pandemic. These disasters interrupt and decrease economic activity, lead to social crises (e.g. migration), drain limited resources towards recovery and lead to human and non-human fatalities (Romero-Lankao et al., 2016; Sillmann et al., 2021). The very concentration of infrastructure, goods, activities and people in cities amplifies the risks, exposing city inhabitants (Elmqvist et al., 2021). Ultimately, cities are also critical components of adaptation policies and concentrate on many emerging factors of global climate risks (Revi et al., 2015).

Human health is also deeply associated with urbanisation. Higher population densities allow for a more efficient distribution of services, and the advantages of agglomeration support the complexification of infrastructure and services (Nicolelis et al., 2021; Pereira et al., 2021). Cities are built to provide increased densities and social interaction (Bettencourt & West, 2010), but these become liabilities during epidemics that thrive on the interpersonal transmission of pathogens, such as COVID-19 (Wu & McGoogan, 2020). Urban areas are sources of many stressors, including pollution, emotional stress, unhealthy mobility (e.g. dependence on automobiles) and poor nutrition (Marmot, 2005; Salgado et al., 2020). Urban inequality reduces accessibility for specific population groups (e.g. ethnic minorities, see Cutter, 1995) in underprivileged locations (Graham, 2016) and informal settlements (Corburn et al., 2020).

Unequal urbanisation is a distinct feature of the Global South in the Anthropocene. Cities in this region often concentrate infrastructure, services and shared social goods (e.g. lively commercial areas, green spaces and urban parks) where the historical (Gilbert & Gugler, 1984) or current elites reside (Feitosa et al., 2021; Romero-Lankao et al., 2016). Urban structure (D. Harvey, 2006) often follows economic development (Borsdorf et al., 2007; Wheaton, 1982) and interacts with the biophysical environment to create hybrid environments (i.e. socio-techno-ecological systems, see Alberti et al., 2018). These environments offer a gradient of location opportunities that sustain social dynamics (Bettencourt & West, 2010), with variable urbanisation quality. For the poorest households, this gradient signifies territorial segregation, social exclusion and increased exposure (De Koning & Filatova, 2020; Feitosa et al., 2021) to the effects of climate change (e.g. floods) and health. The result is a concentration of vulnerabilities to climate and health impacts when increased exposure coincides with a low capacity to withstand hazards (Boubacar et al., 2017; Corburn et al., 2020; Pelling, 2003).

Brazil presents contemporary urban dynamics that make it uniquely suited for the analysis of socio-environmental vulnerability in the Anthropocene. It is one of the most socioeconomic unequal countries in the world (UN-Habitat, 2022), presents an integrated, hierarchical and dense urban network (IBGE, 2008; Nicolelis et al., 2021) and suffers frequent adverse outcomes from extreme weather events (IPCC, 2022; Reyer et al., 2017). Additionally, the COVID-19 pandemic met high socioeconomic vulnerability, ideal conditions for viral transmission and a fragmented government response in Brazil, leading to abnormally high fatality rates (Buss et al., 2021; M. C. Castro et al., 2021). These conditions make the country an ideal candidate for exploring the connections between urbanisation and risk exposure. My previous experience in the country also places me in a privileged position to acquire data and access relevant stakeholders at different scales (e.g. national and local) to support this research (see Appendix D).

This research investigates the unequal attribution of climate and health risks in cities in the Anthropocene. The primary assumption is that more vulnerable urban population groups suffer more intense or lasting adverse consequences from climate and health crises (Revi et al., 2015; Watts et al., 2021). Therefore, this research hypothesises that the adverse outcomes of the COVID-19 pandemic and climate change are more pronounced among vulnerable urban populations in Brazil following a nexus between urbanisation and risk exposure.

To test this hypothesis, I inquire about how hazards interact with the unequal features of urban development in the Global South, considering the nexus between urbanisation and risk exposure. I outline three main topics to answer this question. The first is the interconnected character of the impacts of multiple stressors from climate (e.g. flooding) and health crises (e.g. the COVID-19 pandemic) in urban systems (Revi et al., 2015; Watts et al., 2021) in the Global South. The second is the unequal character of socio-environmental vulnerability, in which urban development shows intense interaction with socioeconomic gradients (e.g. income difference) especially in informal low-income settlements (Corburn et al., 2020; Malanson, 2020) in Brazil (S. L. Li et al., 2021). The third is the potential for interdisciplinary and open scientific methods in geography, seeking to contribute to studying and managing urban inequalities and the crises in the Anthropocene towards a more sustainable and socially just world.

The relevance of this research lies in integrating urban development into risk exposure through socio-environmental vulnerability. By bringing together vulnerability to climate change and health hazards, this research seeks to map factors that increase exposure (such as location choice) and vulnerability (e.g. limited coping capacity from low human development). These insights will expand knowledge on multidimensional vulnerability, highlighting the contribution that longstanding inequality factors have to it. In this sense, inequality can feature in adaptation measures that improve urban resilience against the crises of the Anthropocene while promoting environmental justice.

Moreover, this enquiry supports the integration of global policy agendas at the local scale, such as the Sustainable Development Goals and the New Urban Agenda (UN-Habitat, 2016). To do so, it examines the potential synergies between climate and health crises as they converge in cities. These synergies emerge when cities are viewed systemically (Hoff, 2011; McPhearson et al., 2016). In this light, the urban concentration of exposure and vulnerability factors common to several hazards (e.g. socioeconomic vulnerability, inequality and lacking or inadequate infrastructure) indicates potential triggers for positive systemic changes that policies may explore.

1.1 THEORY

1.1.1 Cities in the Anthropocene

As the climate crisis deepens, cities in the Anthropocene need to adapt (Revi et al., 2015) to withstand the impacts of systemic crises (Sillmann et al., 2022). Moreover, future shocks will affect cities unevenly (Adger, 2006; Pelling, 2003), as global, regional and local spatial development processes are unequal (D. Harvey, 2006). On a global scale, vulnerability and climate justice relate closely; developing countries will face the most losses and damage despite contributing less to climate change (Gu et al., 2015; IPCC, 2022). Health crises will affect developing countries intensely, given urbanisation trends of urban transition marked by poverty in Africa (Paresi et al., 2016; UN-DESA, 2022) and unequal urban development patterns (UN-Habitat, 2022). Furthermore, the existing capacity for coping is low in developing countries. In these countries, increased exposure in the Anthropocene and low investment capacity compound historical deficits in infrastructure and resistive capacity. This combination of adverse factors suggests a significant potential for loss of life and damage to the economy, society and quality of life over the next century (IPCC, 2022; Revi et al., 2015). It also indicates potential synergies in risk reduction, climate adaptation and urban development policies (Hoff, 2011; UN-Habitat, 2016; UNISDR, 2015; United Nations, 2015).

At the local scale, poverty and deprivation often match environmental exposure, following social and market forces (Alberti et al., 2003; Santos et al., 2017) that frequently align with ethnic, religious or gender segregation (Bolin & Kurtz, 2018). Failed adaptation policies and exclusionary urban development exacerbate these problems. They alienate citizens from opportunities or create poverty–vulnerability traps (Adger, 2006; Pelling, 2003) and dispossession cycles (Henrique & Tschakert, 2021) that often force the poor into greater exposure. Socio-environmental vulnerability, therefore, is a developing process involving exposure, resilience and resistance to adverse effects (Pelling, 2003), and its analysis must integrate urban development processes.

Research on vulnerable populations demands special attention to ethics and the unintended consequences of outside interventions. Informal and low-income settlements often face tenure insecurity and are at the edge of legal codes (Patel et al., 2012). Research in these contexts may disrupt local power equilibria, generate unwarranted support expectations and lead to unforeseen consequences (Guaraldo Choguill, 1996). Sensitivity to regional characteristics is crucial, and the humanitarian community offers guidelines on ethics (Slim, 2015). Even so, there is a research gap to be filled on the issue of respect towards research subjects, their agency and their capacity for dialogue (UNESCO, 2021) in the practices of geographic research (Haklay, 2013).

Furthermore, informal, low-income, vulnerable or otherwise contested areas are frequently under-represented or absent from official sources of geographic information (Camboim et al., 2015; Kuffer et al., 2021; Souza, 2012), hindering geographical research and providing ample room for misconceptions and biases (Corbett & Keller, 2005; Patel et al., 2012). New Web 2.0 technologies, such as crowdsourced, volunteered and participatory geographic information, allow for more democratic knowledge production. These practices can critically contribute to how research describes, analyses and supports policies for vulnerable areas in the Global South (Hachmann et al., 2018). Democratising information production can also be framed within the context of interdisciplinarity and open science (UNESCO, 2021). Geography can achieve more robust insights by opening scientific knowledge and engaging societal actors with other knowledge systems (e.g. through participatory practices or citizen science). In this context, societal and interdisciplinary research dialogues can also support tackling complex problems such as climate change or the COVID-19 pandemic, especially in their social dimensions (Basile, 2022; Henrique & Tschakert, 2021; Rose-Redwood et al., 2020).

1.1.2 The urbanisation-risk exposure nexus

This research proposes a framework of the urbanisation–risk exposure nexus articulated by socio-environmental vulnerability to describe the systemic connections between urbanisation and risk exposure in cities from the Global South in the Anthropocene. This framework stems from a select literature review on human vulnerability, multiple stressors and compound risks or hazards (shown in Table 1-1). This framework bridges the problem of vulnerability to climate and health crises. It also guides the remaining contributions of this dissertation within a systematic analysis of the overarching research problem of the unequal distribution of climate and health hazards in cities in the Anthropocene (see Section 1.2).

To present this nexus, I first focus on human systems through socio-environmental vulnerability. In this research, vulnerability is the 'inability to avoid or absorb potential harm' when exposed to hazards (Pelling, 2003, p. 5). Vulnerability is multidimensional; it includes livelihoods, social and economic assets, health, food, education, security and social capital (Adger, 2006; Boubacar et al., 2017; Waters & Adger, 2017). It is also context dependent and dynamic, varying with movement (e.g. migration) and over time (Pelling, 2003; Waters & Adger, 2017). Being context bound means it stems from characteristics and conditions at the individual, community and social scales (Adger, 2006; Pelling, 2003, 2010) and connects it to the topics of environmental justice, race, ethnicity and social class (Bolin & Kurtz, 2018; Cutter, 1995; Travassos et al., 2021). Hence, this investigation seeks to bridge the social aspects of vulnerability (e.g. human development) to its environmental features (e.g. exposure or location opportunities).

Socio-environmental vulnerability also conditions many health outcomes and impacts well-being via the social determinants of health (SDOH) (Marmot, 2005; Salgado et al., 2020) or the 'ZIP code effect' (Graham, 2016). This territorial effect is associated with social and political factors (e.g. belonging to excluded ethnic groups) and social class (e.g. income). The urban poor and other marginalised groups are often exposed and have lower coping capacity (Boubacar et al., 2017), especially in informal, low-income settlements (Corburn et al., 2020; Gran Castro & Robles, 2019; Williams et al., 2019).

Table 1-1: Select literature review results.

Literature bodies	Main insights	Sources
Vulnerability frameworks	Vulnerability is a multidimensional, dynamic process that combines. exposure, sociodemographic characteristics, access to assets, livelihoods and social capital. Vulnerability is contextual and trans-scalar, involving the individual, family and society scales. Vulnerability is not anonymous; it has race, class and ethnicity.	Adger, 2006 Bolin & Kurtz, 2018 Cutter, 1995 Cutter & Emrich, 2006 Salgado et al., 2020 Pelling, 2003; 2010 Satterfield et al., 2004
Multiple stressors	Climate change shows increasing temporal and spatial overlap of stressors (e.g. heat waves, droughts and poor air quality). Cities concentrate exposure. Cities provide economies of scale for resilience. Informal, low-income settlements often combine low well-being and high vulnerability. The poor often live on their resistive threshold, are more exposed and are less capable of coping. Stressors have environmental, technological and social origins.	Corburn et al., 2020 Crutzen, 2002 Elmqvist et al., 2021 Gibbard et al., 2022 Watts et al., 2021
Compound risks or hazards	Hazards may interact directly or through their secondary effects. Frequency of hazard impacts and resistance, resilience and recovery capacity Systemic risks are unique; their outcomes cross system scales and affect multiple locations or sectors of society. Systemic risks have a greater possibility of interacting with other hazards and conflicts, tipping social systems beyond their resistive thresholds. Health and climate hazards may also interact directly or indirectly. Repeated impacts may lead to poverty–vulnerability traps	Cinner et al., 2018 Juhola et al., 2022 Sillman et al., 2022 Zscheischler et al., 2018

Second, it is worth considering the multiple stressors present in cities in the Anthropocene. Climate change will impact the global conditions of exposure (e.g. by increasing extreme event frequency and probability), endanger livelihoods (e.g. by changing weather patterns that affect global supply chains) and increase the frequency and duration of secondary stressors (e.g. air pollution from forest fires) (IPCC, 2022; Monteiro et al., 2022). The effects of different climate and weather hazards may overlap and interact, as seen in Pakistan in 2022, when a heatwave created the conditions for massive flooding (Mallapaty, 2022).

Urban systems often accumulate global infrastructure and population. Cities are focal points for exposure due to their agglomeration and the number of exposed people. It also makes them central to promoting resilience, as economies of scale may increase the efficiency of adaptation policies and speed up the implementation of innovative practices (Elmqvist et al., 2021; UN-Habitat, 2022). The unequal development pattern of urban areas in the Global South creates different vulnerability profiles, which are especially poignant in socially unequal countries (e.g. Brazil, see UN-Habitat, 2022). These profiles allow the impacts of hazards to remain in place longer (e.g. re-infection from new virus variants) and stimulate secondary adverse effects from the initial outcomes (e.g. unemployment and social strife following response measures) (Corburn et al., 2020). The combination of a higher probability of exposure with intense vulnerability in cities of the Global South increases the plausibility of crises that converge on socio-environmental vulnerability (Watts et al., 2021).

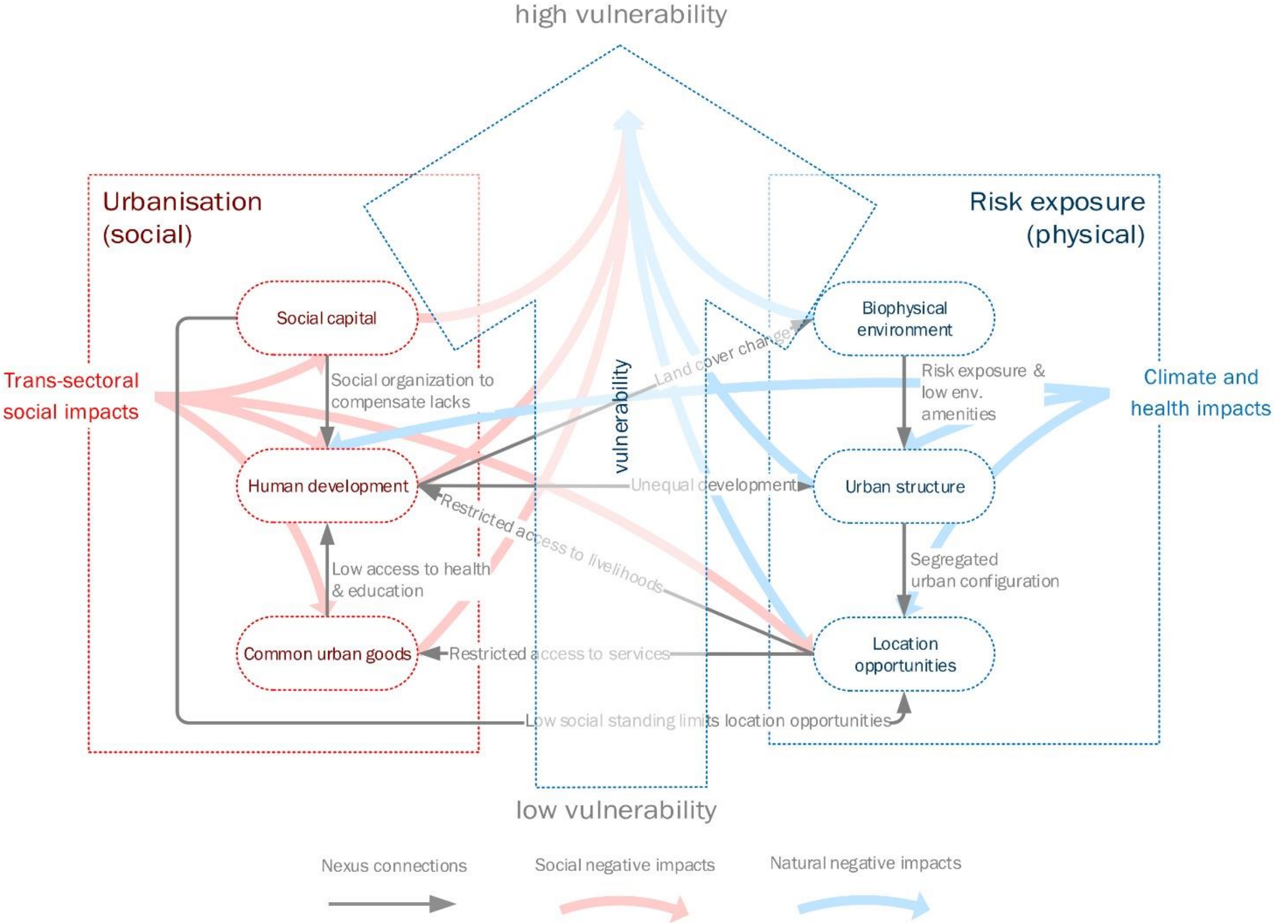
Third, multiple stressors and hazards may interact if they overlap temporally or spatially, creating compound events (Zscheischler et al., 2018). With increasing frequencies and intensities of hazards from a changing climate (IPCC, 2022), resistance and resilience of human systems may become increasingly challenged, potentially leading to spill-over and cascading effects across sectors or spaces (Sillmann et al., 2022). These systemic risks may lead to social tipping points, in which abrupt, irreversible changes lead to long-term, high-intensity losses (Juhola et al., 2022). Health and climate hazards may interact directly (e.g. forest fires lead to pulmonary diseases) or indirectly (e.g. COVID-19 decreases economic activity, hampering adaptation investment). Among the urban poor, the long-term social impacts from multiple events often overlap, in the form of decreased development opportunities and life expectancy (Boubacar et al., 2017). This convergence of social and environmental problems frequently leads to poverty traps (i.e. inexistent upward social mobility), which may increasingly be triggered by climate and health emergencies (De Koning & Filatova, 2020).

This set of interacting factors on multiple scales is complex and challenges treatability by simple analytical means. To this end, I propose using the nexus approach, which translates into defining an analytical structure based on the interactions between the parts of a system and preserving their complexity and external connections. In this case, we focus on the connections between the social and environmental processes of urbanisation and risk exposure.

This approach understands cities as urban ecosystems (Alberti et al., 2003), where heterogeneous agents across multiple scales interact between themselves and with the environment, creating highly diverse social structures and processes (Alberti, 2017). To negotiate such a system's complexity, the framework presented in Figure 1-1 focuses on the relationships between physical and social elements articulated by socio-environmental vulnerability. The framework poses vulnerability as an association between physical and social factors. The physical aspects include the biophysical environment, urban structures and location opportunities, grouped into risk exposure. The social factors fall into urbanisation and are human development, common urban goods and social capital.

The framework includes exposure as an environmental condition that connects the biophysical environment (including the bio-, hydro-, geo- and atmosphere) to the urban structures and the location opportunities that evolve in it. Different location opportunities are associated with risk exposure profiles. We propose urbanisation as a social process stemming from human development and social capital. Human development is the sum of the wealth, education and longevity of a group. Social capital derives from the connections between and within social groups in the city (i.e. its networks). Finally, the common urban goods signify the aggregated benefits of urbanisation, which are opportunities for personal and social development, shared services, goods (e.g. parks) and institutions (Bettencourt & West, 2010).

Figure 1-1: The urbanisation-risk exposure nexus for high-vulnerability population groups.



At the most basic level, the biophysical environment presents assets (e.g. flood-safe areas close to navigable rivers) and drawbacks (e.g. steep hillsides or swamp areas) that influence the development of urban form (Alberti et al., 2003), represented by the biophysical environment–urban structure connection. Urban morphology, in turn, changes the biophysical structure of the environment (Alberti et al., 2018). It adapts the environment to meet social needs through land cover changes and technological interventions, such as the urban structure–biophysical environment connection. The environmental assets and drawbacks add to the distribution of structures and interact with unequal spatial development (D. Harvey, 1978, 2006), generating a diverse landscape of location opportunities, presented in the urban structure–location opportunities connection.

These interactions within the physical aspects of the framework are far from simple and require some detail. Unequal spatial development essentially results in different amounts of value captured into locational and physical assets. The urban land market in developing capitalist countries, then, takes advantage of this heterogeneity to establish a process of unequal distribution of location opportunities (D. Harvey, 1978, 2006), Abramo (Abramo, 2012) called this process 'the urban convention'; high-income families seek self-isolation in locations with the best available environmental assets, attracting (via economic and political influence) public and private investments. Middle-income families follow, seeking to share the benefits of these investments. High-income households usually tolerate them, at least temporarily. Finally, struggling with high land or rent prices, low-income families try to locate as near as possible to the higher social strata to profit from the infrastructure and the job opportunities in the service sector, but proximity to high-income families may drive the latter to seek new exclusive areas away from poverty.

This process is a form of unequal spatial development (D. Harvey, 2006), represented by the human development–urban structure relationship. Under it, land and rent prices increase in the areas receiving improvements (e.g. adaptation measures, such as flood protection systems). Capitalists in the real estate market seek to capture the value thus created, promoting new developments targeted at middle- and upper-class households (De Koning & Filatova, 2020). If low-income groups occupy the newly protected areas, the new investments 'recontextualise' them (Barros, 2012), increasing segregation. When urban development results in segregation, it brings to fruition the location opportunities–common urban goods connection. This relationship establishes a trade-off between accessibility and risk for low-income families. They may opt for distant areas that are affordable and more frequently risk-free but provide few opportunities (Bittencourt et al., 2021). Alternatively, they may choose central regions close to work and public amenities but that are hazard-prone and often informal.

Over time, the result is that poverty and deprivation often match environmental exposure, following social and market forces (Feitosa et al., 2021; Watson, 2009) that frequently align with ethnic, religious or gender segregation (Bolin & Kurtz, 2018), showing the face of the social capital–location opportunities connection. Location opportunities thus also define human development, connecting location opportunities to human development. Higher income and education often mean accessing better locations that, in turn, provide improved opportunities for upward social mobility (Chetty et al., 2014).

Furthermore, the centrality-risk trade-off also defines accessibility to public and private services that form the common urban goods. Healthcare, transportation, public bureaucracy and other services also tend to concentrate on economically central areas or around the urban elites (Gilbert & Gugler, 1984; Janoschka, 2002). Physical distances may determine this accessibility, as does access to the social networks that include public officials (e.g. the cumpadrazgo tradition in Mexico, see Gilbert & Gugler, 1984), clans and extended family relations, shown in the social capital–human development relationship. Finally, accessibility to services, social capital, and location opportunities define many of the social determinants of health (SDOH, see Marmot, 2005), directly influencing human development through life expectancy (the common urban goods–human development connection). The overall result of this system is an unequal attribution of vulnerability, in which the most vulnerable are the poorer and socially excluded.

When hazards affect this complex system, they provoke additional instability that interacts with inequality in its relationships. First, the groups occupying the best environmental areas avoid the most impact. This condition may position them in a privileged position during recovery, creating new opportunities for development from the losses of the affected groups (consciously or not). The unequal attribution of vulnerability means that those most vulnerable face more frequent and intense impacts. This situation may be due to increased exposure and reduced coping capacity. Public policy and community organisation processes often seek to counteract vulnerability (notably in social capital, human development and urban structure), but their success is yet a matter of debate (Hardoy & Pandiella, 2009). Governmental and community response measures are critical but are also inefficient when compared to preventing losses and damage (Hardoy & Pandiella, 2009).

Natural hazards (e.g. floods) impact most the nexus through the biophysical environment, the urban structure and the access to common urban goods. Hazards such as extreme rainfall may alter the topography (e.g. through mass movements or land subsidence) or existing land cover of the affected regions, as well as damage the existing infrastructure and the built stock. Additionally, health emergencies impact common urban goods by overloading health services and suspending certain public functions (e.g. social workers were unavailable during COVID-19 lockdowns in Brazil). In both types of emergencies, the secondary effects impact human development by curtailing economic activity, diverting resources from consumption to recovery and destroying the assets necessary for livelihoods (Boubacar et al., 2017; Cinner et al., 2018; Zscheischler et al., 2018).

Affected social groups might seek to mitigate damage (e.g. by hastily floodproofing their household) or temporarily move out of exposed areas, but the latter is often a last resort (Penning-Rowsell et al., 2013). Temporary migration was especially prevalent during the COVID-19 crisis, as many households sought to avoid contagion by moving to low-density settlements (e.g. into the countryside). To mitigate damage, access to short-term resources (e.g. disposable assets) is critical, as they allow for rapid implementation of preventive measures to protect goods and assets (Pelling, 2010) or temporary relocation (Penning-Rowsell et al., 2013; Waters & Adger, 2017). In low-income contexts, social capital frequently mediates access to resources and informs other adaptation, response and recovery decisions (e.g. by providing examples or disseminating good practices) (Lo, 2013; Lo et al., 2015). Human development is also influential, as it allows access to community or socially shared savings and knowledge that are decisive in emergencies (Boubacar et al., 2017; Pelling, 2003).

The impact of hazards may prompt more intense adaptation. When these interventions worsen the risk for specific groups or areas, they constitute maladaptation, a significant outcome of the urban structure–biophysical environment relationship during hazards (Cinner et al., 2018; Waters & Adger, 2017). Even in well-planned cities, risks may lead to climate gentrification, increasing the vulnerability gradient between the most and the least vulnerable (De Koning & Filatova, 2020). Costly responses to short-term extreme weather events may widen historical gaps in infrastructure provision as they drain investment capacity from long-term adaptation (Cinner et al., 2018) or concentrate on areas with many economic assets (e.g. industrial or advanced services areas) (Waters & Adger, 2017). In more severe cases, adaptation can justify the forceful removal of low-income populations in cycles of dispossession (Henrique & Tschakert, 2021) fuelled by previous inattention and lack of support. Recent examples took place in South Africa, with policies of informal settlements de-densification to combat COVID-19 (Haferburg et al., 2022). Environmental and climate justice, therefore, beg the critical assessment of the existing and potentially widening gap in adaptive capacity within cities in the developing world. This gap reinforces social inequalities and poverty–vulnerability traps (Pelling, 2003).

This framework, therefore, proposes a systemic approach to the urbanisation–risk exposure nexus using socio-environmental vulnerability as an articulating concept. It focuses on urban areas, given their centrality in global, regional and local networks of production, socialisation and migration. This argument does not imply that non-urban areas are less exposed. Instead, it proposes that the effects of agglomeration in cities make them more susceptible to impacts, erode resistive capabilities (Pelling, 2003) and present greater chances for adaptation and loss prevention (Elmqvist et al., 2021). Ultimately, the framework indicates convergence and potential interaction across more than one scale between climate change and the COVID-19 crisis. Being theoretical and exploratory, it requires empirical support, for which we present the studies in the following sections.

1.2 OBJECTIVES AND RESEARCH QUESTIONS

The overarching research problem is the unequal distribution of climate and health hazards in cities in the Anthropocene. In this context, the primary assumption is that vulnerable populations suffer more intense or lasting consequences from climate (Adger, 2006; Pelling, 2003; Revi et al., 2015) and health crises (Corburn et al., 2020; Watts et al., 2021) and often have lower coping and adaptive capacities against these impacts (De Koning & Filatova, 2020; Garschagen & Romero-Lankao, 2015). This research works within the theoretical framework of the urbanisation–risk exposure nexus to structure this investigation (see Section 1.1). This framework proposes urbanisation as a dynamic social process composed of social capital, human development and common urban goods. It also presents exposure as the physical aspects of vulnerability, including the biophysical environment, urban structure and location opportunities.

Based on this framework, this research hypothesises that the adverse outcomes of the COVID-19 pandemic and climate change are more pronounced among vulnerable urban populations of the Global South following the urbanisation–risk exposure nexus. To test this hypothesis, I pose the following research question:

> How do hazards interact with the unequal features of urban development in the Global South, considering the nexus between urbanisation and risk exposure?

The overall research objective is to describe and analyse the system of interacting elements that compose the nexus of urban development and risk exposure in the Global South, considering socio-environmental vulnerability and inequality. To achieve this objective, I propose three specific objectives:

a) To describe the interconnection between multiple stressors from health and climate crises in urban systems from the Global South in the Anthropocene.
b) To assess the role of urban inequality in vulnerability to these multiple stressors.
c) To investigate the potential for interdisciplinarity and open science in geography to study and manage urban inequalities and crises in the Anthropocene.

The first specific objective seeks to validate the nexus framework based on empirical evidence. Recent scholarly work has explored vulnerability (Adger, 2006; Pelling, 2003; Salgado et al., 2020), multiple stressors (Elmqvist et al., 2021; Watts et al., 2021) and compound hazards (Zscheischler et al., 2018). It seeks to fill the research gap between urbanisation and risk exposure from a systemic perspective. The nexus framework presented in this dissertation is the first to bridge these dimensions to the best of our knowledge. Notwithstanding the theoretical plausibility of the framework, it requires empirical support. Hence, the empirical contributions in this dissertation seek to provide evidence that may support or contradict the nexus. Starting with climate change, we investigate informal settlements' coping and response capacities to a large-scale flood event in an urban delta to inquire:

> How do inhabitants of informal, low-income settlements in delta regions respond to extreme flooding? What are the factors that condition these responses?

The persistent location of informal settlements in risk-prone areas is a puzzling phenomenon, at least until one considers the urban development processes that lead to it. I aim to investigate these processes and examine the relationship between the social and physical factors of vulnerability in Chapter 2 of this dissertation. There, I analyse the different landscapes of risk that these processes entail and evaluate the influence of risk perception and risk response capacity in generating increased responses to a flood event. The goal is to track the factors and drivers of response to understand the interrelation of poverty and vulnerability that often lead to entrapment in extremely conditions.

The COVID-19 emergency is another significant facet of the Anthropocene. The pandemic rapidly achieved the role of a systemic crisis (Watts et al., 2021), affecting the whole global system across several sectors (e.g. health, supply chains and migration), albeit with widely varying outcomes. This research asks the following question to study the role of structural socioeconomic vulnerability in influencing the fatalities of COVID-19:

> How do different degrees of vulnerability among Brazilian cities lead to varying survival probabilities of their populations in the COVID-19 pandemic?

The third chapter of this dissertation investigates the 'perfect storm' scenario that was the first year of the pandemic in Brazil. The country presented a fragmented response to the pandemic (Barberia & Gómez, 2020). This response, combined with high pre-existing social and economic vulnerability (M. C. Castro et al., 2021) and the concentration and underinvestment in the health infrastructure (Nicolelis et al., 2021), generated death rates much above the global average (R. R. Castro et al., 2021). The goal of the chapter is to assess whether socioeconomic vulnerability is associated with increased fatality rates, indicating a significant connection in the nexus.

Unlike climate change, the COVID-19 pandemic presents a short timeframe. In a few weeks, it overcame global sanitary barriers and affected most countries, notably those more intensely connected. Analysing human behaviour at the intra-urban scale is central to understanding the pandemic's outcomes on fine temporal and spatial scales. This research, therefore, considers the following question:

> How and why do individuals' demographic characteristics and priorities influence changes in neighbourhood-level mobility patterns under COVID-19?

Mobility and interpersonal contact are essential factors in disseminating COVID-19 cases on an intra-urban scale. The COVID-19 crisis has profoundly changed mobility frequency, length and duration due to containment measures and personal risk perception (Bhaduri et al., 2020; Kopsidas et al., 2021). These changes did not affect all socioeconomic strata evenly (Eyawo et al., 2021; Shi et al., 2022; Wei et al., 2021), often following sociodemographic divisions (Bhaduri et al., 2020; Campisi et al., 2020; Dingil & Esztergár-Kiss, 2021). Using an agent-based model, we aim to simulate human mobility decision making during COVID-19 at the neighbourhood scale in the fourth chapter of this dissertation. This decision-making process will follow an exposure–well-being trade-off among heterogeneous agents.

By accumulating evidence from climate change and COVID-19, I outline the boundaries of the nexus framework. However, this evidence needs to be integrated and begs articulation. Recent literature points towards the convergence of the COVID-19 and climate change crises (Watts et al., 2021). There is a pronounced overlap between the impacts of these crises in highly unequal settings, such as a megalopolis in the Global South, such as São Paulo. This research seeks to answer the next question to add integrative evidence to the elements of the nexus:

> What is the system of connections between urbanisation and risk exposure in cities from the Global South in the Anthropocene? Specifically, are there urban populations that are vulnerable to both the COVID-19 pandemic and climate change, and what are the factors that influence this vulnerability?

By examining São Paulo through multiple scales (e.g. national, regional, metropolitan and intra-urban) and using a mix of qualitative and quantitative methods, I seek to verify the integration of factors presented in the urbanisation–risk exposure nexus. To this end, the fifth chapter of this dissertation first analyses unequal urban development processes and their impacts on vulnerability. Then, we aim to assess the implications of the COVID-19 crisis on different population groups, seeking potential commonalities to vulnerability to climate change.

When considering environmental justice (Cutter, 1995), adaptation policies and research must consider their consequences, such as exposing vulnerable communities to unintended harm (Scholz et al., 2018; Slim, 2015). Policies and analyses that are not mindful of the social and political contexts in which they take place may negatively impact empowerment, privacy and citizenship or promote maladaptation (Glover & Granberg, 2021). This problem is significant when working with informal settlements with high economic vulnerability and suffering from social exclusion (Patel et al., 2012). To this end, this research aims to investigate the role of geographic information in informal settlements by looking into a rapidly expanding set of methods based on Web 2.0 technologies, called volunteered geographic information (VGI) (Goodchild, 2007; Lin, 2013). To investigate this problem, this research considers:

> How do different VGI approaches support citizen participation and user empowerment? What are the opportunities and limitations of VGI for mapping informal settlements in Latin America beyond current authoritative data acquisition procedures?

The sixth chapter of this dissertation will examine the limits to empowerment in the acquisition, management and publication of geographic information from volunteered sources. This approach investigates the required material resources, geographic information system literacy, user agency and involvement of research subjects to classify two research initiatives in Latin America. With this contribution, I seek to reflect on the role of my research, guiding it towards fair, ethical and humane practices (Slim, 2015). This chapter aims to open the discussion with other forms of knowledge, leading to future research in interdisciplinarity and open science (UNESCO, 2021).

1.3 METHODS

To achieve the research objectives and answer the questions outlined above, I designed a multi-methods approach focused on quantitative analyses and reliant on qualitative methods for complementary evidence. All contributions to this dissertation presented interdisciplinary methods and explicitly dealt with social processes in space and time. The spatial scale range was varied, from the national to the intra-urban, seeking to provide interscalar insights into human societies' behaviour. Next, I briefly explore the mixed-methods design, explain the methods in each chapter and outline the data used.

It was decided to avoid the 'monolithic interlocking sets of philosophical assumptions' (Tashakkori & Teddlie, 2010, p. 13) in strict disciplinary research practices (Baerwald, 2010; Smith, 1989). This research took an alternative path and adopted an interdisciplinary approach to responding to the complex nature of the inter-relationships between scales, social groups and places (Alberti et al., 2018; Batty, 2014; Portugali, 2006). With this decision, I did not mean to underplay the contributions of disciplinary studies. Instead, the decision sought to reinforce an integrative approach in the name of a more robust scientific understanding of the research problems from a systemic perspective (Sillmann et al., 2022). This research presents typical geographic techniques, such as hot spot analysis (Getis & Ord, 1992; Ord & Getis, 2010). I complement these techniques with methods from other areas, such as health geography (e.g. the Kaplan-Meier estimator and the Cox proportional hazard model) and behavioural sciences (e.g. thematic analysis).

Chapters 3, 4 and 5 present a concerted effort in a mixed-methods research part of the 'Volunteered geographic information on the COVID-19 pandemic in the Global South' (COVIDGI) project. These chapters offered an iterative sequential, multi-level sampling mixed-methods approach (Tashakkori & Teddlie, 2010) focused on geographic information. In this research, I implemented a methodologically eclectic set of techniques to synergistically integrate qualitative and quantitative data and methods. The goal was to increase the validity of the quantitative results (Tashakkori & Teddlie, 2010) and address the systemic nature of risk by including context-specific evidence and societal values to them (Sillmann et al., 2022). Additionally, I improved the potential for open science through dialogue with social actors at multiple levels and across disciplines (UNESCO, 2021). This research sought a pragmatic and dialectic relationship between them by interfacing with inductive and deductive epistemological traditions. This stance permits a deeper understanding of the research topics while maintaining a clear and critical sense of the broader implications of the results.

In the COVIDGI project, I organised and promoted engagement with key stakeholders in Brazil. In this role, I interviewed, along with Dr Katharina Heider, eight stakeholders from academia (e.g. Federal University of Rio Grande do Sul, UFRGS), government (e.g. the Institute of Applied

Economic Research, IPEA) and social organisations (e.g. Teto Brasil, the Architects Union of the Federal District and the Institute for Transportation and Development Policy, ITDP Brasil). Even if these interviews did not feature explicitly in any of the chapters presented here as data, they provided evidence of the multidimensionality of COVID-19 and helped connect it to structural problems (e.g. inequality). They also supported the interdisciplinary dialogue that this research aims at, showing synergies across different fields (e.g. housing, transportation and health) and guiding its insights into more comprehensive societal applications.

This research caters to open science and open data. To this end, I used only open (Brasil.IO, 2021) and open-access authoritative datasets (Costa & Margutti, 2015; IBGE, 2011; SP Municipal Health Department, 2022). The exception to this rule is the fieldwork data, which are partly published as part of this dissertation and distributed in an open-access platform (see Chapter 5). Making the data available, I seek to increase the reproducibility of results and independent verification of the findings in my contributions, adhering to the findability, accessibility, interoperability and reusability (i.e. FAIR) principles for scientific data management (Wilkinson et al., 2016), best practices in open science (UNESCO, 2021) and ethical guidelines in humanitarian work (Slim, 2015). In this sense, I developed all data preparation and most analysis in this research using Python. To promote open science and reproducibility of results, I published the data and codes in an open-access platform (i.e. GitHub) in different repositories, as indicated below. During my research, I acted as the data steward for the COVIDGI project. In this role, I studied and promoted open science practices, as seen in the open-access publication of all data and code developed in the project (e.g. Chapter 4, below).

In Chapter 2, I combined statistical analysis with logit regression models and spatial analysis using hot spot analysis methods (Getis & Ord, 1992; Ord & Getis, 2010) to evaluate how inhabitants of informal, low-income settlements in delta regions responded to a significant flood event in 2015. I used a dataset from the World Bank (World Bank Group, 2019b, 2019a) with primary data about the responses of a large sample of households (n=1,451) in informal settlements in two regions of the Jacuí River Delta. Of the survey questions, I selected 12 that reported previous, current (in 2015) and future risk perception, risk response (14 different options), individual demographic characteristics (age, sex, income and ethnicity), and others. I used this information as variables in the logit regression models, first regressing against risk perception and then adding stepwise the other data. I implemented this design for three subsets of the original data (all households, households within the flood protection system and outside protection system)[1]. This design resulted in a set of 252 logit regression models that I compared with the low-income hot spots to address whether income could explain location in risk-free areas. This design allows the identification of the main drivers of risk responses and the detection of vulnerability–poverty traps.

In Chapter 3, I integrated open data sources and analytical methods from health geography to investigate how the different degrees of vulnerability among Brazilian cities led to varying survival

[1] The code and data are available at https://github.com/alexandrepereiraarq/vulnerabilitytraps.

probabilities of their populations during the COVID-19 pandemic. First, I examined the evolving literature on COVID-19 in Brazil. I analysed open data about COVID-19 fatalities at the municipality scale (Brasil.IO, 2021) to present a timeline for the first year of the pandemic in the country (i.e. 53 weeks starting in February 2020). Second, I implemented the Kaplan-Meier estimator (Kaplan & Meier, 1958) and the Cox proportional hazard model (Cleves et al., 2008) to investigate the effect of the long-term social variables presented in the social vulnerability index (SVI) (Costa & Margutti, 2015) on COVID-19 fatalities. The analytical design used five cities with more than 100,000 inhabitants as examples of social vulnerability[2]. To this end, I selected one city for each of the five quantiles in the SVI distribution (i.e. the 0, 25, 50, 75 and 100 quantiles), thus encapsulating different social, political and territorial factors. This design allowed for the observation of the survival probability curves for these cities. By comparing these curves with the SVI, one can verify whether more vulnerable cities (higher SVI) had lower survival probabilities. This design outlined the impact of longstanding inequality in Brazil with a rapidly spreading disease. It allowed researchers to ascertain whether the effects of the pandemic are similar between the Global South and North, indicating imperative insights into fighting current and future epidemics.

In Chapter 4, colleagues from the COVIDGI project and I developed an agent-based model (ABM)(BenDor & Scheffran, 2019) to understand how demographic characteristics and priorities influence the agents' mobility choices. To this end, we implemented a model simulating mobility decision making at the neighbourhood scale during Brazil's pandemic[3]. This model represented heterogeneous agents that set destinations and transportation modes that had distinct benefits (well-being) and risks (COVID-19 exposure) associated to them (BenDor & Scheffran, 2019), as reported in the literature (Abdullah et al., 2020; Martin et al., 2020) and the COVIDGI project fieldwork. The model permitted research to analyse the mobility choices of individual agents and the aggregate patterns of segregation that ensued. This also provided the COVIDGI project with rare intra-urban behavioural evidence, filling a gap from other approaches and sources. The model allowed insights into response measures to the health crisis, by investigating behavioural aspects of the relationship between COVID-19 contagion and mobility (Bhaduri et al., 2020; Dingil & Esztergár-Kiss, 2021).

In Chapter 5, I implemented a mixed-method design to analyse the connections between urbanisation and risk exposure in cities from the Global South in the Anthropocene[4]. I also investigated whether urban populations are vulnerable to the COVID-19 pandemic and climate change and which factors influence this condition. This chapter sought to combine methods and sources from previous studies, adding qualitative data and intra-urban analysis. This chapter also articulates these data and procedures across the dimensions of the urbanisation–risk exposure nexus. First, I investigated nuanced, experiential, qualitative data collected during fieldwork in São Paulo (SP) using thematic analysis (Braun & Clarke, 2006, 2012). Next, I complemented the qualitative

[2] The code and data are available at https://github.com/alexandrepereiraarq/COVIDGI.
[3] The code and data are available at https://github.com/Chennan-05/ABM-mobility-behavior-under-COVID-19.
[4] The code and data are available at https://github.com/alexandrepereiraarq/urb_exposure_nexus.

analysis with hot spot and survival analyses on the intra-urban scale. I detected socioeconomic vulnerability hot spots via the Getis-Ord G* statistic (Getis & Ord, 1992; Ord & Getis, 2010) and outlined three regions in the city based on their concentrations: the central, inner-periphery and outer-periphery regions. I compared these three areas to the COVID-19 fatality rates (SP Municipal Health Department, 2022) to explore the correlation between vulnerability and deaths. Next, I implemented the Kaplan-Meier estimator and Cox regression models to verify whether this association is statistically significant at the intra-urban scale. This design integrated vulnerability to climate and health hazards, which are substantial threats to development from converging (Watts et al., 2021) and systemic crises (Sillmann et al., 2022). It also highlighted key aspects of inequality that impact environmental justice (Cutter, 1995) and adaptation policies (Henrique & Tschakert, 2021) in the Global South in the Anthropocene.

In Chapter 6, I explored geographic information's role in empowering low-income, informal settlements in Latin America. To this end, I developed an analytical framework based on the pre-eminent 'Ladder of Citizen Participation' (Arnstein, 1969). This approach stemmed from the literature on geographic information, notably that on crowdsourced (Haklay, 2013), participatory (Verplanke et al., 2016) and volunteered geographic information (Goodchild, 2007; Yan et al., 2020) associated with the development of Web 2.0 technologies. My co-authors and I designed the framework based on four dimensions: user agency, geographic information science literacy, necessary resources and the involvement of the research subjects (i.e. those represented in the data). The framework thus qualitatively analysed two VGI practices—one in São Paulo by the NGO Teto Brasil and the other in Mexico by German and Mexican researchers (Rodriguez Lopez et al., 2017a)—providing an overall score in a hierarchical evaluation of practices of VGI centred on empowerment and sensitivity to the goals from those represented in the data.

1.4 THESIS STRUCTURE

Considering the problems of cities in the Anthropocene, the unequal vulnerabilities of climate change and COVID-19, and the potential for interdisciplinarity and open science in geography, this dissertation proposed a research agenda based on five contributions (Chapters 2–6), listed in Table 1-2, below. Of these contributions, I was the first author of four chapters (Chapters 2, 3, 5 and 6) and a substantial collaborator in the other (Chapter 4). Two of these contributions were published in peer-reviewed journals (Chapters 2 and 3), one is under review (Chapter 4), one is accepted as a book chapter (Chapter 6), and one is in the process of submission (Chapter 5). Chapters 3–5 are part of the COVIDGI project and constitute a mixed-methods investigation, as described in Section 1.3. Each contribution is a chapter in the dissertation that I describe below. Additionally, Table 1-2 presents the focus of these contributions to the research objectives outlined in Section 1.1.2.

Chapter 2 is the first contribution, investigating the factors driving risk responses in informal settlements using statistical and spatial modelling. Chapter 3 also implements statistical modelling and assesses the association of structural socioeconomic vulnerability with COVID-19 fatalities in different regions of Brazil. Chapter 4 presents an agent-based model of mobility choice during the COVID-19 pandemic in Brazil and demonstrates segregation patterns due to risk avoidance. Chapter 5 collects evidence from qualitative and quantitative sources to investigate the urbanisation–risk exposure nexus, using COVID-19 in São Paulo as the case study. Chapter 6 addresses the problem of empowerment in informal communities in Latin America through different practices of geographic information acquisition. The final chapter interprets the findings of the five original contributions above. It also evaluates and discusses their findings and indicates future research opportunities.

Table 1-2. Dissertation structure and contributions to the overarching dissertation objectives.
Source: author.

			Contribution to research objectives		
Chapter	**Title of section or contribution**	**Publication status**	**(A) Multiple stressors**	**(B) Inequality & vulnerability**	**(C) Interdisciplinarity & open science**
1	Introduction		Minor, to all objectives		
2	Santos, A. P., Rodriguez Lopez, J. M., Chiarel, C., & Scheffran, J. (2022). Unequal landscapes: Vulnerability traps in informal settlements of the Jacuí River Delta (Brazil).	Published: Urban Science 6(4). DOI: 10.3390/ urbansci6040076	Minor	Major	-
3	Santos, A. P., Rodriguez Lopez, J. M., Heider, K., Steinwärder, L., & Scheffran, J. (2022). One year of the COVID-19 pandemic in the Global South: Uneven vulnerabilities in Brazilian cities.	Published: Erdkunde, 76(2). DOI: 10.3112/erdkunde. 2022.02.02	Major	Major	Minor
4	Peng, Y., Rodriguez Lopez, J. M., Santos, A. P., Mobeen, M., & Scheffran, J. (2023). Simulating exposure-related human mobility behavior at the neighborhood-level under COVID-19 in Porto Alegre, Brazil. Cities, 134 (May 2022), 104161.	Published: Cities, 134. DOI https://doi.org/10.1016 /j.cities.2022.104161.	-	Major	Minor
5	Santos, A. P., Rodriguez Lopez, J. M., & Scheffran, J. (2023). Connecting Covid-19 and Climate Change in the Anthropocene: Evidence from urban vulnerability in São Paulo.	Preparing for submission.	Major	Major	Minor
6	Santos, A. P., Colombo, V. P., Heider, K., & Rodriguez Lopez, J. M. (2023). Comparing volunteered data acquisition methods on informal settlements in Mexico City and São Paulo: A citizen participation ladder for VGI.	Published: S. Lopez (Ed.), Socio-Environmental Research in Latin America. Springer.	-	Minor	Major
7	Conclusion		Minor, to all objectives		

2 UNEQUAL LANDSCAPES: VULNERABILITY TRAPS IN INFORMAL SETTLEMENTS OF THE JACUÍ RIVER DELTA (BRAZIL)

Peer-reviewed publication[5]:

Santos, A. P., Rodriguez Lopez, J. M., Chiarel, C., & Scheffran, J. (2022). Unequal Landscapes: Vulnerability Traps in Informal Settlements of the Jacuí River Delta (Brazil). *Urban Science*, 6(4), 76. https://doi.org/10.3390/urbansci6040076

ABSTRACT

How just are risk responses that worsen vulnerability in the long term? Should the urban poor be left with self-reliance when facing hazards in the Anthropocene? This research investigates urban development and vulnerability in the Anthropocene. While it is known that informal settlements face greater hazards than most urbanized areas, there are different landscapes of risk. The analysis explores divergent risk-response strategies among households according to their residents' risk perception and response capacity in two different landscapes of an urban delta using logit regression models. These models evaluate the associations between 14 response options to floods and control for factors of income, age, number of residents in the household, location, access to vehicles, and self-identified ethnicity. This study uses data from the Living with Floods Survey by the World Bank to investigate risk responses to the 2015 flood in the Jacuí River delta. The analysis considers a large sample of households (n = 1,451) in informal settlements. The results show the intense influence of income on location choice and response capacity. We also found that income is a more robust social descriptor of response capacity than age or ethnicity. Risk perception proved limited in determining response strategies and can be associated with resignation to losses from floods. We argue that these results suggest trade-offs between short- and long-term responses to hazards in informal settlements in coastal and delta regions, which link adaptive behaviour to environmental justice.

Keywords: risk response, flooding, informal settlements.

[5] Text and tables were reformatted, and tables reordered to fit dissertation layout. Spelling was adjusted to British English, for consistency with other sections of the dissertation.

2.1 INTRODUCTION

Responses to risk events often require decisions under conditions of high uncertainty. Responses are limited by the capacity to understand risks, assess potential damage, and implement adaptation or coping strategies to prevent losses. Urban poor communities frequently face difficult decisions during these crises, such as relocating to avoid harm, creating potential opportunities for theft in vacated households, or failing to prevent losses of immovable assets (e.g. their houses) located in risk-prone areas. The increasing magnitude of hazard events, the limited support capacity from authorities, and failures in distributing support provision (e.g. during Hurricane Katrina, mostly Black poor were left unattended) raise questions of fairness in pushing the urban poor toward self-reliance during environmental crises, such as coastal or riverine floods (Cutter & Emrich, 2006). They also present trade-offs between responding to short-term weather shocks and adapting to long-term climate change (Cinner et al., 2018). These issues demonstrate a research p in the poverty–vulnerability traps fostered by unequal development. To address this gap, this research seeks to unravel some of the connections between vulnerability (Adger, 2006; Pelling, 2003; Revi et al., 2015) and urban development (Batty, 2014; Paresi et al., 2016) in the Anthropocene (Crutzen, 2002; Gibbard et al., 2022).

The concept of the Anthropocene helps bring to the foreground the degree to which human transformations have altered natural systems on a global scale (IPCC, 2022). It is telling that these changes ushered in a series of impacts that are significantly detrimental to cities, such as rising sea levels and increased frequency of extreme weather events, demonstrating the face of the climate crisis (Scheffran, 2020). Cities are a nexus of multiple problems in the climate crisis. On the one hand, urban areas are responsible for most energy consumption and global CO_2 emissions (ca. 70%). On the other hand, urban areas are also dangerously exposed to sea-level rise and coastal storms (Elmqvist et al., 2021). This paper explores the potential losses and damage for coastal and deltaic cities in the Anthropocene, their connections to environmental justice (Bolin & Kurtz, 2018; Satterfield et al., 2004), and risk–risk trade-offs (i.e. when there are no risk-safe choices available) (Cummings et al., 2020). It does so by analysing flood hazard responses in the delta region of the Jacuí River in Porto Alegre (Brazil). We present this case as an example of the combination of exposure and low coping capacity that is present in many urban deltas globally, but more acutely so in the Global South (Bangalore et al., 2019; Deinne & Ajayi, 2021; Tessler et al., 2015). We analyse flood responses to understand the role of risk information and response capacity based on a large sample of households in informal settlements of the delta (n = 1,451). Our findings show that structural inequality is the most significant risk differentiator, notably through spatial location and response capacity.

2.1.1 Urban development and compound effects of hazards

Global urban growth is marked by unequal patterns of development that lead to differential levels of vulnerability to the impacts of climate change (Garschagen & Romero-Lankao, 2015). While cities in developed countries have some measures of risk-management policies and infrastructure in place, many cities in the Global South lack financial resources or coordination for climate adaptation while facing rapid growth and unequal spatial development patterns (Monteiro et al., 2022). Power asymmetries, social norms, and political relations skew infrastructure distribution (e.g. when caste systems or political clout influence the distribution of infrastructure), resulting in the unequal provision of adaptation measures (Cinner et al., 2018; Henrique & Tschakert, 2021). More urbanization does not always result in increased vulnerability (Garschagen & Romero-Lankao, 2015); more unequal urban development does, though. More affluent households buy access to safe locations, increasing demand and pushing up prices which excludes the socially vulnerable to exposed areas (De Koning & Filatova, 2020).

Considering the predicted changes in rainfall and extreme weather events, highly vulnerable areas in coastal or deltaic regions will be increasingly challenged (Boubacar et al., 2017; Tessler et al., 2015). In these areas, increased rainfall variability, extreme weather events, and rising sea levels can produce large-scale damage and loss of life (Brondizio et al., 2016). Cities in the urban deltas of developing countries face the compounding effects of high exposure and low resistive or responsive capacities (Bangalore et al., 2019; Romero-Lankao et al., 2016). Furthermore, urban development patterns in these cities often concentrate on infrastructure and services in small upper-class sectors, leading to increased overall vulnerability.

Unequal urban development is cyclic in nature (D. Harvey, 2006). Areas with better environmental conditions attract residential demand. This increased demand leads to investment by the market supply sectors (e.g. real estate developers) and higher prices. Investment leads to renewed demand, especially among affluent households, which leads to new investments, and so forth. One of the results of these valuation cycles is the exclusion of low-income households from areas with good environmental quality (De Koning & Filatova, 2020). The Latin American urban development model (Borsdorf et al., 2007) exemplifies this process—with preferential investment in areas where the rich, and often powerful, are located to the detriment of the poorer segments of the population (Gilbert & Gugler, 1984)—but similar examples may be found in Africa and Southeast Asia (e.g. Lagos and Jakarta) (Pelling, 2003).

Public housing and risk-prevention policies often seek to contain or mitigate the risk distribution thus generated but are often insufficient for current or historical demand (Gilbert & Gugler, 1984; Hardoy & Pandiella, 2009). These development processes effectively exclude many of the urban poor from the formal land market, and environmentally fragile areas become a de facto solution for housing and access to opportunities (Santos et al., 2017; Winsemius et al., 2018). This condition connects hazards to other social differentiators, such as poverty and ethnicity, since informal, low-income settlements (ILISs) often concentrate poor households from underprivileged ethnicities and are more vulnerable to hazards (Bolin & Kurtz, 2018; Dodman et al., 2019; Gran Castro & Robles, 2019). ILISs in urban deltas combine high exposure with other aspects of vulnerability, such as social or ethnic exclusion, low-quality or non-existent infrastructure, little tenure security, and restricted access to resources and services.

Given this setting, this paper considers the following research questions: How do inhabitants of ILISs in delta regions respond to extreme flooding events? What are the factors that condition these responses? This paper presents two possible perspectives, one related to risk perception and the other based on response capacity. The following sections explore response motivation and capacity, the risk–vulnerability relationship, and the empirical research context.

2.1.2 Risk response motivation and capacity

Behavioural research on risk response often assumes a centrality of risk perception (Bubeck et al., 2013). Many risk models also assume a certain homogeneity of response and rationality among risk-prone actors (Lo, 2013; Lo et al., 2015). These assumptions contradict the empirical evidence frequently found in ILISs, where residents invest time, effort, and resources despite looming disaster risks (Penning-Rowsell et al., 2013). An argument could be made that risk is one factor considered, along with accessibility to economic opportunities, relative tenure stability, and strong social and family ties. A similar reasoning is found in protection motivation theory (PMT), which decouples risk appraisal from coping appraisal, highlighting the differences between acknowledging a risk and assessing one's own capacity to withstand it (Bubeck et al., 2013).

Furthermore, without the financial possibilities of buying access to land (Watson, 2009), the urban poor have historically developed land occupation and acquisition methods that circumvent formal land markets (Abramo, 2012; Barros, 2012; Gilbert & Gugler, 1984; Santos et al., 2017). Location choice for urban families means a risk–risk trade-off: either accept risk to improve access to jobs and services or seek locations far enough to be cheap but risk social exclusion (D. Harvey, 2006; Janoschka, 2002; Wheaton, 1982). This trade-off establishes a contradiction around risk perception: Some families choose to expose themselves. To test this contradiction, we propose a hypothesis aligned with behavioural risk response theory: The higher the risk perception, the higher the probability of a response to this risk (hypothesis H1).

Finally, risk response capacity is often missing where it is most needed (Adger, 2000). Traditional approaches in risk modelling often assume that risk perception is necessary for an adequate risk response (Lo et al., 2015), meaning that policies addressing the risk information deficit increase resilience. Contrary to this simplicity, individual agency in hazard response is heterogeneous, given the differences between the perceived efficacy of response against the impacts, individual response implementation capacity, and the cost assessment between responses and potential negative consequences from inaction (Bubeck et al., 2012). These factors are often mediated through social capital (Lo, 2013) or political bias at the individual, family, or community scales (Pelling, 2003). Financial constraints may severely limit response capacity (e.g. not affording transportation costs for evacuation) and increase damage and losses (e.g. when households accumulate their investment in physical, immovable, but fragile assets) (Adger, 2006). Consequently, the alternative hypothesis is that the higher the response capacity, the higher the probability of responding to risk (H2).

2.1.3 Poverty–vulnerability traps

Considering the families that somehow choose to settle in risk-prone areas, careful examination of the deciding factors may provide nuanced considerations of behaviour that is often described as reckless (Ajibade & McBean, 2014). One critical factor is possessing some form of tenure (e.g. from legal certificates to collective or ethnic land rights or tolerated, albeit irregular, occupancy) (Hardoy & Pandiella, 2009). Another factor is kin relations that allow access to land, supporting social networks, and familiarity with the context (Hjälm, 2014; Penning-Rowsell et al., 2013). Furthermore, the poor may depend on access to more affluent neighbourhoods for many economic activities (e.g. service sector jobs or daily work) and opportunities for upward socioeconomic mobility (i.e. for one family generation to ascend to a better socioeconomic condition than the previous generations) (Bergman et al., 2019; Feitosa et al., 2012).

The price of land is also a determinant. When urban planning enforcement has little efficacy, risk-prone areas enter the urban land market through informality (i.e. land sold, ceded, or rented, despite having no official approval or certification) (Abramo, 2012; Hardoy & Pandiella, 2009). The land or buildings available for low-income families often present discounted prices due to low accessibility (e.g. settlements at the edges of urbanization in rural or natural areas), tenure insecurity (e.g. derelict central buildings or unused peripheral plots), hazard incidence (e.g. the flood-prone areas frequent in deltas and coastal regions), or absence of credit for their purchase (e.g. when tenure cannot be proved, or legislation forbids occupation). The discounts thus obtained lower the acquisition threshold, often allowing families to access locations that benefit from market integration and service provision (De Koning & Filatova, 2020). However, this accessibility is a short-term gain, and hazard incidence or tenure insecurity may lead to unforeseen or variable losses in the long run (Boubacar et al., 2017).

Evolving city risk profiles in the Anthropocene mean that risks considered unlikely one or two generations ago are more tangible to the current inhabitants. However, suppose a low-income family has achieved a semblance of stability in a given location, profiting from the investments of previous generations. In that case, the new, higher risk profile presents an unfair trade-off: assume the potential risk of significant losses in the current location from hazards, or absorb certain, albeit limited, losses from starting anew somewhere else. Additionally, some increased vulnerability may be attributed to the settlers in these areas; for example, alterations to the terrain contour at the microscale that increase the risk of flooding or mass movements. This notwithstanding, the overall risk profile has a more significant contribution from technological interventions in other locations, such as altering a river course and reducing floodwater retention areas in the watershed, expanding urbanization, and reducing permeability at the city or regional scale.

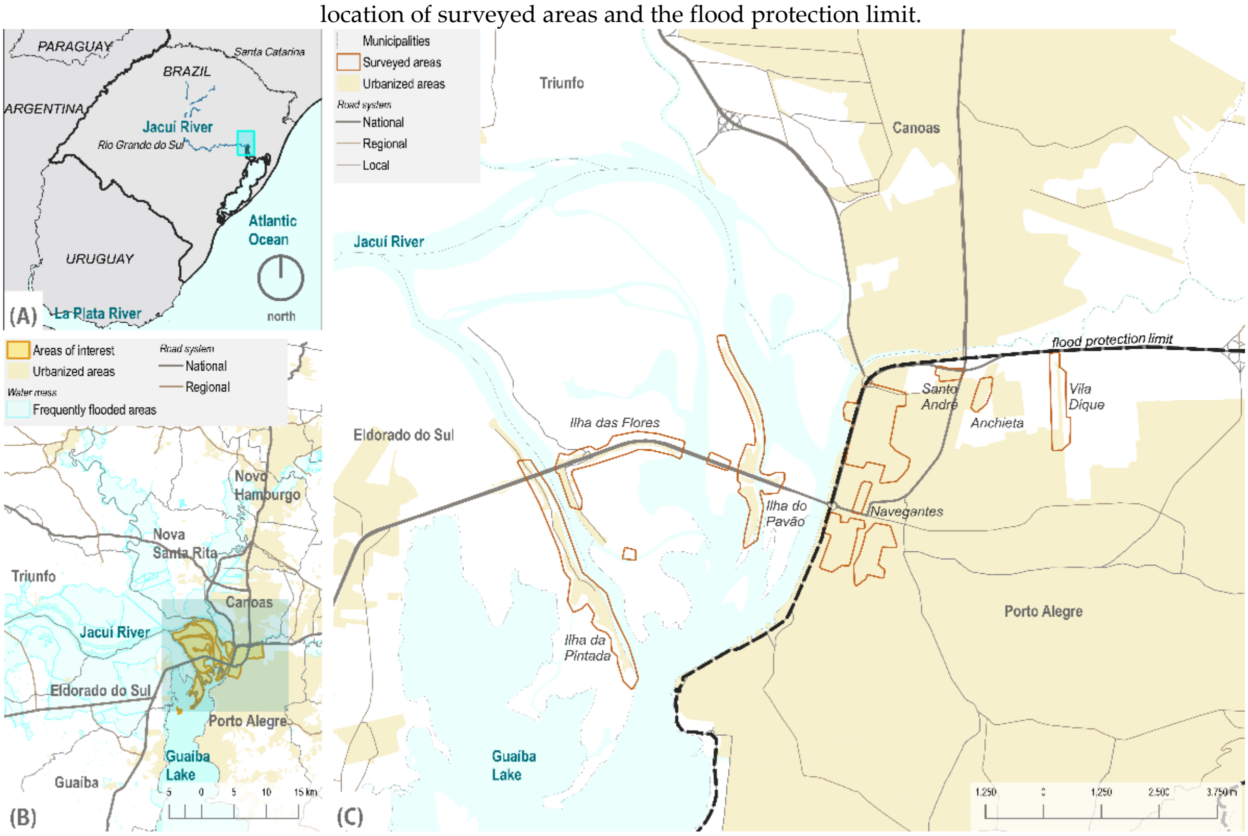
Ultimately, low-income families' location choices occur under pressure from market and political forces, the need to access services, and the evolving risk profiles of informal urban areas. This far-from-trivial decision-making process leads many low-income families to settle into different risk landscapes where they face increased exposure and decreased response capacity and resilience. Over time, repeated hazard impacts on especially vulnerable households establish a cycle in which poverty leads to exposure, which results in losses that increase poverty (Boubacar et al., 2017; De Koning & Filatova, 2020). Cycles such as these can effectively lock specific populations into vulnerable conditions, eliminating conditions for resilience or social mobility. This is a complex process involving different individual and community factors (e.g. family composition and social capital distribution) that may lead to a variety of outcomes, even among the poor. Scholarly research has defined similar conditions as cycles of dispossession (Henrique & Tschakert, 2021), climate gentrification (De Koning & Filatova, 2020), or vulnerability traps (Boubacar et al., 2017; Pelling, 2003).

This context demonstrates the complex relationship between response capabilities and risk perception. This research seeks to investigate whether risk perception or response capacity is the primary driver of response. We are aware that this complexity may not be fully explained by two simple independent and mutually exclusive arguments, as tested in this paper. Furthermore, both statements are possibly related beyond simple contradiction (i.e. the inclusion of one begets the exclusion of the other), may be determined by similar factors, and may not exclude one another. Notwithstanding these limitations, framing a contradiction between risk perception and response capacity allows us to contrast these elements of risk response using a sizable empirical dataset. This design also lays the groundwork for more complex research setups in future work, focusing, for example, on the interrelationships between response capacity and risk perception.

2.1.4 Urban floods in informal settlements: components of anthropogenic and natural hazard exposure in the Jacuí river delta

This research focuses on the Jacuí River delta in southern Brazil. This region's climate is temperate, with no dry season and hot summers (Reyer et al., 2017). The Jacuí River flows 710 km from the highlands in the northwest of the Rio Grande do Sul state into the Guaíba Lake, forming a delta some 110 km from the Atlantic Ocean with marshes, swamps, inlets, and 30 islands (Figure 2-1). Climate change will impact the Jacuí delta in the coming century. Robust evidence shows increased flow trends in the Patos Lagoon basin (where the delta is located) and south-eastern South America. Future predictions indicate that extreme weather events that lead to floods will be more frequent, including extreme rainfall and tropical cyclones (IPCC, 2022; Magrin et al., 2014). Rising sea levels and southern winds may induce more frequent surges at the Patos Lagoon, damming the Guaíba Lake and resulting in significant flooding when combined with heavy rainfall (Marques, 2012).

Figure 2-1. Location of surveyed areas: (A) location in the south of Brazil; (B) surveyed areas in the Jacuí delta; and (C) location of surveyed areas and the flood protection limit.



The Jacuí River delta occupies 22,836 hectares of the Pampa and Atlantic Rainforest biomes. Land use in the delta includes agriculture, fishing, mining, shipping, and urbanization (Fundação Zoobotânica et al., 2014). The cities of Porto Alegre, Canoas, Nova Santa Rita, Triunfo, Charqueadas, and Eldorado do Sul lie at its margins, housing 1,971,299 inhabitants (IBGE, 2020). Porto Alegre is the capital of Rio Grande do Sul state and the largest city in the delta, with 13.2% of the state population distributed in 471.85 km^2 (IBGE, 2020).

Two regions in Porto Alegre are among the most affected by fluvial or pluvial flooding: Arquipélago and Humaitá-Navegantes. These regions present different risk landscapes associated with exposure to flooding, built environments, and the socioeconomic composition of their populations. The Arquipélago region has 44.2 km^2 of islands integrated into the delta water regime and exposed to riverine flooding (Allasia et al., 2015). The Arquipélago region also presents a Human Development Index of 0.659, the second lowest in the city (PNUD et al., 2013), and faces critical public security issues (e.g. drug trafficking and organized crime) (World Bank Group, 2019a). The Humaitá-Navegantes region has 15.11 km^2 in the 'continental' section of the city. In the past, the area had a similar exposure to flooding as the Arquipélago region. To remedy exposure, the city implemented a flood protection system in 1974 with 68 km of walls, levees, and 18 water pump stations (Allasia et al., 2015). Today, instead of riverine floods, it faces pluvial flooding in the form of chronic stormwater overflow caused partly by the river flood protection system that does not pump water out effectively (Martinbiancho et al., 2018).

Historical records of the water level at Guaíba Lake present major flood events in the delta in 1873, 1928, 1936, 1941, and 1967. The national disaster records database includes additional disasters from 1972–1973, 1988, and 2015. The flood event on October 10, 2015, is considered the most recent large-scale flood event and is the reference for the World Bank investigation analysed here (World Bank Group, 2019a). The 2015 flood developed after several days of intense rainfall in the Jacuí, Caí, and Gravataí watersheds and an intense southern wind-induced surge from the Patos Lagoon. The water level reached 2.94 m above sea level (2.5 m above its average level). Civil Defence reports indicate the displacement of over 8,300 people in Porto Alegre, an estimated USD 6,369,836 in public service losses, and USD 23,382,041 in housing and infrastructure damage (BRL 19,858,602 and BRL 72,895,850, respectively), equivalent to 13.6% of the city's yearly GDP (World Bank Group, 2019a).

2.2 MATERIALS AND METHODS

This research was centred on the primary data from the Living with Floods survey, as presented below. It also employed secondary data (e.g. census and physical datasets) for supporting analysis (e.g. low-income hot spots).

2.2.1 Survey structure and methodological considerations

The household survey that was the focus of this paper was part of a broader investigation by the World Bank and the Porto Alegre municipal government. The World Bank investigated the legal, financial, and local governance structures related to flood risk management using secondary data and implemented a survey to collect primary data and examine the direct and indirect social impacts of flooding. The survey offered a structured questionnaire to residents in the Arquipélago and Humaitá-Navegantes regions. The World Bank published survey methods (World Bank Group, 2019b) and a report (World Bank Group, 2019a) in their channels. For this paper, we independently accessed and analysed the microdata from the household survey to present it for the first time in a peer-reviewed format.

The survey examined the perceived risks and impacts of the October 2015 flood and investigated four types of vulnerabilities—physical (households and their immediate surroundings), socioeconomic, institutional, and community-related—and vulnerability from risk perception (or lack thereof). Toward this aim, the survey presented 161 questions organized into four groups: risk perception and willingness to adapt, social and economic impacts of floods, response measures adopted after the 2015 event, and the socioeconomic characteristics of the residents (World Bank Group, 2019a).

2.2.2 Data collection, correction, and validation

The World Bank wanted to improve the accuracy of information about flooded areas, because there were no previous studies exclusively on them in this region (World Bank Group, 2019a). Previously available information on floods came from impact estimations (e.g. physical modelling of flood surfaces), Civil Defence reports, and the national population census. The latest Brazilian census occurred in 2010 and presented two problems. One is that the World Bank investigation was already in the late stage of the 10-year census wave; the survey took place seven years after the census. Second, the smallest census spatial unit was the 'tract,' which did not separate flooded and non-flooded areas. These problems add bias to the data in the form of outdated population estimates and homogeneous demographics about different population groups. The areas present fluctuation in the resident population that heightens the impact of outdated data. Furthermore, data in these areas are difficult to collect, as organized crime often restricts access to outside surveyors (including those of the census).

The World Bank local survey team collected household data for two months, in June and July 2017, following a sampling proportion of flood-prone households in each census tract of the areas of interest. The areas of interest included the Arquipélago and Humaitá-Navegantes administrative regions of Porto Alegre. Figure 2 presents the urban landscape of the research sites: the more intense urbanization in the flood-protected region in Humaitá-Navegantes and the peri-urban, informal, and risk-prone setting of Arquipélago, respectively. Figure 2-2 shows the locations of the areas of interest.

Figure 2-2. Landscapes in the areas of interest: (A) landscape in the Humaitá-Navegantes region; (B) landscape in the Arquipélago region.
Source: The World Bank (2017), used under permission.

(A) (B)

The survey team was composed of the World Bank staff, responsible for management, methods, and supervision, and a local professional surveyor team. The surveyors interviewed residents in Portuguese for about 40 min during household visits, and the residents provided information on all the answers. The team designed the sample around the ca. 8500 households in flood-prone areas of the Arquipélago and Humaitá-Navegantes regions (World Bank Group, 2019a). The sample's most prominent criterion was spatial distribution (i.e. being affected by flooding), adopting sampling quotas proportional to the census tract population of approximately 17% of the total population in each tract of the flooded regions. The team did not consider other sample distribution criteria (e.g. gender, age, or other) because of high population fluctuation, outdated census data, and security concerns. Public safety played a significant part in the survey implementation, and local power structures and organized crime limited access to the population. Notwithstanding these limitations, the high sample proportion limits sampling bias and provides sufficient response variety among the selected population. Furthermore, the World Bank dataset is the first to specifically investigate these flooded areas, improving the outdated and imprecise previous data and providing a benchmark for future studies.

2.2.3 Data analysis

The authors of this investigation received, from the World Bank, a sample of 5,474 individual anonymized answers from 1,484 households as a spreadsheet (i.e. an Excel XLS file). From these households, we discarded 33 responses, as they contained incomplete data, leaving 1,451 households for analysis. The data identified the regions where households were located (e.g. Arquipélago, Humaitá-Navegantes), but no disaggregation within these regions. We prepared and recoded the data as necessary for analysis, identifying the data type (e.g. categorial, continuous), correcting punctuation and data format, and simplifying data units (e.g. converting all temporal data into hours). We recoded the variables into numerical keys (i.e. dummy variables) to process the data in the regression models. After preparation, we implemented regression models and generated descriptive statistics. The supplementary material includes the Python (data preparation) and Stata (regression models) codes, and the data used in the analyses.

The analyses included an initial, global, and exploratory association analysis of the dataset, which indicated a set of variables representing risk perception and risk response with more frequent associations. To test the hypothesis that risk perception is a critical response driver (hypothesis H1), we used regression models, with risk perception as the dependent variable and risk responses as the independent variables. To test the hypothesis that response capacity (i.e. capacity to respond by short-term coping or long-term adapting) explains risk response (hypothesis H2), we added the control variables of income, age, self-identified ethnicity, access to cargo vehicles, and the number of residents per household. The assumption was that having more significant income and access to transportation means increased capacity. At the same time, older residents living in more populous households and of Black or Pardo ethnicities would have lower capacity.

We also tested for additional variables (e.g. education, employment, and gender), but the results were not statistically significant or suffered from collinearity. The analysis's primary purpose was to measure the influence of risk perception and capacity variables on effective risk response, mainly looking for alternative or complementary explanations. We opted for a logistic regression specification due to the binary character of our dependent variable (risk response), and we decided on the well-known logit method (Long & Freese, 2006).

We additionally performed a hot spot analysis of poverty in the areas of interest. The research used the Getis-Ord Gi* (Getis & Ord, 1992; Ord & Getis, 2010) statistic to identify the region's significant concentrations of poverty. This study implements the optimized hot spot analysis in ArcGIS Pro, which automatically adjusts model parameters for multiple testing and spatial dependence. The input data for the hot-spot analysis were point features derived from the census information (IBGE, 2011) at the tract scale (finer scale available).

2.3 RESULTS

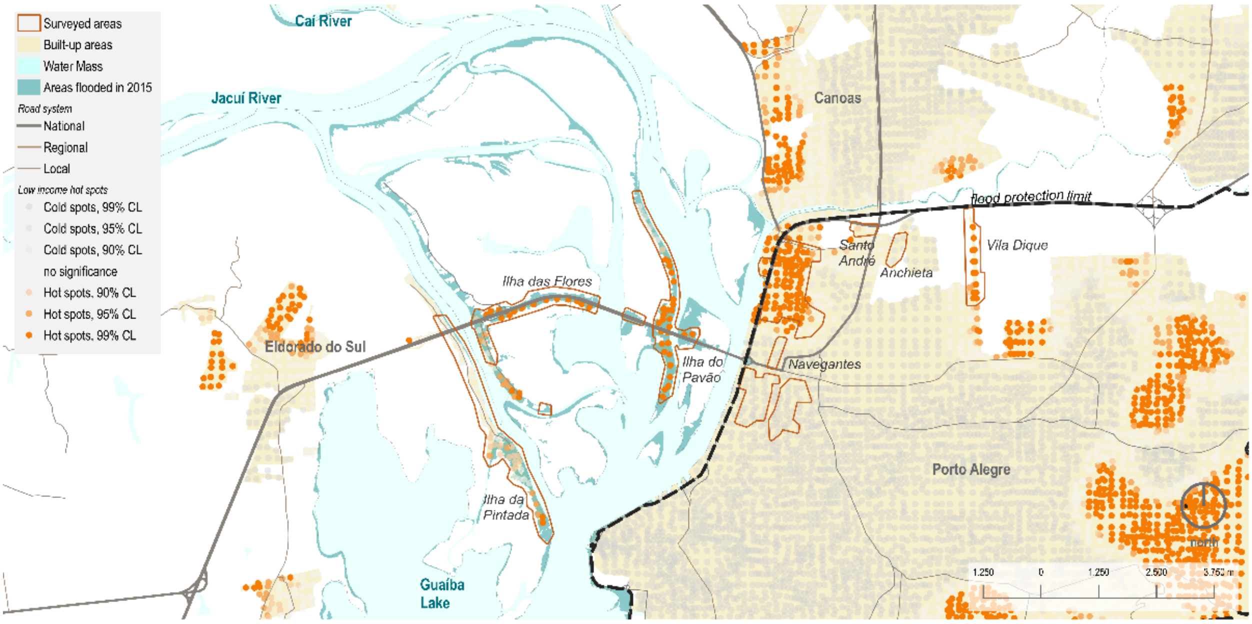
2.3.1 Characteristics of the sample

The sample included all residents from the surveyed households, and the information came from self-identification. Most residents were young (32.28 mean, 21.73 S.D.), had a low level of education, and had a low monthly income (USD 390.06 mean, 430.18 S.D.), with many family members sharing the same household (4.58 mean persons per house, 2.27 S.D.). Precarious employment or unemployment was frequent among active working-age residents (42.23% of households).

There was a substantial difference between the neighbourhoods within the city's flood protection system and those on the delta islands, describing the two risk landscapes seen in Figure 2-3. The hot spot analysis shows that all areas in the Arquipélago region were poverty hot spots with a 99% confidence level. A similar pattern was present in three areas of the Humaitá-Navegantes region, notably in the Humaitá neighbourhood and Vila Dique. The data for the surveyed households are presented in Table 2-2. Those on the islands had a lower percentage of non-white ethnicities and were younger. The most significant disparity, though, was in risk perception, which was much more prevalent among those living on the islands, suggesting an association with frequent past-hazard experience.

The sampled households resided in areas affected by the 2015 floods, albeit to different degrees depending on the risk landscape they are located in. Most households (79%) had single-story houses. Stilts were part of the building tradition of the Arquipélago region, but residents had recently replaced them with stone masonry foundations, perceiving the latter as more modern, even if more exposed. Exposed brick masonry was the most common building standard, but 11% of households were composed of reused wood and were very vulnerable. Many houses presented open-air sewage (24%) and deposits of garbage or construction debris (30%) in their immediate environments. Most residents in the sample (80.4%) declared that they owned their houses. Still, tenure security is a persistent issue in the area (World Bank Group, 2019a), and further information is necessary to determine its degree of formality.

Figure 2-3. Location of surveyed areas, protection status, hot spots of low-income households, and areas affected by the October 2015 flood.



2.3.2 Risk perception

Risk perception was low among residents, as reported in the form of knowledge about potential exposure, as presented in Table 2-3. The survey structure established that only households affected by the 2015 floods (826, 56.93% of the total) answered the question about potential exposure. About 19.92% of these households knew about their exposure (n = 289), and 246 were located outside the flood protection system. Only 5.51% of households estimated that water could reach the levels of the 2015 flood. Most of these were outside the flood-protected areas. Despite the low previous risk perception, future risk expectations were high, as presented in Table 2-4. Most households expected their house to flood in the next ten years, as 69.75% thought it was inevitable or probable (n = 1,012).

2.3.3 Risk response

Table 2-1 shows that the most frequent risk response was to adapt the household's interior by lifting furniture or objects (52.38%, n = 760). The second most frequent response was preparation before the flood (31.08%, n = 451). Turning off the power was third (30.05%, n = 436), followed by household evacuation (26.26%, n = 381). Less frequent responses included passive coping mechanisms in the form of prayer (23.57%, n = 342), modifying the house's exterior to prevent damage (moving vehicles, animals, and objects to higher places, 22.47%, n = 326), or placing obstacles around the house to prevent interior flooding (12.06%, n = 175). Responses based on community reliance, social capital, or support from authorities account for smaller proportions. Only 8.75% (n = 127) of households sought help from the authorities or community leaders, 8.27% (n = 120) provided other family and community members with information, and fewer still sought information or participated in support groups (n = 49 and 30, respectively).

Response strategies varied greatly depending on the location of the household, as expected. Of the 14 possible responses, the families outside the flood protection system adopted risk responses much more frequently (n = 8) than those inside the protection system. The distribution of answers stating that they evacuated and stocked food reserves was the most dissimilar between the protected and unprotected regions. Of the total households adopting these risk responses, 90% were in unprotected areas. The second group of responses followed, with roughly 80% concentration among those unprotected: asking for help, adjusting the interior, turning off power, seeking and providing information on responses, and joining a community group.

Table 2-1. Bivariate analysis of risk response options against household location.

At this Point [When the Water Reached the House], What Have You Done to Protect Yourself and the House?	**Flood Protection Status**	**Risk Response Option Frequency among Households**	
		By Household Status	In All Households
Evacuate (RP1)	1 = protected	35 (2.41%)	381 (26.26%)
	2 = unprotected	346 (23.85%)	
Turn off power (RP2)	1 = protected	106 (7.31%)	436 (30.05%)
	2 = unprotected	330 (22.74%)	
Place obstacles to block water entry (RP3)	1 = protected	82 (5.65%)	175 (12.06%)
	2 = unprotected	93 (6.41%)	
Adjust interior (RP4)	1 = protected	168 (11.58%)	760 (52.38%)
	2 = unprotected	592 (40.80%)	
Adjust exterior (RP5)	1 = protected	61 (4.20%)	326 (22.47%)
	2 = unprotected	265 (18.26%)	
Stock food reserves (RP6)	1 = protected	16 (1.10%)	177 (12.20%)
	2 = unprotected	161 (11.10%)	
Seek information (RP7)	1 = protected	12 (0.83%)	49 (3.38%)
	2 = unprotected	37 (2.55%)	
Join a community alert group (RP8)	1 = protected	7 (0.48%)	30 (2.07%)
	2 = unprotected	23 (1.59%)	
Ask for help (RP9)	1 = protected	19 (1.31%)	127 (8.75%)
	2 = unprotected	108 (7.44%)	
Provide information (RP10)	1 = protected	27 (1.86%)	120 (8.27%)
	2 = unprotected	93 (6.41%)	
Pray (RP11)	1 = protected	98 (6.75%)	342 (23.57%)
	2 = unprotected	244 (16.82%)	
Other (RP12)	1 = protected	221 (15.23%)	274 (18.88%)
	2 = unprotected	53 (3.65%)	
Nothing. There was no time (RP13)	1 = protected	74 (5.10%)	128 (8.82%)
	2 = unprotected	54 (3.72%)	
Prepare before the flood (RP14)	1 = protected	120 (8.27%)	451 (31.08%)
	2 = unprotected	331 (22.81%)	

Table 2-2. Identification of variables for the study in the original database.

Variable	Description			
Risk response	Categorical scale, non-ordered. RP1 = Evacuate, RP2 = Turn off power, RP3 = Place obstacles to block water entry, RP4 = Adjust house's interior: move objects higher, RP5 = Adjust house's exterior: move objects higher, RP6 = Stock up food, RP7 = Seek information, RP8 = Join a community alert group, RP9 = Ask for help from leader or Civil Defence, RP10 = Provide information about what to do, RP11 = Pray, RP12 = Other, RP13 = Nothing, there was no time, RP14 = Adapt the household to flooding before the event.			
Ethnicity	Categorical scale, non-ordered. ETC = White, ETB = Black, ETN = Native, ETP = 'Pardo'			
Variable	**Description (range)**	**Flood protection status**	**Households by flood protection status**	**Households total**
Flood protection status	1 = inside flood-protected areas, 2 = outside flood-protected areas	1 = protected 2 = unprotected	592 (40.80%) 859 (59.20%)	1,451 (100%)
Variable	**Description (range)**	**Flood protection status**	**Mean by status of households (S.D.)**	**Mean in all households (S.D.)**
Risk perception (RPC)	1 = NA, 2 = Knew household could be flooded, 3 = Did not know (1–3)	1 = protected 2 = unprotected	1.53 (0.84) 2.17 (0.84)	1.9 (0.89)
Gender (GEN)	1 = NA, 2 = Female, 3 = Male (1–3)	1 = protected 2 = unprotected	2.46 (0.53) 2.50 (0.54)	2.48 (0.50)
Cargo capacity (CCA)	1 = NA, 2 = Small capacity only, 3 = Large capacity (1–3)	1 = protected 2 = unprotected	2.72 (0) 2.77 (0.47)	2.74 (0.50)
Number of residents in household (NRS)	Numerical (1–19)	1 = protected 2 = unprotected	4.74 (2.32) 4.47 (2.26)	4.58 (2.27)
Monthly income (INC)	Numerical, USD (00.00–4811.40)	1 = protected 2 = unprotected	425.90 (439.22) 370.19 (422.33)	390.06 (430.18)
Age (AGE)	Numerical, years (0–120)	1 = protected 2 = unprotected	33.50 (22.72) 31.40 (20.99)	32.28 (21.73)

Table 2-3. Flood risk perception among households.

Variable	Description	Flood Protection Status	1 = Yes: By Household Status	1 = Yes: In All Households	2 = No	3 = No Answer	Total
Flood impact in 2015	Was this house/building flooded in October 2015?	1 = protected	173 (11.92%)	826 (56.93%)	574 (39.56%)	51 (3.51%)	1,451 (100%)
		2 = unprotected	653 (45.00%)				
Previous knowledge about risk exposure	Did you already know this house or building could be flooded?	1 = protected	43 (2.96%)	289 (19.92%)	498 (34.32%)	664 (45.76%)	1,451 (100%)
		2 = unprotected	246 (16.95%)				
Hazard impact estimation	Did you imagine the water could reach that level when you built or moved here?	1 = protected	15 (1.03%)	80 (5.51%)	707 (48.73%)	664 (45.76%)	1,451 (100%)
		2 = unprotected	65 (4.48%)				

Table 2-4. Future flood risk assessment among households.

		Flood Protection Status	1 = Certainly or Probably: By Household Status	1 = Certainly or Probably: In All Households	2 = Not Likely or Not at All: By Household Status	2 = Not Likely or Not at All: In All Households	3 = No Answer	Total
Future risk expectation	Do you believe your home may be flooded in the next ten years?	1 = protected	362 (24.95%)	1,012 (69.75%)	196 (13.51%)	359 (24.74%)	80 (5.51%)	1,451 (100%)
		2 = unprotected	650 (44.80%)		163 (11.23%)			

Table 2-5. Logit regression analysis for set (B): residents inside the flood protection system for risk-response alternative RP1: evacuate the area. Acronyms follow the definitions in Table 2-2.

Variable	Model 85	Model 86	Model 87	Model 88	Model 89	Model 90
Did you know about flooding? Yes (RPC)	−1.074 ** (0.0)	−0.8814 ** (0.0)	−0.8829** (0.0)	−0.7441 ** (0.003)	−0.8952 ** (0.0)	−0.8524 ** (0.001)
Monthly income (INC)		−0.0007 ** (0.0)	−0.0007** (0.0)	−0.0007 ** (0.0)	−0.0007 ** (0.0)	−0.0008 ** (0.0)
Age (AGE)			0.0006 (0.911)	−0.0063 (0.319)	0.001 (0.86)	−0.0062 (0.335)
Caucasian (ETC)				−0.1462 * (0.013)	12.9931 (0.99)	18.7544 ** (0.0)
Native (ETN)					13.8464 (0.989)	19.7517 (.)
Pardo (ETP)					13.0029 (0.99)	18.9396 ** (0.0)
Black (ETB)					12.6047 (0.99)	18.5492 ** (0.0)
How many people live in this household now? (NRS)						−0.1442 * (0.02)
Small cargo capacity transportation mode only (CCA)						0.5754 (0.118)
Number of observations	672	614	614	614	614	614
chi^2	22.3588	39.2620	39.2745	46.5209	44.0775	53.4634
Prob > chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.0395	0.0767	0.0767	0.0909	0.0861	0.1045

Dependent variable: Risk perception. **and * denote significance at the 0.01 and 0.05 levels, respectively.

Table 2-6. Logit regression analysis for set (C): residents outside the flood protection system for risk-response alternative RP1: evacuate the area. Acronyms follow the definitions in Table 2-2.

Variable	Model 169	Model 170	Model 171	Model 172	Model 173	Model 174
Did you know about flooding? Yes (RPC)	0.0182 (0.832)	0.0494 (0.585)	0.042 (0.643)	0.0263 (0.774)	0.0058 (0.949)	−0.0129 (0.89)
Monthly income (INC)		−0.0001 ** (0.003)	−0.0001 ** (0.008)	−0.0001 ** (0.006)	−0.0001 * (0.027)	−0.0001 ** (0.007)
Age (AGE)			−0.0074 ** (0.001)	−0.0043 (0.065)	−0.0076 ** (0.001)	−0.0045 (0.055)
Caucasian (ETC)				0.0944 ** (0.0)	−0.574 (0.072)	−0.5439 (0.091)
Native (ETN)					−0.2606 (0.564)	−0.1484 (0.744)
Pardo (ETP)					−0.013 (0.969)	0.028 (0.933)
Black (ETB)					−0.7101 * (0.047)	−0.7537 * (0.037)
How many people live in this household now? (NRS)						0.1034 ** (0.0)
Small cargo capacity transportation mode only (CCA)						0.2008 (0.101)
Number of observations	2.277	2.065	2.065	2.049	2.065	2.049
Chi^2	0.0450	10.1098	21.7742	33.8552	49.6160	66.1073
Prob > chi^2	0.8319	0.0064	0.0001	0.0000	0.0000	0.0000
Pseudo R^2	0.0000	0.0035	0.0076	0.0119	0.0174	0.0233

Dependent variable: Risk perception. **and * denote significance at the 0.01 and 0.05 levels, respectively.

2.3.4 Association between variables under the logistic regression approach

We analysed the data with logistic regression models, where risk response was the dependent variable. We regressed each response option separately on risk perception (in the form of previous knowledge of exposure) and residents' socioeconomic and location characteristics. While Table 2-2 presents the descriptive statistics for these variables, Table 2-1 presents an example of the six models run for each risk-response option (RP1–RP14). In these models, we added the control variables stepwise to test the robustness of the main effect (risk perception, [RPC]) and alternative explanations. Model 85 thus tests only against the main effect, model 86 tests for RPC and adds income (INC), and so on until model 90, which includes RPC, INC, age (AGE), ethnicity (ETC, ETN, ETP, and ETB), number of residents (NRS), and limited transportation capacity (CCA). For the models, we used individual-level survey data to account for different ethnicities, ages, and incomes within each household. We ran these model combinations and response options, grouping residents into sets: (A) with residents located in all areas (n = 5,291 residents, models 1–84), and two sets classified according to their location, (B) with residents in the flood-protected risk landscape of Humaitá-Navegantes (n = 2,194 residents, models 85–168) and (C) with residents in the unprotected risk landscape of Arquipélago (n = 3,097 residents, models 169–252). The 252 models thus generated feature in the supplementary materials.

Table 2-5 presents the logit regression results for the 'evacuate the area' risk response for set (b). Significant factors include risk perception, income, and the number of people in the household (negative association), as well as age and 'Pardo' ethnicity (positive association). We checked the specifications of models 85–90 with the chi-squared test of each model. The results varied between 22.36 (0.00) and 53.46 (0.00) for models 85 and 90, respectively. We report R^2 as usual in logistic regressions (Long & Freese, 2006).

Table 2-6 presents the results for set (c). Significant variables are income, Black ethnicity, and the number of people in the household (negative association). We tested the specifications of the models using the chi-squared method. In the logistic regressions, the chi-squared test generated values between 0.05 (0.83) and 66.11 (0.00) for models 169 and 174, respectively. This test evaluated whether all variables were significant, rejecting this hypothesis with at least a 5% probability, as usual. Ultimately, this model accepts the test as valid because at least one of the explanatory variables affected the response 'evacuate the area' and explains whether the residents evacuate or not. We report the R^2 to describe the model's explanatory power, but it should be interpreted cautiously as recommended by the literature because logistic regressions present considerable uncertainty in this measure (Long & Freese, 2006).

Table 2-7 compares the models with all dependent variables (e.g. models 90 and 174, above) for each risk-response option for the three sets of residents: (A), (B), and (C). In this table, we present only the significant associations between variables graphically coded for positive (■ and □, at 0.01 or 0.05 significance levels, respectively) or negative associations (● and ○, similar significance levels).

As expected, the results suggest divergent strategies between locations. The results show a general agreement between the responses of set (A) and those of set (C), which is intuitive, as the residents in the latter consisted of 58.53% of the former. Sets (A) and (C) had more frequent significant associations than set (B), which can be explained by the lower number of observations in the latter (mean 585 observations in [B], 2,089 in [C], and 2,772 in [A]).

Table 2-7. Synthesis of regression models for risk response and risk perception for sets: (A) all residents (risk landscapes 1 and 2), (B) residents in flood-protected areas (risk landscape 1, Humaitá-Navegantes), and (C) residents outside flood-protected areas (risk landscape 2, Arquipélago). Acronyms follow the definitions in Table 2-2.

	Set (A) all households (risk landscapes 1 and 2)													
	RP1	**RP2**	**RP3**	**RP4**	**RP5**	**RP6**	**RP7**	**RP8**	**RP9**	**RP10**	**RP11**	**RP12**	**RP13**	**RP14**
RPC	■	●	●				○	●			●			
INC	●		■						●	●	●	■		□
AGE	●								●				□	
ETC	○		□			□						●		
ETN					○	■				○				
ETP			□			□				●		●		
ETB	●				○					○		●		
NRS			■		○								□	●
CCA					■	□							●	

	Set (B) households in flood-protected areas (risk landscape 1, Humaitá-Navegantes)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
RPC	●										■		○	●
INC	●	■		■									●	□
AGE							□				■		□	
ETC	■													
ETN														
ETP	■													
ETB	■													
NRS	○				●	□							■	●
CCA		●					□							□

	Set (C) households outside flood-protected areas (risk landscape 2, Arquipélago)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
RPC		●	●				○	●	●					●
INC	●		■	●					●	○	●	■	■	□
AGE									●					
ETC						□						●		
ETN										○				
ETP						□				●	○	●		
ETB	○													
NRS	■	■		■			□				○		○	
CCA				□	■	■		○		□			●	

Colours represent location. Black = all areas, blue = protected areas, and red = unprotected areas. ● and ○ = denotes a negative association with significance at the 0.01 and 0.05 levels, respectively. ■ and □ = denotes a positive association with significance at the 0.01 and 0.05 levels, respectively.

The commonality between all sets is the influence of income, which is the most frequently associated factor. Income was negatively associated with evacuations and was positively associated with preparation before floods. One substantial difference between the sets is risk perception. First, it is mainly associated with variables within sets (a) and (c). In set (a), it is positively associated with RP1, evacuation, while in both sets, it is negatively associated with strategies connected to staying in the household during the flood: RP2, powering off, and RP3, placing obstacles to prevent flooding of the house. It is also negatively associated with responses connected with social capital—RP7, seek information, RP8, join community group, and RP9, ask for help from the authorities—in both sets. These results contradict hypothesis H1 in favour of hypothesis H2, as discussed below.

Concerning response strategies, the most frequent association among all sets is RP1, evacuation. Counterintuitively, it has more significant associations within set (b), where fewer evacuations took place (2.41% of households). It is positively associated with Caucasian, Pardo, and Black self-perceived ethnicities, and negatively with risk perception, income, and the NRS. In set (c), families evacuated more frequently (23.85% of households); the associations were negative to income and Black self-perceived ethnicity, and positive to the NRS. RP1 has opposing associations with the NRS in each household: negative for set (b) and positive for (c). Social capital responses (RP 7–10) mainly had negative associations in all sample sets. Reliance on public authorities is reported by RP9, which presents negative associations with income, age, and risk perception.

2.4 DISCUSSION

The literature on resilient and adaptive behaviour has gradually shifted from perfect rationality toward models based on social capital, cognition, and community influence (Lo et al., 2015). Social motivation theories (e.g. PMT) place distinctions between response efficacy, the capacity to implement responses, and the cost assessment between responses and potential impacts (Bubeck et al., 2013). These shifts acknowledge the complexity of making decisions in uncertain, dangerous situations such as flood events (Bubeck et al., 2012). Approaches that consider entitlements, assets, and livelihoods have increased this complexity (Garschagen & Romero-Lankao, 2015). These approaches pose frequent trade-offs in avoiding short-term environmental hazards that may lead to exposure to new or increased economic, political, or social risks in the long run (Adger, 2006; Pelling, 2003). On the individual level, psychological factors such as attachment to place, belief in change, and feeling of control inform decisions critically, as do capacities based on mobility, employability, and social networking (Waters & Adger, 2017). Consequently, risk-response decisions are anything but trivial and warrant investigation that considers social response patterns from the bottom up.

This study investigated individual and household responses with statistically significant empirical data from socially vulnerable, low-income communities in the Jacuí River delta. Our study focused on risk perception and risk-response capacity in flood-prone regions, considering the two competing hypotheses that risk perception is the critical driver of response (hypothesis H1) or that risk-response capacity drives responses (hypothesis H2). The results from logit regression models run for 14 risk-response options allow us to reject hypothesis H1 in favour of hypothesis H2, as presented in Table 2-7, exemplified in Tables 2-5 and 2-6, and discussed below.

On the first level, these models indicate that location and income are the principal factors in risk response. The location's role is clear, as responses were more intense in the areas exposed to riverine floods, demonstrated by the number of households affected by the floods in the Arquipélago region. Income plays a double role in defining the landscapes of risk: it influences location choice toward risk-prone areas (Bolin & Kurtz, 2018; De Koning & Filatova, 2020; Gran Castro & Robles, 2019) and limits response capacity (Bubeck et al., 2013; Pelling, 2003) for poorer families. The robust negative association between risk perception and income across sets (A), (B), and (C) signals that the poorest in the sample have had direct experience with flooding in the past. This pattern represents the association between social and environmental injustices by excluding the urban poor from hazard-free areas. This exclusion pattern is evident when one considers that these flood-prone areas had some of the lowest income and Human Development Index levels in the city (Allasia et al., 2015; PNUD et al., 2013; World Bank Group, 2019b) and presented high-confidence poverty hot spots in the Getis-Ord* analysis.

On the second level, the association of income is more robust than other social descriptors, such as age or self-perceived ethnicity. Considering that the analysed sample was more exposed than most other families in the city (World Bank Group, 2019a), this demonstrates income's persistent differentiating effect, even within exceptionally vulnerable groups. This further presents income as a significant factor in coupling the social and environmental factors in the landscapes of risk where the households settled. Coupling takes place, as household income was significant in determining their social vulnerability while also influencing their access to environmentally safe areas. Affluent households secure access to safe areas (i.e. coupling low social and environmental vulnerability factors), while poor households are priced out of them (i.e. coupling high social and environmental vulnerability factors). This differentiation of risk landscapes may also be perceived among the urban poor in this analysis. Table 2-2 shows that the poorest households in this sample were in the unprotected areas (i.e. high-risk landscape), while the households in the protected areas (i.e. low-risk landscape) were poor, but less so (ca. 13% higher income). Recent findings present similar evidence for the COVID-19 pandemic (Lorenz et al., 2021; Santos, Rodriguez Lopez, Heider, et al., 2022), suggesting a further negative association between vulnerability and social justice.

Third, risk perception was negatively associated with most strategies among the exposed Arquipélago households. This fact evidences some degree of normalization of hazards and resignation to the impacts. This resignation is evident when considering the negative association of risk perception with the strategy of preparing the household before floods (RP14, see Table 2-6); families living in the most exposed areas faced frequent, low-level damage and losses to which they had minimal capacity to respond appropriately. This argument aligns with previous research indicating that perceived response efficacy is critical in decision-making during flooding events (Bubeck et al., 2012). The low reliance on public agents among these families (reported by RP9) may also indicate risk-warning fatigue (Penning-Rowsell et al., 2013). On the one hand, authorities are responsible for issuing warnings, even when weather patterns are uncertain. On the other hand, exposed families become used to flood risk and may discredit future warnings if past ones did not lead to substantial damage. Moreover, repeated risk experiences can lead to resignation (i.e. acceptance that damage are inevitable), irrespective of new warnings (Penning-Rowsell et al., 2013). These considerations reinforce the rejection of hypothesis H1.

The negative association pattern between social justice and vulnerability is further perceived when considering response capacity. At the city level, there is low reliance on public agents by affected families, as reported by the World Bank (World Bank Group, 2019a) and evidenced by the negative associations of the 'seek help' strategy. At the community level, there was evidence of low influence from social capital in the responses, given that most residents did not engage in collaborative strategies (e.g. RP7, 'seek information' or RP9, 'provide information'). It is also noticeable that the association of these strategies to risk perception is predominantly negative, signalling that more vulnerable families are less reliant on community help. This limited role of social capital eliminates alternative explanations for hypothesis H2.

The low financial capacity of the exposed families was a bottleneck to the response options available to them. The evacuation was not possible or not effective in the absence of means of transportation and a workforce sufficient to move assets, documents, and goods out of residences in time. This is apparent by the negative association between evacuation strategy (RP1) and income. The positive association of this strategy with the NRS indicates that it is a last resort, in line with previous research (Penning-Rowsell et al., 2013). Families evacuated to preserve the health of household members, even if incurring further losses when abandoning the household (they may be looted during the absence of their residents, for example) (World Bank Group, 2019a).

2.5 CONCLUSIONS AND OUTLOOK

The urban poor constantly face unfair trade-offs in their location choices, often assuming high exposure to risk, job loss, and deficient services. This problem presents a research gap, despite recent advances in the topic of poverty traps. This research addressed this gap by investigating poverty–vulnerability traps fostered by unequal development. We implemented spatial and statistical analyses of empirical data in an urban delta of the Global South in two different landscapes. The relevance of this approach is to shed light on risk-response decision-making across different risk landscapes. The approach further explores the connections between unequal development and climate change in the Anthropocene, providing evidence of the persistent role played by income (and inequality) in vulnerability.

This paper assessed poverty concentrations through hot spot analysis, presenting clear spatial exclusion patterns among the urban poor. These patterns allowed nuanced analysis of the landscapes of risk to which two groups of urban poor households are exposed: the urbanized, less poor (but far from affluent), and flood-protected Humaitá-Navegantes region (landscape 1), versus the high social vulnerability, exposed, and infrastructure-lacking Arquipélago (landscape 2).

We implemented an in-depth analysis of risk responses through 252 logit regression models. These models evaluated the association between risk perception, income, age, ethnicity, and other characteristics in 14 responses to a large-scale flood event in 2015. The results show the distinct impact of the event across the two risk landscapes of the Humaitá-Navegantes and Arquipélago regions. These models also present low influence from risk perception, which is associated with resignation to losses from flooding (that is, the normalization of hazard impacts). Finally, the results indicate the persistent role of income as the most robust factor influencing risk responses. These observations allowed us to reject the hypothesis that risk perception is the key factor in risk response. Instead, they support the competing hypothesis that risk-response capacity is a determinant, especially in ILISs.

This investigation presented a limited sample, with little explanatory power regarding the behaviour of non-exposed households (see Section 2.2.2), and new surveys in areas frequently affected by floods could provide new insights. This limitation does not, however, hinder the analyses we present here, but rather provides generalizing potential to these findings. This is relevant, as the changing risk profiles of the Anthropocene may expand exposure to the regions adjacent to those customarily flooded. Further surveys could also identify additional factors behind each risk-response decision-making process. For example, what is the influence of attachment to a place in evacuation decisions? It is also crucial to understand the rationality of settling and remaining in exposed areas after repeated floods, and cognition studies would be welcome to explain behaviour and vulnerability.

As a concluding observation, we highlight the self-reinforcing connection between social exclusion and flood vulnerability. As reported previously in the literature (Henrique & Tschakert, 2021; Pelling, 2003), low-income families are often pushed into exposed situations to which they are not equipped to resist or adapt. Over time, repeated hazards erode savings and assets, which are usually physical investments in the exposed residence itself. With worsening risks from climate change (IPCC, 2022) and anthropogenic intervention in riverine systems, the risk profiles of these families evolve, increasing their vulnerability. The current attachment to exposed places (e.g. family, social ties, livelihoods, and immovable assets) puts these families in a position where a cruel trade-off must be made between risking losses in the short-term and accepting further social exclusion in the long run by relocating. We argue that this condition is an example of a poverty–vulnerability trap, as previously reported (Adger, 2006; Pelling, 2003), with profound implications for social and environmental justice (Bolin & Kurtz, 2018; Henrique & Tschakert, 2021; Satterfield et al., 2004).

2.6 SUPPLEMENTARY MATERIALS

The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/urbansci6040076/s1, Table S1: Individual scale dataset for the set (a); Table S2: Individual scale dataset for the set (b); Table S3: Individual scale dataset for the set (c); including question dictionary; Tables S4–S17: Logit models results for the set (a), with all residents in the sample; Tables S18–S32: Logit models results for the set (b), with residents located inside the flood protection system (risk landscape 1); Tables S33–S47: Logit models results for the set (c), with residents located outside the flood protection system (risk landscape 2); Table S48: Variables dictionary.

All data and code developed for the analysis presented in this paper are available at https://github.com/alexandrepereiraarq/vulnerabilitytraps.

3 ONE YEAR OF THE COVID-19 PANDEMIC IN THE GLOBAL SOUTH: UNEVEN VULNERABILITIES IN BRAZILIAN CITIES

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ABSTRACT

The first year of the COVID-19 pandemic in Brazil provided one of the most severe examples of its impacts on health and society. The country had death rates above the global average and acute impacts in increased unemployment, poverty, and threats to food security marked along ethnic and social lines. This study asks how different degrees of vulnerability between Brazilian cities lead to varying survival probabilities of their population in the phases of the pandemic in the country. To answer this question, this research presents a descriptive and analytic exploration of the relationship between vulnerability and COVID-19 from February 2020 to February 2021. We describe this period in seven distinct phases, characterised by geographic units, vectors of virus transmission, and infected cases and fatality numbers. In this context, we implement an exploratory survival analysis of COVID-19 fatalities using the Kaplan-Meier estimator (KME) in a set of cities with different social vulnerability degrees. The KME is a common analytic tool in medicine, and we implement it in a geographic investigation to focus on the temporal dimension of the crisis and examine socio-territorial vulnerability. Our results present a clear association between vulnerability and COVID-19 deaths. Highly vulnerable cities show low survival probabilities, and there are statistically significant differences in survival probability between low- and high-vulnerability cities. Further research should advance by investigating spatio-temporal dynamics, providing fine-resolution empirical information, and addressing behavioural components related to COVID-19 cases and deaths in the Global South.

Keywords: COVID-19, Brazil, Survival analysis, Vulnerability.

3.1 INTRODUCTION

The first year of the coronavirus disease 2019 (COVID-19) pandemic in Brazil provided one of the most extreme examples of its impacts on health and society. Not only did Brazil present death rates above the global average (M. C. Castro et al., 2021), but the country also faced severe secondary impacts that included suspension of domestic production, increased unemployment, poverty, and threats to food security. These impacts burgeoned upon existing structural fragilities in the economy and infrastructure. Economic fragilities include high dependence on commodity exports and a high degree of work informality. The country also lacked health infrastructure, with underinvestment and geographic centralisation (e.g. the concentration of intensive care unit [ICU] beds) reducing response capacity (ECLAC, 2020).

However, existing structural fragilities do not account entirely for the observed high incidence and death rates. These problems, combined with uneven and hierarchical features of Brazil's territory and society, set the stage for high overall fatality and blatant unequal distribution of the burdens of the pandemic. The high connectivity of 'super-spreader cities' and enduring local inequalities show the long roots of the Brazilian social divide (R. R. Castro et al., 2021; Nicolelis et al., 2021; Ribeiro et al., 2021). Beyond structural features, the lack of national coordination and overall stringency for non-pharmaceutical interventions (NPIs), conflicting information about prevention and treatment, and the lack of conforming to protective behaviour fuelled the poor performance of the country during the pandemic (Barberia, Cantarelli, et al., 2021; Candido et al., 2020).

In short, the impacts of the pandemic in Brazil were unevenly distributed and marked along ethnic and social lines. This research seeks to investigate the relationship between existing uneven characteristics, divergent response behaviour, and the impacts of COVID-19 in a large country in the Global South. Therefore, it is fitting to start this investigation by asking how vulnerability relates to COVID-19-related deaths during the first year of the pandemic in Brazil. As the first part of a more extensive investigation, this paper will examine vulnerability and COVID-19 deaths from an exploratory perspective using survival analysis focusing on the temporal dynamics of the first year of the pandemic in the country.

3.1.1 The first year of COVID-19 in Brazil

Official sources register the first case of COVID-19 in Brazil on 25 February 2020. By the end of the first year of the pandemic (24 February 2021), Brazil had 10,438,360 cases and 253,372 deaths. These figures rose sharply from March 2021 onwards, reaching 365,223 deaths at the end of May. Despite representing 2.71% of the global population, Brazil accounted for 10.57% of global COVID-19-related fatalities on 24 February 2021, signalling an abnormally high number of deaths over the period.

Evidence of the introduction of the virus in the country comes from genome sequencing, which shows that initial cases came through more than 100 international contacts, mainly from Europe (Candido et al., 2020). Following this introduction, the spread was fast: Before 30 days, COVID-19 reached all 27 states (M. C. Castro et al., 2021). From March to May 2020, cases spread through the national highway and airport system due to a lack of domestic travel restrictions. Those cities best connected to the heterogeneous and hierarchic transport systems became super-spreaders (Nicolelis et al., 2021). This dynamic evolved until July with intense interaction between state and regional capitals and their areas of influence. As case numbers grew exponentially in the major cities, many people sought refuge in smaller towns, which resulted in dispersing cases to most of the country's territory. A return effect then occurred; as cases outgrew the hospital capacity in smaller cities, the population moved back to state and regional capitals, seeking ICU support. This led to a new surge of infections in the regional and state centres and an exponential increase in deaths due to the saturation of the health infrastructure, especially in São Paulo (Nicolelis et al., 2021). Contradictorily, these developments led to the relaxation of controls on social interaction across the country (i.e. NPIs). With the lack of controls and conflicting information, a series of super-spreader events occurred during festivities in late December (Christmas and New Year's Eve) and in February (Carnival). Finally, the last phase of this period presented the collapse of the health system across the country, with deaths peaking due to a lack of ICU beds, respirators, medicine, and medical staff from March to May 2021 (Freitas et al., 2021).

The lack of a nationally coordinated strategy to contain virus contagion was a salient feature of the Brazilian case. The national government opted to focus on protecting economic activity and responding to the pandemic by treating cases at hospitals, a highly criticised posture (M. C. Castro et al., 2021; Freitas et al., 2021; Matta et al., 2021). This stance also imposed the burden of decision, financing, and implementation of responses on state and municipal actors and created intense conflicts between regulating authorities (Barberia & Gómez, 2020). The ensuing heterogeneous response at the local level alternated restrictions and relaxation of control measures, at times following politically partisan lines. Research indicates Rio de Janeiro state as a case where political interference with sanitary measures led to a compromised response and the most intense dispersion of cases. In this case, issues include haphazard distribution of resources, ICU bed shortages, corruption accusations, and political infighting, among others (M. C. Castro et al., 2021).

Brazil does not lack experience with pandemics, however. The *Sistema Único de Saúde* (SUS, translated as the Unified Health System) is unique as a universal, comprehensive, and free health system for countries above 100 million inhabitants and performed well against the HIV/AIDS pandemic (M. C. Castro et al., 2021).. Despite the differences between these pandemics (e.g. the contagion mechanism for COVID-19 is much faster), the country had integrated information systems, centralised coordination from the national to the community level, and a federated democratic health governance structure. Response measures against COVID-19 were, nonetheless, fragmented, stemming primarily from state-level coordination and, even then, prone to conflicts and contradictions (Barberia, Cantarelli, et al., 2021).

3.1.2 The uneven impacts of the pandemic in Brazil

Brazilian inequality fuels unevenness in the exposure to, resistance to, and resilience against the impacts of the pandemic (M. C. Castro et al., 2021). On the national and regional scales, the high connectivity of urban centres and metropolitan regions makes them more exposed. During the first weeks of the pandemic, the international travel hubs were key spreaders (e.g. São Paulo, Rio de Janeiro, Brasília, Fortaleza, and Manaus). Overall, São Paulo led in cases and death numbers, followed by Belo Horizonte, Recife, Salvador, Fortaleza, and Teresina (Nicolelis et al., 2021). At the regional scale, highly connected cities presented cases first and in more significant numbers than less connected areas (Candido et al., 2020; Nicolelis et al., 2021). Between cities of similar connectivity, those with less strict NPIs or varying stringency over time had more cases than those implementing consistent measures (Barberia, Cantarelli, et al., 2021). Local and in-state spill over effects were frequent in urban agglomerations (e.g. metropolitan regions). Death figures varied geographically according to the saturation of the health system (i.e. more critical cases than ICU beds), notably during the later phases of the first year (Bezerra et al., 2020). At the urban scale, geographical factors include access to health services (e.g. ICU beds and mechanical respirators) (Pereira et al., 2021) and income when associated with ethnic profiles (i.e. deaths were more frequent among Black and Pardo[6] individuals) (S. L. Li et al., 2021).

A significant relationship exists between the prevalence of chronic non-communicable diseases (CNDs) and COVID-19 cases and deaths. CNDs are pre-existent health conditions that increase the risk of acquiring an infectious disease and the odds of dying once infected (Brasil & Ministério da Saúde, 2022). Official data shows that 62% of the hospitalised patients[7] diagnosed with COVID-19 declared at least one CND. This figure rose to 72% of fatal cases (Brasil & Ministério da Saúde, 2022). The relationship between CNDs and COVID-19 reinforces the uneven geographic expressions of the social determinants of health (SDOH). SDOH are the unequal conditions of living, growing, and ageing that impact health and well-being, generated by the unfair distribution of money, power, and resources between and within countries. They include environmental factors related to urbanisation, ranging from primary material conditions (i.e. housing, sanitation, and access to services such as health

[6] Pardo is an ethnic classification that mixes components from indigenous, black, and white phenotypical characteristics. Implemented as early as 1872, it still features in the official census.

[7] That is, cases grave enough to merit hospitalization. Figures reference the period from March 2020 to March 2021.

care) to community and societal aspects of urban living, such as social capital and neighbourhood security (Marmot, 2005; Salgado et al., 2020). Therefore, these territorial components of SDOH interacted with behavioural, infrastructural, and territorial features to establish an uneven resistance to the pandemic at multiple scales (e.g. from international to community).

The relationship between the vulnerability to COVID-19 and preceding structural fragilities in the country also merits careful consideration. During the first weeks of the pandemic, the initial introduction of the virus came from international travellers, and the vulnerability to COVID-19 in Brazil seemed like that reported in Europe. During the initial stages of domestic transmission, intense restrictions on social activities from March to May 2020 meant that individuals directly involved in travel (e.g. lorry drivers) had distinct roles in spreading the virus. When the economic impact of restrictions pressured livelihoods, workers in other categories (e.g. cleaners, day labourers) started a trade-off between heightening their exposure and maintaining income. Local governments started to lower restrictive measures around May 2020, when virus vulnerability factors began to transition from age towards more classic environmental and social factors (e.g. lack of sewage or access to health services). At later stages, the social vulnerability would intensely interact with exposure and lack of resilience: Lacking or diminishing income brought isolation, hunger, and restricted access to services (including health care). These interactions would last through the first year, and the COVID-19 pandemic would increase the country's social divide. This context generated dire impacts in the form of short-term disenfranchisement, long-lasting health issues, and an enormous number of deaths among those already vulnerable: the urban poor, slum dwellers, the homeless, women, and non-White ethnicities (S. L. Li et al., 2021; Pereira et al., 2021).

The connections between COVID-19 and vulnerability are by far not exclusive to Brazil. In developed countries, studies mapped factors such as age, comorbidities, or access to health services as important drivers of mortality (Dowd et al., 2020; Grekousis et al., 2022). Among developing countries, the literature suggests a more diverse set of factors, including lack of infrastructure, housing, or transportation; inequalities according to ethnicity; economics; and environmental conditions (Fallah-Aliabadi et al., 2022). These studies fail, however, to provide integrative methods to connect structural, behavioural, and social features of vulnerability to COVID-19 outcomes. To this end, this investigation seeks to expand established vulnerability frameworks (Adger, 2006; Boubacar et al., 2017) by proposing the integration of the inequalities embedded in the uneven characteristics of society and urbanisation with natural hazards (Elsey et al., 2016; Ezeh et al., 2017), adding COVID-19 to this set.

In Brazil, critical gaps also exist in the intersection between the direct impacts of COVID-19 (i.e. health issues and deaths) and the secondary effects of the pandemic.

Secondary effects are caused by the disease (lower life expectancy, decreased quality of life) and by response measures (i.e. decreased economic activity and employment, increased inequalities). This study proposes structuring a comparable, replicable methodology utilising open data to fill the gap of a multidimensional vulnerability framework oriented towards the Global South. To this end, this research presents an exploratory analytical approach based on vulnerability as the first stage in developing such a framework.

This study asks how different degrees of vulnerability between Brazilian cities lead to varying survival probabilities of their population in the phases of the pandemic in the country. The central hypothesis is that the population in more vulnerable cities would have lower probabilities of surviving COVID-19 during the first year of the pandemic. This research presents an exploratory survival analysis of deaths during the first year of the pandemic in Brazil to test this hypothesis. This analysis focuses on the temporal dimension of the crisis and controls for vulnerability in the territory and society by selecting a set of cities with different Social Vulnerability Index (SVI) values (Costa & Margutti, 2015). In the context of geographical research, this study seeks to advance on the correlation of COVID-19 to spatial characteristics of certain locations, namely the vulnerability of a selected set of cities.

The following section presents the design of this study, utilising open and authoritative data sets to estimate the survival probability for each epidemiological week of the first year. Next, we present the methods for survival analysis, to be exact the Kaplan-Meier estimator (KME). The presentation of results follows, highlighting the consistent effects of vulnerability to COVID-19 fatalities during the period, albeit under some uncertainty. We discuss these findings and present the context for further studies. These include addressing the components of vulnerability (i.e. exposure, resistance, and resilience), using other survival analysis tools such as multivariate Cox regression analysis, implementing analysis on finer spatial scales, developing fieldwork, and performing modelling experiments that will follow in future articles and developments of the database created here.

3.2 METHODS

This investigation implements an exploratory approach combining descriptive and bivariate analysis between vulnerability and COVID-19 deaths in Brazil during the first year of the pandemic. We propose this design to assess the dynamic of COVID-19 deaths over time. To this end, we describe the first year of the pandemic based on existing sources and data and then implement survival analysis with the KME. The KME provides the survival probability curves for different populations in the country. Survival analysis is a widespread analysis technique in medical research, including studies related to COVID-19 (Chen et al., 2020; Shang et al., 2021). We decided on survival analysis with the KME because it is a statistically robust method for comparing populations (Collet, 2003) and is simple to interpret in the interdisciplinary context of integrative geography. Therefore, the innovation here lies in applying a technique from medical research to an interdisciplinary problem, such as the relationship between vulnerability and COVID-19. In this context, this analysis advances research on the geographies of disease and ill health by linking long-term human behaviour (i.e. accumulated patterns of socio-territorial vulnerability) to short-term impacts of the pandemic (i.e. fatalities). To test the robustness of results, we extend the KME with the Cox proportional hazards model in Appendix A.

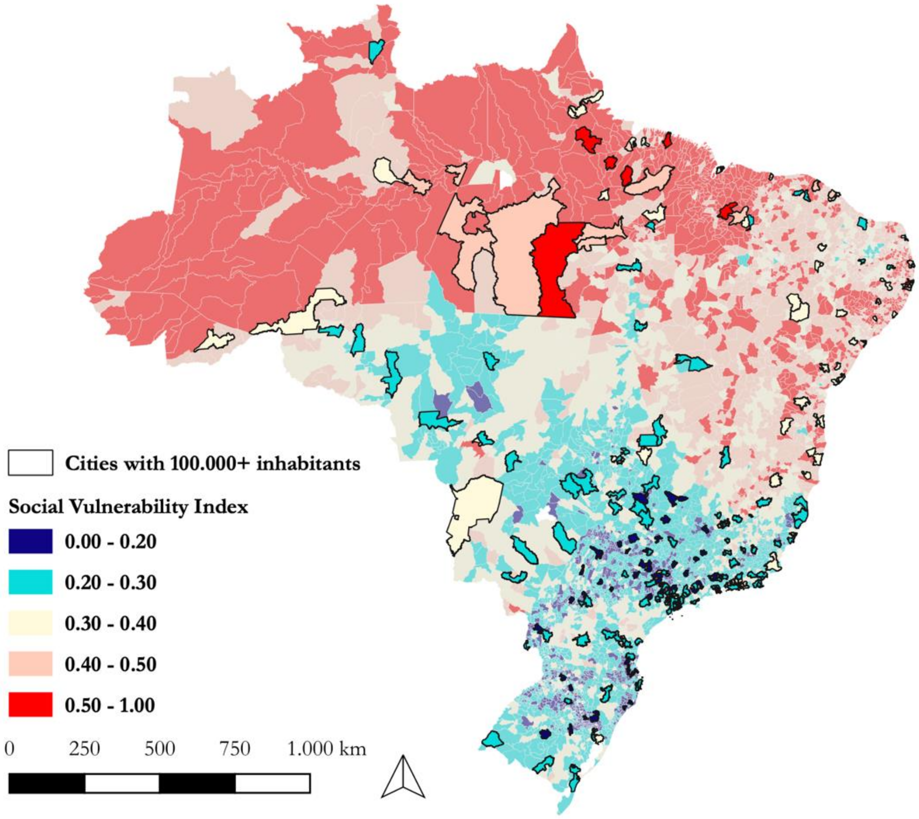
3.2.1 Methodological design

The study design considers the group of Brazilian cities with more than 100,000 inhabitants. From these cities, we analyse the SVI (Costa & Margutti, 2015), selecting five examples from the distribution of vulnerability in the country. This sample seeks to describe the country in its diversity through a synthetic measure of vulnerability. This approach presents the advantage of simplicity, encapsulating geographic factors in a single measure, which is beneficial for our first advance on the topic and welcomes further complexity in other stages of research.

The SVI is a measure derived from the territorial and demographic characteristics of the country. The index uses 2010 census data (the latest available), and Figure 3-1 demonstrates its national distribution. The index overcomes the limitations of poverty measures by including sixteen indicators in three main dimensions: urban infrastructure, human capital, and work and income. This widened approach to deprivation targets the multiple dimensions of human development, going beyond income by relating deprivation to livelihoods and access to assets at the household scale. The data varies from 0 to 1 (with 0 meaning no vulnerability) (Costa & Margutti, 2015). Death figures come from Brasil.IO, an open data initiative that aggregates cases and death figures reported by municipal health authorities (Brasil.IO, 2021). Brasil.IO has a significant reputation, and prominent scientific publications feature it as a data source (M. C. Castro et al., 2021; Nicolelis et al., 2021). This analysis considers death figures more reliable than COVID-19 cases, as regional differences severely influence the latter in testing policies (i.e. most cities only test patients with severe symptoms during hospital admission, but there are exceptions).

By selecting cities with more than 100,000 inhabitants, we seek to implement a ‘most similar approach’ that avoids inflated variance found in cities with smaller population sizes. Therefore, we aim to counteract a limitation of data, which is that despite the large numbers of aggregated fatalities across the country, weekly quantities for individual cities vary greatly, due to factors that are at times not epidemiologically relevant (e.g. tallying and processing issues).

Figure 3-1. Social vulnerability index distribution in Brazil and location of cities in the sample.
Source: authors, with data from IPEA (2015).



The study includes a sample of five cities at significant points in the SVI distribution from the group of cities under consideration. These cities have SVI scores closer to the minimum; the median values of the 25, 50, and 75 percentiles; and the maximum SVI value in the country. When more than one city had the same SVI score, we selected the one with a larger population, as presented in Table 3-1 and Figure 3-1. This sample includes cities with a range of geographical conditions (e.g. from the North to the South regions), encapsulating different political, social, and territorial factors, and seeks to provide a significant, albeit limited, representation of the country during the period. This sample might inadvertently include some bias because we only restrict the minimum number of inhabitants and not the maximum. Forthcoming analysis should also address other sources of bias, such as the regional, social, or political context.

Table 3-1. Descriptive statistics for the cities in the sample.
Source: authors, based on data from IPEA (2015).

City name/State	Population (2020)	SVI score	Approximate SVI quantile	Accumulated COVID-19 cases (24.02.2021)	Accumulated COVID-19 deaths (24.02.2021)
Tubarão/SC[8]	106.422	0.121	Min. value	14,062	218
Parnamirim/RN[3]	267.036	0.247	25%	16,051	256
Feira de Santana/BA[3]	619.609	0.336	50%	29,106	498
São José de Ribamar/MA[3]	179.028	0.449	75%	1,748	151
Breves/PA[3]	103.497	0.603	Max. value	3,578	102
Brazil	211,707,713	0.326	-	10,438,360	253,372

3.2.2 Analytical method

This research implements a survival analysis using the KME to compare the survival function of inhabitants who died from COVID-19 in a sample of large Brazilian cities. Survival analysis evaluates the time until a particular event occurs. Medical research uses survival analysis to evaluate the effect of a treatment in different cohorts (e.g. those taking medication and those taking a placebo) or the impact of behaviour on mortality. Its applications are broader, though, including event history analysis in political science (Box-Steffensmeier & Jones, 1997). Its central elements are the events (e.g. death of a patient) and the duration until the patient faces the event (i.e. the length from the time of origin until the event).

As any experiment needs to be completed within a given time, the KME delimits a window in which it considers the probabilistic curve of events. In the case of this study, we observe the fatalities during the first year of the pandemic and set aside fatalities after this period or the absolute majority of people who are still alive. The KME, therefore, has a temporal frame and gains strength by comparing what the method calls 'reduced groups' of a population (Kaplan & Meier, 1958). This grouping allows us to analyse the statistical structural differences of subpopulations without leaning on other assumptions. Smokers and non-smokers in a population are the groups used in a classic application of this non-parametric analysis to the problem of deaths due to lung cancer. In this study, we deal with cities that show different vulnerability degrees and deaths over 53 weeks. With this research setup, we can thus draw causal conclusions between the cities as if the analysis were a quasi-experiment performed statistically.

The advantage of this method is that it enables the analysis of binary models (e.g. alive or dead status) with qualitative and discrete dependent variables (represented as reduced

[8] Brazilian state acronyms, by region, are: North: AC=Acre, AP=Amapá, AM=Amazonas, PA=Pará, RO=Rondônia, RR=Roraima, and TO=Tocantins; Northeast: AL=Alagoas, BA=Bahia, CE=Ceará, MA=Maranhão, PB=Paraíba, PE=Pernambuco, PI=Piauí, RN=Rio Grande do Norte, and SE=Sergipe; Centre-West: DF=Distrito Federal, GO=Goiás, MT=Mato Grosso, and MS=Mato Grosso do Sul; Southeast: ES=Espírito Santo; MG=Minas Gerais; RJ=Rio de Janeiro; and SP=São Paulo; South: PR=Paraná; RS=Rio Grande do Sul; and SC=Santa Catarina.

groups) along with the temporal development of discrete events (Collet, 2003). Equation 3-1 defines the survival function.

Equation 3-1. Survival function in the Kaplan-Meier Estimator.
Source: COLLET (2003).

$$S_t = \prod_{k=1}^{t}(1 - h_t)$$

S_t estimates the survival probability of a person at time t, which is the product of probabilities of not experiencing a death event in each of the intervals up to and including time t.
h_t represents the conditional likelihood of death at time t.

The KME provides a graphical representation of events along a timeline. The categorical dependent variable expresses the phenomenon that we seek to explain. The independent variable is the product of probabilities that the death event has not occurred at a given time (or that the event occurs after time t). Based on these probabilities, it is possible to test the main argument that the different groups have varying risks of death (Cleves et al., 2008) based on their vulnerability degrees.

Using the KME, this analysis estimates the survival functions composed of the COVID-19 fatalities in five cities (i.e. survival probability is the independent variable). The dependent data are the fatalities in each of the five cities and the time at which they took place (represented in epidemiological weeks). This analysis presents cities selected according to their degrees of vulnerability. This means that when classifying Brazilian cities larger than 100,000 inhabitants according to their SVI, this analysis includes those nearest to the median of each quartile as representatives of different degrees of vulnerability. As we consider only fatal cases for the sampled cities during the analysis period, the probability starts with 1 at time 0 (i.e. when there is a 100% chance of dying after that moment) and ends at probability 0 at time 53 (when all individuals under consideration were already dead). The analysis timeframe considers the first year of COVID-19 in Brazil, starting on 25.02.2020 and lasting until 24.02.2021, encompassing 53 weeks, whereas data was available until 17.04.2021. We aggregate deaths at the week scale, with the official Brazilian epidemiological weeks[9] as the reference.

3.3 RESULTS

The phases of the COVID-19 pandemic during the first year in the country are presented in Table 3-2. The existing literature provides plenty of evidence for Phases 1 through 4 (Candido et al., 2020; M. C. Castro et al., 2021; Nicolelis et al., 2021), whereas we

[9] For the Brazilian Epidemiological Calendar, see the Health Ministry website http://portalsinan.saude.gov.br/calendario-epidemiologico-2020/43-institucional/171-calendario-epidemiologico-2021.

outline Phases 5 through 7 based on available case data and ongoing research. Phase 1 reflects the initial introduction of the virus from international travel, notably from Italy and the USA (Candido et al., 2020). Phase 2 shows domestic-level dissemination through national highways and domestic flights. In the first week, the contagion reached seven Brazilian states (São Paulo, Rio de Janeiro, Bahia, the Federal District, Alagoas, Minas Gerais, and Rio Grande do Sul). Before 30 days following the introduction, it was present in every state (Roraima was the last, on 21 March). In Phase 3, domestic-level transmission took root through intra-regional and intra-urban contagion fuelled by work relationships, notably among front-end attendants and essential and domestic workers (Matta et al., 2021). The increase in domestic-level transmission signalled a transition from higher socioeconomic classes towards lower-paid workers, with more significant proportions of Black and Pardo individuals and concentrations moving away from central neighbourhoods towards the cities' peripheries (S. L. Li et al., 2021). Lack of resistance (e.g. due to CNDs, malnutrition, or lack of access to the health infrastructure) became critical as cases led to deaths. Mortality among traditionally vulnerable populations (e.g. women, along with Black and Pardo ethnicities) grew (Baqui et al., 2020; S. L. Li et al., 2021), outpacing the initial internationally exposed (and mostly White) travellers. In Phase 3, domestic spread at the national scale followed 26 major land routes (and river routes in Amazonas) connecting state and regional capitals. In Phase 4, the result of a self-reinforcing dynamic occurred between regional health centres and the country's hinterland. When people travelled to smaller cities seeking less exposure, they inadvertently brought the contagion with them. Those suffering from COVID-19 in these small cities, along with their accompanying relatives, would then seek ICU beds in health centres, bringing more contagion that led to doubling figures, reaching 4,437,986 cases by September. From September to November 2020, the fifth phase presented overall relaxation of NPIs across the country, with a gradual return to normal levels of social interaction, despite the increase in cases and the first death spikes. This relaxation was conflictive, resulting in institutional disputes between branches of government on national, state, and local scales (Barberia & Gómez, 2020).

Even though some cities remained stringent, the limited measures in others, combined with increased travel during national holidays at the end of the year and Carnival, created a series of super-spreader events in the sixth phase of the pandemic (from November 2020 to February 2021). In this phase, Brazil's performance stood out as contrary to the trend in other countries with more than 100,000 deaths in the period (the United States of America, Mexico, India, the United Kingdom, and Italy), signalling the contribution of local factors (Freitas et al., 2021). During this phase, cases reached 10 million, and the first local collapses of the health system occurred. The first capital to breakdown was Manaus (Amazonas), where scenes of asphyxiating patients were prominent when oxygen production was insufficient. This context would result in the final phase for the period, marked by the health system's failure across the country on 22 March, when no state capital had less than 80% occupation of its ICU beds and 18 had more than 90%. Deaths would peak at 4,148 per day on 8 April (Freitas et al., 2021).

Table 3-2. Major phases of the first year of the COVID-19 pandemic in Brazil, according to the literature and secondary data.
Source: authors, based on data from Brasil.IO (2021).

Phase	Geographic unit	Main vectors	Approximate dates	Week numbers[10]	Acc. cases[11]	Acc. deaths[11]
1	Global international hubs	International airports	02.2020–03.2020	1–5	3,669	97
2	National and regional centres	National highways and domestic flights	04.2020–05.2020	6–13	348,836	22,165
3	State capitals and regions of influence	State highways and road transport	06.2020–07.2020	14–21	2,058,210	78,643
4	National and regional health service centres	Local hospitals' saturation	08.2020–09.2020	22–30	4,437,986	135,018
5	Population centres at every scale	Relaxation of NPIs, during conflicts between authorities (federal/local)	10.2020–mid 11.2020	31–38	5,708,802	163,207
6	Population centres at every scale	Increased social interaction on holidays	late 11.2020–02.2021	39–53	10,438,360	253,372
7	National and regional health service centres	Health system collapse	02.2021–05.2021	54–60	13,675,356	365,223

Based on this context, we then compare the populations of different cities and their survival curves using the KME. First, we estimate the survival probabilities of the population of the more vulnerable cities (i.e. the city with the maximum SVI, Breves/PA[3] [BRV], and the city at the 75th percentile, São José de Ribamar/MA[3] [SJR]). Then, we contrasted these cities against the less vulnerable ones (i.e. cities with SVI scores at the 25th percentile and the minimum, Parnamirim/RN[3] [PAR] and Tubarão/SC[3] [TUB], respectively). The median SVI value provides a definitive reference (Feira de Santana/BA [FDS]). For this paper, the hypothesis is that survival functions will present divergent behaviour (considering time and death events) due to differences in the degree of vulnerability of the cities in the sample.

Figure 3-2 presents the accumulated absolute death plots for the five-city sample, selected based on their vulnerability degrees. These curves describe the evolution of deaths over time and compare these cities against the pandemic phases, albeit including potential bias from the definition of the group of cities under consideration. During Phase 1 (weeks 1 to 5), there are no deaths in the sample, which is consistent with expectations, as cases were

[10] We adopted a simplified linear numbering of weeks to describe the period. Week 1 is equivalent to the epidemiological week 09 of 2020, and week 60 equates to the epidemiological week 15 of 2021.
[11] Accumulated cases and deaths take the last day of the last epidemiological week in the period as a reference. That is, phase 1 has data up to 28.03.2020 and phase 7 up to 17.04.2021.

concentrated in major international hubs (e.g. São Paulo, Rio de Janeiro). Phase 2 presents the first deaths in the sample, notably among the more vulnerable cities of BRV and SJR. All cities except TUB have accelerated growth in deaths during Phase 3. Deaths proliferate in PAR, FDS, and SJR, with the latter experiencing 53% of its total deaths during the period. This is consistent with the pandemic phases in the country, as the medium-sized cities in the sample started to receive more cases from state capitals as domestic-level transmission became the rule. The more vulnerable cities (BRV and SJR) reach a plateau in Phase 4, with death growth levelling off afterwards. PAR and FDS still present growth, and TUB accelerates, reaching 80 deaths sharply. Phase 5 presents a continued increase in deaths in FDS, which remains consistent throughout the following period. The other cities in the sample are stable in this phase and start to differentiate only during the next phase. In Phase 6, FDS sustains its growth, reaching 498 deaths in week 53. TUB has accelerated deaths, progressing rapidly from 80 to 218 deaths, a similar behaviour to PAR, the other less vulnerable city. The most vulnerable cities (BRV and SJR) are stable during the last phase, and the latter presents a renewed increase in deaths only in week 54, which is outside the scope of the analysis.

Figure 3-2. Accumulated deaths for the five selected Brazilian cities, from week 0 (25.02.2020) to week 53 (24.02.2021).
Source: authors, based on data from Brasil.IO (2021).

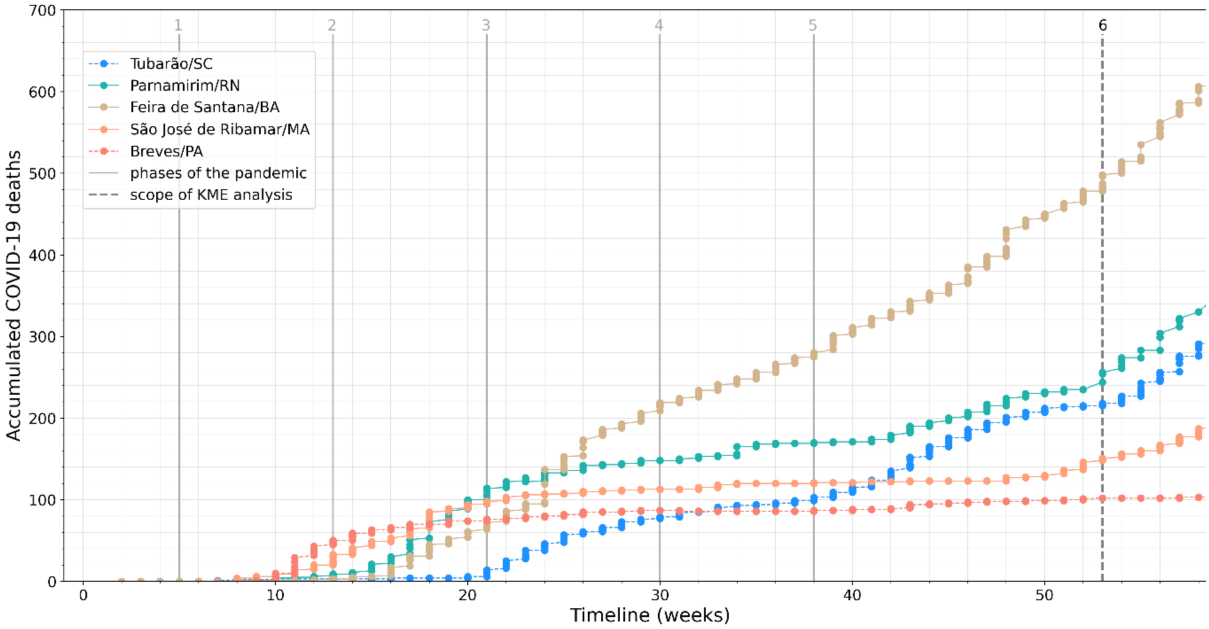
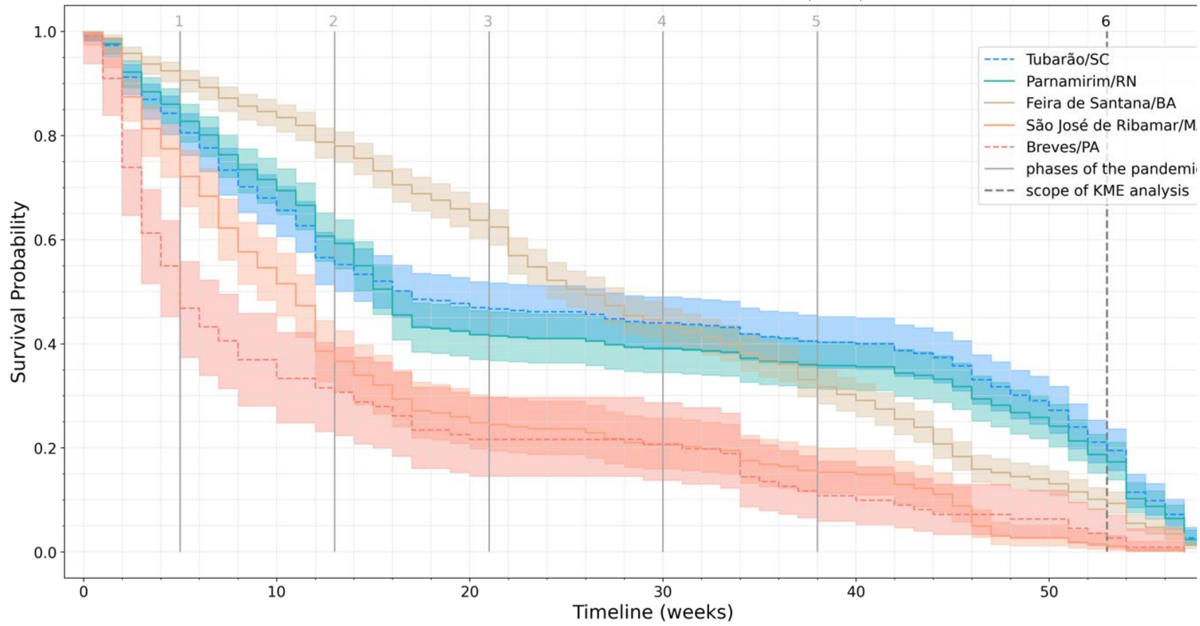


Figure 3-3 presents the survival probability curves and their confidence intervals for the selected cities. The lines represent the estimated survival probability as a function of time for each level of vulnerability (represented by each city), whereas the shaded areas show the 95% confidence intervals. This analysis allows for the evaluation of the proportional evolution of death rates in each city. This neutralises the bias from the city population size found in

Figure 3-2, complementing the analysis, and showing the impact of vulnerability on survival probabilities.

Figure 3-3. Survival function for the five selected Brazilian cities using the KME, from week 0 (25.02.2020) to week 53 (24.02.2021).
Source: authors, based on data from Brasil.IO (2021).



The behaviour indicated in the survival probability curves is sufficiently different in statistical terms. This is demonstrated by the shaded part of the probability curves that show consistent behaviour throughout the period and no overlap between the confidence intervals of the cities, except in the early weeks of the timeline (weeks 0 through 10), when trends are still differentiating. More specifically, the curves show that the populations of TUB and PAR (cities with lower vulnerability) have greater survival probabilities for much a longer period than those of SJR and BRV (cities with higher vulnerability) during the analysis period. TUB has the most significant survival probability in the sample, and the survival curves decline as vulnerability increases. The clear distinction between the high- and low-vulnerability groups first increases from week 20, grows further at week 34, and only diminishes after week 50, when all probabilities approach zero. These distinctions remain statistically significant under additional testing using a log-rank test, which is available in Appendix A. This test shows a statistically significant difference between the groups and contradicts the null hypothesis (i.e. no difference).

The temporal variation of the curves demonstrates a sharp initial decrease in the survival probability for the city with the highest vulnerability (BRV), followed by a stabilisation from weeks 10 to 34. This implies that the impacts of the pandemic were more severe sooner and that this city’s population had lower chances of survival in comparison with the others in the sample. TUB, the city with the lowest vulnerability, has a milder decrease in survival probability and reaches a plateau from week 18 to week 42. Then, it presents a shaper decrease in survival, which is expected, as fatalities tend toward zero by the end of the analysis. This means that the population of this city had a greater survival probability for a longer period than the others in the sample. The exception is the somewhat unexpected behaviour of FDS, which varies linearly during the period. Figure 3-2 partially demonstrates this exceptional character as well, showing a sustained growth in deaths during the analysis. The evolution of survival probabilities indicated by the KME shows that the populations in cities with higher vulnerability had marked decreases in their survival chances already at the initial phases, dropping to roughly 0.3 at week 10, 0.2 on week 30, and as low as 0.15 on week 34. This indicates low resilience, derived from high vulnerability, and contrasts the behaviour exhibited by the low-vulnerability cities.

The confidence intervals of the survival probability curves touch at several points in the timeline, which is consistent with expected results. Curves touch within the pairs of vulnerability degrees (e.g. between TUB and PAR) but not between pairs (e.g. between PAR and SJR). This means the BRV curve touches that of SJR from weeks 12 on, indicating some uncertainty about the explanatory potential of the vulnerability–fatalities relationship. Despite BRV showing the lowest survival probability, its probabilities mix with SJR to the degree that analysing BRV and SJR separately could be misleading. The same behaviour is present between TUB and PAR. However, we see that, for almost the entire analysed period, the statistical differences between the pairs with the highest and lowest vulnerability are evident, and occasional overlaps are due to the construction of the study (i.e. limited to the beginning and end of the curves).

3.4 DISCUSSION

The survival curves do not offer grounds to reject the hypothesis of this study, suggesting the influence of vulnerability on the probability of survival against COVID-19. This result is in line with previous research that indicates a correspondence between increasing vulnerability and the impacts of COVID-19 (Baggio et al., 2021; S. L. Li et al., 2021). By adopting a synthetic vulnerability index as the control variable, this analysis indirectly accounts for variations in its different dimensions. This simplified approach provides an exploration of the link between vulnerability and the direct impacts of COVID-19, with results that are sufficient to support the current hypothesis.

The research design presented in this paper is exploratory and, therefore, limited. It uses a small sample of cities and does not control for other alternative explanations. The decision to use a synthetic index for vulnerability has the advantage of simplicity but implies the acceptance of the associated factors as equally influential. In the same light, the study is not explicit about geographical variations (e.g. from social, political, or regional factors) that are potentially associated with COVID-19 fatalities. These and other sources of alternative explanations should be addressed in future and expanded versions of this design. Literature also indicates certain factors that this analysis omits, including structural, behavioural, and policy features. Noteworthy structural features are the hierarchy between city centres (e.g. differentiation in connectivity, centrality, and polarisation that lead to increased exposure) (Nicolelis et al., 2021; Pereira et al., 2021). Behavioural factors consist of mobility intensity between and within cities (Kraemer et al., 2020) and adherence to NPIs (e.g. social distancing and restricting movement) (Barberia, Cantarelli, et al., 2021; Candido et al., 2020). Finally, policy factors include integrating social, health, and education policies (e.g. providing income supplements, advising on mask-wearing) (Ha et al., 2020).

This analysis also includes personal differentiating factors only in an implicit manner within the vulnerability index. Further studies should consider social and demographic characteristics such as ethnicity, income, education, and gender explicitly. The geographic distribution of these factors and the associated SDOH are critical topics for intra-urban studies that still merit development. Furthermore, considering SDOH and behaviour in multidimensional approaches to COVID-19 vulnerability has significant potential to orient policy during recovery. One example is providing temporary hospital and ICU beds, which further exacerbates inequalities in health infrastructure, is costly, is prone to corruption, and has a limited effect beyond the critical response phases. This analysis suggests positive feedback between the uneven character of Brazilian society and territory and the COVID-19 pandemic, though. This feedback suggests alternative solutions such as improving the existing resistance and resilience of the population, therefore centring on social fairness and long-term improvement. Measures could include minimum income policies, the provision of access to potable water, and fighting malnutrition (Matta et al., 2021). These solutions would significantly improve resilience in high-vulnerability conditions (e.g. among homeless or slum-dwellers) and create conditions that promote adherence to NPIs.

This research offers topical contributions to both the geography of diseases and illnesses and the spatial distribution of health policies. Regarding the first topic, this approach is easily reproducible in other contexts. Researchers can replicate it with data for other countries or regions with minor adjustments. The simple data requirements also mean these methods are accessible to regions in the Global South, where disaggregate data is scarce, less frequently updated, or non-existent (Elsey et al., 2016). These methods also provide an exploratory tool to assess the correlation of synthetic vulnerability indexes on fine spatial and temporal scales (i.e. individual cities and epidemiological weeks). Despite the currently limited sample, the methods presented here can be expanded to larger groups of cities, correlating vulnerability and COVID-19 using large data sources. Furthermore, the SVI synthesises aspects of urban infrastructure, human capital, and work and income. This integration provides an overarching measure of social and environmental factors that connects research on COVID-19 with broader geographic themes (Ezeh et al., 2017). One example of social characteristics of the population and places that further research should explore is the inequality and power structures that are deeply entwined with the contrasting vulnerability levels found in Brazilian society and exemplified in this study's sampled cities.

This investigation also provides potential policy outlooks. Considering the provision and accessibility of health services, this contribution indicates that improvements in basic living conditions and infrastructure (e.g. minimum income, sewage) contribute to lowering the demand for health services even during viral pandemics (Cummins et al., 2007). By identifying vulnerability hot spots, future research can also predict where future demand is likely to concentrate, as well as the ability to point to structural inequalities that contribute to systemic risks (Sillmann et al., 2022).

Methodologically, forthcoming studies from this group plan to explore direct and secondary impacts of COVID-19 in detail. The next logical step is to expand the generalisation of the analysis with the Cox proportional hazards model (Cox et al., 1984). With this model, one can regress the survival probabilities against vulnerability and other factors such as mobility degree, size, and rank of the city (in the Brazilian urban network hierarchy). Along these lines, a more significant number of cases would provide a more consistent sample, and similar experiments within the country's five regions (North, Northeast, Centre-West, South-West, and South) could show regional variations in the vulnerability–survival relationship. Investigation into finer geographical scales could also provide insights into the behavioural components of resilience (e.g. adherence to NPIs and motivations for non-compliance).

Complementary to SDOH and demographic features of resistance, behavioural components affect exposure and resilience. During the first year of the pandemic, the lack of access to work and livelihoods threatened a significant part of the Brazilian population that could not work remotely or had informal work (Matta et al., 2021). In this group are the essential workers from care and health professions, along with commerce employees, such as supermarket cashiers, drivers, and delivery personnel. The pandemic also affected a large portion of the urban informal workers, who either work on the street (e.g. street sellers, car washers) or survive on hand-to-mouth income with sporadic employment in construction, gardening, and cleaning. Similar impacts also pressured rural workers in the Global South, threatening livelihoods (Petersen et al., 2021). The absence of comprehensive social support measures during the pandemic meant that these workers could not effectively socially isolate themselves (Matta et al., 2021) or had to survive on reduced income for an indeterminate time. We argue for further analysis into vulnerability considering trade-offs between livelihood preservation and protective behaviour.

In contrast, other groups in Brazil did not adhere to NPIs due to ideological motivations. Certain people behaved in ways not protective to either themselves or society due to a series of resistances, similar to examples in the USA, France, or Germany (e.g. *Querdenker* or anti-maskers) (Hu et al., 2021; Rose-Redwood et al., 2020). Within this group are conspiracy theorists, advocates of preventive treatment (e.g. hydroxychloroquine treatment), supporters of thanatopolitics (Sparke & Anguelov, 2020), and those against vaccination (Barberia, Cantarelli, et al., 2021). For research in geography, these deviations from the behavioural norm are especially interesting in responses to COVID-19. These deviations impose changes to exposure and vulnerability at concise time scales and at the individual's resolution, challenging aggregate, or averaged approaches. Therefore, when considering the continuation of the study at hand, measures of vulnerability to COVID-19 should include behaviour as a critical component, directed by ideological motivations or guided by livelihood preservation at fine temporal and spatial scales.

3.5 CONCLUSION

The first year of the COVID-19 pandemic in the uneven Brazilian society provided extreme examples of its impacts on health and well-being. This paper presents some of these impacts and explores how the underlying differences in vulnerability influence their repercussions in five representative cities during this period. Our results present a clear association between vulnerability and COVID-19 deaths. The more vulnerable cities in the sample had lower survival probabilities than those of lower vulnerability during the whole length of the study. By looking at the temporal dynamic of the first year of the pandemic, this study provides insights into the different phases of the pandemic in the country. The more vulnerable cities in the sample presented earlier spikes in deaths and sharper increases during the initial phases of the pandemic (e.g. Phases 2 and 3 in Table 3-2), signalling lower resistance to contagion. The consistent difference in survival probability between low- and high-vulnerability cases supports the argument for SDOH in COVID-19 fatalities.

This exploratory approach provides insights into the connection between vulnerability, behaviour, and the impacts of COVID-19 in a large, unequal, developing country. This study shows the contribution of behaviour in COVID-19 vulnerability through the mismatch between death rates and relaxation of NPIs during the latter phases of the pandemic in Brazil (Phases 5 through 7 in Table 3-2). This striking characteristic of Brazil leaves many questions regarding the social impacts of individual and community decision-making on protective behaviour that begs further research from a geographic perspective (e.g. concerning society, space, and time).

As the long-term nature of the crisis dawns on the academic community, future research should focus on integrative approaches around the primary and secondary effects of

COVID-19 in the Global South. First, the spatio-temporal dynamics of COVID-19 and its interaction with environmental and demographic factors at the community scale is a substantial gap in research. Insight into this would provide much-needed evidence and guidance for policymaking in actionable yet tractable complexity. Second, research requires empirical evidence that represents the differences in society in a timely and accurate manner. Updated social indicators at the community scale would allow research to move away from aggregate and imprecise measures that compound the impacts on the most vulnerable by focusing on averaged expectations of resilience and resistance. Third, behaviour is an essential component in preventing contagion and curbing deaths. To orient response measures to more efficient and fair policies, research must account for the motivation to adopt (or resist) protective behaviour. In this direction, research must address contradicting phenomena, such as poor people betting on their lives when they choose to protect their livelihoods by increasing their exposure. For fairness' sake, research must also address the affluent, ideologically oriented denialism that hampered Brazilian response policies during this period.

Finally, the issues addressed in this paper are central to the pandemic recovery efforts in Brazil. It is impossible to lessen the direct impact of the pandemic in the country, with over 600,000 dead and still unaccounted for damage to life expectancy and quality. Compounding these harms, the indirect impacts will also challenge the country in the coming years. As livelihoods were lost, education was postponed, and savings were depleted, many families will struggle to face eventual upcoming crises. With reduced economic activity and increased inequality, the country is also severely more limited in managing inherent future risks after the first year of the pandemic than it was before. These compounding stressors show how systemic shocks have consequences beyond the immediate area or time of effect. The systemic quality of natural shocks is, in turn, embedded in the socio-environmental vulnerability-versus-COVID-19 relationship analysed in this paper. Climate change is a highly probable future stressor for the country, with potential global impacts that could lead to spill over effects similar to those from the pandemic (IPCC, 2022). If the country wants to learn lessons from the COVID-19 crisis, it would do well to address systemic risks by improving multidimensional resilience.

3.6 SUPPLEMENTARY MATERIAL

The code and data used in the KME analysis are available at https://github.com/alexandrepereiraarq/covidgi.

4 SIMULATING EXPOSURE-RELATED HUMAN MOBILITY BEHAVIOR AT THE NEIGHBORHOOD-LEVEL UNDER COVID-19 IN PORTO ALEGRE, BRAZIL

Peer-reviewed publication[12]:

Peng, Y., Rodriguez Lopez, J. M., Santos, A. P., Mobeen, M., & Scheffran, J. (2023). Simulating exposure-related human mobility behavior at the neighborhood-level under COVID-19 in Porto Alegre, Brazil. Cities, 134(104161). https://doi.org/10.1016/j.cities.2022.104161

ABSTRACT

Modelling experts have been continually researching the interplay of human mobility and COVID-19 transmission since the outbreak of the pandemic. They tried to address this problem and support the control of the pandemic spreading at the national or regional levels. However, these modelling approaches had little success in producing empirically verifiable results at the neighbourhood level due to a lack of data and limited representation of low spatial scales in the models. To fill this gap, this research aims to present an agent-based model to simulate human mobility choices in the context of COVID-19, based on social activities of individuals at the neighbourhood. We apply the viable model to the decision-making process of heterogeneous agents, who populate the system's environment. The agents adapt their mobility and activities autonomously at each iteration to improve their well-being and respond to exposure risks. The study reveals significant temporal variations in mobility choices between the groups of agents with different vulnerability levels under the COVID-19 pandemic. Agents from the same group with similar economic backgrounds tend to select the same mobility patterns and activities leading to segregation at this low scale. We calibrated the model with a focus on Porto Alegre in Brazil.

Keywords: Agent-based model, Mobility, COVID-19, Exposure, Vulnerability, Segregation.

[12] Text and tables were reformatted. Spelling was adjusted to British English, for consistency with other sections of the dissertation.

4.1 INTRODUCTION

Mobility is a critical factor in the spread of the COVID-19 virus and not surprisingly, COVID-19 has deeply affected the way we move. The COVID-19 crisis impacted human mobility directly since response measures frequently involved social isolation to break the links in the virus infection chain. This impact on mobility has been not fairly distributed (Eyawo et al., 2021; Shi et al., 2022; Wei et al., 2021), and it has followed socio-demographic characteristics of the population (Bhaduri et al., 2020; Campisi et al., 2020; Dingil & Esztergár-Kiss, 0032021). Certain impacts referred to changes in mobility choice, which showed significant heterogeneity based on a person's age, car ownership, and economic status. Bhaduri et al. (2020) and Dingil and Esztergár-Kiss (2021) show the significant mobility shift from public shared transportation modes (e.g. bus or metro) to private transportation modes (individual private car or motorcycle) during the COVID-19 pandemic. However, Kopsidas (2021) highlighted that this shift is only present among travellers who can afford the cost of private transportation modes. Some public transport users also restricted their daily mobility and to prevent the risk of COVID-19 (Kopsidas et al., 2021). In the end, the purposes of mobility no longer centred around the same daily routines from before the COVID-19 outbreak. New routines varied highly between the need for self-isolation (especially critical for vulnerable groups), the need for work (vital for daily labourers), essential shopping demands (e.g. food and medicine), and non-essential trips (e.g. entertainment) (Abdullah et al., 2020; Campisi et al., 2020).

People changed their priorities of mobility choice during the pandemic, moving from traditional considerations (e.g. time and cost of travel, or comfort) to pandemic-related concerns (e.g. adoption of masks by other travellers, cleanliness, or social distance)(Abdullah et al., 2020; Martin et al., 2020). In order to minimize the exposure to the risk of COVID-19, people are constantly adapting their mobility behaviours (Bhaduri et al., 2020). Kopsidas (2021) found that low-income citizens are reluctant to use public transportation for long periods of time, and Abdullah (2020) showed that most trips during a pandemic were for purchasing groceries. However, all these reviewed models only investigate tendencies in human mobility behaviour at higher aggregate scales than neighbourhoods, and do not explain well how COVID-19 affects human mobility choices at a finer scale (neighbourhood).

Statistical research of mobility patterns has often been conducted on large spatial scales. At the national level, there are datasets from Apple and Facebook, which can be applied to investigate the national human mobility tendency. You (2022) determined that mobility continued to decline in European countries during the first year of the pandemic, driving became the primary mobility pattern in Australia, and walking became popular in New Zealand. At the city level, Facebook data and many governmental mobility data are available. Liu et al. (2021) and Schmahmann et al. (2022) focused on metropolitan cities and observed a decline in inner-city mobility and an increase in out-migrants.

Existing COVID-19 literature shows that although many studies investigate the impact of COVID-19 on human mobility, there are yet two significant research gaps: a) we know less about how humans adapt their mobility behaviour by offsetting the benefits of mobility against the risk of exposure to COVID-19 risk at the individual level; b) there is scarcity of neighbourhood-level mobility data or similar that allows cross-sectional analysis at the social scale about COVID-19. These gaps present the need to develop an innovative and operational approach to understand the collective human mobility pattern that integrates individual characteristics within a geographic neighbourhood environment. To fill the research gaps, we implemented an agent-based model to simulate individual human mobility choices and aggregate patterns at the neighbourhood scale. The resulting simulations could bridge mobility pattern analysis between the individual and urban scales.

One objective of this model is to fill the gap of data on human mobility behaviour between the urban and individual scales during the pandemic. A number of studies characterized the correlation between COVID-19 and changes in human mobility patterns by analysing open and authoritative data sources at the national or city scales (Jiang et al., 2021; Mendolia et al., 2021; Tamagusko & Ferreira, 2020) or survey data at the individual scale (Abdullah et al., 2020; Bhaduri et al., 2020; Dingil & Esztergár-Kiss, 2021). However, the analysis of human mobility during the COVID-19 pandemic is missing at the intraurban scale, especially in cross-sectional studies that allow tracing connections between ethnic, socioeconomic, and behavioural factors to COVID-19 exposure. We define the intraurban as equivalent to the 'neighbourhood or community scale', which immediate geographical areas surrounding residential places, bounded by streets, train tracks, and political divisions. This neighbourhood scale of analysis is especially relevant to its cohesive mobility networks (Saxon, 2021) and the associated social capital (Alessandretti et al., 2020), which relate to exposure and resilience to COVID-19 impacts respectively. Furthermore, the pandemic significantly decreased traveling length of daily mobility (Bhaduri et al., 2020; Dingil & Esztergár-Kiss, 2021), leading to more representative mobility patterns at the neighbourhood scale. This research builds upon ongoing investigations by our team using urban and intraurban open data sources to understand the vulnerability of Brazilian cities, seeking to bridge these scales with artificial data.

We analysed human exposure to demonstrate the impacts of COVID-19 risk on mobility choices at the neighbourhood scale. Human exposure establishes a link between the threats of environmental COVID-19 risk to human health and helps explain the impact of COVID-19 on an emergent perspective (Epstein, 2005; Kennedy, 2012) from the individual to neighbourhood scale. Human exposure has been often used to assess environmental stress, including air pollution, heat stress, heavy matter (Lund et al., 2020; Shin & Bithell, 2019; Yang et al., 2018). Exposure simulations link individual characteristics (health status, travel tools) to their mobility paths (Yang et al., 2018). Traditional mobility modelling includes factors such as well-being, travel time, speed, and cost of travelling as determinants on human mobility choices (Brandon et al., 2020; Lund et al., 2020; Yang et al., 2018). In our research, we address these multiple criteria and couple them to the impacts of the pandemic using a weighted decision-making function for individual mobility choice.

The research question addresses how and why the individual demographic characteristics and priorities influence changes at the neighbourhood-level mobility pattern under COVID-19. We focus on the rationality of these decision-making processes, applying the values and investments for agent-based interaction and learning for environmental systems (VIABLE) framework in an Agent Based Model (BenDor & Scheffran, 2019). In this framework, the agents learn from the feedback of their previous cycles and synchronously adjust decisions (mobility choices) in the next iteration to dynamically achieve the agent's target values (well-being or exposure). In this model, we implement an experiment using three agent groups based on individuals with specific demographic characteristics. The hypothesis is that differences in individual level characteristics and COVID-19 exposure concerns lead to different mobility patterns at the neighbourhood-level. We expected to find some segregation in location or mobility mode.

4.2 METHODS

This section aims to illustrate the method of the agent-based mobility choice model under COVID-19. We first present the basic components of the model. Second, we will show the decision-making procedures of agent mobility choice. Third, we will present the model calibration based on empirical data. The model is coded in NetLogo 6.2.0. More information can be found in the supplementary material.

4.2.1 Agents

In this model, an agent is a hypothetical individual citizen with demographic properties of age, pre-existing medical conditions, house location, family status, and economic background. The diversity of the urban population allows each individual to have a unique travel behaviour. To manage this complexity, we divided people with comparable characteristics into various proxy groups. For each agent type, we infer an initial vulnerability level, expected well-being, priority for performing activities outside their household, and priorities to each transportation mode at their disposal. This classification can surely be extended or modified, and we plan to do so in later implementations. We think of the agent groups as typical representatives of an urban society (i.e. the city of Porto Alegre) in a middle-income country (Brazil) under COVID-19 pandemic.

We categorized these citizens into three groups according to their age and wealth level (Table 4-1) and determined their vulnerability to COVID-19 according to these two criteria (Bruine de Bruin, 2021; Pearman et al., 2021). On one hand, age and wealth level are the primary constraints for human mobility behaviour during COVID-19. According to behaviour theory (Krapfl, 2016; Malone, 2014), individuals interact with the environment according to their ability and psychological willingness. In this model, we present the ability as their income, verified as a critical factor of travel flexibility in the epidemic by Yabe et al. (2020). Bruine de Bruin (2021) and Munayco et al. (2020) state that the COVID-19 risk perceptions and human mental health largely change with age. On the other hand, the citizens' age and self-perceived economic stress to COVID-19 greatly influence their vulnerability. Lawal (2021) research showed younger individuals are generally more stressed and have low coping abilities. In contrast, older individuals have less stress due to a better economic background (Bruine de Bruin, 2021). Although age is a prominent risk factor for death from COVID-19, it is not positively associated with the risk of infection. Bruine de Bruin (2021) identified that the infection risk is highest for middle-aged persons between 30 and 39 years old, and the infection risk of the elderly is low. Therefore, we translated Bruine de Bruin's (2021) statistical ranking of the likelihood of infection, mental stress, economic status, and job loss likelihood by age group into literal values as vulnerability evaluation standard (see 0). In this model, we define three types of agents, and Table 4-1 presents their characteristics. The vulnerability level is ranked from 0 to 1, and agent types are assigned with a normalized vulnerability value calculated according to the vulnerability evaluation standard.

The first type is called 'rich and old' (identified as 'GPone'), and we assign them the low vulnerability parameter of 0.3. We associate older agents (45-60 years old) with low vulnerability to COVID-19 as they are wealthy, have unrestricted access to medical resources, have more mobility choices, enjoy high levels of mental health, and do not depend upon other family members (Bruine de Bruin, 2021). Agents in this group represent the manager or director professional occupation category, which drives them to the office and leads to a high well-being expectation of 0.7. The second group represent the 'young and poor', like the clerical or junior qualified worker professional categories (GPtwo). These agents are young people (18-30 years old), living paycheck to paycheck. Although agents from this group have a higher risk of job loss due to the ensuing economic crisis, and no savings (Lawal, 2021), they have greater recovery capacity from the disease (Bruine de Bruin, 2021), and do not have dependents. Hence, we assign agents of this type with a medium vulnerability value of 0.5, and an expected well-being parameter of 0.3, meaning they need little to satisfy their expectations. Finally, the third group (called 'young family', GPthree), are middle-aged citizens who rind on everyday life to build their families' future, representing the middle management professional category. They have young children in school, and some savings, but are stressed and prone to adverse health conditions due to intense work demands (Bruine de Bruin, 2021). This group physically perceives a higher infection risk from COVID-19 (Bruine de Bruin, 2021), and therefore we assign them a high vulnerability level at 0.7, and an average well-being expectation of 0.5.

The model uses the parameters of well-being and exposure as the major criteria for driving agent decisions. Well-being is an abstract value, representing agents' satisfaction with their physical, mental, and emotional needs. The well-being W_i is in a range of between 0 and 1, where 0 represents absolute lack of well-being and 1 is the highest well-being possible. Each type of agent has a different well-being expectation, which varies along their economic status. Agent group one, which has more savings and better quality of life, is assigned with high expected well-being of 0.7 with certainties (random number) changing with individual agents. Agents leave their household to improve their well-being in professional, education, or purchase activities. Once the agents' accumulated well-being values have exceeded their expected well-being value, they turn back home. Agents face trade-offs between their need of well-being and the risk of being exposed to COVID-19. Human exposure is an important parameter to assess human health risks (Barr, 2006). In this model, the exposure parameter measures an agent's exposure to COVID-19 risk in their environment. Each location and transport modes have an associated exposure level. These environmental exposure factors interact with the agents' vulnerability parameters and accumulate exposure over time. Once the agents exceed an exposure value of 1 (i.e. a high health risk), they immediately chose to go home.

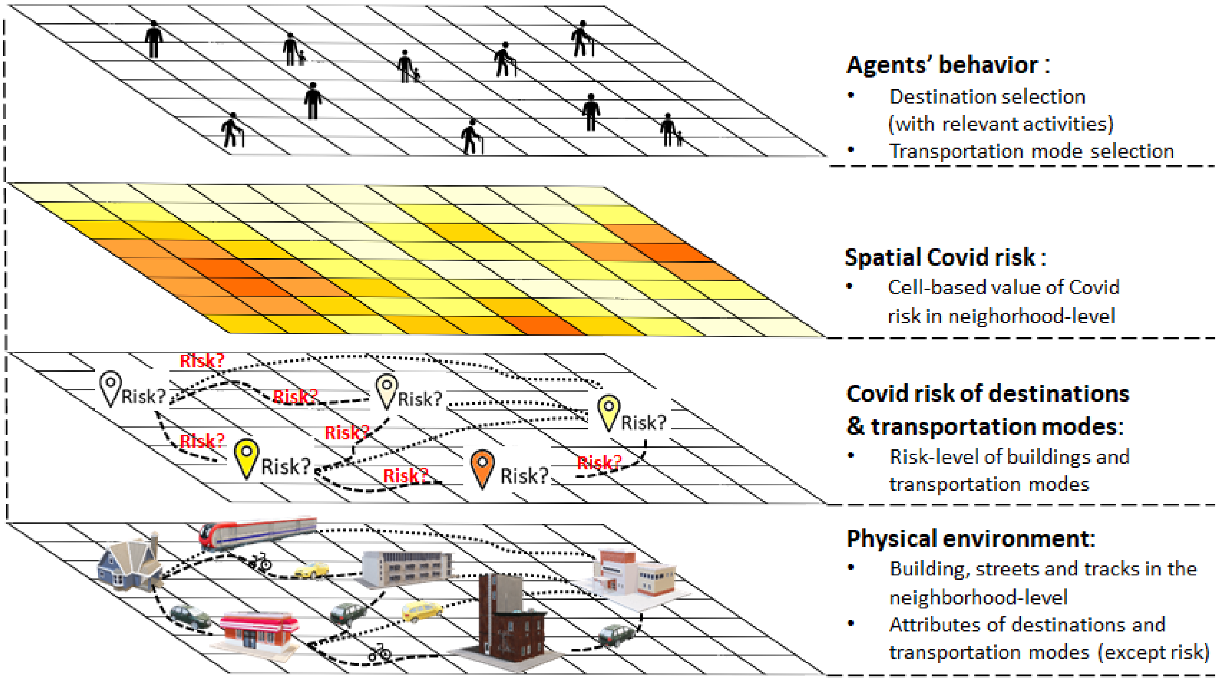
Table 4-1. Agent Groups and attributes.

Attributes of individuals	a. Age b. House location c. Exposure d. Well-being e. Family status			
Attributes from groups	**f. Vulnerability level**	**g. Expected well-being level**	**h. Priority of activities**	**i. Priority of transportation mode**
GPone (rich and old): 45-60 years old, married, independent children, have private cars, have much savings.	0.3	0.7 + (random number < 0.2)	P-school = 0 P-office = high P-leisure = high P market = low	P-car = high P-bus = low P-metro = low
GPtwo (young and poor): 18-30 years old, single, no car, not much savings.	0.5	0.3 + (random number < 0.2)	P-school = 0 P-office = high P-market = high	P-car = 0 P-bus = high P-metro = high
GPthree (young family): 30-45 years old, married with children, have private cars, have some savings.	0.7	0.5 + (random number < 0.2)	P-school ≈ P-market ≈P-office ≈P-leisure low	P-car = high P-bus = low P-metro = low

4.2.2 Environment

The modelling environment is a composite of the spatial environment (Leyk et al., 2009; Yang et al., 2017) and the COVID-19 risk environment at the neighbourhood scale (Figure 4-1). Agents access different attributes of the integrated environment and make decisions about their mobility pathways concerning destinations and transportation modes.

Figure 4-1. Environmental layers of the agent-based mobility choice model.
Adapted from Yang et al. (2018).



The spatial environment is an artificial landscape at the neighbourhood scale, including the agents' homes and facilities such as markets (or supermarkets), offices, schools, and leisure. The speed and cost attributes of the transport modes are derived from information from the São Paulo Meteorological Institute, the Brazilian Transportation Code, and international agencies such as Global Price (Table 4-2).

Table 4-2. Speed and cost values of transportation modes.

Transportation mode	Speed (km/h)	Value applied	Source	Cost of itinerary (USD)	Value applied	Source
Bus	40	40	(Brasil, 1997)	0.44 (single trip)	0.44	(Global Price, 2020)
Metro	60	60	(São Paulo Metrô, 2022)	0.77 (single trip)	0.77	(São Paulo Metrô, 2022)
Walking	5	5		0	0	
Bicycle	16	16		0	0	
Car	30–60 (speed limits on local road or avenues)	45	(Brasil, 1997)	Mean 2021 fuel price: 1.003636 USD/L Fuel consumption (km/L): 13.8	0.072 × dist.	(FIA Foundation, 2020; Trading Economics, 2021)
Taxi	30–60 (same as car)	45	(Brasil, 1997)	Starting tariff: 1.08 + Tariff per km: 0.59	1.08 + (0.59 × dist.)	(Numbeo, 2021)

The risk environment is composed of two layers, including COVID-19 spatial risk layer (the accumulated risk in each cell) and a COVID-19 risk layer for destinations and transportation routes.

The first layer of COVID-19 risk is currently an artificial layer assessed by considering the spatial distribution of COVID-19 infection cases. In the next step development of the model, It can be assessed by a variety of factors, including historical data on air quality, population density, housing concentration and traffic density (Dlamini et al., 2020; Pluchino et al., 2021). Our research team is currently developing a neighbourhood-level spatial COVID-19 risk maps for Porto Alegre and São Paulo that will subsequently be integrated into this model. The second map layer, COVID-19 risk in destinations and transportation routes, is assessed by an average weighted sum function of three components: air conditions, general type of contact person (such as general public, know co-workers, suspected COVID-19 patients)(OSHA, 2020), and hygiene based on our evaluation standard (see 0). The air conditions of the destinations and transportation refer to the ventilation condition of the indoor environment, which is one of the crucial means to reduce the virus transmission risk (C. Li & Tang, 2021; Xu et al., 2021). Adequate ventilation in public buildings could significantly reduce COVID-19 transmission by particle filtration and avoid air recirculation (Morawska et al., 2020). Therefore, we combine the three factors to present the risk level of different destinations and transportation modes by applying the equal-weighted sum function (see 0). The normalized risk level of destinations and transportation modes are illustrated in Table 4-3.

Table 4-3. The risk level of destinations and transportation modes.

Destinations	House	Office	School	Market	Leisure facilities	
normalized risk level	0.00	0.37	0.40	0.43	0.50	
Transportation modes	**Bus**	**Metro**	**Walking**	**Biking**	**Car**	**Taxi**
normalized risk level	0.43	0.43	0.27	0.23	0.10	0.40

4.2.3 Mobility behaviour

The COVID-19 outbreak changed the daily routines of most citizens. In the model, we represent this impact by agents balancing well-being and exposure. On the one hand, well-being increases as agents visit destinations that fulfil their necessities (e.g. education, work, leisure). On the other hand, each time an agent leaves social isolation (i.e. goes out of their home), they are exposed to COVID-19, and must select a transportation mode that minimizes exposure. This mechanism is implemented by dynamically adapting agents' priorities towards destinations (seeking more well-being) and transportation modes (avoiding exposure).

Figure 4-2 illustrates the decision-making framework for the agent-based model. Over the course of a day, from 8:00 to 22:00, agents go through the process of selecting their next destination and their preferred mode of transportation at each tick (every 2 hours). The model begins by determining if the agents will move out of their homes, by checking if the agents' current well-being levels are below their expectations and if their COVID-19 exposure is below 1. If any of these conditions are note met, the agents stay in their homes for that period. The agents then select their destinations and the associated transport modes. In doing so, they are exposed to COVID-19 risk at the chosen transportation mode ($risk_t(t)$) and, upon arrival, to the risk at the selected destination ($risk_f(t)$), accumulating exposure ($E_i(t)$). They will then perform the activity at that destination and accumulate their well-being (W_i (t)). The exposure $E_i(t)$ of an agent i at time-step t is then estimated using the Equation 4-1, and the well-being $W_i(t)$ is estimated by the Equation 4-2. Next, the model checks each agent's well-being and exposure. If the agent's well-being does not reach their expected value and exposure is still under 1, the agent continues moving. The model then automatically addresses the agent's priority towards different destinations and transportation modes to increase its well-being while minimizing exposure. At the end of each day, the risk value of destinations and transportation modes are updated for simplicity's sake (we assume sterilization measures are in place). The values of agents' exposure and well-being are computed again at the end of the day because of their hygiene and consumption actions. The exposure level of the agents becomes a minimum value of 0.01, and the well-being W_i is randomly assigned to a lower value.

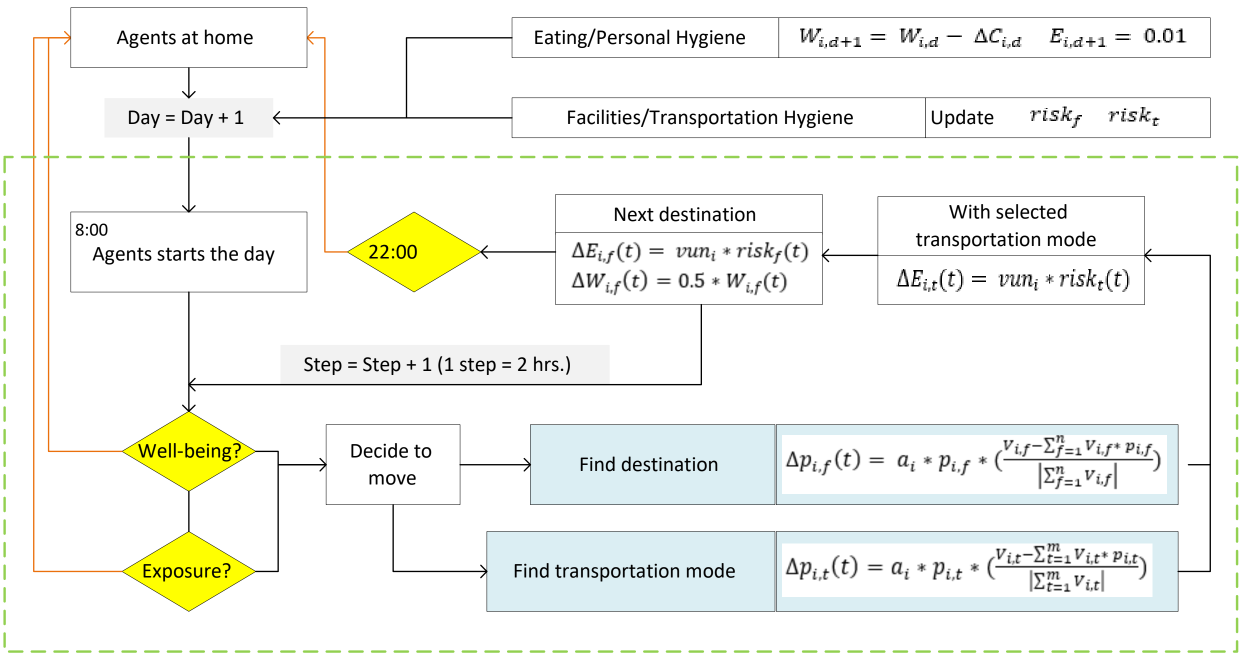
Equation 4-1. Exposure of an agent i at time-step t

$$E_i(t) = E_i(t-1) + \Delta E_{i,f}(t) + \Delta E_{i,t}(t) = E_i(t-1) + vun_i * risk_f(t) + vun_i * risk_t(t)$$

Equation 4-2. Well-being of an agent i at time-step t

$$W_i(t) = W_i(t-1) + \Delta W_{i,f}(t) = W_i(t-1) + 0.5 * W_{i,f}(t)$$

Figure 4-2. The decision-making framework.



4.2.4 Modelling the decision-making process for choosing mobility pathways

In the model, agents choose their mobility pathways in each time interval, including destinations and transportation modes. The decision on the mobility pathways is based on the agent i's priority p_i for the f different destinations and t different transportation modes. The marginal value of value functions $V_{i,f}$ and $V_{i,t}$ change the priorities. The destinations value function $V_{i,f}$ is the weighted sum of $Wellbeing_f$ and $Exposure_f$ of each destination (Equation 4-3). The transportation mode value function is the weighted sum of transportation $Speed_f$ transportation $Cost_t$ and potential COVID-19 $Exposure_{i,t}$ in each mode (Equation 4-4). All terms in the functions are normalized, allowing comparison between them. The parameters α, β, γ, δ, and ε represent the weights of each term (i.e. the agent's perception of each term). These value functions are based on the work of BenDor and Scheffran (2019) and were adapted for this mobility choice ABM.

Equation 4-3. Destinations value function.

$$V_{i,f} = \alpha_i \frac{(Wellbeing_f - min\, Wellbeing_f)}{(max\, Wellbeing_f - min\, Wellbeing_f)} + \beta_i \frac{(max\, Exposure_{i,f} - Exposure_{i,f})}{(max\, Exposure_{i,f} - min\, Exposure_{i,f})}$$

Equation 4-4. Transportation mode value function.

$$V_{i,t} = \gamma_i \frac{(Speed_t - min\, Speed_t)}{(max\, Speed_t - min\, Speed_t)} + \delta_i \frac{(max\, Cost_t - Cost_t)}{(max\, Cost_t - min\, Cost_t)} + \varepsilon_i \frac{(max\, Exposure_{i,t} - Exposure_{i,t})}{(max\, Exposure_{i,t} - min\, Exposure_{i,t})}$$

According to the VIABLE model (BenDor & Scheffran, 2019), the agents can rationally address their priorities for different destinations and transportation modes in each tick based on the marginal value of different choices (Equation 4-5 and Equation 4-6).

Equation 4-5. Destinations marginal value function.

$$p_{i,f}(t) = p_{i,f}(t-1) + \Delta p_{i,f}(t) = p_{i,f}(t-1) + a_i * p_{i,f}(t-1) * \left(\frac{V_{i,f} - \sum_{f=1}^{n} V_{i,f} * p_{i,f}(t-1)}{\left|\sum_{f=1}^{n} V_{i,f}\right|}\right)$$

Equation 4-6. Transportation mode marginal value function.

$$V_{i,t} = \gamma_i \frac{(Speed_t - min\, Speed_t)}{(max\, Speed_t - min\, Speed_t)} + \delta_i \frac{(max\, Cost_t - Cost_t)}{(max\, Cost_t - min\, Cost_t)} + \varepsilon_i \frac{(max\, Exposure_{i,t} - Exposure_{i,t})}{(max\, Exposure_{i,t} - min\, Exposure_{i,t})}$$

4.2.5 Simulated scenarios

We implemented a focus group in Porto Alegre (December 2021) in the Menino Deus neighbourhood. Before the focus group, six persons answered a structured questionnaire to investigate transportation mode selection before and after COVID-19 outbreak (see 0). After that, we followed the questionnaires with an in-depth interview in a group format. This data provided us with the parameters for the scenarios below.

To understand the collective mobility patterns under COVID-19, we adjusted the values for the weighting parameters (α, β, γ, δ, and ε) to demonstrate the effect of exposure on agent mobility behaviour under different scenarios. To understand the importance of individual factors in the mobility decision-making process, we applied the combinations of parameters featured below to illustrate the variation of human mobility patterns.

Table 4-4. Model scenarios and parameters.

Activity	Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Destination selection	Well-being (α) weight	GPone α = 2 GPtwo α = 4 GPthree α = 3	GPone α = 2 GPtwo α = 4 GPthree α = 3	GPone α = 2 GPtwo α = 4 GPthree α = 3	GPone α = 2 GPtwo α = 4 GPthree α = 3
	Destination exposure (β) weight	No concern, All groups β = 0	Low-level concern, All groups β = 1	Medium-level concern, All groups β = 3	High-level concern, All groups β = 5
Transportation mode selection	Speed (γ) weight	All groups γ = 4	All groups γ = 4	All groups γ = 4	All groups γ = 4
	Cost (δ) weight	GPone δ = 1 GPtwo δ = 5 GPthree δ = 3	GPone δ =1 GPtwo δ =5 GPthree δ =3	GPone δ = 1 GPtwo δ = 5 GPthree δ = 3	GPone δ = 1 GPtwo δ = 5 GPthree δ = 3
	Trans. mode exposure (ε) weight	No concern, All groups ε = 0.	Low-level concern, All groups ε =1	Medium-level concern, All groups ε = 3	High-level concern, All groups ε = 5

The severity of COVID-19 in Brazil fluctuated over time, leading to temporal variation of the impacts on mobility (as reported by the focus group participants). We adopted this fluctuation into the construction of the modelled scenarios. For this models purposes, we can adapt the chronology of the pandemic in Brazil from Santos and colleagues (2022) to five stages. In March 2020 the first cases were detected and saw limited growth. Then a brief period of containment followed until August 2020 and was superseded by a period lacking control. This stage led to severe increase in contagion and deaths between March and June 2021. After this, the country achieved vaccination for most of its adult population, entering a period of relative normalcy around September 2021. Therefore, we propose four scenarios to simulate human mobility patterns under different levels of exposure. Scenarios 1 to 4 depict different weights for exposure (β and ε) and cost (δ) (Table 4-4). The scenarios have fixed values for the priorities for well-being and speed (α and γ, respectively), with speed value varying between agents, dependent on their economic status.

Scenario 1: A world without COVID-19 (no exposure concern). The first scenario simulates the mobility behaviour of agents that have no concern about their exposure to COVID-19 risk. The zero weights presented in the value function (β and ε) have been implemented by agents who do not consider COVID-19 as a concern for their movement. It represents the situation before COVID-19 outbreak, just as the responders interviewed by our focus group. The responders decided where and how to go only by considering the cost, speed, and well-being of their movement.

Scenario 2: Starting the pandemic (low level of exposure concern). The second scenario depicts the situation once agents have a minimum concern over COVID-19 and start adapting their destination and transportation mode choices. It simulates the initial phase of the epidemic. The public only saw the first signs of the epidemic, thus a low-level concern of exposure to COVID-19 has been considered by the responders of our interview.

Scenario 3: The pandemic is among us (medium level of exposure concern). The third scenario presents the mobility behaviour when people's concern about exposure increases to the medium level. From our focus group, we find that people started altering their mobility behaviours to reduce the likelihood of being infected as the pandemic spreading.

Scenario 4: Perfect storm (high level of exposure concern). In this scenario, the weight of exposure was set to the highest value of 5, which depicts the human mobility behaviour when the primary concern is exposure. This scenario intense impact on daily life from the pandemic, expressed by record number of cases and deaths, for example.

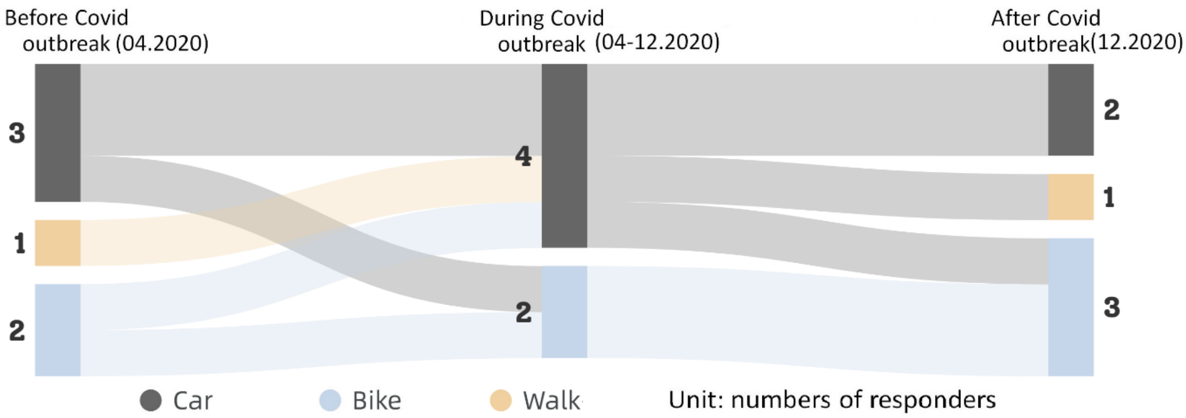
4.3 RESULTS

This section presents two sets of results. The first, are qualitative empirical information collected in a focus group in an upper-middle-class neighbourhood in Brazil. The second set is composed by simulation results from ABM scenarios that represent the periods of the pandemic according to exposure levels, and the need for travel to satisfy agents well-being. These results are presented below and discussed in the following sections.

4.3.1 Results from qualitative research

In the focus group, most of the participants who owned or had access to a car choose it as their primary transportation mode during COVID-19, as shown in the Figure 4-3. During the initial months of the COVID-19 outbreak, four of our responders choose the car and two others switched to the bicycle. Only one participant owned a car and did not use it primarily. He reported greater interest on the perceived health benefits of biking and adopted this mode of transportation during the pandemic and afterwards combined with more frequent tele-working. This presents a deviant case for our model, including factors of perceived health benefits and tele-working that can be addressed in later implementations.

Figure 4-3. Preferred transportation modes of survey respondents.



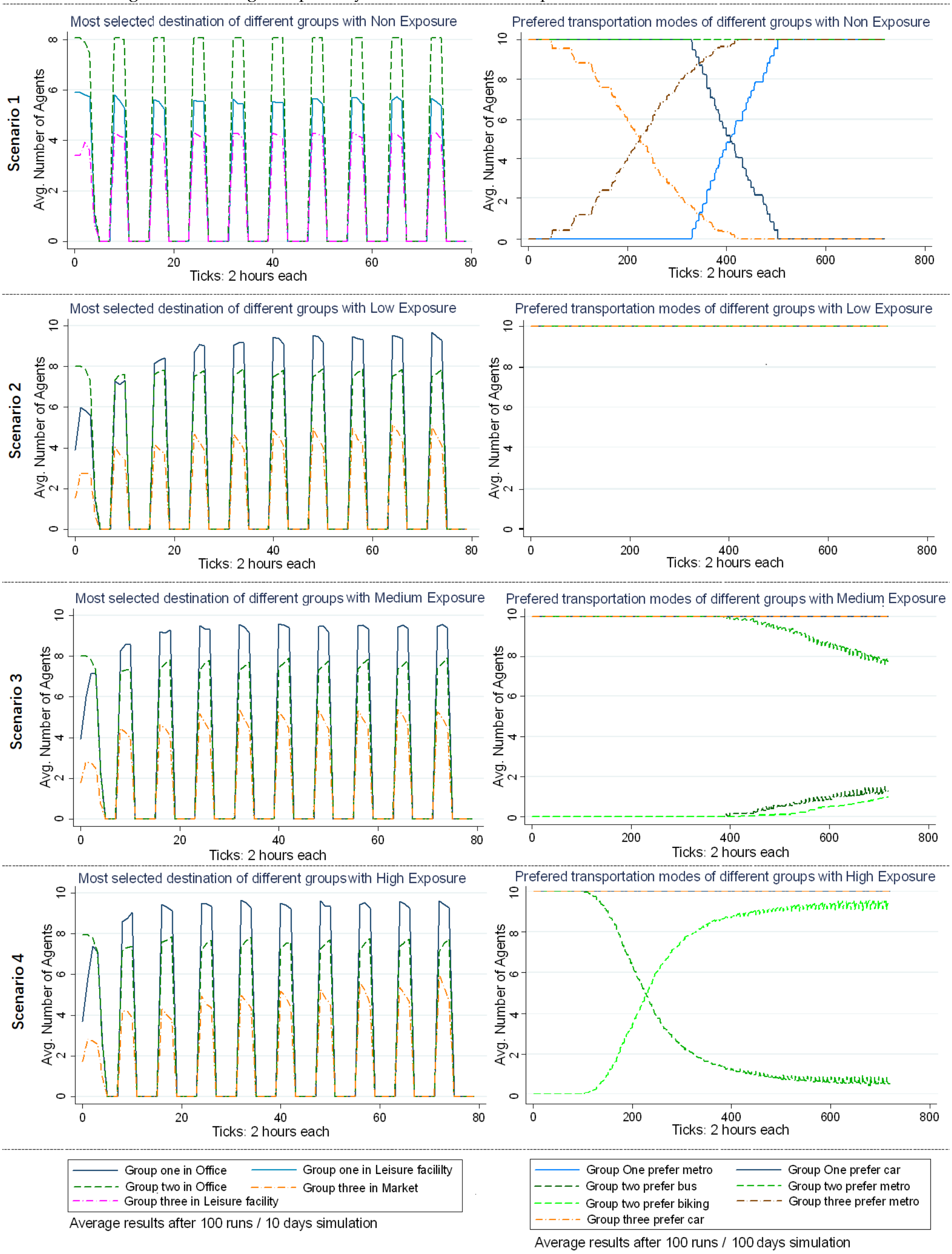
4.3.2 Mobility segregation pattern of model simulation

From the simulated results of the model scenarios, we found a mobility segregation pattern between destinations and transportation modes at the neighbourhood scale. Figure 4-4 shows that agents are segregated by types in the destination selection and segregated by car ownership status in the transportation mode selection under different exposure priorities. In Figure 4-4, the X-axis represents ticks of 2 hours each, which means 8 ticks represent the 16 hours of the day from 8:00 to 24:00. The Y-axis shows the number of agents from each group in the scenarios (values are the averages of 100 model runs).

The right side of Figure 4-4 portrays how agents of different groups segregated while selecting their destination. As people are concerned about exposure risk, markets and offices become the preferable destinations. Agents from GPtwo (i.e. 'young and poor') are the only ones that keep their primary destination consistent regardless of exposure concerns. Since they rely on their salaries to live, they choose their workplaces as their primary destination even when concerned about the exposure. Unlike the 'young and poor', agents from GPone (i.e. 'rich and old') and GPthree (i.e. 'young family') have more financial resources or savings, so they are more flexible in choosing destinations. Leisure facilities are the most popular destination among them when they are not concerned about exposure at all. However, once the COVID-19 outbreak sets in, GPone and GPthree choose different locations as their primary destinations. Once GPone is more concerned about exposure, most of them choose their offices as their primary destination. Agents from GPone are wealthy (e.g. company directors) and do not need to go to the market as they rely on delivery services for their daily necessities. As they become more concerned about exposure, they go more frequently to their workplace. It is due to double advantages of high well-being and low exposure risks of the workplaces compared to other destinations. Nonetheless, some of other agents from GPone will not choose to go out, as their well-being exceed their expectations even after the previous night's degradation. GPthree, which is the most vulnerable one, tended to choose the market as their primary destination. Indeed, for GPthree, there are also approximately 4-5 people who chose office as their primary use (see 0). It is only slightly lower than the average number of people choosing the market. This is because they perceive the market as having a higher marginal value than the office.

The left side of Figure 4-4 shows the variation in the preferred transportation mode under the scenarios. The effect of exposure largely influences the choice of transportation modes. When there is no concern about exposure (Scenario 1), all agent groups tend to use the metro from a specific time point. This is caused by the priority parameters for speed and cost of transportation mode. However, once agents are concerned about exposure (Scenarios 2 - 4), all agents who own a vehicle switch to private cars as it largely reduces their exposure (e.g. agents in GPone and GPthree). Agents from GPtwo, who do not have access to a car, also switch to other safer individual transportation modes (e.g. bicycles). In Scenario 3, we find that agents from GPtwo switch from metro to bus or biking. In the early phase, the agents avoid high exposure by switching between public transport modes. They switch from one public transportation mode to another once they find that the density is too high in the first one. Over time, agents learn from their previous choices, so some agents offset the high speed of public transportation to the less risky option of biking. In comparison, when agents are highly concerned about their exposure (Scenario 4), most of those who do not own a car will quickly change their transportation mode to biking. Only a minority of agents still chooses the metro when they are highly concerned about the speed of transportation. In summary, the private car and biking become as primary transportation modes during the pandemic.

Figure 4-4. Changes in primary destination and transportation mode in different scenarios



4.3.3 Sensitivity analysis of agents' exposure concern

To understand the influence of agents' exposure concern, we generate results based on Scenarios 1 to 4 and show the number of agents arriving at the market as an example in Figure 4-5 (the model runs for 10 days, results are the averages of 100 runs). Graphs with the numbers of agents in other destinations feature in Appendix B.

Figure 4-5. Results of agents arriving in market (Scenarios 1-4).

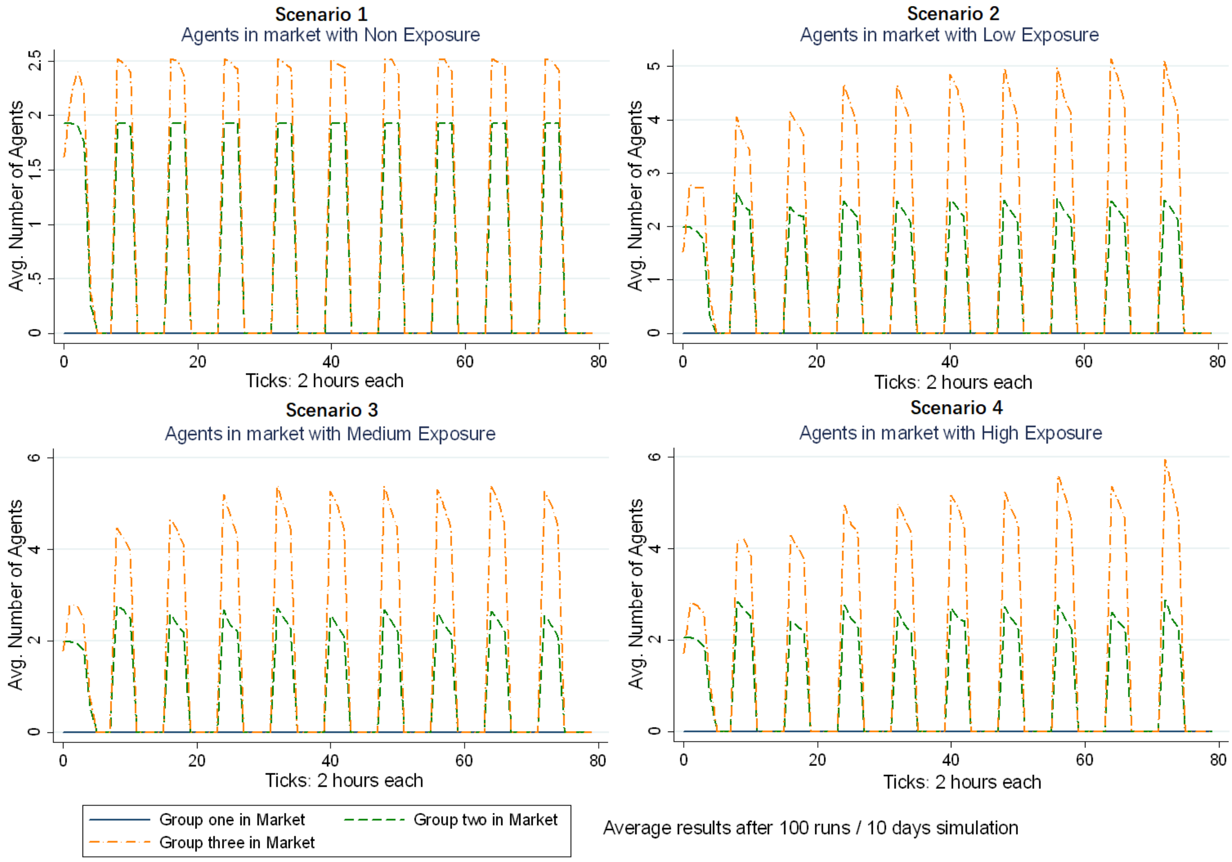


Figure 4-5 portrays the average number of agents located in a destination (market as an example) in each group under each scenario. These results show that with increasing concern about exposure, agents with higher vulnerability will adapt destination their choices more frequently than other agents. The average number of agents in the market will increase along with the increase of exposure concern. This increase occurs in a linear way, allowing more agents to choose the market as a destination when concern is present in the neighbourhood environment. The average number of agents in other different destinations also show a linear increase (such as GPthree to school) or decrease (such as GPone in leisure facilities) with the increasing exposure priority (see 0).

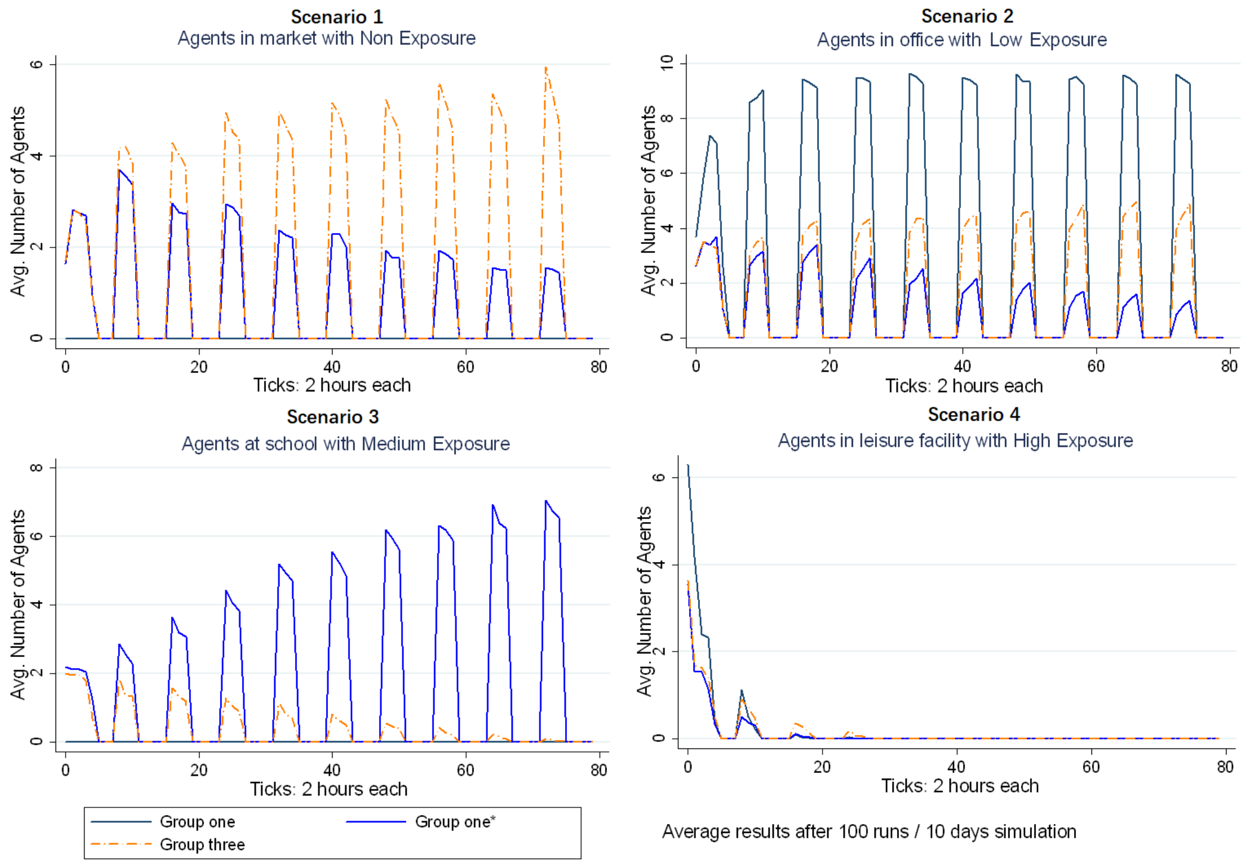
There is a special case in Figure 4-5. GPone does not go to the market under any circumstances, which could be explained by its initial settings. As a wealthy group, we assume they have a staff who is responsible for their grocery shopping, so their priority to go to the market is zero.

4.3.4 Emergent mobility behaviour of agent

Additionally, one final scenario includes a special agent group, called GPone*. This scenario seeks to understand how agents' aggregate mobility behaviour is influenced by the agents' demographic characteristics. This agent group, called 'rich and old, with family', has the same demographic characteristics of GPone but receives the same initial destination priority of GPthree. This parameterization suggests a group of wealthy and older persons who have families and must, therefore, take their children or grandchildren to school. The hypothesis for this scenario is that even with the same destination priorities of GPthree, GPone* will behave differently, given its lower vulnerability. The simulation results are shown in Figure 4-6.

From Figure 4-6, it is easy to find that although GPone* (i.e. 'rich and old, with family') has similar destination choices to GPthree at the start, their choices change significantly over time. When the initial priority of destinations is equalized, agents from GPone* are more likely to send their children to school rather than to go elsewhere. This is because they feel secured by driving their children to school with a private car. On the other hand, schools are much less risky than markets or leisure facilities.

Figure 4-6. Results change in destination selection if agents' initial priority varies



4.4 DISCUSSION AND CONCLUSIONS

Our model contributes to the research on mobility behaviour by representing mobility choices based on well-being demand and human exposure. This model design complements previous agent-based models (Drchal et al., 2019; Martinez & Viegas, 2017) by analysing the trade-offs between exposure and well-being under different social conditions. This model is better suited for environments in which the daily routines are disrupted. With the VIABLE framework in the decision-making process, the model represents the step-by-step variation of agents' priority between different transportation modes. In addition, the decision-making processes of agents based on individual target values results in aggregated mobility behaviour. This is one of the most interesting uses of modelling to experiment with artificial plausible situations (Epstein, 2008).

The aggregate mobility behaviours show how citizens move at the neighbourhood scale. Thus, this study proposed a method for simulating neighbourhood-level human mobility behaviour from the individual perspective connected with a focus group, demonstrating the potential to compensate for data scarcity between individual and city scales.

To verify the feasibility of the model, we compared the simulation results with the statistical outcomes from other cities. This paper tests different exposure scenarios to investigate public mobility behaviour under different perceptions. First, the results demonstrated that a different group of agents tend to show dynamic segregated mobility behaviours in selecting destinations and transportation modes. This is the most novelty outcome of our research, which no previous research has pointed out. Second, offices and markets have become more popular destinations. The market has also been proved as a highly selected destination during the pandemic in statistical research in Jakarta (Nanda et al., 2022). Third, private cars and biking gradually became the primary transportation mode during the pandemic, which has also been identified in some other research. The private car usage rate increase during the pandemic in Utah (Palomino et al., 2021) and in Lahti (Kareinen et al., 2022), and Cerasoli et al. (2022) found that citizens preferred bike-friendly public transport even after the pandemic in Roma. Finally, the emergent behaviour of GPone* also identified that agents with higher income would be more flexible in selecting their mobility patterns, which has also been approved by Yabe et al. (2020) in Tokyo.

Our research focuses on the aggregated agent-based mobility behaviour at the neighbourhood level, demonstrating more insights into citizens' intentions to move in the context of the pandemic. However, there are still shortages in comparison with other research focusing on human mobility behaviour across cities. For instance, Schmahmann et al. (2022) research across New York using the daily mobility data defined a border in/out migrant phenomenon across the city, and in particular, the bounce rate of in-migrant after the first year of the pandemic is comparatively low in the commercial districts in and around Manhattan. In Beijing, Liu et al. (2021) also found that over 43% of residents left Beijing, and only 16% returned after the COVID-19 outbreak. Moreover, the mobility pattern is closely correlated to the city network resilience. Refined epidemic control measures of urban transport networks in Beijing cause fewer negative impacts on the overall population mobility behaviour (Mu et al., 2022). The current model also has the potential to be extended on larger spatial scales to understand interurban mobility patterns.

The model application in the context of COVID-19 has shown flexibility to handle a variety of environmental shock scenarios. This model could, therefore, also provide insights to other shocks, such as other disease outbreaks, floods (Taberna et al., 2020), heat waves (Yang et al., 2017) or volcanic eruptions (Jumadi et al., 2020). The main assumption is that agent mobility decisions are based on their perception of the benefit, cost, and exposure between different mobility pathways. The parameters used to describe their perception are flexible enough to model human mobility behaviour in which agents prioritize well-being, speed, cost, or exposure.

The focus group activity is part of qualitative research that stems from the assumption that perceived reality is a major driver of behaviour. The results allowed us to improve the settings of the model (parameters and values) and the construction of the proposed scenarios. The model used individual characteristics and choices based on exposure and well-being to produce results at the aggregate scale that are in line to the behaviour reported by the participants in the focus group. The fact that we could find similar results, for example segregation, coming from the qualitative and the modelling perspectives provide an initial level of validation (i.e. validation by replication).

This article presents various assumptions and points to be improved with better data. The agent description is limited, the current model only addresses three types of agents, and this excludes the mobility behaviour of other age groups (e.g. children or people over 60 years old), and ignores many other social factors (e.g. ethnicity or gender). In future research, we plan to include more heterogeneous agents in the model. We conducted a qualitative study in Brazilian cities and derive different agent types from demographic analysis of its respondents. The model will then be extended to include these variant agent types to explore the well-being and exposure-based human mobility pattern more comprehensively at the neighbourhood scale.

4.5 SUPPLEMENTARY MATERIAL

The documentation and codes of the agent-based mobility model are available at https://github.com/Chennan-05/ABM-mobility-behavior-under-COVID-19.

5 CONNECTING COVID-19 AND CLIMATE CHANGE IN THE ANTHROPOCENE: EVIDENCE FROM URBAN VULNERABILITY IN SÃO PAULO

ABSTRACT

Global crises such as climate change and the COVID-19 pandemic do not affect cities uniformly. These crises converge in urban areas and often interact through their primary and secondary impacts with the vulnerability of urban populations. This paper investigates urban development dynamics and socio-environmental vulnerability in a megalopolis in the Global South, São Paulo (Brasil). Our goal is to assess the connections between urbanisation and risk exposure, a gap in vulnerability research when considering climate and health hazards. We implement an innovative mixed methods research design using thematic, hot spots, and survival analysis techniques. Two focus groups at the central and peripheral regions of the city provide qualitative data, while open data sets and COVID-19 case microdata (n= 1,948,601) support the quantitative methods. We find a complex system of relationships between urbanisation and risk exposure. Socioeconomic vulnerability characteristics of the population do not explain exposure entirely but significantly contribute to risk-prone location choices. Additionally, social vulnerability factors such as low income and social segregation are highly concentrated in São Paulo, coinciding with substantial COVID-19 fatality rates during 25 months of the pandemic. Finally, qualitative analysis helps us overcome the limitations of quantitative methods on the intraurban scale, indicating contrasting experiences of resilience and resistance during the health crisis. While the low-income group faced mental health and food security issues, the upper-middle-income sample took advantage of opportunities arising during the pandemic to improve work and well-being. We argue that these results demonstrate potential synergies for climate adaptation and health policies in combating socio-environmental vulnerability at the community scale. Environmental justice is thus paramount for global development agendas such as the Sustainable Development Goals, Sendai Framework, and the Paris Agreement.

5.1 INTRODUCTION

The impacts of climate and health crises do not affect cities uniformly. The COVID-19 pandemic showed concentrated adverse outcomes in developing countries (Levin et al., 2022), and extreme events like the 2022 monsoon in Pakistan (Mallapaty, 2022) show the destructive potential of coupled events (Zscheischler et al., 2018) in high vulnerability settings. A research gap exists between climate and health crises, notably through the interaction of their direct and indirect outcomes (Watts et al., 2021). By framing the COVID-19 pandemic as a systemic crisis (Sillmann et al., 2022), this paper seeks to investigate the relationship between urbanisation and risk exposure in a mega-city from the Global South in the Anthropocene. This investigation presents a critical evaluation of the role of inequality in urban climate and health vulnerability, revealing synergies across factors and stressing the contribution of environmental justice to adaptation and sustainable development policies.

Research recognises climate change and COVID-19 as converging crises (Watts et al., 2021). Despite the marked differences in exposure mechanisms and temporal scale of these crises, both affect the health and well-being of citizens globally. However, the impacts of these crises are not evenly distributed on the global or local scales. Taking COVID-19 as an example, some countries presented effective measures to protect vulnerable groups and avoid excess deaths. Other countries showed behavioural, political, or infrastructural failures to face the pandemic, resulting in abnormally high death rates, especially among developing countries' poor and ethnic minorities (Levin et al., 2022). The vulnerability to COVID-19 can be associated with low socioeconomic status and behavioural and infrastructural factors, as pointedly demonstrated by the Brazilian case (M. C. Castro et al., 2021; Nicolelis et al., 2021). In Brazil, the combination of historically high social vulnerability, a densely connected urban network, and a fragmented government response created the conditions of a 'perfect storm'. São Paulo was at the heart of the crisis as a significant and enduring hot spot in the country (Nicolelis et al., 2021).

Behavioural components associated with COVID-19 fatalities were inaction from authorities and lack of adherence to non-pharmaceutical interventions (e.g. social distancing)(Levin et al., 2022). Infrastructural components were also significant, such as limited healthcare provision capacity, lack of accessibility to healthcare, and lack of resistive capability from particular population groups (M. C. Castro et al., 2021; Nicolelis et al., 2021). On the one hand, behavioural components depend on social capital and political particularities (Barberia, Plümper, et al., 2021). On the other hand, infrastructural and resistive capacity are connected to long-term social features, such as inequality and socioeconomic vulnerability (ECLAC, 2020; Lorenz et al., 2021). Furthermore, the COVID-19 crisis may offer lessons for climate change adaptation (Fuentes et al., 2020; Ruiu et al., 2020), especially around climate justice (Bolin & Kurtz, 2018; Satterfield et al., 2004).

Ultimately, urbanisation interacts with risk exposure in cities in the Anthropocene. This is notable when considering the biophysical qualities of the environment, the changes made to adapt it to urban structures, and the resulting location opportunities thus produced. Moreover, these physical aspects of vulnerability interact with unequal development and social inequality through factors such as human development, social capital, and the accessibility to common urban goods (e.g. access to public services or areas). In this paper, we argue that the connections within this complex system form a nexus that can be articulated through socio-environmental vulnerability. The following sections present the convergent character of crises in the Anthropocene and explore the components within this complex system.

5.1.1 Converging crises in the Anthropocene

In the Anthropocene, cities are focal points for health and climate hazards, being especially exposed due to their concentration of goods, flows, information, and people. Cities also display intense dependence on external resources, often from global supply chains (Elmqvist et al., 2021). In this sense, when crises become systemic (i.e. leading to cascading impacts across regions and sectors)(Sillmann et al., 2022), cities and their inhabitants may show decreased coping capacity due to these external dependencies, the interconnections between sectors and internal inequalities (Elmqvist et al., 2021; Romero-Lankao et al., 2016).

Additionally, health and climate hazards have secondary social impacts in the form of threats to livelihoods (e.g. activity interruption mandates and crop destruction, respectively), increased social exclusion (e.g. from increased stigma and forced migration), and diminished upward social mobility (e.g. from interrupting education due to economic hardship). These secondary effects lengthen the time in which the impact of a given crisis is felt and are more intense for vulnerable populations. Primary and secondary effects of these hazards may interact over time, reinforcing themselves while diverting resources from long-term adaptation (Cinner et al., 2018; Zscheischler et al., 2018). The potential combination of impacts and existing stressors in urban systems (e.g. pollution, mental stress, and poverty) is a dire challenge that current and future generations will face (Henrique & Tschakert, 2021; IPCC, 2022). The unequal global, regional, and local distribution of risks and impacts of these crises is also a critical topic in the environmental justice and sustainable development fields (UN-Habitat, 2022).

5.1.2 Urban development and risk exposure

Unequal urban development (D. Harvey, 2006) resulted in a legacy of stark contrasts in cities of the Global South. Urban development often followed colonial ties, concentrating infrastructure and institutional presence around commodity exporting facilities and regions (Gilbert & Gugler, 1984). In Latin America, this resulted in highly-segregated urban structures with strong centre-periphery patterns (Borsdorf et al., 2007). Recent development complexified this legacy (e.g. through suburbanisation) but was insufficient to provide distributed access to services, infrastructure, and work opportunities (Feitosa et al., 2021). São Paulo is an example of this pattern, as the advantages of urbanisation, like advanced services and increased interaction (Bettencourt & West, 2010), benefit only a part of the population in highly-educated, professional intellectual categories that live in the central region or wealthy suburbs (Feitosa et al., 2021).

Most of the population's access to public and private services depends on location, which comes at a premium (Bógus & Taschner, 1999). The ongoing unequal development means the poorest households will face systematic risks from weather (Travassos et al., 2021) and health hazards (e.g. COVID-19, see S. L. Li et al., 2021). We argue that the development process of the city often evolves according to the search for self-segregation from the elites (Caldeira, 1997) based on their access to individual mobility (Sullivan-Wiley et al., 2019) while expropriating anthropic and natural negative externalities to the society (Abramo, 2012). Among these externalities are naturally hazardous areas (e.g. flood-prone regions) and regions lacking infrastructure or that are disconnected from services. These areas lacking fundamental environmental quality have lower prices and thus become the *de facto* settlement opportunities for many low-income families (Santos et al., 2017).

This unequal spatial development establishes a gradient of environmental vulnerability, from the concentration of infrastructures and services on one pole to the clustering of hazards and lack of infrastructure on the other. This pattern is far from isolated, as location opportunities (and risk exposure) strongly correlate with socioeconomic and ethnic characteristics globally (Bolin & Kurtz, 2018). As a result, low-income families in São Paulo often face a risk-risk trade-off: They may choose to live in the peripheries in inaccessible locations or accept environmental risks in areas close to the city centre (Santos, Rodriguez Lopez, Chiarel, et al., 2022; Travassos et al., 2021). This trade-off opposes safety to economic development, as some families will choose to locate in risk-prone areas if that means benefitting from work opportunities and services or having some tenure security. Over time, and with a changing climate, the socio-environmental vulnerability of these families may increase if the losses incurred in weather events, for instance, eliminate savings or destroy immovable assets (e.g. when a storm or landslide carries away a self-built house). For vulnerable families, repeated short-term weather or health impacts may sap adaptive capacity, preventing long-term adaptation (Cinner et al., 2018). Ultimately, this trade-off may lead to poverty–vulnerability traps (Boubacar et al., 2017; De Koning & Filatova, 2020; Pelling, 2003) or motivate dispossession cycles when local authorities forcefully seek to correct the situation by relocating the affected households (Henrique & Tschakert, 2021).

Given the convergence of these crises, the unequal attribution of risks and response capacity, and the centrality of cities in the Anthropocene, this paper seeks to unravel some of the connections between socio-environmental vulnerability (Adger, 2006; Pelling, 2003; Revi et al., 2015) and urban development (Crutzen, 2002; Gibbard et al., 2022). The aim is to examine the relationship between urbanisation and risk exposure in a mega-city from the Global South. This research, therefore, inquires: What is the system of connections between urbanisation and risk exposure in cities from the Global South in the Anthropocene? Specifically, are there urban populations in São Paulo (Brazil) vulnerable to both the COVID-19 pandemic and climate change, and which factors influence this vulnerability? The assumption is that socioeconomic adverse factors increased the risk of deaths during the COVID-19 pandemic in São Paulo (SP) and mirror vulnerability to climate change. To verify this assumption, we hypothesise that areas lacking human development include social and environmental vulnerability factors common to climate change and COVID-19 (hypothesis H1) and that urban hot spots of these factors coincide with greater COVID-19 fatality rates (hypothesis H2).

In the following sections, we first present the methods in this research, notably the mixing of qualitative and quantitative data and analyses. Next, we offer three results in the thematic matrix, the hot spots analysis and the survival analysis. In the discussion section, we approach the system of connections between urbanisation and risk exposure based on empirical findings. We conclude by pointing out the advances and open questions for future research.

5.2 MATERIALS AND METHODS

This section presents a mixed-methods research design that includes a thematic analysis of the material from two focus groups, geospatial analysis with hot spots methods, and survival analysis. This research combined quantitative and qualitative methods using a sequential, iterative, and multi-sampling design (Tashakkori & Teddlie, 2010). The qualitative data include two focus groups held in SP in March 2022, and we studied them using thematic analysis methods (Braun & Clarke, 2012). Quantitative data sources included the Social Vulnerability Index (SVI) (Costa & Margutti, 2015) and the COVID-19 fatalities data (Brasil.IO, 2021; SP Municipal Health Department, 2022).

5.2.1 Fieldwork and thematic analysis

Quantitative data sources offer limited evidence on the experiences of the impacts of systemic crises, thus obfuscating significant factors (Sillmann et al., 2022). We look towards qualitative methods to report on these experiences and answer the research question of the factors that drove COVID-19 vulnerability in SP. Qualitative methods provide nuanced and context-specific evidence that complements quantitative analysis in a mixed-methods design (Braun & Clarke, 2012; Tashakkori & Teddlie, 2010). Empirically, the qualitative approach seeks to fill in the gaps from quantitative sources, explaining the experience and behaviours during the pandemic.

We obtained the qualitative data during fieldwork in two focus group sessions held on March 13 and 15 in the Benfica community (Guaianases neighbourhood) and the SP city centre. The lead author of this paper participated in the focus group sessions held in Portuguese. The research team recorded and transcribed the sessions and then coded the transcripts from a deductive, semantic, and realist approach to support thematic analysis (Braun & Clarke, 2006, 2012). We analysed the coded content of the focus group sessions using thematic analysis methods (Braun & Clarke, 2006, 2012), which consists of identifying common and relevant themes across the cases to support the research question. We opted for these methods due to their flexibility and accessibility to non-experts in qualitative methods involved in mixed methods designs. Further detail on the fieldwork design, focus group implementation, and coding is available in Appendix C.

5.2.2 Hot spot analysis

This investigation focused on the concentration of socio-environmental vulnerability in the city of SP. This focus derives from the association of socioeconomic factors with mortality from COVID-19 (Bermudi et al., 2021; Levin et al., 2022; S. L. Li et al., 2021) and from climate hazards (Bolin & Kurtz, 2018; Cutter & Emrich, 2006; Travassos et al., 2021). To this end, we implemented a series of hot spot analyses to identify the statistically significant areas of concentration of vulnerability factors. This study used the Social Vulnerability Index (SVI) (Costa & Margutti, 2015) for these models. The SVI is the demographic opposite of the well-known human development index (UNDP, 2022), presenting unfavourable social conditions that threaten well-being and future development.

Using this data, we implemented the Optimised Hot Spot Analysis tool in ArcGIS Pro 2.2.2 to answer the research question: Which populations are vulnerable to climate change and the COVID-19 pandemic? The assumption is that lower human development leads to higher impacts from COVID-19 in the form of higher fatality rates. We derive this assumption from the literature (Corburn et al., 2020; Levin et al., 2022; Lorenz et al., 2021) and prior research (Santos, Rodriguez Lopez, Heider, et al., 2022). The tool calculated the Getis-Ord Gi* statistic using multiple fixed-distance spatial relationships and automatically tested distances to discover the most significant statistical concentrations of high values (i.e. hot spots) or low values (cold spots). The tests sought to reject the null hypothesis (e.g. eliminating clusters that could be random). The results were the z-scores and p-values for each spatial feature, indicating confidence intervals of 90, 95, and 99% (ESRI, 2022).

5.2.3 Survival analysis

To study the association between adverse social factors and the impacts of COVID-19 in SP, we implemented survival analysis using the Kaplan-Meier Estimator (KME). We employ the KME to analyse the survival probabilities of different populations over a predefined period (Kaplan & Meier, 1958). KME is a recurrent method in medical research to evaluate the effects of treatments or the impact of behaviour on mortality. However, its broader applications include political science (Box-Steffensmeier & Jones, 1997) and health geography (Chen et al., 2020). This method observes fatalities within a given time window for different population subgroups (also called 'reduced groups'), permitting the analysis of statistical differences between these groups without other assumptions.

We implement these models with the SP municipal COVID-19 fatalities geocoded microdata from January 2020 to November 2021 (SP Municipal Health Department, 2022). Data preparation included eliminating invalid records (e.g. without geographic references) and aggregating fatalities per epidemiological week and census district. We provide additional survival analysis with the Cox proportional hazard regression (Cleves et al., 2008) in Appendix C. Data and the Python code feature in the supplementary materials.

5.3 RESULTS

5.3.1 Focus groups and thematic analysis

This investigation focused on SP, one of the largest cities in Latin America and the wealthiest city in Brazil. Population estimates suggest 12,396,372 inhabitants in 2021 (IBGE, 2022). Despite its significant economic performance, SP is also a highly unequal and segregated metropolis. Human Development Index levels vary within the city from 0.479 in Vila César (a rough equivalent to Yemen) to 0.965 (equating to that of Norway, the highest ranked in 2021) in Berrini, Jardim Paulistano, or Vila Madalena (Costa & Margutti, 2015; UNDP, 2022). Urban development patterns mean an intense core-periphery distribution of wealth, public goods (e.g. public institutions, open spaces, infrastructure), and life expectancy (Baqui et al., 2020). Professional categories explain the segregation patterns, with intellectual and more affluent individuals in the central regions and poorer manual labourers in the peripheries (Bógus & Taschner, 1999). Recent decades witnessed some complexification of this process that was not yet sufficient to counter the historical segregation (Feitosa et al., 2021).

During all stages of the pandemic, SP remained with high contagion ratios and fatality rates (Bittencourt et al., 2021; Nicolelis et al., 2021). COVID-19 in SP showed a shift from the initial concentration of cases in the central (wealthier) areas of the city of SP (e.g. Butantã, Lapa, Pinheiros, Vila Mariana, Moema, Jabaquara) towards the peripheries. Roughly six weeks after the introduction of the virus (on February 26) from Italy and the USA (Nicolelis et al., 2021) in the more affluent neighbourhoods, cases and deaths concentrated heavily in peripheral regions of the city (e.g. Brasilândia, Sapopemba, São Mateus, and Cidade Tiradentes) (Travassos et al., 2020). Seroprevalence and COVID-19 risk analysis in the SP state showed a distinct increase in hospitalisation and deaths due to location (e.g. reduced access to healthcare in low-income neighbourhoods), ethnicity (e.g. Black and Pardo groups) and hospital type (e.g. public hospitals) (R. R. Castro et al., 2021). When controlling for comorbidities, the patient's income was the most persistent differentiator in the case-fatality ratios (Lorenz et al., 2021).

Table 5-1. Case study areas descriptive statistics.
Source: authors from PNUD and IPEA.

Case study area	Income class	Urban layout	Distance from CBD	Human Development Index 2010 (PNUD)
1 – Expanded centre	Upper- middle	Formal	0 – 12 km	0.869 – 0.942 (Sé, Lapa, Mooca, Pinheiros e V. Mariana)
2 – Benfica	Low	Informal	22.7 km	0.681 (Guaianases)

The central and peripheral areas presented in Table 5-1 provided participants with contrasting socioeconomic backgrounds. In the expanded centre, we found the middle-upper income and university-educated residents of the city's central region (referred to from now on as ‘central region group’, or CRG). In Benfica, we found the low-income, informal workers and settlers of the outer periphery of the city of SP (referred to as the ‘periphery region group’ or PRG), as illustrated in Figure 5-1. CRG had seven participants (five women and two men), from 20 to 34 years old, including three self-identified White persons, one Black, and three Pardo (i.e. ‘Brown’ ethnic classification specific to Brazil). Income in this group varied between US$0 and US$ 1,812.40 and the living conditions were high, with complete infrastructure and access to city services. The PRG participants lived in the Benfica community, part of the Machado slum cluster in the Guaianases neighbourhood, roughly 23 km from the centre. The group included 10 participants (seven women, three men) from 19 to 48 years of age, including two self-identified White persons, two Black, and six ‘Pardos’. Income in the periphery group varied from US$0 to US$ 394.00, and living conditions were low, including lacking sewage and safe water supply, households built out of improvised materials (e.g. wooden boards, often without waterproof flooring) and on a slope near the flood-prone margins of a local creek.

Figure 5-1. Central region focus group (right) and periphery region group (left).
Sources: COVIDGI, Bibiana Borda (right) and Katharina Heider (left). They are used under authorisation.

We summarised the main topics reported in the focus groups and provided the coded transcripts in Appendix C, where we identified each extract by its paragraph number. The focus groups showed that the COVID-19 pandemic impacted most sectors of society and all aspects of life. The location, socioeconomic status, and ethnicity characteristics of our sample defined the conditions to cope with the adverse effects of the pandemic: The centrally located, upper-middle income, and primarily White participants in CRG suffered less and fared better. Surprisingly, several participants from CRG reported improving their lives during the pandemic (e.g. adopting telework or active transportation modes) and expect to maintain these improvements in the long term. As expected, the peripherally located, low-income, and primarily Black and Brown people in PRG were already under strain, faced more intense impacts and had a lower capacity to respond and cope. The hardship from the secondary effects of the pandemic and social responses (e.g. reduced economic activity and active social segregation) surpassed expectations, causing intense losses that will hinder the development of the PRG in the long term.

To further analyse the commonalities and differences between these groups and identify the factors of vulnerability to COVID-19, we implemented the cross-thematic matrix presented in Table 5-2. The matrix focuses on four themes, (A) Intensification of threats to livelihoods, (B) changing behaviour: by choice or out of need, (C) capacity to cope, respond, and adapt, and (D) new opportunities and factors of resilience. Considering the case-study areas first (across the matrix rows), we perceive the most significant difference between the groups: Changes in CRG presented options with different cost-benefit relations, while in PRG, changes were risk-risk trade-offs, with some loss embedded in every choice. Furthermore, adaptation in CRG most often meant long-term improvement, while in PRG, the lack of resilient options meant impacts from COVID-19 compounded with historically high vulnerability status. As impacts superimpose, the community suffered physically and mentally (e.g. hunger, diseases, depression, and stress), sapping human development and hindering the conditions for future growth. Public welfare did not soften these impacts, being primarily insufficient.

Table 5-2. cross-thematic matrix for the SP focus groups.

Themes / Cases	**(A) The intensification of threats to livelihoods**	**(B) Changing behaviour: by choice or out of need?**	**(C) Capacity to cope, respond and adapt**	**(D) New opportunities/ factors of resilience**	Cross-case observations
Central region group (CRG)	temporary threats to education, stress in the work environment	telework allows active mobility, local and online shopping	high individual capacity, available family resources, healthcare access	new habits increase well-being, resources to seize opportunities	Negative impacts were temporary, long-term improvement
Peripheral region group (PRG)	severe threats, unemployment, food insecurity, mental health issues	a risk-risk trade-off: unemployed or exposed, long-term losses	limited capacities, lack of access to health, and impacts translate into losses	reduced resilience, but community organisation is a (new) lifeline	Long-lasting adverse effects hinder the development
Cross-thematic observations	CRG: impacts within the coping threshold. PRG: the threshold was very low and impacts high.	exposure to new behaviour in both groups, but all choices in PRG involve losses	polarised coping, CRG: capacity and additional resources; PRG: 'territorial overload.'	seizing opportunities needs resources, leading to increasing inequality	

Theme (A), the intensification of threats to livelihoods, illustrates the different prospects. Barbara, from CRG, reported that due to a toxic work environment, she felt forced to quit her job in November 2020. Despite this setback, she had access to the resources necessary to transform it into an opportunity. Barbara reported accelerating her original plan of finishing her graduate course (specialisation in project management) and then seeking new employment. After quitting, she capitalised on her new certification, interviewing at Teto Brasil and securing a position soon after. This example of turning adversity around contrasts with the bleak overall situation in PRG. Several participants from it reported being unemployed months after social isolation measures (e.g. closing non-essential retail) had been eased. Carlo puts it concisely: 'It's because [when] COVID arrived, jobs were gone...' (SP CSA2, pp 108). Unemployment in the community added to increased food prices, as Richele reported: 'And when the food started to increase, with rice at 30 BRL, tell me if I was impacted by this, people, because rice went to 30 BRL (…) Gee, this is absurd, people, I can't do it.' (SP CSA2, pp 478). Food insecurity rapidly developed, and hundreds of people queued for daily meals prepared by the community association. When we held the focus group, there was no short-term prospect for improvement.

Theme (B), 'Changing behaviour: by choice or out of need?' shows the crisis changed daily life, inserting new elements to all participants. Participants of CRG mention wishing to keep some of these changes, notably telework and active mobility. They see those as improving their choices in daily mobility and quality of life. In PRG, the changes went against participants' desires, notably concerning work. On the one hand, some wished they could work, but social isolation measures (e.g. closed bars and nightclubs) or reduced economic activity (e.g. reduction in construction work) prevented them from doing it. These participants prioritised livelihoods: They would be willing to work despite recognising it meant exposure to COVID-19. On the other hand, many wished they could properly adopt social isolation, remaining at home and receiving welfare until the contagion risk lowered, as Robert (PRG, pp 473) puts it, 'Yeah, well, that's what I'm talking about because if we could really afford it, I doubt that anyone would want to leave here to go to work, take a bus or do anything like that.'

Theme (C), 'Capacity to cope, respond, and adapt', demonstrates that the conditions against which the impacts played out were significantly different. Despite the far-reach of the pandemic impacts (i.e. affecting families, livelihoods, and socialisation, taking lives, and resulting in long-term health deficiencies), the focus groups revealed significant differences in individual and community capacities to withstand them. Concerning health, for example, the PRG had frequent mention of adverse health conditions (e.g. bronchitis, asthma, and heart diseases) and challenging access to health services, indicating a reduced capacity for coping (i.e. ability to bear the impacts) or adapting (i.e. changing behaviour to avoid negative outcomes). In CRG, there were adverse effects, mainly concerning mental health, but participants reported finding support in their families, friends, and health services. Some went as far as to say it was easy to access testing and medical consultations when necessary, using private insurance, public health clinics, or finding support even at work, as Anna (CRG, pp 300) explains:

> (…) we also had the [… concern with the] mental health of our employees. [… We adapted] the policies that we have as a team but also opening spaces to talk and understand how people are feeling after this change of work and virtual work, how tiring it really is.

Theme (D) presents the interplay of choice, existing conditions, and the impacts, identifying the elements of resilience (i.e. adaptation or resisting enough to go back to previous conditions without losses). CRG participants reported that some actually 'built back better' their lives after the pandemic's worst phases. By adopting healthier habits (e.g. active mobility) and seizing opportunities like telework, they improved their lives, got promotions, and added new activities to their work. Anna (CRG, pp 274) puts it clearly:

> It increased because I work at Teto […], teach online courses [and take university classes]. I wouldn't have the chance to do all three things because of mobility. […] This mobility [...] increases […] the opportunities.

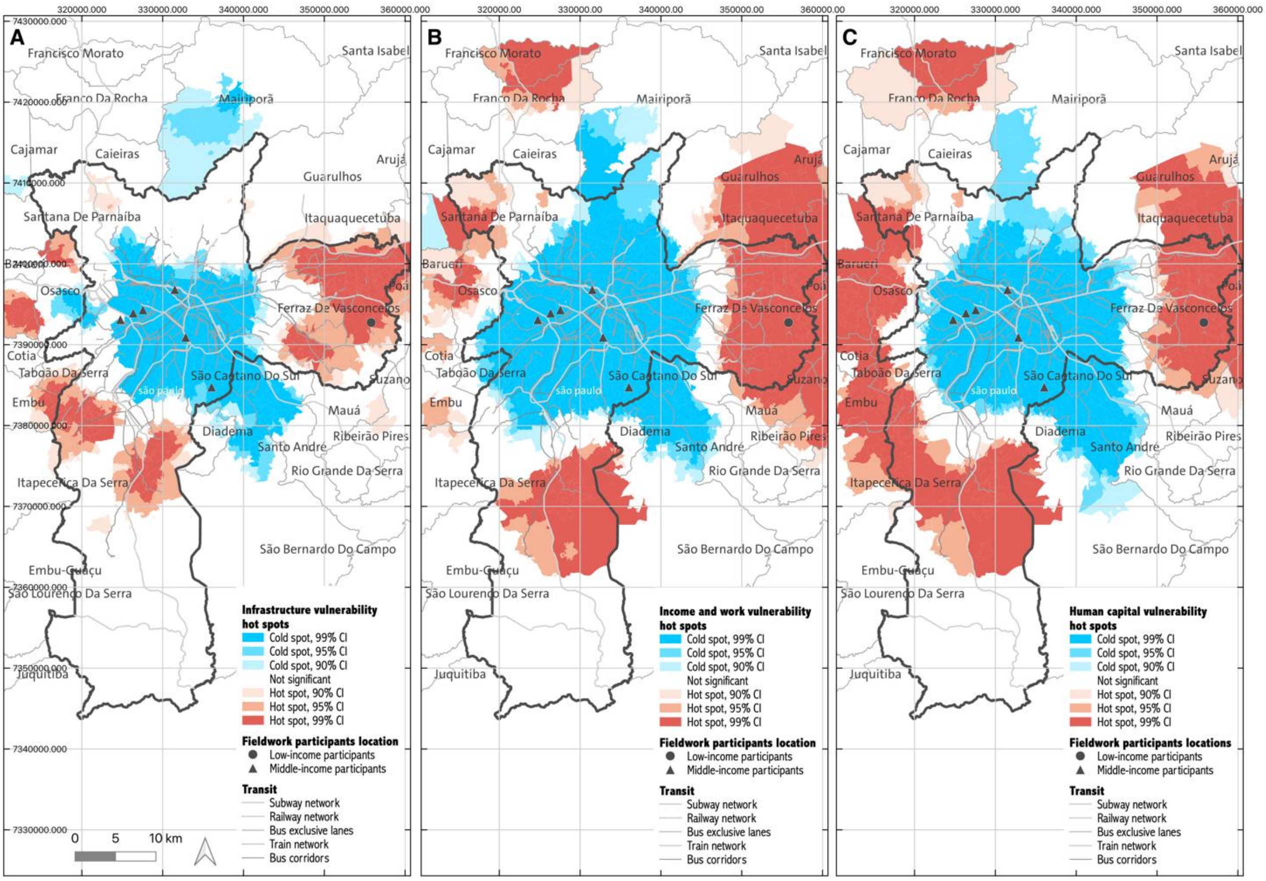
Ultimately, there were opportunities from the crisis for work and family relations. However, participants employed individual or social resources (e.g. savings or family support) to seize these opportunities. When these resources were missing, not only were the prospects passed on by, but the impacts were often harder to resist. The focus groups in SP, with participants from contrasting social strata, show increased inequality, with living conditions improving in CRG and deteriorating in PRG. These results further support hypothesis H1, demonstrating marked differences in resistive capacity (e.g. low thresholds of economic and physical health in PRG versus ample support in CRG), exposure, and resilience. They also indicate that crises have profound socioeconomic impacts that reverberate beyond their immediate impact areas or social groups, often interacting systemically.

5.3.2 Hot spots analysis

This section presents the analysis of the concentration of vulnerability factors and the fatalities from COVID-19 during 100 weeks in 2020 and 2021. It uses the established Getis-Ord G* (Getis & Ord, 1992) statistic on the SVI data from IPEA (2015) for the metropolitan region of SP. In Appendix C, we provide further evidence from the human development index (UNDP, 2022). The SVI hot spots presented clear core-periphery patterns in the SP metropolitan region, as seen in Figure 5-2. All the SVI dimensions presented a concentric pattern around the SP city centre, with cold spots (i.e. absence of vulnerability) in the centre and hot spots at the periphery.

Infrastructure was the most concentrated dimension (see Figure 5-2a), with very high-confidence hot spots (99% CL) almost exclusively in SP, in the neighbourhoods of Itaquera, Guaianases, and Jardim Paulista to the east, and Grajaú, Capão Redondo and Cidade Dutra to the south. Similarly, there were three very high-confidence cold spots (99% CL): The main one in the SP centre spreading southeast towards the ABC region, a westerly one in the Rio Pequeno neighbourhood of SP and Osasco, and a northerly one in the city of Mariporã. The income and work dimension had a more dispersed spatial distribution than infrastructure (see Figure 5-2b), with a significant very high confidence (99% CL) hot spot in the eastern region of SP. A southeast extension shows a concentration of low vulnerability towards the ABC region, while a southwest extension includes the neighbourhoods from Rio Pequeno to Santo Amaro. To the north, the cold spot consists of the southern areas of Mariporã. Finally, human capital is more spatially dispersed (see Figure 5-2c). The marked difference is that while income and work have unconnected very high- and high-confidence hot spots to the west of SP, human capital presents one very high-confidence hot 'arc' in this area. This 9.5 km wide crescent starts in Grajaú and progresses towards Osasco and Barueri.

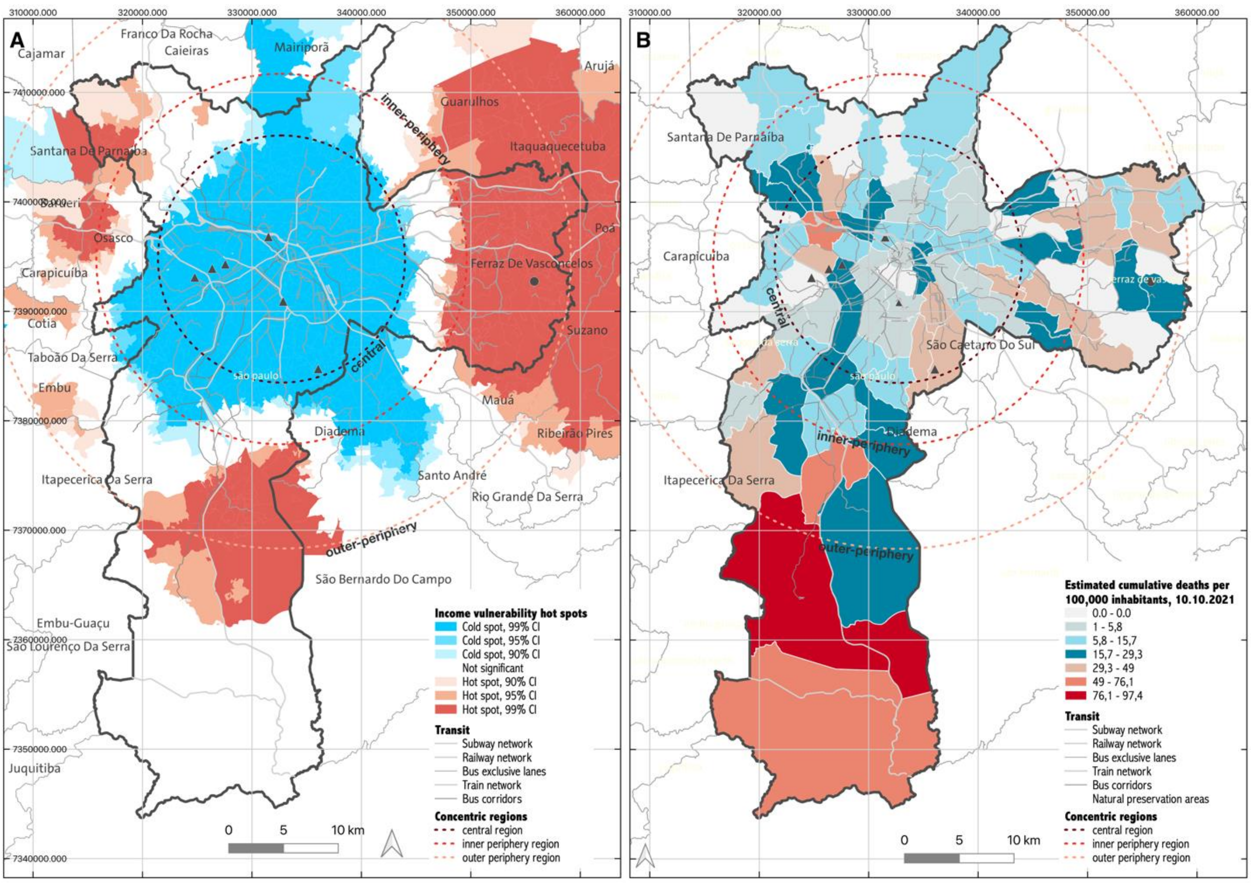
Figure 5-2. Vulnerability hot spots analysis in SP and vicinity: income and work, infrastructure, and human capital dimensions.
Source: authors, based on IPEA (2015).



The socioeconomic vulnerability levels hence define three concentric rings, the central has low vulnerability, the next has no statistical significance, and the third clusters high and very high vulnerability, as seen in Figure 5-3a. The first ring stretched roughly 11 km from the SP City Hall and concentrated very high-confidence cold spots (99% CL) in all dimensions: income and work, infrastructure, and human capital. The second ring ranged from 11 to 16 km and presented statistically insignificant results due to high variance (i.e. heterogeneity in the SVI scores). The third ring ranged from 16 to 26 km and contrasted sharply with the first, with very high-confidence hot spots (95 and 99% CL) for all vulnerability dimensions. A south-eastern vector was the exception to this concentric pattern: The industry-rich region of the ABC, including Santo André, São Bernardo do Campo, and São Caetano do Sul, was a significant cold spot in all vulnerability dimensions, especially human capital.

Next, we compared the vulnerability hot spots with the distribution of cumulative COVID-19 fatalities in SP per 100,000 inhabitants calculated from official microdata (n = 1,948,601)(SP Municipal Health Department, 2022). We calculated fatality rates for each census district, as featured in Figure 5-3b (available for every month between 02.2020 and 11.2021 in Appendix C). We compared the fatality rates concentration over time in each of the three concentric areas in SP: the central, inner-periphery, and outer-periphery regions. This division considers the concentric patterns identified in SVI above (and HDI in Appendix C) and the significant and persistent core-periphery segregation patterns of SP described in the literature (Bógus & Taschner, 1999; Feitosa et al., 2021).

Figure 5-3. Income vulnerability hot spots and cumulative deaths per 100.000 inhabitants in the SP census districts on 10.10.2021.



The central region concentrates all the very high confidence SVI cold spots (and the very high confidence HDI hot spots). This region clustered fewer COVID-19 fatalities for most of the period, and deaths also accumulated later (see the timeline in Appendix C). The inner periphery has statistically insignificant hot spots and presents a moderate concentration of fatalities. In the early stages (e.g. 04–05.2020), fatalities begin in this region (and in the extreme south). Throughout 2020 this pattern remains until February 2021. The third region is the outer periphery, which includes all very-high confidence vulnerability hot spots. This region had few fatalities in 2020 but presented the highest fatality rates of the period under analysis. From February to November 2021 (when the health system collapsed, see Freitas et al., 2021), all districts with very high fatality rates, except four, clustered in the outer periphery region.

These results present evidence towards the convergence of vulnerability hot spots and COVID-19, supporting hypothesis H2. However, the limitations of the study design do not allow us to draw causal relations between them. Both effects may share causalities and influencing factors outside the scope of this analysis. Furthermore, these results show an overlap between known spatial opportunity gradient (e.g. the rings from Bógus & Taschner), the SVI clustering (i.e. a straightforward centre-periphery configuration) and the COVID-19 fatality rates concentration. To remove alternative explanations, we turn to the temporal analysis of the pandemic using the Kaplan-Meier estimator.

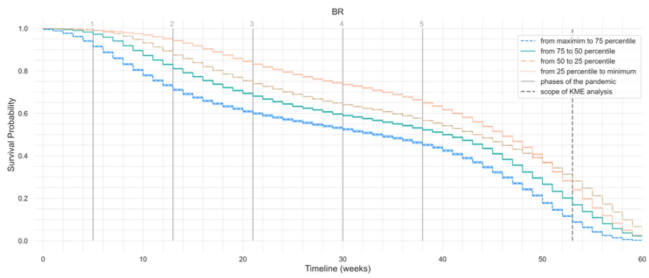
5.3.3 Survival analysis

COVID-19 proved to be a highly dynamic phenomenon. It depended on micro-scale human behaviour by spreading quickly due to interpersonal contact. Previous research indicated a statistically significant association between Brazil's structural socioeconomic vulnerability and COVID-19 fatalities (R. R. Castro et al., 2021; Santos, Rodriguez Lopez, Heider, et al., 2022). In this investigation, we tested this association for three spatial scales in Figure 5-4.

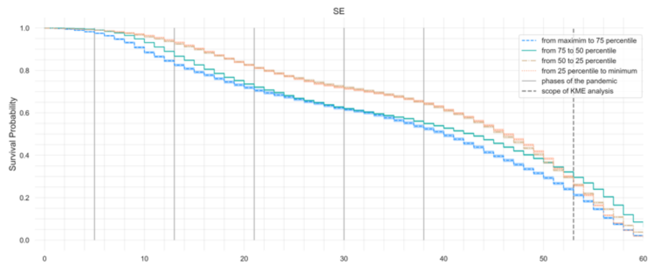
Starting at the national scale, we grouped all 5,570 Brazilian municipalities into four classes, organised according to the quantiles in which they feature in the national SVI distribution (for method information see Santos, Rodriguez Lopez, Heider, et al., 2022) and estimated the survival probabilities using open data (Brasil.IO, 2021). This scale showed a clear distinction between the SVI quantiles, with more vulnerable quantiles presenting lower survival probabilities early in the series. In the regional scale, we grouped 1,668 municipalities in similar fashion and the results were distinct for each pair of SVI classes. Low- and very low-vulnerability municipalities presented higher survival probabilities for most of the series. The exception was after week 50, when the probability curves for these cities crossed the curves for the high- and very high-vulnerability municipalities. The results for SP used micro-level data (SP Municipal Health Department, 2022) aggregated to the census district scale, again classified using the SVI quantiles. These results were not statistically significant, as curves and their error surfaces touch during all the series, partially contradicting the national and regional scales.

Figure 5-4. Survival probability curves for Brazilian cities and districts grouped by SVI quantiles: (A) Brazil (cities), (B) Southeast region (cities), and (C) São Paulo Metropolitan Region (districts).

(A)



(B)



(C)

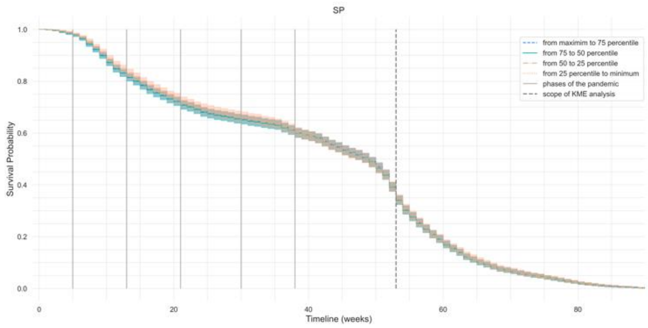
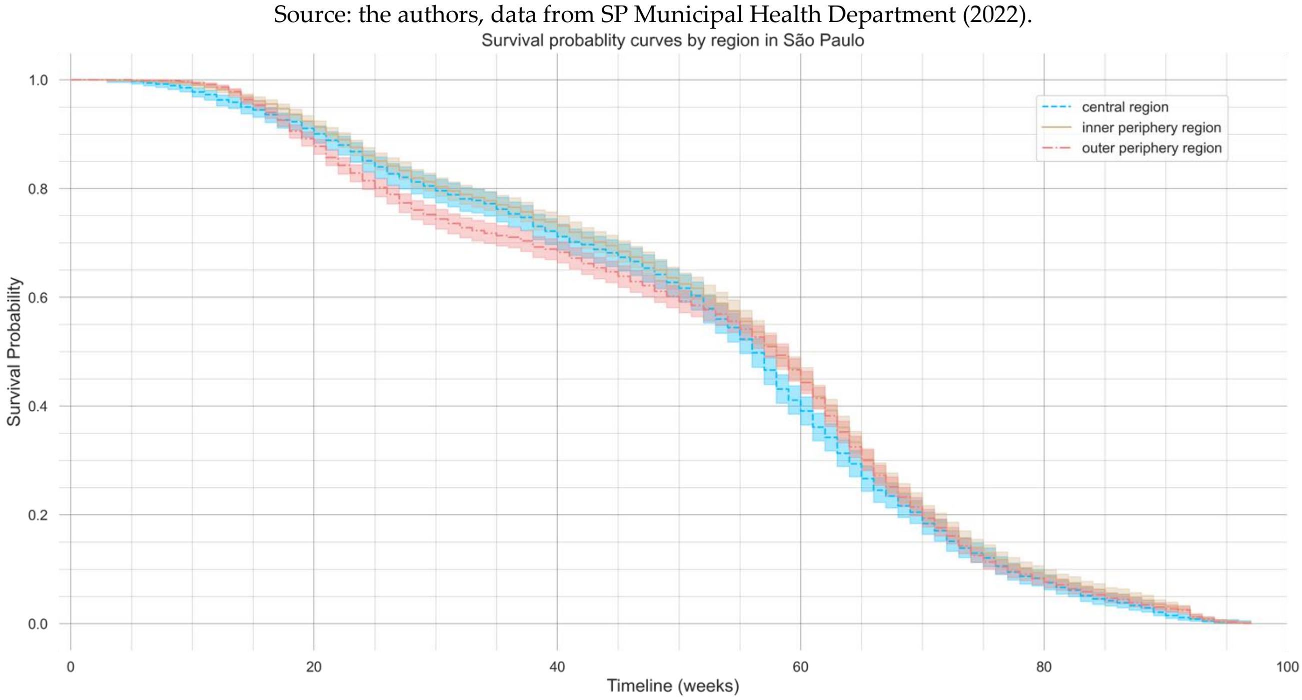


Figure 5-5. Survival probability curves for the central, inner-periphery, and outer-periphery regions of SP from 02.2020 to 11.2021.

Source: the authors, data from SP Municipal Health Department (2022).



Seeking alternative explanations to the previous results, we classified the districts according to the vulnerability rings identified in the hot spot analysis (as presented in Figure 5-3). Figure 5-5 illustrates the survival probabilities curves for the central, inner, and outer periphery regions. These curves showed two overall patterns: A general similarity between these areas (i.e. high-mortality periods take place almost simultaneously) and two periods in which the outer periphery and central regions behave differently. The latter pattern showed partial statistically significant associations between socioeconomic vulnerability and COVID-19 fatalities, roughly following the distance from the city centre. The explanatory potential of the results is limited, though, as the curves and their error surfaces overlapped during segments (e.g. between weeks 45 and 55) of the 100 weeks under analysis. The second pattern indicates that between weeks 20 and 40, the inhabitants in the outer periphery faced a sharp drop in their survival probabilities. Survival probabilities then stabilise, mixing with the curve from the inner periphery and central regions in week 45. The central curve also has a temporary differentiation, decreasing survival probabilities sharply between weeks 55 and 65. After this period, all regions are statistically indistinguishable. The general pattern, though, shows an intense drop in survival probabilities from week 55 to week 70, with a decreasing rate of probability decrease from then on. Further testing with the Cox Proportional Hazard model provided similar evidence. These results, therefore, present partially supporting evidence for hypothesis H2, as there were associations between low human development and COVID-19 fatalities in some periods.

5.4 DISCUSSION

Scholarly research on multiple stressors indicates that cities risk interacting impacts from compound hazards (Sillmann et al., 2022; Zscheischler et al., 2018). Combined effects may increase damage and push societies beyond their resistive capacity. In the Anthropocene, cities are focal points of the impacts of human-induced global changes (Alberti et al., 2018; Elmqvist et al., 2021). Furthermore, cities in the Global South present inequality that interacts with the ongoing climatic changes (Hardoy & Pandiella, 2009; Tessler et al., 2015), generating climate gentrification (De Koning & Filatova, 2020), dispossession cycles (Henrique & Tschakert, 2021), or poverty–vulnerability traps (Boubacar et al., 2017; Santos, Rodriguez Lopez, Chiarel, et al., 2022). Despite these advances, there is still a gap in research between vulnerability and urban development. This gap is especially relevant when considering the environmental justice aspects of the unequal attribution of risks (Bolin & Kurtz, 2018; Zebisch et al., 2021), social determinants of health (Salgado et al., 2020), and the evolving risk profiles of cities in the Anthropocene (Elmqvist et al., 2021).

This research inquired about the system of connections between urbanisation and risk exposure in cities from the Global South in the Anthropocene. We present the assumption that a nexus between urbanisation and risk exposure emerges from socio-environmental vulnerability. To test this assumption, we put forth two complementary hypotheses: The first is that areas lacking human development include vulnerability factors common to climate change and COVID-19 (hypothesis H1) and the second is that low human development urban hot spots coincide with increased COVID-19 fatality rates (hypothesis H2). To verify these hypotheses, we presented three results. The qualitative investigation using thematic analysis explored the contrasting experiences of the pandemic in São Paulo. Then we examined the spatio-temporal association between structural socioeconomic vulnerability and COVID-19 fatalities with hot spot analysis and the Kaplan-Meier estimator. The qualitative result supports hypothesis H1 and provides no evidence to falsify it but is not designed to assess causality. The latter results (hot spots and KME) partially support hypothesis H2 and point to more complex causation between vulnerability and COVID-19 fatalities. We will explore these observations below.

The qualitative results from the focus groups support hypothesis H1. They show a widening gap in resilience between the central and peripheral groups. This gap signals the impacts of location choice and uneven development patterns (D. Harvey, 2006) found in previous research (Revi et al., 2015; Santos, Rodriguez Lopez, Chiarel, et al., 2022). The qualitative results exemplified the social and environmental determinants of health (Marmot, 2005; Salgado et al., 2020), such as difficulties accessing public health services, high stress, challenges obtaining nutritious food, and frequent comorbidities among the peripheral group. These overlapping adverse conditions contrast with the straightforward access to services reported by the central group (even during peak periods in the pandemic).

These experiences denote a convergence between social status and location choice, influencing exposure (e.g. by allowing self-isolation to the central group through home-office) and resistive capacity (e.g. by limiting health service access to the peripheral group). The concentration of resilient behaviour in the central group and multidimensional vulnerability in the peripheral group reinforces this observation, supporting the conjunction of urbanisation with risk exposure. Moreover, these results present compelling evidence that the secondary effects of the health crisis (i.e. unemployment, isolation, emotional, financial, and psychological stress) are as significant as the health concerns from contagion. This evidence should bring to focus the multidimensional aspect of the impacts of systemic risks, which may spread to different areas of well-being (Sillmann et al., 2022). This observation is a central challenge to measuring the crises outcomes, as they may affect well-being in multiple areas, some of which are often absent from direct measures of impact (e.g. loss of life or economic indexes).

The analysis of vulnerability hot spots in Figure 5-3 and Figure 5-4 demonstrated a partial overlap between the impacts of COVID-19 and structural vulnerabilities. First, they show marked differences between the two areas investigated in the focus groups. These differences indicate an alignment between the social determinants of health (Levin et al., 2022; Salgado et al., 2020) and climate risk (Travassos et al., 2021) and the core-periphery and segregation dynamics reported in the literature (Feitosa et al., 2021) and classic models of SP (Bógus & Taschner, 1999). These results allowed the outlining of three regions concentrating marked degrees of vulnerability, featured in Figure 5-4: A central area, essentially free from vulnerability, an intermediate region in which concentrations are not evident, and a peripheral region, where vulnerability hot spots were frequent in all its dimensions (i.e. infrastructure, income and work, and human capital). The overlay of COVID-19 fatality rates to these regions from February 2020 to November 2021 shows consistently higher fatality rates in the outer periphery region, therefore supporting hypothesis H2.

Finally, the Kaplan-Meier estimator sought statistical evidence of the association between low human development and COVID-19 fatalities. The results partially support hypothesis H2, indicating the need for further investigation. This method provided the survival probability curves for different population groups in two configurations (i.e. according to vulnerability or to the concentric regions) and in three different spatial scales (i.e. national, regional, and intraurban), shown in Figures 5-4 and 5-5. The results at the national (Figure 5-5a) and regional (Figure 5-5b) scales support hypothesis H2, even if the latter shows some deviant behaviour. The curves show a pairing of probability curves: The very low- and low-vulnerability curves superimpose, and the high- and very-high vulnerability curves combine similarly, leading to some uncertainty.

This uncertainty becomes significant on the intraurban scale (Figure 5-4c). All lines overlap, which contradicts hypothesis H2 since there is no significant difference between the population's high- and low-vulnerability segments. Scale dependency is a known issue in adaptation research and may affect vulnerability (Waters & Adger, 2017). Plausible explanations include the significant individual factors in COVID-19 dissemination (e.g. risky behaviour as going to parties), data limitations, and the impact of personal health factors (e.g. comorbidities, age, or gender). The latter could also explain why a more aggregate geographical segmentation of the population in the three regions (i.e. central, inner, and outer periphery, shown in Figure 5-5) provided more statistically significant results. The survival curves for the regions show statistically distinct behaviour in parts of the time series. The increased fatality in the outer periphery between weeks 15 and 45 is noteworthy, supporting hypothesis H2. The sudden drop in survival probabilities in the central region between weeks 50 and 70 contradicts hypothesis H2 and signals that other factors started dominating the city's fatality curves. Possible factors could include the return of the population to SP seeking medical attention (Nicolelis et al., 2021) and the collapse of the emergency health system (Freitas et al., 2021) between March and July 2021, or differences in vaccination uptake, that marked fatalities in the second year of the pandemic.

5.5 CONCLUSIONS AND OUTLOOK

The relevance of this investigation is to connect urbanisation with risk exposure in a nexus that revolves around socio-environmental vulnerability. This connection is central in finding synergies between sustainable development, urbanisation and risk reduction policies (e.g. the SDGs, the New Urban Agenda and the Sendai Framework, respectively) (UN-Habitat, 2016; UNISDR, 2015; United Nations, 2015). To this end, this research implements a mixed-methods approach including multiple samples and scales of analysis (e.g. metropolitan, census tract, and individual scales) and qualitative (i.e. thematic analysis) and quantitative methods (i.e. hot spots and survival analyses).

Our results indicate that social and environmental factors significantly contribute to vulnerability to COVID-19. Unequal development patterns explain most socioeconomic vulnerability in SP and part of the COVID-19 fatality concentration in the period. These factors also increase exposure (e.g. through location) and decrease resilience (e.g. by reducing adaptive capacity) to climate change. However, they also signal potential synergies between policies of socioeconomic inclusion and development and climate adaptation. Furthermore, they bring important lessons to local adaptation pathways, as these should be inclusive, context-sensitive, and counter inequality (Henrique & Tschakert, 2021). These results also show how systemic crises often have secondary effects (Juhola et al., 2022; Sillmann et al., 2022) that penalise those more vulnerable disproportionately (Bolin & Kurtz, 2018; Watts et al., 2021). Finally, these results show meaningful spatio-temporal interaction between vulnerability and urban development.

Concerning the intradisciplinary character of this investigation, there is room for improvement. The mixing of the methods in this research took place by comparing evidence and insights across epistemologies. For example, the high-vulnerability factors identified in the individual experiences during the focus groups helped shape the quantitative vulnerability assessments in the hot spots and survival analyses. More integrated designs could explicitly use qualitative data for calibrating quantitative studies or fuse qualitative and quantitative data interdependently (Tashakkori & Teddlie, 2010). Regarding the generalisation of results, this research focused on one city, albeit at different scales. Integrating multiple scales of analysis in research is innovative, primarily since the results from one scale support analysis on others, promoting the robustness of the inferences thus obtained. Since the methods presented here use well-established data gathering and analytical methods and mostly rely on open data (except for the fieldwork), they are easily reproducible in other regions of the country. Replication is further supported by publishing the codes and datasets under an open-access license in an established platform (i.e. GitHub, see supplementary materials). Comparative studies in other regions of the Global South would be especially welcome to provide further evidence or refute the findings of these analyses.

This investigation advanced on hypothesis H1, supporting the connection between climate change and COVID-19 via social and environmental features. It shows connections between human development, the alterations of the biophysical environment and the location opportunities hence derived. Furthermore, it demonstrated that adverse socioeconomic characteristics often match poor environmental quality (e.g. lack of infrastructure and risk exposure), notable in the peripheral regions of SP. This research also tested hypothesis H2, with results varying between the scales in KME. The hot spots analysis showed evidence for the overlay of low human development and COVID-19 fatalities, but the KME study indicated that more factors are at play (e.g. individual behaviour, comorbidities, age or gender). These factors may be more influential than the territory or community at the intraurban scale, requiring further research. Hot spot analysis, including time (e.g. emerging hot spot analysis) and fixed effects analyses, can provide additional evidence in future studies.

The evidence from the qualitative fieldwork shows pronounced indirect impacts of the pandemic and its containment measures, leading to divergent experiences. The evidence demonstrates that the participants of the central, upper middle-income group improved their lives during the pandemic. At the same time, the peripheral, low-income group suffered from food insecurity, depression, anxiety, and lack of access to public services. It points to the necessity to regulate location opportunities equitably, supporting community organisation (instead of top-down interventions), and correcting the historical bias toward investing in adaptation where needed the least (e.g. in central areas). They also point at synergistic issues, in which interventions may simultaneously address several Sustainable Development Goals and targets of the New Urban Agenda (e.g. zero hunger, good health and well-being, and climate action). These insights are critical for adaptation policies against climate change and other systemic crises since they unfold at multiple scales and sectors and, therefore, interact intensely with the inequality of society in the Anthropocene.

5.6 SUPPLEMENTARY MATERIALS

The data preparation and analysis code are available, along with raw data and results, at the Urbanisation-Risk Exposure nexus GitHub repository: (available at https://github.com/alexandrepereiraarq/urb_exposure_nexus).

6 COMPARING VOLUNTEERED DATA ACQUISITION METHODS ON INFORMAL SETTLEMENTS IN MEXICO CITY AND SÃO PAULO: A CITIZEN PARTICIPATION LADDER FOR VGI

Peer-reviewed publication[13]:

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ABSTRACT

In the early 2000s, Web 2.0 technologies prompted an explosion in geographic data that include Volunteered Geographic Information (VGI), a set of methods that brings user contribution to the centre of data acquisition. These methods increase the capacity of community-driven and local initiatives to create geographic information and close existing data gaps in authoritative sources. Informal settlements constitute an example of where a major vacuum exists, as maps are often incomplete, outdated, or imprecise. However, quality issues regarding VGI frequently arise, as do questions on citizen participation and empowerment. This study explores how different VGI approaches support citizen participation and user empowerment, in tandem with the opportunities and limitations of VGI to map informal settlements in Latin America. We propose a VGI comparison framework to evaluate citizen participation in two informal settlement mapping projects in São Paulo and Mexico City. Such a framework includes four categories: (1) required material resources; (2) required geographic information system (GIS) literacy; (3) user agency; and (4) involvement of research subjects. The results demonstrate that higher citizen involvement in São Paulo stems from the inclusion of residents through participatory mapping methods. Conversely, the Mexico City's case demonstrates how crowdsourcing may happen irrespective of and contrary to the goals from those represented in the data. We suggest that VGI is a powerful tool for generating timely and precise data on informal settlements, but research subjects should have agency over geographic information collected about them.

Keywords: Citizen Participation; Participatory Mapping; Volunteered Geographic Information; Informal Settlements; Latin America.

[13] Text and tables were reformatted. Spelling was adjusted to British English, for consistency with other sections of the dissertation.

6.1 INTRODUCTION

From the early 2000s, there was an explosion of available geographical information made possible by Web 2.0 technologies, including volunteered geographic information (VGI). VGI is a set of methods based on users' contributions to the acquisition of geographic information (Goodchild, 2007). With the introduction of VGI, consumers of geographic information (formerly passive) can become active data producers. These methods marked geographic information (GI) production, which transitioned from being highly technical and opaque to the average citizen to become a synonym of inclusion in an increasingly digital society. This transition took place due to the advent of geotagged big data, characterized by the ubiquitous use of global navigational satellite systems (e.g. GPS), the surge in geo-marketing, and the massive adoption of personal location sensors (D. Sui et al., 2013a; Yan et al., 2020). Despite the undeniable advantages of the availability of GI, this explosion of data generation brought about problems such as unwanted surveillance and breaches of privacy (Bertone & Burghardt, 2017), including commercial use and political misuse of volunteered information (e.g. the Cambridge Analytica scandal) (Sharma, 2019), and unwarranted governmental or private surveillance (Ricker et al., 2015).

One response to the privacy and data-ownership concerns is to take control of the means of production, editing, and dissemination of information. Open and free data movements, along with collaborative stances at intellectual production (e.g. collective intelligence, peer-production, co-creative labour), constitute efforts in this direction (Yan et al., 2020). VGI falls within this scope, most notably because of its emphasis on blurring the boundaries between users and consumers of information that create, enlarge, review, and otherwise contribute to the information. Examples of this phenomenon encompass open GI platforms such as OpenStreetMap (F. Harvey, 2013). VGI presents a hybridization of roles between those who record and collect GI, those who use it, and those represented by it. This relationship is not inherently fairer, but the distributed ownership and agency provide active roles to citizens that otherwise would be passive subjects in the different mapping efforts.

This chapter adopts a broad definition of VGI, which includes participatory, collaborative, and open-sourced GI methods. By doing this, we deliberately opt not to break VGI away from techniques such as public participatory geographic information systems (PPGIS), as proposed by some authors (Verplanke et al., 2016). Instead, we explore the differences between techniques within a mapping methods spectrum, in which participation is in the centre.

This chapter presents a study on the application of VGI to map informal settlements in Latin America. The questions that structure this research are: (1) How do different VGI approaches support citizen participation and user empowerment? (2) What are the opportunities and limitations of VGI in mapping informal settlements in Latin America beyond current authoritative data acquisition procedures? These questions stem from the realization that authoritative sources such as registries, census, or urban planning documents do not adequately portray informal, illegal, peripheral, or otherwise deprived settlements. A recent stream of community or volunteer-driven mapping experiences made possible by Web 2.0 interaction creates novel geographic information (GI) sources, closing some existing gaps in authoritative data sources. These applications also present issues of empowerment, privacy, and citizenship, on which this investigation focuses. Methods and tools employed within the VGI spectrum directly impact citizen participation and empowerment (Corbett & Keller, 2005; Reynard, 2018) which are two of its main premises and require clarification. To address these issues and clarify differences in terms of methods and expected outcomes of VGI, we propose a framework for assessing citizen participation in VGI and applying it to two case studies: peripheral urbanization in Mexico City and participatory mapping in inner-city slums in São Paulo. The novelty in this research resides in our focus on user empowerment as the driver for a ladder of user participation in VGI.

This chapter addresses citizen participation and empowerment questions from a comparative perspective in the VGI experiences and research spectrum. The following section provides an overview of the theoretical questions regarding user participation in VGI and the lack of data on informal settlements. The methods section presents a comparison framework for VGI applications based on citizen participation that collects environmental and socioeconomic data in these settlements at varying resolutions. In the results section, we present the analysis of two contrasting case studies using the citizen participation framework. The discussion section reflects on the breadth of the VGI spectrum, notably the empowerment of users, volunteers, and citizens through the VGI applications. It also discusses the potential of VGI to provide quality geographic information about informal settlements in developing countries. We conclude with remarks on the necessity of interdisciplinarity and participatory processes in research and policy development, most notably when socioeconomic inequality is a relevant factor.

6.1.1 Lack of information about informal settlements

VGI presents advantages to GI's democratization, most notably the distributed data acquisition and the reduced distance between producers and users of GI. As with other Web 2.0 technologies, it dramatically expands the role of information in everyday life for millions of people, which increases the pace at which data are produced and used (D. Sui et al., 2013b; Yan et al., 2020), as seen in location-based devices. However, despite the increased integration predominant in the developed world, differences persist across regions and demographics. Overall, men have more facilitated access than women have, and the developed economies present much better access than the least developed countries (LDCs, as defined by UN-DESA, 2021). Men in developed countries would be the upper end of the technology accessibility spectrum, as close to 90% of them have access to the web. At the opposing end, only 14% of women in LDCs have access (International Telecommunications Union, 2019). This stark contrast exemplifies the differences in place, gender, income, and other socioeconomic factors that determine the ability to access, produce, and disseminate GI (Corbett & Keller, 2005; D. Sui et al., 2013b)

At the urban scale, the most vulnerable areas are frequently under-represented or absent from official sources (Camboim et al., 2015; Kuffer et al., 2018; Mahabir et al., 2018; Souza, 2012). Deprived areas, such as slums, squatters, or informal settlements, often miss key geographic features in commonly available data sources (Hachmann et al., 2018). The missing elements may be settlement size, incomplete boundaries, total population, number, and location of buildings and enterprises (Hachmann et al., 2018; Patel et al., 2012). Initiatives such as Missing Maps (Scholz et al. 2018) and the Muungano wa Wanavijiji non-governmental organization (Lines & Makau, 2018) seek to counter these problems and demonstrate the breadth of existing challenges. The lack of cartographic representation of socially vulnerable settlements furthers their symbolic and physical exclusion. It may present severe challenges for research and policy, may hinder development and access to fundamental civil rights (Patel et al., 2012) negatively influence self- and outside perception of communities (e.g. in political instances)(Corbett & Keller, 2005), and lead to biases against communities (Watson, 2009).

In this context, our research helps level the playing field by increasing data transparency. It provides NGOs, public institutions, international organizations, and researchers with a straightforward way of visualizing irregular settlements' structure and spatial dynamics (e.g. urban expansion) over time. We assume that transparency promotes good governance and fair transactions. When information is not openly available, local elites' incentives for exploitation and opportunistic behaviour increase (e.g. due to control of information such as land market dynamics, regulations, and political clout). Currently, available information about the conditions and dynamics of informal settlements is not sufficient or robust, which politicians and local officials routinely mismanage or exploit (Rodriguez Lopez et al., 2017a).

At the community level, the lack of data commonly means underrepresenting a population, its business, culture, and assets (Corbett & Keller, 2005), increasing the difficulty to access credit, for example. Land tenure is a critical issue, as the lack of tenure rights often stems from outdated or incomplete registries. These issues may stoke conflicts (Hachmann et al., 2018), sapping long-term agency from communities and endanger small-scale businesses and services (Patel et al., 2012). When population or household data are missing, public infrastructure planning often underestimates the demand for services and investment. Public and private interventions also face increased uncertainty. Planning is less precise, procurement and contracting often occur based on broad assumptions, and projects need longer development cycles, as they compensate for inexistent essential information (Pedro et al., 2017; Pedro & Queiroz, 2019). In these cases, the costs for implementing public goods or services increase and public officials often divert resources from the desired results to the initial phases of planning.

From the city management perspective, it is notorious that the lack of information severely hinders urban planning (S. Zhang, 2019). Along with political and economic factors, lack of information and the limited cognition caused by it fuel a *tabula rasa* approach to design. In this approach, urban master plans and spatial projects often circumvent, exclude, or seek to replace informal settlements entirely (Watson, 2009). Strategic policies are frequently ineffective when essential information is missing (Patel et al., 2012), especially when considering the undocumented and dynamic nature of land-use in informal settlements that challenge conventional land-use tools like zoning and cadastral plans (Hachmann et al., 2018). The lack of information may lead to misconceptions, creating myths or partial truths that disrupt public policy effects or make them poorly adapted to the intended population groups (Patel et al., 2012).

The lack of demographic data and GI on informal settlements also has negative public health implications. For instance, coarse spatio-temporal resolutions of health and demographic data challenges the implementation of targeted interventions to prevent or mitigate outbreaks (Elsey et al., 2016; WHO, 2010). In addition, the informal settlements' socioeconomic and spatial characteristics exacerbate the risks of communicable and non-communicable diseases (Corburn et al., 2020; Ezeh et al., 2017). Physical and social factors are key health determinants (Barton & Grant, 2006). In this sense, combining the georeferenced settlement and health data becomes crucial to plan effective interventions (Friesen et al., 2020). Poor health data (e.g. coarse, lacking precision or outdated) significantly challenge planning and implementing such interventions that are critical to tackling urban health inequities.

In this regard, monitoring systems that provide longitudinal data on slums (e.g. NUHDSS in Nairobi, Kenya) play a critical role in health decision-making at the intra-urban scale by providing health data with the appropriate spatio-temporal resolution. Monitoring systems like these can benefit from VGI by integrating local communities' contributions, which may provide critical insights to combat health emergencies like the COVID-19 pandemic, for example. Furthermore, much of the literature focuses on the spatial-time scan (e.g. the nature of the non-linear dynamics), early warning systems (Hohl et al., 2020), or resilience (Scheffer et al., 2001, 2012). At the same time, there is a lack of research addressing changes that affect the structure of social or environmental systems (i.e. irreversible regime shifts). The COVID-19 pandemic presents regime shifts in many areas (e.g. health, social interaction, policy, political debate, among others). VGI could complement existing information and work along other sources of information to represent system states and processes with increased spatial and temporal resolution. These improvements can play a significant role in the coming decades, notably when considering populations often missing from official sources (e.g. the squatters, slum dwellers, and others).

6.1.2 Citizen participation in VGI

This work proposes a description of the broad spectrum of VGI techniques and methods from the perspective of citizen participation, focusing on user agency. This stance emphasizes the 'volunteered' in VGI, which is essential in differentiating this group of techniques from other processes of geographic data acquisition. To this end, we must define user agency in the context of VGI. This chapter defines agency as the capacity to exercise control over one's thought process, motivation, and action. This definition encapsulates the cognitive processes of imagining what one wants to implement, being motivated to do so, and believing in one's capacity to implement it without suffering too steep adverse effects or costs in the process (Bandura, 2001). In the context of VGI, agency translates into understanding GI to the point of identifying oneself as an agent (either a producer or editor of information) and believing in one's capacity to register or to analyse GI with the available means once the motivation to do so exists. The trade-offs involved in this definition of agency in VGI pitch technical capacity (Robinson et al., 2017), on the one side, and motivation to use or create GI on the other (Verplanke et al., 2016).

The recent evolution in GI effectively demonstrates how decreased technical barriers to data production (e.g. Web 2.0 technologies) sparked a flow of interactive production of information, breaking the virtual monopoly of specialists over GI (S. Zhang, 2019) and creating VGI (Goodchild, 2007). In this process, the advent of participatory mapping tools and methods increased users' perceived capacity to create new information by themselves. This capacity increase led to more ambitious goals from users, generating new solutions that further challenged previous restrictions in GI authorship.

VGI is still arguably torn between its contributors' active or passive character (Haklay, 2013; S. Zhang, 2019), despite user agency's importance in its evolution. Passive approaches analyse the digital spatial footprint from research subjects (e.g. geotags from social media) independently from their control (Yan et al., 2020). Intermediate approaches include crowdsourcing efforts (e.g. Missing Maps, Wikimapia, and OSM) that help eliminate gaps in mapping, but whose goals are not the participation per se, but the data generated by it (D. Sui et al., 2013a). Direct subject involvement is the mark of active approaches. Participatory mapping and PPGIS (F. Harvey, 2013; S. Zhang, 2019), such as Slum Dwellers International (SDI) and Mapping Kibera, often feature active approaches. These aspects beg the investigation on the levels of citizen participation in VGI, how they relate to empowerment and the lasting benefits of VGI beyond the data itself.

VGI research seldom measures citizen empowerment, although it is often implicit in VGI campaigns and studies (Corbett et al., 2016). In this sense, it is helpful to make the relations between citizen participation, empowerment, and VGI explicit. According to Sherry Arnstein (1969), citizen participation is a prerequisite for empowerment, as it assumes active citizen engagement in decision-making and community development processes. Following this line of thought, to empower citizens through VGI, there must be methods, tools, and goals accessible to citizens, even non-specialists.

Moreover, as the accessibility of VGI methods increases, they collect to more plural and representative GI. From a technological perspective, though, accessibility can lead to an oversimplification of the available tools, therefore, constraining the use of the resulting GI. To avoid this contradiction, VGI should adapt its tools and processes to maximize citizen participation in the production, interpretation, and use (or reuse) of GI without compromising the quality of the data produced. This improvement may enhance citizen participation and change policy and intervention priorities thanks to more diverse information and better-informed citizens.

We propose to describe the spectrum of VGI between two extremes in user participation: on one side, there are technical capacity and access to resources; on the other, are users' perceived capacity to exercise control over their GI and the motivations behind its production (agency). The following section presents a framework for comparing and evaluating VGI applications based on their ability to be replicated by ordinary citizens – and thus, to effectively foster citizen participation in the production of GI. Arnstein's 'Ladder of citizen participation' (1969) is the inspiration for the framework, as it is a rung-based structure that hierarchically sorts VGI applications in a synthetic index. The latter builds on four assessment categories: 1) user agency in VGI; 2) required material resources to implement mapping; 3) necessary GIS literacy level to achieve results; 4) degree of involvement of research subjects. These four categories encompass criteria shared among most VGI applications and allow comparisons between applications in different contexts.

6.2 METHODS

This section presents the comparison framework for citizen participation in VGI. This framework assesses citizen participation and empowerment in VGI initiatives, providing a novel, multidimensional and hierarchically structured comparison tool. Ultimately, the framework aims to improve VGI research and practice by making explicit the resources (e.g. material, informational, and capacity), the agents (i.e. the users, producers, and subjects of GI), and their involvement (e.g. agency and stages of direct participation) in the VGI processes. This framework innovates by bringing to light critical factors in GI production that are usually subsumed in traditional analysis, revealing the purpose, tools, participation, and empowerment in VGI practices.

Table 6-1 presents the framework and includes 16 criteria. The criteria belong to four categories that describe the tension between technical resources and GIS literacy, on the one hand, and user GI agency and the degree of involvement of research subjects (i.e. people living in the observed area), on the other. Each criterion can receive a value of zero or one, identifying the absence (zero) or presence (one) of that criterion in the case under study. Therefore, each category can receive from zero to four points, which adds up to a total VGI Participation Score (VPS). A high VPS (beyond 9 points, for example) would indicate a significant level of citizen participation in the VGI process Table 6-2). Researchers analysing the VGI practices may assign a point for each criterion as a qualitative appraisal (e.g. expert opinion) of a case under scrutiny.

This qualitative assessment advances on a structured approach to evaluate the processes and practices involved in VGI. By focusing on the process rather than on the resulting data, this framework seeks to distance VGI from a technocratic discourse. Instead, the framework emphasizes the social relevance of GI in the specific context in which it is generated – that is to say, to what extent the process and resulting GI contribute or harm people directly related to that context. The analytical categories in the framework highlight the conditions of the data subjects to participate in VGI processes, the degree to which the processes are proposed or designed to work jointly with the subjects (e.g. high, or low dependency on sophisticated techniques, and knowledge transfer potential). These characteristics allow researchers to understand VGI practices and data in connection to the social context that they describe. Ultimately, the framework seeks to support VGI practitioners and researchers to address more explicitly the purposes and motivations behind data acquisition, utilization, and the degree to which they are accessible and under the control of the subjects described in the data.

Table 6-1. Categories and criteria for the VGI citizen participation score.
The criteria add up to a VGI participation score (VPS), which ranges between 16 (total citizen participation) and 0 (no citizen participation).

Categories	Criteria	Categories	Criteria
User GI agency	Transparency Editing capability Two-way data flow Control over data format and publication	**GIS Literacy**	Specialization Experience Geomatics GIS software
Resources	Software license Data license Mobile hardware Human resources	**Involvement of research subjects**	Data collection Data management Data interpretation Usage and impact of data

VPS scores build a ladder of participation and empowerment in VGI, mirroring the example from Arnstein (1969) in creating a hierarchical evaluation of practices that involve communities and techno-scientific content. In Table 6-2, scores between 0 and 4 fit into the class of non-participation. In this class, there are constraints to citizen participation. User agency is limited or non-existent (e.g. veiled GI collection, absence of derivative uses), required literacy limits the effective use of the application to experts, while the necessary resources curb dissemination or replication by the public (e.g. expensive proprietary software or required coding or geodesy knowledge). Scores between 5 and 8 depict limited participation; they signal that some participation exists but is usually constrained to predetermined options and goals defined independently from data subjects and users. In this class, influence on the agency and goals of VGI still weigh away from the citizens. Scores between 9 and 12 mean significant participation. In this class, users generally have high agency levels, controlling data usage and transparency. Applications may still need resources but do not require specialization (e.g. volunteer engagement, free GIS software, mobile phones as GPS data sources). In this class, research subjects have overall control of the data but are not yet at the helm of the mapping process (e.g.

external parties may set the purpose of data or custody). Scores between 13 and 16 mean citizen empowerment, which supports open participation and replication of methods by any citizen interested in VGI. The top tier means nearly full user agency (e.g. users know, control, and reuse the data as they wish). There are few prerequisites in GIS knowledge, few necessary resources (e.g. user-friendly applications with very low technical literacy, little to no ground-truthing), and direct involvement of research subjects in knowledge production through VGI.

Table 6-2. Evaluation and interpretation of the VGI participation score.

VGI participation score	Interpretation	Examples
13-16	Citizen empowerment	Participation and replication are possible even by the general population. Users have control over data reuse. Little to no resources are prerequisites.
9-12	Significant participation	Overall data controlled by researchers, there may be supervision or mediation by specialists. Non-specialized resources.
5-8	Limited participation	Participation is constrained to predetermined options of agency, technology, and goals. Some specialized resources are necessary.
0-4	Non-participation	Lack of GI knowledge hinders citizen participation, technology, and resources. Users have no control of the results (e.g. veiled GI collection).

In the framework, four criteria describe user agency in GI. The first is the capacity for users to know they generate geographic data that are being collected and reused by others. High-ranking applications will provide transparency and fine-tuned control over geographic data and meta-data collection, while low ranking applications will be opaque or even misleading in presenting their data collection methods. The second criteria are the capacity for users to visualize, share and edit data in the application. Low ranking applications will limit user edits, while high-ranking applications will provide practical tools that are easy to master. Next, data flow should be accessible in both directions, meaning users may input and access information in the application, allowing derivative works. Finally, applications should provide complete data in editable formats, avoiding proprietary or simplified formats that limit derivative works to lower quality than the original input (e.g. image formats, data without geolocation).

GIS literacy stems from specialized knowledge, practical experience with GI, proficiency in geomatics, and proficiency in GIS software packages required to obtain and analyse the data. Indeed, these technical aspects may constitute substantial barriers to applying VGI methods, which often require facilitators between the technology and the public (Robinson et al., 2017). In this sense, the user of high-ranking applications could be a layperson, while the tools would only require a cursory understanding of GI (map reading) and GIS software (visualizing or adding information to non-specialized Earth observation platforms). Conversely, in low-ranking applications, the user would need specialized knowledge, and tools would require good cartographic skills and knowledge of geodesy, GIS software, and, if applicable, spatial statistics.

Resources in VGI applications refer to access to software licenses, complete and timely support data (e.g. Earth observation imagery), mobile hardware (e.g. portable GPS devices), and the level of dependence on human resources (either specialized or not) to achieve the necessary results. The costs for licensed software and hardware and volunteers' availability can be highly restrictive to implementing VGI methods (Reynard, 2018). On this basis, high-ranking applications would only rely on free software and openly accessible data without the need for on-site data validation or intensive use of human resources. Conversely, low-ranking applications rely on licensed software and data, on-site data collection, and specialized hardware.

Finally, the research subjects' level of involvement in collecting, interpreting, and using geodata is determinant to distinguish different data collection methods (Verplanke et al., 2016). Indeed, the control of research subjects over data is particularly relevant when GI supports social integration through citizen empowerment (Corbett & Keller, 2005). In this sense, high-ranking applications would present active research subjects' involvement in geodata collection, management, and interpretation, notably towards the subjects' goals and motivations. Conversely, low ranking applications could exclude the research subjects or implement data interpretation and use without the subjects' knowledge or control.

6.3 RESULTS

Using the framework of citizen participation in VGI, we compared two VGI projects, which mapped informal settlements in Latin America (Table 6-3). In the first case, researchers from the University of Hamburg (Germany) combine human and remote sensing data in a hot spot analysis framework to map informal settlements on Mexico City's fringes. In the second case, the NGO Teto uses a participatory GIS approach to map communities in São Paulo. Both projects aim to fill the gap of authoritative geographic data on informal settlements, resulting in similar outputs, albeit through different methods and with differing purposes. In the São Paulo project, volunteers produced VGI with the communities' consent using a participatory approach. This effort aimed to foster local changes to improve the living conditions in selected informal settlements. The Mexico City project brings two data sources together: VGI and remote sensing data to develop hot spot maps that explicitly aim to conflict between nature preservation and urgent housing needs.

Table 6-3. Comparison of two VGI projects in informal settlements in Latin America.
Teto uses a participatory GIS approach to map communities in São Paulo (left). Researchers from the University of Hamburg (Germany, right) combine human and remote sensing to map informal settlements in Mexico City.

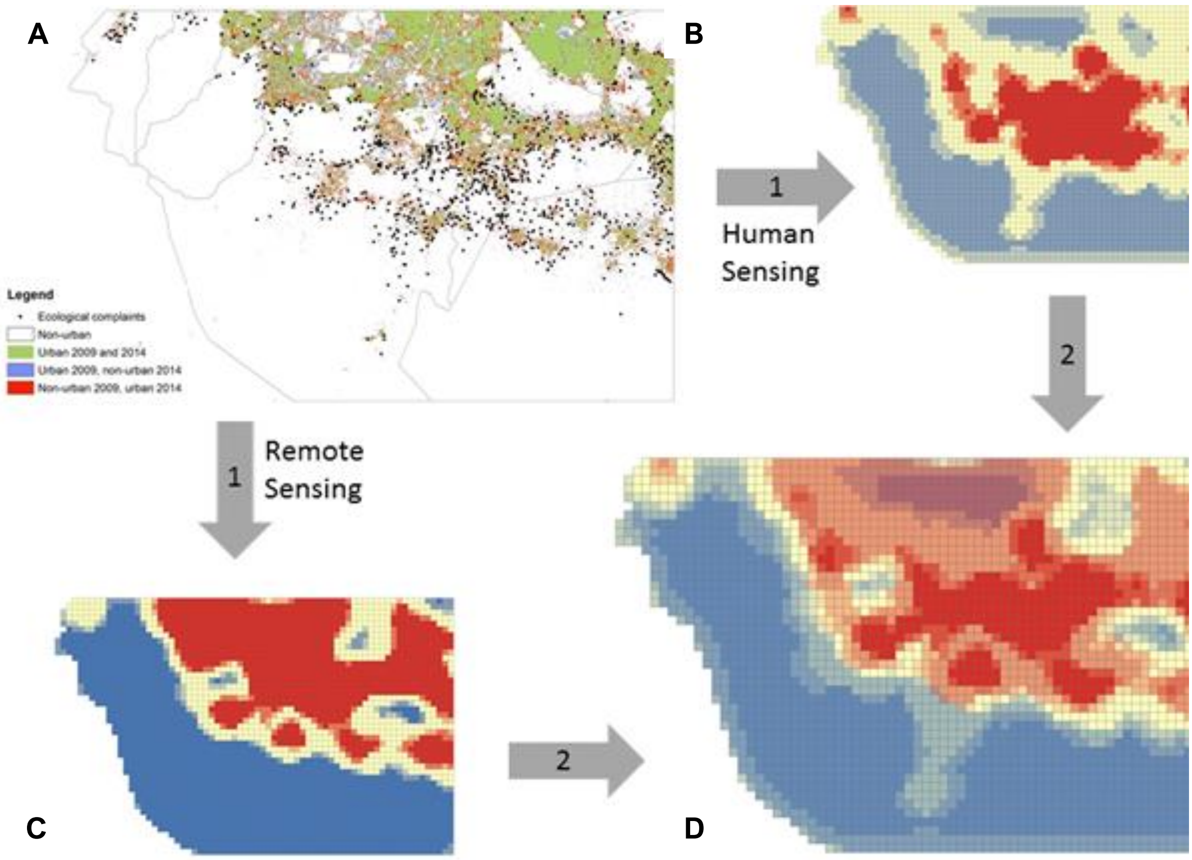
VGI aspect	São Paulo case	Mexico City case
Volunteer workforce (data agents)	Volunteers of the NGO Teto: mainly college students and professionals (usually studying or working in architecture, engineering, geography, and urban planning).	Locals file a complaint at the *Procuraduria Ambiental y del Ordenamiento Territorial del Distrito Federal* (PAOT). VGI comes from PAOT (September 3, 2015), and the researchers further analysed it.
Other sources of data (not volunteered)	Raster data: Georeferenced orthomosaic generated from drone images (online GeoTIFF imported in QGIS) / Georeferenced VHR satellite imagery openly available online. When available, polygon information on topography, hazards, and other themes.	Raster data: Researchers obtained RapidEye satellite imagery (from the German Aerospace Centre) through the German Federal Ministry of Economy and Energy funding. Vector and demographic data from Mexico's National Census 2010 (INEGI 2010), vector data of road systems from OpenStreetMap (OSM 2015)
Data proprietors	Satellite imagery distributed by Google. Drone imagery and resulting maps jointly owned by Teto and the communities where the surveys take place	RapidEye data from the German Aerospace Center. Ecological complaints from PAOT and 2010 census data from Mexico's National Census Bureau (INEGI 2010), both distributed under open access.
Input data	Raster data: Georeferenced orthomosaic generated from drone images (GeoTIFF imported in QGIS) / Georeferenced VHR satellite imagery (dynamic XML or URL layer imported in QGIS).	Raster data: RapidEye satellite images, vector data: ecological complaints (PAOT), demographic data (INEGI 2010), road systems (OpenStreetMap 2015)
Site visits required	*In situ* work is required	*In situ* work is not required
Data resolution / accuracy	Very high resolution (<1m)	High-resolution satellite imagery (5m, input)
Tools	QGIS (free, open software)	ArcGIS (commercial software)
Targeted audience/ application	Project designers and advocates in Teto and community members	Government, NGOs, and researchers
Purpose of VGI	To collect settlement data for Teto's development/advocacy projects	To bring to light a conflict between nature preservation and housing needs
Output data	More accurate geographic information: filling gaps in existing (authoritative) sources, increased resolution, updated information	More accurate geographic information: filling gaps in existing (authoritative) sources, increased resolution, updated information

6.3.1 Research in Mexico: human and remote sensing perspective

Mexico City's rural-urban area lies in the Federal District's southern part. The city depends on water sources outside the urban area (e.g. the Magdalena River south of Mexico City). Land management is especially sensitive in the so-called ‘preservation zone’, where informal expansion may contaminate the water supply (Jujnovsky et al., 2012). The mapping process aimed at creating more transparency in the conflict between nature conservation and housing demand in an unequal society. When conflicts are visible, society can dialogue to develop solutions. Societal dialogue is a critical response to unequal development dynamics (D. Harvey, 2006) especially those that present conflicts between vulnerable groups and common social goods.

In this case, the data agents are local citizens and researchers. Any resident from Mexico City may file environmental complaints voluntarily in person with the 'Procuraduria Ambiental y del Ordenamiento Territorial del Distrito Federal' (PAOT), through the phone, or electronically (e.g. via email or on PAOT's website). Complaints include animal abuse, water misuse, noise, or irregular settlement in the preservation areas, among others. Each complaint generates a record in a database that includes descriptive fields and the geographic coordinates and address of the problem. The researchers included complaints filed between 2002 and 2013 in their analysis, representing the 'human sensing' data (i.e. people generating geographic information)(Rodriguez Lopez et al., 2017a).

Figure 6-1. A graphic summary of the hot spot analysis of VGI and remote sensing data in Mexico City and their combination.
(A) area of interest; (B) the human sensing hot spots; (C) the remote sensing hot spots; and (d) the combined hot spots (human and remotely sensed). Red cells represent hot spots (high concentration of complaints or identified urbanization); blue cells represent cold spots (low concentration of complaints or identified urbanization). The confidence range of the hot spots analysis was 90-99%, source: Rodriguez Lopez et al. (2017a).



The research team then combined the 'human sensed' data with high-resolution satellite imagery (5 m) from the RapidEye satellites. The German Federal Ministry of Economy and Energy funded the RapidEye satellite imagery for that research project (Rodriguez Lopez et al., 2017a). The researchers classified these data in two land cover classes, urban and non-urban, for 2009 and 2014. Further change-detection analysis described the urban expansion (i.e. the difference in urban area between 2009 and 2014) in and around nature preservation areas. The study then quantified urban growth in the protected areas, detecting and highlighting the hot spots of this dynamic (i.e. areas in which there was an intense concentration of urbanization). The Getis-Ord Gi* statistic detected the hot spots and provided increased precision for research and policy about the ongoing environmental and social conflict. Finally, the analysis integrated the OpenStreetMap road system (as another VGI source) with census data to assess socioeconomic conditions and the drivers of peri-urbanization (Heider et al., 2018; Rodriguez Lopez et al., 2017a). The analysis output (Figure 6-1) included the combined hot spots derived from human and remote sensing in a grid of polygons with a spatial resolution of 561 m. The authors published the data, results, and further methodological details under open access (Rodriguez Lopez et al., 2017b).

The goal of this research was twofold: first, to increase transparency by providing new data to the academic and policy development publics on the dynamic. This transparency opens the debate beyond local power brokers (e.g. local legislators and public officials involved in land grabbing) and provides evidence to local advocacy groups such as housing rights or environmental NGOs. Second, the research aimed at shining a light on trade-offs between housing rights and environmental protection policies in an unequal development setting. Within this context, the most vulnerable will suffer from the enforcement of regulations (e.g. expulsion from informal settlements in preservation areas). At the same time, the root causes remain untouched (e.g. lack of land-market regulation or inefficient housing policies), reproducing prejudices in regulatory instances and keeping encroachment-exclusion cycles in place (Zérah, 2007). This research followed an ongoing investigation that included Mexican academics who constantly dialogued with local authorities (Rodriguez Lopez et al., 2015). With its results, this dialogue can better address the preservation-housing conflict and provide a more level playing field, exposing bias in information (e.g. complaints are more frequent in affluent areas) that stem from the inequality of the social process itself.

6.3.2 Research in São Paulo: participatory GIS

Since 2014, Teto has conducted community assessment activities in different informal settlements located in peripheral areas of São Paulo. These activities take place with the community's informed consent and include surveys that combine mapping campaigns and the collection of georeferenced household data to analyse the communities' demographic, socioeconomic, and spatial characteristics. The NGO and the communities use these data to support slum-upgrading projects such as constructing emergency shelters or improving shared open spaces. This process includes a round of discussions on the possible collaborations with the Teto that result in a joint agreement regarding the scope of Teto's participation and the necessity of conducting spatial and socioeconomic surveys.

Teto's community assessments rely on high-resolution spatial data collected through VGI. The mapping process results in detailed community maps locating the settlement extent and identifying significant features that include each building's footprint and use (e.g. residential or community facility) and primary road access. Data also indicates household locations, basic socioeconomic data (e.g. household members and housing conditions), and household-specific demands for infrastructure (e.g. need for more streetlights or better road access). Teto, its volunteers, and the community collaborate in these activities, and the resulting data supports projects and advocacy initiatives co-developed by the community and Teto.

Teto's volunteers are university students or recent graduates (often from Architecture and Urbanism) engaged in enhancing living conditions in informal settlements, come from other city regions, and are generally much less vulnerable than the informal settlements' population. The volunteers provide technical expertise for the mapping effort, given their university training, even if they are not GI experts. Currently, this is a workaround for the lack of technical literacy in the communities, which are often some of the most vulnerable in São Paulo. The downside of this workaround is that community dwellers rarely participate in the vector data (i.e. point, line, and polygon data, commonly collected with GPS or similar devices) collection process, although their knowledge registers as GI through the interaction with the volunteers and surveys. Community dwellers also join the data validation and interpretation processes, as explained further below.

Figure 6-2. Teto's mapping process, step-by-step
(1) acquiring drone or satellite imagery; (2) digitizing building footprints, with on-site verifications using Google My Maps; (3) validating GI data to obtain geographic information that may support upgrading projects. Elaborated by the authors, based on Google Earth (2018) and Pessoa Colombo (2019).

Vector mapping campaigns have a fixed timeframe, usually lasting eight weekends. Groups of four to six volunteers divide the work in each campaign, with each volunteer covering between 1.5 and 2 ha, depending on the settlement's complexity; hence, the number of available volunteers limits the process. Based on the aerial imagery, the volunteers first manually digitize each building's perimeter in QGIS (a free and open-source GIS software), considering each roof to correspond to one building (step 1 in Figure 6-2). Teto prefers freely accessible satellite imagery, as its combination with accessible software enhances the replicability of the method. In some cases, private partners (e.g. DroneDeploy and Ponto360) provided higher-resolution drone aerial imagery. Then, the volunteers check the accuracy of the digitized built environment on-site (step 2 in Figure 6-2). Satellite imagery may be outdated or lack resolution; therefore, on-site verification is essential in informal settlements. The Google My Maps platform (which is free but not open) allows the visualization of the digitized building footprints on mobile phones, facilitating on-site verifications. Finally, the surveys collect land use, infrastructure, and demand information (step 3 in Figure 6-2). Volunteers then georeferenced the tabular information from the survey into the centroids of the building outlines. This workflow requires each volunteer to use a smartphone and at least one computer per mapping campaign to digitize the final map. In addition, a reasonably good Internet connection is necessary.

At the end of each mapping campaign, Teto and community leaders organise focus groups that validate and interpret the collected data through a horizontal dialogue with the community (Santos Melo et al., 2021). Community leaders use printed maps to situate geographically specific demands. This way, they turn geographic data into information, which they use to plan future interventions. They use large, printed maps (e.g. in ISO A0 format) in these discussions that allow more spontaneous annotations (Figure 6-3). Such discussions based on printed materials are crucial to overcoming technological and material barriers to participation in geographic information. In this way, local knowledge enhances geographic data. This process also allows the co-development of community projects between the NGO and the inhabitants.

The cartographic outputs consist of two features generated in QGIS: a polygon feature containing the buildings' footprints and a point feature indicating the households' locations and non-residential structures. Teto usually manages those datasets, but community leaders can also manage them independently and locally when capacity (e.g. hardware, software, literacy) is available. However, most of the data restitution to communities is through printouts, in the form of reports illustrated by graphs and maps. Therefore, the outputs are high-resolution geo-datasets combining descriptive data of socioeconomic and environmental aspects of the community. Teto uses the outputs to support slum-upgrading projects, as they allow identifying the most vulnerable areas that require more urgent interventions. The type of interventions varies, but the most common are new single-family housing units (replacing shacks with new structures), improved accessibility (e.g. stairs, bridges) and community facilities. In collaboration with the community, Teto then plans and designs all interventions, including the election of beneficiaries in the case of housing projects.

Figure 6-3. Focus group co-organized by Teto and local community leaders to enhance geographic information.
Source: Teto.

6.3.3 Comparison under the VGI participation framework

This section presents the VGI participation scores for the two cases under analysis. We evaluate whether these VGI initiatives attain citizen empowerment or significant participation (at the higher tiers of the VPS score) or are limited in participation or non-participatory at all (at the lower levels of the scale). For this analysis, we start by considering user GI agency and then observe the required GIS literacy, the required resources and finally, the degree of involvement of the research subjects in producing and managing the GI.

Overall, the results show the contrast between the two cases. When comparing VGI participation scores, the Mexico City case attained five out of 16 possible points, representing limited participation. Teto's mapping process in São Paulo shows significant participation with a total VPS of 10 points. Below, we present the assessment of each case under the VPS comparison framework (Table 6-4).

Table 6-4. VGI participation score results.

Criteria	Case 1: São Paulo	Case 2: Mexico
GI Agency	**4**	**2**
transparency of data usage	1	1
possibility of data editing	1	0
two-way data flow or exchange	1	0
format of data communication or publication	1	1
Tech Literacy	**1**	**0**
no formal specialization in GI science	1	0
no practical experience with GI	0	0
no proficiency in geomatics	0	0
no proficiency in GIS software	0	0
Required Resources	**2**	**2**
no licensed GIS software	1	0
no licensed data	1	0
no mobile/external hardware (GPS or drone)	0	1
no intense human resources	0	1
Involvement of Research Subjects	**3**	**1**
data collection is done by or with research subjects (RS)	0	0
data management is done by or with RS	1	0
data interpretation by RS	1	0
data aims to foster local changes (physical or social)	1	1
Total score	**10**	**5**

The case study in Mexico comprises data acquisition from locals, georeferencing by the planning authority, and hot spot analysis by an independent research team. This case scores two out of four points in the GIS Agency category. Residents in Mexico City (who may not live in the informal settlements) produce the data through complaints filed over multiple media (e.g. phone, email) and inform a geographic location. From that point on, PAOT manages the case with no further user input. In this sense, the data producers have spatial knowledge about the fact but have no data editing or exchange possibilities. However, the researchers published the project's data (including the complaints and results) under open access (Creative Commons License, by attribution – CC BY) to enable dissemination in academia (Rodriguez Lopez et al., 2017b). Open access to the PAOT's database breaks the barriers around the information on these conflicts. The Mexico case scores no points in the tech literacy category because replicating the process, especially the hot spot analysis, requires specialized knowledge in GIS and geomatics. The case meets two criteria in the 'required resources' category because the research team used licensed software and remote sensing data for hotspot mapping, limiting participation. However, neither GPS, drone imagery, nor fieldwork was required, widening participation possibilities.

The involvement of research subjects is particularly complex in the Mexico case. In our appraisal, the Mexico case scores only one point because only part of the research subjects is involved in data collection and under conflictive circumstances with other residents. The locals do not manage or interpret data, the other criteria in the framework (see Table 6-1). PAOT collected the complaint data, and it was not available to citizens as aggregate information, which in turn creates a conflict in information as PAOT might use the data to foster physical or social changes independently from the goals of all inhabitants in the area. Furthermore, the locals who file the complaints may do it motivated by protecting the preservation area (which is a common good) but against the housing need of those in the informal settlements in the region. The opening of the data potentially allows more groups to see this conflict, even if limited to an academic audience. The open data, combined with the analysis of the conflict, can foster debated social action. They are, nonetheless, independent from the research subjects and do not contribute to this score.

In summary, the hot spot mapping project in Mexico City reached limited participation with a score of 5 out of 16 due to the high level of tech literacy required for the analyses, costly resources (software and data), and the lack of research subjects' involvement. However, transparency of data usage and availability in open access publications enable a medium ranking in GI agency.

The case study in São Paulo scores four out of four points in the GIS Agency category. Both data producers and users are fully aware and have control of GI's collection, management, and publishing. The research subjects also enforce their interests and data privacy concerns, controlling the shared GI content. In terms of tech literacy, the case study scores only one point. Neither data users nor data producers need any formal specialization, but previous experience with GI dramatically facilitates the work. In this sense, Teto's volunteers act as VGI facilitators, building the bridge between the community and the use of geographic information tools and methods. Regarding material resources, the São Paulo case meets two criteria: the data and software are freely accessible, but the method demands on-site verification, which requires mobile hardware for geolocation and generates transportation costs. Besides, human resources affect the geographic extent of the output.

Regarding the involvement of research subjects, São Paulo's case merits three points. While Teto's volunteers collected part of the data without the active contribution from research subjects (community dwellers), the latter oversaw the process and maintained control over data retrieval, reproduction, or deletion at any time. At the end of each mapping campaign, the community validates the data and employs it to support its projects. The digital data are stored and managed by Teto, but data are also shared with community leaders or organizations when capacity is available (e.g. personal computers).

The São Paulo project achieves significant participation thanks to community involvement. The participatory approach is visible in the maximum rating of four in GI agency and three out of four in the involvement of research subjects. However, tech literacy for professional remote sensing and the required fieldwork resources were still high within the mapping process, leading to one and two points in these categories, respectively. The total VPS is 10 out of a possible 16, highlighting gains in agency and research subjects' involvement. The participatory approach shows compromises with the technical and resource requirements for working in GI, especially when little to no preliminary data are available.

6.4 DISCUSSION

This chapter asked how different VGI approaches support citizen participation and user empowerment and what are the opportunities and limitations of VGI in mapping informal settlements in Latin America beyond authoritative data sources. Considering the first question, we argue that, despite its qualities, VGI also presents potential issues to informal communities, notably regarding privacy (Elwood, 2010; Sharma, 2019) ownership over information (Hachmann et al., 2018; S. Zhang, 2019), and changes in political power (Corbett & Keller, 2005). Due to privacy and political power concerns, this framework makes explicit the resources and agents in the VGI processes. It decouples the relationship between data producer and data subject, revealing inherent potential conflict and cooperation. Therefore, it provides critical insights in VGI beyond data quality by potentially illuminating conflicts, considering processes (rather than the products) and their societal implications. It brings light to critical factors in GI production that are usually subsumed in traditional analysis, highlighting purpose and tools and the participation and empowerment of the agents involved in VGI.

From this perspective, the framework contrasts the case studies to reveal the importance of control over information by those represented in it. In Mexico City, observation from distant and anonymous complaints separates the data producers from its subjects. In addition, although the research team published their work in an open-access journal, their findings are hardly accessible for the informal settlement dwellers and more likely to remain inside academia. In São Paulo, users have veto powers over information dissemination. The decoupling this framework provides expands previous research, in which crowdsourced methods (also called passive or contributed) and participatory (named active or volunteered) approaches are often at odds (F. Harvey, 2013; S. Zhang, 2019). At the same time, the technological compromises in the São Paulo case (e.g. the necessary facilitation from the NGO staff) widen the discussion on the empowerment potential from VGI. By keeping the mapping outputs aligned with the communities' interests, this approach preserves a critical aspect of agency, where external resources collaborate to produce VGI, even if community members seldom collect vector data themselves (Hachmann et al., 2018).

Considering empowerment (Cochrane & Corbett, 2018; Corbett & Keller, 2005), the low VPS scores of the Mexico case in the agency and the research subjects' involvement detect a potential decrease in the community's socio-political power. This detection demonstrates the capacity of the framework to assess these dimensions. This decrease in power stems from a conflict of interests in which the interest of data producers (i.e. locals who complain about informal settlements) is opposed to the interest of research subjects (i.e. locals who live in informal settlements). The framework exposes this contradiction, as it makes the agents and subjects of VGI explicit. This disclosure is a noticeable advance from previous research, which often omits the data subjects. VGI practices that inform and provide control to the data subjects over the GI about them provide more empowerment in this sense. These features are present in the São Paulo case, where collaborative and participatory

VGI initiatives provide local inhabitants with control over the GI about their settlements. This increased control creates new political representation capacity (e.g. on advocacy for land tenure rights) and supports more precise settlement improvement plans (e.g. housing, infrastructure).

The second research question examined the potential and limitations of VGI to provide information for research and policy development in informal settlements. Our results show that VGI can offer unedited GI on informal settlements at varying spatio-temporal resolutions, in line with previous research (Beukes & Mitlin, 2014; Bolay et al., 2016; Hachmann et al., 2018; Lines & Makau, 2018). VGI provided the location and quantity of land cover changes over a large region in Mexico. Considering the undocumented and dynamic nature of land-use in peri-urban informal settlements, volunteered sources of GI such as the PAOT are valuable complements to conventional ones. For instance, PAOT provided timely information on environmental changes in peri-urban settlements that would otherwise remain invisible to authorities. In São Paulo's case, VGI covered a much smaller extent but at a more detailed spatial resolution. This in-depth mapping allowed tracing building footprints, a piece of information that is often non-existent for informal settlements but vital for slum upgrading projects (Hachmann et al., 2018).

Even in relatively affluent cities like Mexico and São Paulo, data on the built environment and dwellings in informal settlements are approximate and, at times, inconsistent. This lack of precision and completeness leads to sub-informed decision-making (Pedro et al., 2017; Pedro & Queiroz, 2019), which is especially harmful to spatial interventions (Hachmann et al. 2018), risk management (Goodchild & Glennon, 2010) and health policy (Corburn et al., 2020; Elsey et al., 2016). VGI can arguably foster synergistic opportunities and prevent unnecessary problems during interventions in these areas by providing locally sourced, updated, and fine-scale data. Despite the lack of focus of the framework on data quality assessment, it still provides a relevant contribution to the methods available for mapping, analysing, and understanding informal settlements (Kuffer et al., 2016, 2018), especially from the community perspective or at the local scale (Hachmann et al., 2018; Williams et al., 2019).

Although VGI can provide data on informal settlements with high spatial and temporal resolutions, it presents limitations. From a scientific perspective, limitations in the replicability of methods and reproducibility of results challenge VGI-related research in general. Especially when VGI initiatives employ participatory practices, the solutions tend to be context-specific, as in São Paulo. Crowdsourced methods, with lessened empowerment, provide massive, at-a-distance data collection but are easily biased and may contradict the interests of those represented in the data, as we show in Mexico City. The lack of access to input volunteered data (sometimes inevitable due to ethical considerations) often hampers reproducibility. The replicability of methods is susceptible to the evolution of VGI sources and data formats (Ostermann & Granell, 2017). In Mexico and São Paulo's cases, both VGI datasets contain personal data of some kind and demand editing before sharing, limiting the reproducibility of results.

Regarding replicability, both cases relied on tools and methods discussed in previous publications (Colombo et al., 2019; Rodriguez Lopez et al., 2017a) and are highly replicable. Nevertheless, their replicability relies on moderate-to-high levels of tech-literacy and material resources, limiting their reach into lay audiences from a practical perspective, as the framework exposes. This problem reflects very different approaches regarding the public's active involvement in knowledge production within the VGI spectrum (Hachmann et al., 2018; S. Zhang, 2019), which the framework brings to light and helps discuss. This problem is central in contexts where GI is supposed to promote the empowerment of marginalized communities. This centrality is true for informal settlements but is a general problem of society's relationship with technology in unequal development conditions. The active participation of citizens in the production of VGI and the transfer of knowledge and GI tools, therefore, remain critical aspects for VGI research (Corbett & Keller, 2005).

6.5 CONCLUSIONS

This chapter provided a comparison framework highlighting the 'volunteered' side of VGI. This framework revealed user agency and citizen participation as critical aspects in GI acquisition, management, and dissemination. Even though much of the literature assumes an intrinsic association between VGI, participation, and empowerment, we observed far more complexity in this relationship than previously thought. The framework made a clear distinction between passive and active participation in VGI. Specific forms of VGI may not include participation from those mapped (i.e. the research subjects) and may even be at odds with their interests, as shown in Mexico.

The framework also showed the implications of differences in the participation intensity and the data contributors' composition. Differences among the authors and subjects of data may feed specific biases into the resulting GI. These biases are present in VGI and authoritative sources, albeit for divergent reasons, but often result in the under- or derogatory representation of vulnerable populations. This framework provided tools to assess the GI acquisition processes, considering these biases and the restrictions vulnerable populations face to access methods and tools to produce information. To do so, this framework differentiated VGI practices along with their agency levels, considering the data producers, on the one hand, and data subjects, on the other. This differentiation aimed at increasing the precision with which research and policy understand and use VGI as a resource to achieve 'people-truthing.' The framework provided increased precision to this aim, indicating that VGI practices ranking high in VPS may work as a grass-roots data validation. A critical reflection was that VGI projects geared at vulnerable populations need facilitators to overcome the existing technological barriers to participation (e.g. expertise and resources). More research could foster collaboration in the data collection stage of VGI, which currently depends on relatively sophisticated geospatial technologies.

We must also recognize the many limitations of this framework despite its potential relevance. First, this framework did not integrate traditional data quality assessment practices (e.g.

completeness and accuracy), limiting its comparison to a qualitative measure. Second, other limitations arise from analysing only two cases, which are far from exemplifying the whole spectrum of VGI. Even if these cases provided evidence for the framework's initial design, more examples would refine the methodology and possibly lead to adjustments in the score (e.g. weights for each criterion). Third, the cases did not stem from a comparative research design. A more systematic and structured set of cases could provide increased precision and critical insights. Given these shortcomings, further research should include more systematic comparisons that vary across a more comprehensive set of case studies. Research would profit from regional diversity, including variations in socio-political systems, data landscapes, and participatory traditions.

This chapter highlighted some of the significant limitations to research and policy and revealed an overall lack of timely, complete, and precise GI on informal settlements. We propose that VGI will play a central role in filling these gaps, given the importance of informal settlements for future development, the multiplicity of actors involved, and the necessity for self-reliance and determination in these communities. Therefore, further research should encompass an information environment that integrates authoritative, open, and volunteered sources of information to the top of their potential. This approach means moving VGI beyond the physical description of the environment into other dimensions of geographic information where local participation is critical, notably on land-use conflicts (as seen in Mexico City), slum-upgrade projects (as shown in the São Paulo case) and even public health.

Informal settlements face extreme social vulnerability and exposure to risks that their own socioeconomic and spatial characteristics increase. Because VGI allows obtaining updated, longitudinal information on populations, it can provide timely and precise data to support spatio-temporal analyses on health emergencies. In health research, VGI can also foster community empowerment by shifting priorities towards marginalized populations' unmet needs. In this direction, our future research efforts will focus: The COVID-19 pandemic exposed spatial and social vulnerabilities that are yet unaddressed by VGI research. We aim to address these problems with open, authoritative, and volunteered information sources that together provide timely and fine-scale data on vulnerability, impact, and social behaviour in the pandemic context. We expect future research will provide GI science with an integrated approach to identifying spatial and temporal tipping points. This contribution will help decrease uncertainty in decision-making against present and future public health emergencies when considering the specific social and spatio-temporal features of cities in the Global South.

7 SYNTHESIS

This chapter presents two sections. The first section includes a summary of the original research contributions in this dissertation. The second discusses and evaluates these contributions and provides overarching conclusions relevant to geography, academic research and society.

7.1 SUMMARY

Vulnerability and urban development are interdependent in the Anthropocene. Cities demonstrate the intensity of humanity's alterations to the global biophysical environment (McPhearson et al., 2016). They are also large-scale artefacts (Portugali, 1996) constructed to fit our needs and provide room for increased social interaction (Bettencourt & West, 2010). The multiple stressors cities face in the Anthropocene thus engage urban systems in their social, technological and environmental aspects (Alberti et al., 2018), generating impacts, demanding resilience and leading to adaptation strategies (Elmqvist et al., 2021; Henrique & Tschakert, 2021). To define these strategies, it is central to understand the role that urban inequality and vulnerability play in distributing losses and damage from climate and health impacts (Adger, 2006; Levin et al., 2022; Pelling, 2003; Watts et al., 2021). This significance is heightened when one considers the need for global sustainable development (UN-Habitat, 2016) and environmental justice (Cutter, 1995).

The unequal distribution of climate and health risks in cities in the Anthropocene challenges research to understand the interconnections between social and physical processes in cities. This dissertation assumed that vulnerable population groups tended to suffer more from environmental (Pelling, 2003; Revi et al., 2015) and health crises (Levin et al., 2022; Watts et al., 2021), potentially leading to entrapment in vulnerability-poverty cycles (Cinner et al., 2018; De Koning & Filatova, 2020; Pelling, 2003). Based on these assumptions, we asked how hazards interact with the unequal features of urban development in the Global South, considering the nexus between urbanisation and risk exposure. To respond to this question, we designed an analytical framework based on socio-environmental interaction. This framework sought to describe the interconnections between the multiple social and environmental stressors affecting urban systems in the Anthropocene and to assess the contribution of urban inequality in fomenting vulnerability to these stressors, namely, those from climate change and the COVID-19 pandemic.

The first contribution of this dissertation investigates the relationship between inequality, risk perception and risk response capacity. Informal settlements in urban deltas from the Global South exemplify the chain of deprivations that create an unequal distribution of risks in cities in the Anthropocene. To evaluate this unequal attribution, we look towards the Jacuí River Delta, where the unequal urban development processes of Porto Alegre (Brazil) presented low-income families with a difficult choice: They could either access jobs and urban services by settling in central but exposed locations or face segregation and isolation at the city's peripheries. Those families that chose to locate in central areas invested their efforts in developing (socially and economically) landscapes exposed to flooding. High-intensity floods, exacerbated by climate change, interrupt this development and push them into poverty. By examining the risk responses of 1,451 households located in two landscapes of risk in the delta (one within a flood protection system and another outside it), this research sought to understand the factors that conditioned risk responses against a significant flood event in 2015. I implemented logit regression models and hot spot analysis that demonstrated a limited influence from risk perception, surprisingly. A sense of resignation against losses explains this apparent contradiction. Family wealth emerged with a double role: income defined which families could afford to locate in safer locations, while it also improved response capacity. This means that, among the most vulnerable, limited response capacity and poor location quality co-depended on income. This mutual reliance on wealth signals a self-reinforcing relationship between vulnerability and poverty that traps citizens in vulnerable conditions. These findings are central to adaptation policies and environmental justice, especially since Brazil lacks comprehensive and detailed adaptation measures for cities and informal settlements.

The second contribution in this research expanded the analysis to the topic of COVID-19. I sought a geographic approach to the health crisis, investigating how socioeconomic deprivation is associated with vulnerability. This approach went beyond epidemiological research that flooded the literature with virus spread metrics, models and case-fatality calculations. It is innovative by examining long-term social vulnerability factors (e.g. longevity, income, work and human capital) against COVID-19 survival probabilities. We selected a sample of five cities in different regions of Brazil and estimated the survival probabilities according to the SVI using health research methods (e.g. the Kaplan-Meier estimator and the Cox proportional hazard model). The results indicated consistent associations between social factors and COVID-19 fatalities, as more vulnerable cities presented lower survival probabilities across the period. These results challenged research and policy focusing solely on medical interventions (e.g. hospital treatment), highlighting the importance of promoting multidimensional health and reducing structural vulnerability to prevent excess deaths from health emergencies in the long term.

Next, we investigated the role of mobility behaviour. Since structural vulnerability does not explain all the variability in COVID-19 fatalities, research must consider interpersonal contact. At the intra-urban scale, it is a crucial driver of exposure and without contagion, there are no grounds for vulnerability. Therefore, by analysing decision making in mobility behaviour, researchers may learn what drives high-exposure behaviour, especially when considering individuals' demographic characteristics and priorities. Chapter 4 used an agent-based model to present a simulation of heterogeneous agents making decisions to increase their well-being (e.g. shop or work) and to avoid exposure. The results showed an emergent segregation pattern between travel modes and locations. On the one hand, when agents could afford individual transportation modes (e.g. cars or ride-hailing apps), they opted to avoid interpersonal contact. On the other hand, those agents that could not afford private transportation took high-exposure modes (e.g. buses) as they needed to work, shop or attend education. This segregation signalled a new dimension of inequality, highlighting the role of socioeconomic status (and income) in mobility choice and response capacity. It innovates by demonstrating that income may also define risky behaviour, hence coupling high exposure and low coping capacity.

One common element between COVID-19 and climate change crises is vulnerability. Notably, the structural elements of vulnerability (e.g. access to income, livelihoods, education and fixed and mobile assets) often coincide. Chapter 5 uses a mixed-method approach and combines qualitative and quantitative methods to depict the connections between urbanisation and risk exposure in the Global South. The qualitative methods provided a rich description of two diverging experiences during the pandemic: one experience came from the well-located and low-vulnerability central region of São Paulo and another from the remote and high-vulnerability region of the outer periphery of the city. Quantitative methods then identified high vulnerability concentrations and analysed survival probabilities across these regions. The results from both qualitative and quantitative methods coincided by pointing at structural vulnerability as a driver of the more intense impacts of the pandemic. Among the least vulnerable, a narrative of 'a crisis is an opportunity' emerged as people improved their lives, adopted healthier habits (e.g. active mobility like walking or cycling) and received promotions at work. Among the most vulnerable, the experience was one of deprivation of the most fundamental rights (including access to food and medication) and restricted mobility from financial constraints and threatened livelihoods. Some conflict also ensued in the evidence, as the structural vulnerability influence could not be traced at fine scales (e.g. the district level) but was consistent in more aggregate intra-urban and concentric regions. As the central regions presented fewer deaths and a greater survival probability, there was an alignment with the qualitative evidence. This conflict pointed to further research, notably behavioural aspects (possibly extending those of Chapter 4), comorbidities and personal social determinants of health (e.g. gender and age).

Finally, the sixth chapter reflects on geography itself. When working with vulnerable populations, research can be unsettling and can even lead to unintended damage (e.g. by exposing research subjects to scrutiny outside their control and agency). Since geographic information is the basis for research in the field, researchers must be mindful of the societal implications of their investigations. With these problems in mind, that chapter examined the volunteered data acquisition methods used in informal settlements in Mexico City and São

Paulo. It presented a qualitative analysis framework with the objectives of assessing citizen empowerment in different VGI practices and verifying the potential of VGI to provide much-needed data on informal, low-income settlements in the Global South. By decoupling the data producers from the data subjects, the contribution exposed potential conflicts in their objectives that could lead to greater vulnerability for disenfranchised citizens. This should be a fundamental concern for research in geography, stressing its political power and potential interference from academic work in local social structures. Research can effectively lead to benefits that are circumscribed to academic practice but impose unintended damage to the local community (e.g. by divulging the location of tenure-insecure communities that may be expelled or pressured into resettlement). Our analysis also indicates that participatory practices have greater chances of preserving the data subjects' agency, hence minimizing potential damage and increasing empowerment through knowledge transfer.

7.2 CONCLUSIONS

This research enquired how hazards interact with the unequal features of urban development in the Global South, considering a nexus between urbanisation and risk exposure. The interdisciplinary mixed methods approach presented in its five original contributions provide a body of evidence that demonstrates the components of the nexus and verify its connections. In this context, these contributions answered the research questions by indicating that urbanisation is an unequal process that interacts with environmental features to significantly influence exposure to health and climate hazards. A notable factor was human development, which contributes directly to location choice (e.g. through gentrification and expropriation) and coping capacity (e.g. by reducing public services accessibility). Evidence from flooding demonstrate the connection to climate change, while COVID-19 represents a systemic health crisis. I find no reason, therefore, to reject the main hypothesis. On the contrary, this body of evidence achieves the research objectives. Furthermore, the summary presented above allows for three main conclusions, to which I turn next.

First, systemic crises such as climate change and the COVID-19 pandemic have intersectoral and social consequences that disproportionately affect the most vulnerable. This research demonstrates that the interinfluences in these crises outline a nexus between urbanisation and risk exposure that presents feedback mechanisms with vulnerability, even if exposure factors differ. Being infected by a virus is radically different from suffering from flooding, for instance. However, low human development causes higher exposure to COVID-19 and weather hazards. In the first case, threatened livelihoods (e.g. hand-to-mouth living standards) force people out of social isolation and into high-risk transportation modes, despite fears of contagion. In the second case, household location choices mediated by unequal development (e.g. climate gentrification) push low-income groups into risk-prone areas, such as floodplains.

Furthermore, vulnerability factors consistently amplify the adverse effects of health and climate impacts, reducing coping thresholds and response capacity to levels in which the only choices available entail losses to some degree (e.g. the choice between hunger while in isolation or anxiety when working under exposure). This research explored the social and environmental interaction leading to exposure and vulnerability at multiple scales (e.g. global, regional, and local), revealing that they are underpinned by inequality, as are most current human endeavours. Ultimately, this research advances in addressing the complex system of urbanisation and risk exposure by explicitly modelling its components and testing many of its connections through a concerted mixed-methods investigation.

Second, crises may overlap, interact or couple over different time scales, connecting response and adaptation measures when resources are limited. These measures may further inequality if unchecked. Urban segregation, climate gentrification, and the widening of the social gap may arise as unfair outcomes of response and adaptation measures in urban development processes. These measures may increase the concentration of damage and losses among the most vulnerable, given the interconnections within the urbanisation–risk exposure nexus. For example, investments generate climate gentrification that expels vulnerable populations to unprotected sites. Subsequently, these measures must promote social and environmental justice and mitigate inequality, both actively and explicitly. The unequal attribution of risk due to differential access to spatial opportunities is a central mechanism and merits a focus on urban, health and climate policies, connecting these policies to the regulation of urban development.

Third, interdisciplinarity, open science practices and humanitarian ethics are focal in research with vulnerable populations. Systemic crises need to account for contextual, societal and subjective factors in risk perception and decision making. Thus, it is imperative to combine qualitative and quantitative evidence, avoiding overgeneralisation and 'one-size-fits-all' measures. Geographic research may alter fragile balances of power by exposing vulnerable groups to outside scrutiny, even if unintended. This research countered this risk by defining its research agenda with the support of stakeholders within and beyond academia and by promoting international collaboration. This dissertation also addresses community empowerment directly by devoting one of its contributions to reflecting on the acquisition, management and dissemination of geographic information. Furthermore, I promoted knowledge discovery and innovation by adopting FAIR scientific data stewardship principles in all quantitative analyses. Qualitative data presents further challenges (e.g. privacy), and ongoing efforts seek to publish results soon. When combined with the data-intensive approach in this dissertation, these principles make it a distinguished contribution to the reproducibility of results and the validation and dissemination of scientific insights.

Methodologically, I employed a series of qualitative and quantitative methods. Initially, this research implemented each research tradition separately. As the investigation matured, I increased integration to promote the robustness of insights and counteract bias. The fieldwork contribution and stakeholder engagement contributed significantly to tempering results and binding insights into their societal context, thus reducing uncertainty. I also innovate in geographic methods, as several contributions to this dissertation include spatio-temporal analysis and tracking and analysing the rapidly changing phenomenon of the COVID-19 pandemic. This feature may support future research in health and climate crises through a systemic perspective by explicitly addressing the temporal emergence of phenomena. Finally, I promote interdisciplinary research by integrating methods from health and behaviour research when appropriate to the investigated problems. Interdisciplinary research was therefore central to addressing the multidimensional nature of vulnerability.

The research outlook is promising for interdisciplinary research and the mixing of methods. The challenges faced on the intra-urban scale require further in-depth research on the drivers of vulnerability at the neighbourhood and household scales. Policy analysis also offers room for expansion by testing scenarios and pathways in which the nexus identifies fundamental interactions and critical factors (e.g. behaviour or social determinants of health) that promote increased resilience and fairness in adaptation. Investigating little-explored aspects of the nexus (e.g. social capital) will also provide new insights into its complex interinfluences. This dissertation builds on the groundwork of vulnerability to connect it to urban development. It thus demonstrates new research perspectives for urban studies, health geography and vulnerability research.

The COVID-19 crisis demonstrated the systemic consequences of keeping highly vulnerable populations exposed to the pandemic. The persistent viral circulation and the emergence of new variants should serve as potent warnings. They signal that the resilience of a society is often as strong as that of its weakest members. Hence, fairness in adaptation and development policies should become a social endeavour, at least for self-preservation if not for justice.

Ultimately, the urbanisation–risk exposure nexus presents synergies based on the socio-territorial inclusion of the most vulnerable that benefit global adaptation and development policies. Therefore, the results in this dissertation contribute to integrating key aspects in global policies, such as the Sustainable Development Goals, the New Urban Agenda (concerning urban development) and the Sendai Framework (regarding risk mitigation). By putting forth evidence of the role of inequality in risk attribution, this research also contributes to arguments of environmental and climate justice at the urban scale, which are vital issues for local governments in the implementation of the Paris Agreement. Finally, as our shared urban planet faces the Anthropocene, this research seeks to shine a light tinted by fairness onto future decisions.

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APPENDICES

APPENDIX A EXTENDED METHODS FROM CHAPTER 3

The practice of using survival analysis aims at analysing the relationship between variables to identify the explanatory variables for the modelling. As a first step, a log-rank test helps us to rule out the idea that the survival functions are equal (i.e. the null hypothesis) by indicating a statistically significant difference between populations. In our case, we selected five cities with different degrees of vulnerability, which refer to the median points at the 0, 25, 50, 75, and 100 quantiles of the Social Vulnerability Index (SVI) (IPEA, 2015). For each of these cities, we observed COVID-19 death events (Brasil.IO, 2021) for 53 weeks, from February 2020 to February 2021. Table A-1 presents the results of the log-rank test for these cities, considering the events in these 53 weeks and tests whether the cities present equal survival functions.

Table A-1. Log-rank test results for levels of cities' vulnerability

City name/State	Approximate SVI quantile	Events observed	Events expected
Breves/PA	100 (maximum value)	110	23.64
São José de Ribamar/MA	75	262	208.35
Feira de Santana/BA	50	780	952.90
Parnamirim/RN	25	422	374.77
Tubarão/SC	0 (minimum value)	375	389.34
Total		1.949	1,949
$Chi^2(4) = 389.49$			
$Pr > Chi^2 = 0.0000$			

The log-rank test checks for equality between strata for the vulnerability variable. It has a p-value of 0.0000, indicating statistically significant differences. Therefore, vulnerability would be included as a potential candidate for the final model.

Under survival functions, this appendix explores the proportional hazard regression with help of the Cox Proportional Hazard Model (Cleves et al. 2004, Chapter 9). In this model, two populations will be running the following experiment:

$$hazard\ ratio\ (t, x_{1,} x_0) = \frac{h\ (t, x_1, \beta)}{h\ (t, x_0, \beta)} = e^{\beta\ (x_1 - x_0)}$$

The determinants for the occurrence of a defined event or not (called hazard ratio of death) will be explained by the data of vulnerability. The generalization of the model takes form as Cox and Oakes (1985) have indicated.

$$h(t, x) = exp^{x'\beta}$$

Where for the different populations χ, the model approximates the hazard ratio for a baseline h0 and the regression coefficients ßi. Since each city represent a different degree of vulnerability (from the SVI quantiles), we chose to code vulnerability as a categorical variable, and we analyse with a dummy approach. Table A-2 shows the results for this Cox regression, which takes Breves/PA as the baseline.

Table A-2. Cox regression results for levels of cities' vulnerability

Dummy variables	Coefficients	Std. errors	z	p>|z|
São José de Ribamar/MA	-1.333917	.1147102	-11.63	0.000
Feira de Santana/BA	-1.799799	.1043954	-17.24	0.000
Parnamirim/RN	-1.447441	.1081719	-13.38	0.000
Tubarão/SC	-1.611916	.1097128	-14.69	0,000
Number of observations: 1,949				
LR Chi2(4) = 226.25 Pr> Chi2= 0.0000				

The most important interpretation is the direction of the coefficients. In these results, the coefficients are negative with respect to the baseline of the regression. This means that, if all other variables are constant, a given inhabitant of one of these populations has a lower probability of dying at the time of the study than an inhabitant of the baseline. These results are in line with our expectations and indicate that cities with higher vulnerability have lower survival probability. In this sense, an increase in vulnerability in the model leads to an increase in hazard.

These results do not provide additional evidence to falsify the hypothesis. They complement and strengthen the Kaplan-Meier Estimator (KME) implemented in our main analysis. The results of the log-rank test and the Cox regression, therefore, provide additional support for the results from KME. The same limitations in controls remain, though. Therefore, further research should explore for other control variables and interaction effects in this context.

APPENDIX B EXTENDED METHODS AND RESULTS FROM CHAPTER 4

B.1 Vulnerability evaluation standards

Table B-1. Vulnerability evaluation standards

Vulnerability level	Low 0	3	5	7	High 10
a) Depression/Anxiety		45-60	30-45	18-30	
b) Infection		45-60	18-30	30-45	
c) Losing job		45-60	18-30	30-45	
d) Run out of money		45-60		18-30; 30-45	
e) Independent kid		no		yes	

Note: the ranking by different age group according to the Bruine de Bruin (2021)'s and Munayco et al. (2020)'s statistical research.

B.2 Vulnerability levels of agent groups

Table B-2. Vulnerability levels of agent groups

	a)	b)	c)	d)	e)	WSM	Normalised value
GPone	3	3	3	3	3	3	0.3
GPtwo	7	5	5	7	3	5.4	0.5
GPthree	5	7	7	7	7	6.6	0.7

B.3 Risk level evaluation standards

Table B-3. Risk level evaluation standards

Risk level	**Low**				**High**
	0	**3**	**5**	**7**	**10**
a) Air condition1	Air at home or own car	Open outdoor	Indoor Good ventilated	Indoor Poorly ventilated	Aerosol exposure to COVID-19
b) Contact person2	Only family	Often contacted person	General public	Suspected COVID-19 patients	COVID-19 patients
c) Hygiene		Disinfection		NON	

Note1: with both outdoor and indoor environments, the risk level will be 4. Note2: If crowd, risk level + 1.

B.4 Risk level of destinations and transportation modes

Table B-4. Risk level of destinations and transportation modes

	a)	b)	c)	WSM	Normalised value
House	0	0	0	0.000	0.00
Office	5	3	3	3.667	0.37
School	4	5	3	4.000	0.40
Supermarket	5	5	3	4.333	0.43
Leisure facilities	6	6	3	5.000	0.50

	a)	b)	c)	WSM	Normalised value
Bus	5	5	3	4.33	0.433
Metro	5	5	3	4.33	0.433
Walking	3	5	0	2.66	0.266
Biking	3	4	0	2.33	0.233
Car	0	0	3	1	0.1
Taxi	5	4	3	4	0.4

B.5 Mobility grid instructions

Respondents answer interviews with the mobility grid tables according to the changes in their mobility in the period from 2018 to 2021. The mobility grid is inspired by the work of 'Brazil/UK Healthy urban mobility project' (Jones, 2019) based on Schoenduwe et al. (2015) and adapted by our Health and urban mobility team to Brazil in 2020. This encompasses two years before the pandemic, which provide a benchmark, and two years during the pandemic, which report the dynamics of adaptation to varying risk perception levels. The table below provides the coding applied by researchers in the COVIDGI project to the semi-structured answers provided by respondents of the mobility grid.

Table B-5. Legend for the Mobility Grid

Areas	**Codes**
Family/Relationships	0 = no impacts; 1 = positive impacts; -1 = negative impacts
Places of Residence	0 = no change; 1 = change
distance to city centre	0 = city centre; 1 = near city centre; 2 = inner periphery; 3 = outer periphery; 4 = metropolitan area
Places of study	0 = doesn't study; 1 = studies
distance to city centre	0 = city centre; 1 = near city centre; 2 = inner periphery; 3 = outer periphery; 4 = metropolitan area
Workplaces	0 = no change; 1 = change
distance to city centre	0 = city centre; 1 = near city centre; 2 = inner periphery; 3 = outer periphery; 4 = metropolitan area
Car ownership	0 = never available; 1 = partially available; 2 = always available; 3 = transit pass
Modes of transport	1 = first; 2 = second; 3 = third; 4 = fourth
Health Block	
Surgeries/Hospitalization	0 = no; 1 = yes
COVID-19	0 = no; 1 = yes
Fractures	0 = no; 1 = yes
Diagnosed diseases	0 = no; 1 = yes
Body weight variations	0 = no; 1 = positive; -1 negative
Other important health conditions	0 = no; 1 = yes
COVID-19 Block	0 = no changes in mobility behaviour; 1 = changes

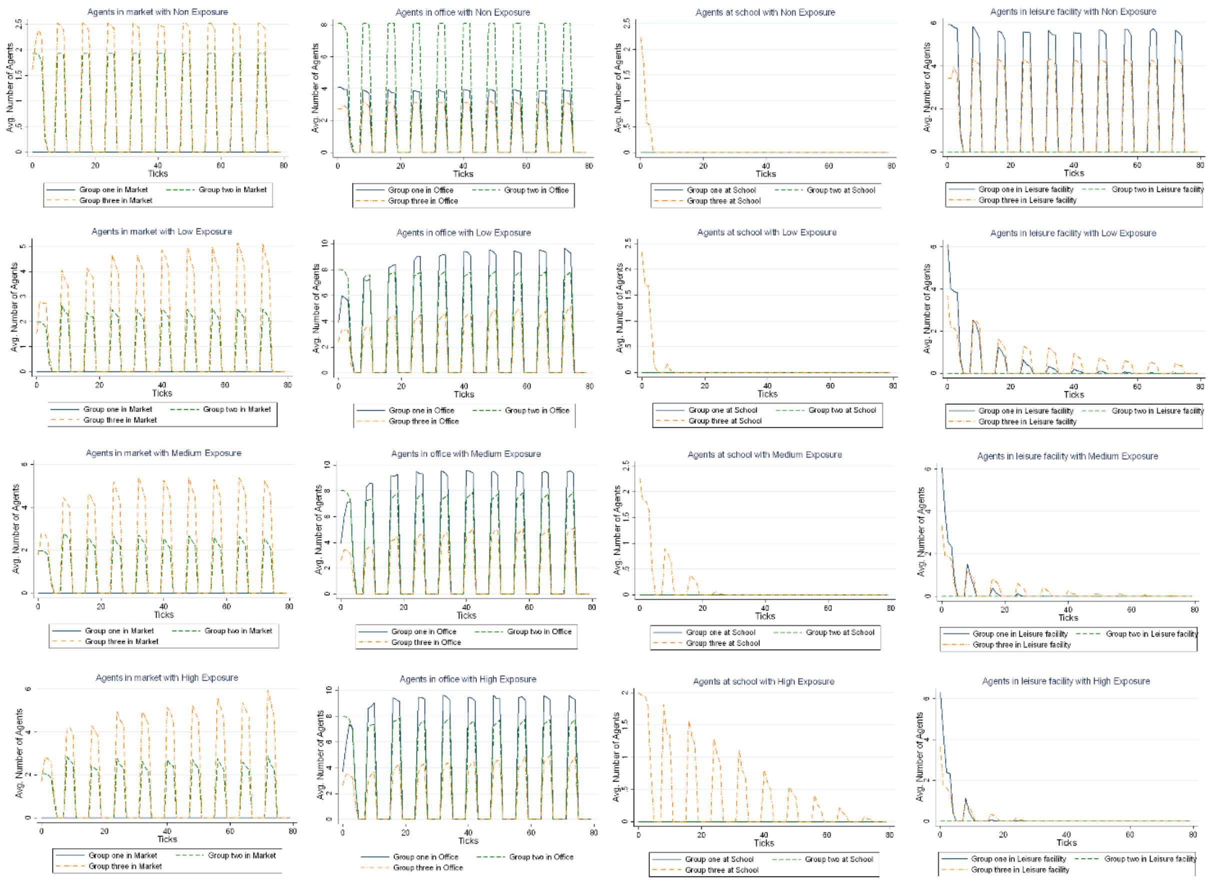
B.6 Mobility grid template

Figure B-1. Mobility grid template

Responder		2018				2019				2020			
AREAS	History	1°	2°	3°	4°	1°	2°	3°	4°	1°	2°	3°	4°
Family/Relationchips	Important family events, examples: leaving the parents' home, marriage, birth of children, divorce, death or illness in the family, retirement, etc.)												
Places of Residence	Indicate the places you've lived over the years												
Places of study	Indicate the locations you have studied over the years. Ex: college, technical school, college, courses, postgraduate, etc.												
Workplaces	Indicate the places where you have worked over the years. For example, internship, temporary employment, informal work, formal work.												
Car ownership	Car never available												
	Partially available car												
	Car always available												
	It has transit pass												
Modes of transport	Car/Bike (App, Ride)												
	Subway/Bus/VLT												
	Bicycle/Skateboard												
	Hike												
Health Block	Surgeries/Hospitalization												
	COVID-19												
	Fractures												
	Diagnosed diseases												
	Body weight variations												
	Other important health conditions												
COVID-19 Block	Changes in mobility behavior due to pandemic												

B.7 ABM extended results

Figure B-2. ABM extended results



APPENDIX C EXTENDED METHODS AND RESULTS FROM CHAPTER 5

C.1 Fieldwork design

We developed the qualitative research through a multi-methodological process containing three instruments. We applied each instrument to people residing in the two selected areas in two cities (36 participants in total, 19 in Porto Alegre and 17 in SP). The selection of different regions seeks to enable comparisons (of the maximum dissimilarity type). For this purpose, we included areas with less vulnerability in the form of formal, middle-class neighbourhoods and complete infrastructure, as well as places of greater vulnerability, such as popular class neighbourhoods and informal settlements, with multiple needs.

We implemented three instruments: a short demographic questionnaire, the mobility and health biography grid, and the focus group discussions. The short demographic questionnaire collected data related to sociodemographic issues, mobility choices, and exposure behaviour during the COVID-19 pandemic. The mobility and health biography grids represent a timeline of mobility behaviour over the last four years - from 2018 to 2021 (based on the work of Jones, 2019). This time window aims to establish a visual record of the mobility and health experience before the pandemic, as well as the dynamics of change during the period. The focus groups took place separately among the group of participants in each selected area, totalling four sessions. Of these sessions, we analyse only the results for SP in this investigation. Similarly, we focus only on the focus group results and leave the remaining material for further investigation.

A trained researcher applied the first and second instruments individually with participants. The researcher interviewed the low-income participants in presence, in a community association near their place of residence. The researcher used videocalls to contact the high and middle-income participants. The researcher carefully guided the unstructured interview of the focus groups (Y. Zhang & Wildemuth, 2009). The researcher developed a script with guiding questions for the focus groups, based on the collective (i.e. among the fieldwork team) evaluation of the individual results. Then focus groups followed a dynamic, open discussion focused on the motivations behind the behavioural changes reported during the COVID19 pandemic, as well as the differences between the participants in their decision-making regarding exposure to the virus. The information obtained through the individual instruments was not shared with the participants during the focus groups or came up only through the voluntary decision of the participants. We held the groups in person with the prior consent of all participants, in a space that could adhere to the current COVID-19 regulations at the city in which each took place.

Focus groups participants came from convenience samples. For the middle-income, central group, we invited university students from the University of Sao Paulo, through professors at the Faculty of Architecture and Urbanism. This sample was complemented by workers at the Teto Brasil NGO that lived in the central region of the city. In both cases we allowed snowballing, accepting referrals from the participants. Besides the Teto workers, participants did not know more than one other person in the group, showing little familiarity and previous interpersonal knowledge. For the informal workers and settlers at the outer periphery group, we also relied on a convenience sample through the Fenix community association, which was in turn referred to us by the Teto Brasil team. Teto had recently developed projects at the community (building bathrooms, a community kitchen, and a library). All participants from this group presented close ties to the community leader and demonstrated high interpersonal connections with her.

Participants provided informed consent on the photographing, recording, transcription, and analysis of their data. We guaranteed privacy by removing personal information from the transcripts (e.g. addresses, names from participants or their relatives) anonymizing all participants and restricting access to the recordings to the research project principal investigator, data steward, and those responsible for the transcription only. The broader research team had only access to the pseudonymized version of the data, onto which we based this investigation.

As an international cooperative study, this investigation abided by the principles of ethics in research as outlined by the Bylaws for Safeguarding Good Scientific Practice and Avoiding Scientific Misconduct at Universität Hamburg (Universität Hamburg, 2014) and the Guidelines for

Safeguarding Good Research Practice. Code of Conduct (DFG, 2019) in Germany and the resolutions 466/2012 and 510/2016 from the Ethics in Research Committee of the Federal University of Rio Grande do Sul in Brazil (Research Ethics Committee of the Federal University of Rio Grande do Sul (CEP/UFRGS) approved this fieldwork plan on 27.01.2022. The approval is registered at Plataforma Brasil under CAAE 54068521.0.0000.5347).

C.2 Focus groups

The focus groups were open group interviews that followed a similar script. The script focused on questions regarding the experience of COVID-19 for the period from March 2020 (when first cases were detected in SP) to March 2022. We understood the scope of the 'experience of the pandemic' as a broad set of impacts, including health impacts (i.e. contagion and other health conditions among participants or their families), social impacts (including their general well-being in the period, changes to livelihoods, education, and work), and impacts on their daily mobility (i.e. location of residence and work or education, distance travelled, mode of transportation, and access to online work, education, or purchasing).

The groups allowed for a dynamic dialogue to emerge, taking the script as a general guide for the collective reflection on the participants' experiences in the period. Prior to each group, the researchers evaluated the results of preliminary individual, structured interviews conducted with the participants on the week before the group sessions (which are not analysed here). These interviews concerned the same topics, focusing on establishing the pre-, during, and post-pandemic biographical framing of the mobility experience of the participants.

We transcribed the results of the focus group orthographically, reproducing spoken words and sounds, including hesitations and cut-offs in speech (signalled by '…'), laughter (identified by 'laughter'), and other interjections (e.g. 'hummm', 'ah'). We have only edited for clarity, including observations between square brackets ([…]) when implied meaning was found.

C.3 Coding

Coding was mostly deductive, although we included some codes after taking part in the focus groups in person and performing the initial observation of the transcribed and recorded data (e.g. 'resilience – build back better'), achieving a partially inductive approach. Our analytic approach did not override completely the participants' experiences but framed them under the theoretical lenses of vulnerability (Adger, 2006; Pelling, 2003), social determinants of health (Marmot, 2005), and a broader ideological framing of the unequal spatial development (D. Harvey, 2006). We took notes during the analysis of the preceding individual interviews, during the focus groups, and during coding to complement the sources of data for this analysis. Consistency was guaranteed by independent coding from two. The fieldwork was evaluated and approved by the ethics committee of the Federal University of Rio Grande do Sul, and supporting information is available upon request.

C.4 Coded transcripts

The coded transcripts are available at the Urbanisation-Risk Exposure nexus GitHub repository at https://github.com/alexandrepereiraarq/urb_exposure_nexus.

C.5 Summary of findings from focus groups

Table C-1 presents a summary of findings from the focus groups in São Paulo (March 2022).

Table C-1. Summary of SP focus groups.

Theme	What did the participants report?
(a) Intensification of threats to livelihoods	The slowdown of economic activity and closure of certain sectors in government regulations meant many participants were unemployed. In PRG, this also meant increased exploitation of work relations and submitting to high-exposure jobs (e.g. nurses in emergency wards). Cost of living increases coupled with lack of income pushing the PRG community into food insecurity. Government welfare was too short in time and low in value.
(b) Changing behaviour: choice or necessity?	Mobility changed drastically, with a sharp drop in public transport use. Participants avoided public transport modes the most (e.g. bus, metro, due to high exposure) and adopted individual transportation modes instead. In CRG, the alternatives were ride-hailing apps (e.g. Uber), bicycles, or cars. In PRG, participants took up walking, limiting their accessibility and increasing community isolation. In the CRG, participants adopted tele-working/learning, and many wish these to remain (convenient, allows new opportunities). Some kept their work while relocating to low-incidence areas (e.g. to countryside). In PGR, jobs in cleaning, construction, or retail did not allow tele-work. Residents faced a risk-risk trade-off: some exposed themselves in high-risk activities, others kept self-isolation, mostly because of unemployment, threatening their livelihoods.
(c) Capacity to cope, respond and adapt	Access to healthcare was polarized: CRG participants had trouble accessing tests during limited periods, no trouble to access healthcare (using private insurance); PRG participants faced severe limitations to access tests (even when displaying symptoms) and healthcare. Testing difficulties included long travel and waiting times to health clinics and strict eligibility criteria (e.g. being symptomatic and having contact with a confirmed case). In both, political clout provided a shortcut to the services. Difficulty for testing meant uncertain risk evaluation (e.g. 'I only found [I had COVID-19] by accident') and underreporting. Outside sources provided extended coping and response capacity: in CRG, family helped avoid exposure (e.g. moving back to the parents' house), access healthcare and provided individual mobility (e.g. private car). Participants form PRG had very low initial coping capacity, therefore they community organization and partnerships with external institutions provided coping capacity (e.g. fighting food insecurity).
(d) New opportunities/ factors of resilience	In CRG, several report improvements: reuniting with family, furthering education, changing careers, and new jobs (e.g. teaching online). Participants will keep daily life improvements: buying local, active mobility, and online shopping. In PRG, online shopping is limited by income, and active mobility is an imposition of low income, diminishing accessibility to jobs and services. Few new opportunities (e.g. emergency response healthcare) Resilient behaviour was frequent in CRG (e.g. going back to normal or improving). In PRG, the struggle was to contain 'inevitable' damage, social impacts of the pandemic still reverberated. Social capital is a latent resilience resource, from family (CRG) or through community organization (PRG).

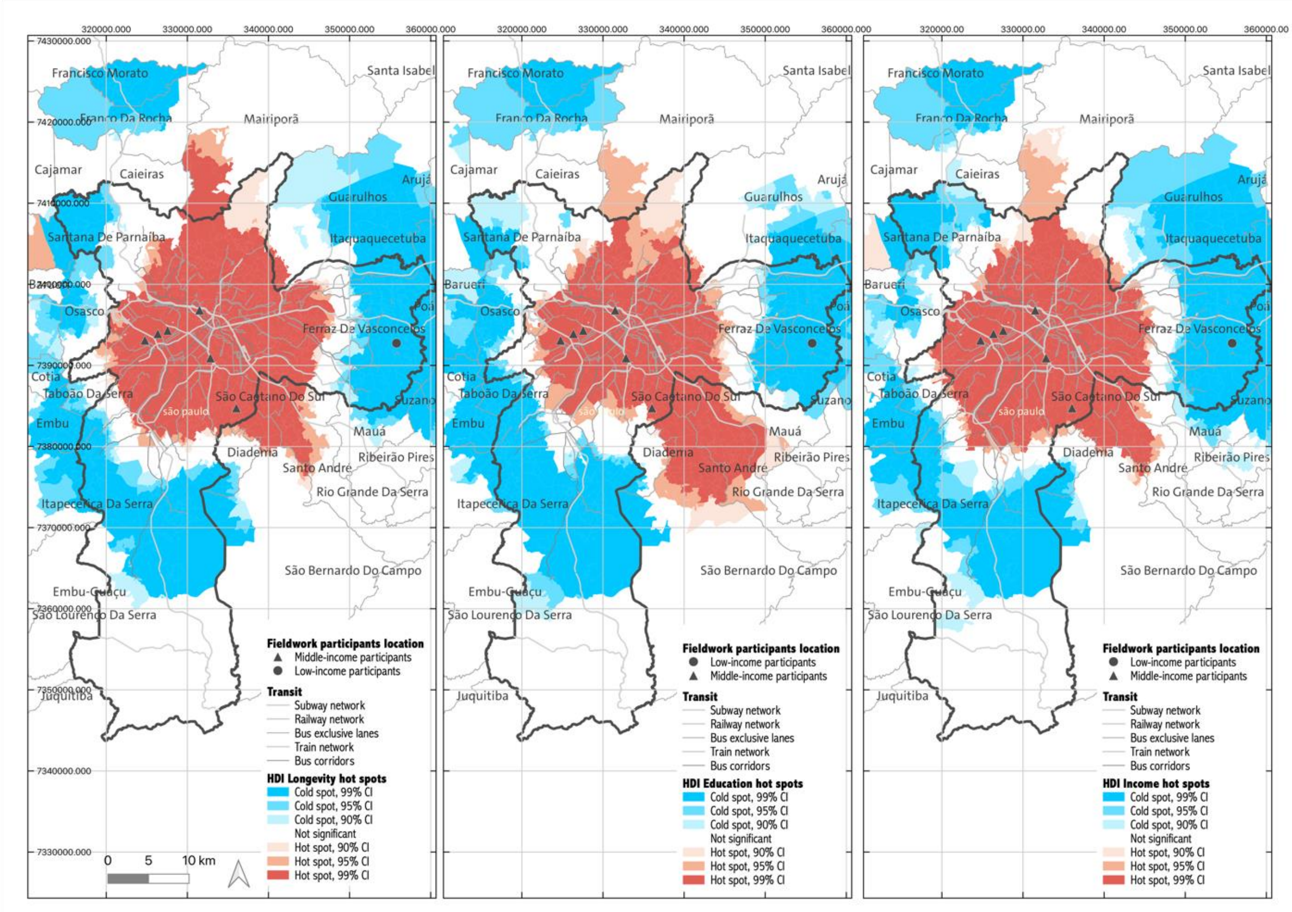
Table C-1. Summary of SP focus groups.

Theme	What did the participants report?
(e) Impacts on health and well-being	All participants got COVID-19, but none had grave consequences. Long COVID is present, though, and some lost relatives. Mental health was a prevalent theme in the form of fear, anxiety, depression, weight variation, confusion, loneliness, anger, and emotional stress. Fear of infection, loss of income, and isolation were significant triggers. Coping varied between those with healthcare support, and those without.
(f) Perception of risk and reasons for exposure	All participants seemed keenly aware of the risks from exposure. This perception shaped most of their decisions during the period, including working, mobility, leisure, and relations with family and friends. Risk perception was flexible, though. Resignation feelings were common in PGR, where participants perceived they could not afford self-isolation. Others in PRG and CRG reported going to parties, despite awareness of the risk involved. Family and friends were frequently seen as less dangerous than strangers. Participants cited public transport modes as high-exposure spaces. Hospitals and parties also.

C.6 Human development hot spot analysis

Figure C-1 presents the HDI hot spots analysis. In the HDI distribution, there is one large very high-confidence (99% CL) hot spot with roughly 11 km from the Sé district (the most central in the city) for all dimensions: longevity, education, and income. A south-eastern vector is an exception to this concentric pattern: The industry-rich region of the ABC, including Santo André, São Bernardo do Campo, and São Caetano do Sul is a significant hot spot in all dimensions, especially education. The very high-confidence (99% CL) cold spots for all dimensions are similarly distributed and follow a concentric pattern ranging from 26 to 33 km away from the city centre. On the east of the city, this fringe includes the neighbourhoods of Itaquera, Guaianases, and Cidade Tiradentes and is interrupted by the ABC region. To the south, a cold spot includes the urbanised part of Grajaú, Jardim Ângela, and Capão Redondo, while to the west, the cold spots include municipalities contiguous to SP, like Osasco and Taboão da Serra. To the north, the metropolis is sparsely populated, and a new cold spot is present in the municipalities of Franco da Rocha and Francisco Morato, roughly 26 km from the centre of SP. The HDI dimensions are very similar spatially, with education presenting a more concentrated hot spot in SP, with a larger extension to the southeast into the ABC region. Income has the larger central hot spot, with up to 16 km from the city centre. Income presents cold spots that are far more concentrated than longevity or education, especially to the east of the SP central region.

Figure C-1. Human development index hot spots analysis in SP and vicinity: longevity, education, and income dimensions.
Source: authors, based on IPEA (2015).



C.7 Cumulative COVID-19 fatalities per 100,000 inhabitants timeline

Using microdata from the SP City Health Department (SP Municipal Health Department, 2022), we calculated the cumulative deaths per 100,000 inhabitants metric for every census district in SP for every week between 02.02.2020 to 30.11.2021 (initial and final dates in the data sets after clean-up). To this end, we used Geopandas (Jordahl et al., 2022) to read, prepare and clean the data. Data input used the following data files obtained from the SP City Health department COVID-19 webpage (SP Municipal Health Department, 2022):

1. dados-sindrome-gripal-esus-sao-paulo-sp-jan-ago-2020.csv
2. dados-sindrome-gripal-esus-sao-paulo-sp-set-dez-2020.csv
3. dados-sindrome-gripal-esus-sao-paulo-sp-jan-fev-2021.csv
4. dados-sindrome-gripal-esus-sao-paulo-sp-mar-abr-2021.csv
5. dados-sindrome-gripal-esus-sao-paulo-sp-mai-jun-2021.csv
6. dados-sindrome-gripal-esus-sao-paulo-sp-jul-ago-2021.csv
7. dados-sindrome-gripal-esus-sao-paulo-sp-set-nov-2021.csv

From these CSV files, we included the fields ID, age, gender, race, census tract, case classification ('classificacaoFinalModificada' values 1, 2, 3, 4 indicate a positive COVID-19 status), case outcome ('evolucaoCaso' value 'Óbito' indicating death), initial symptoms date ('dataInicioSintomas'), and outcome date ('dataEncerramento'). The data set at this stage included 4,487,156 records. From these data, we had to eliminate inconsistent records according to the following criteria:

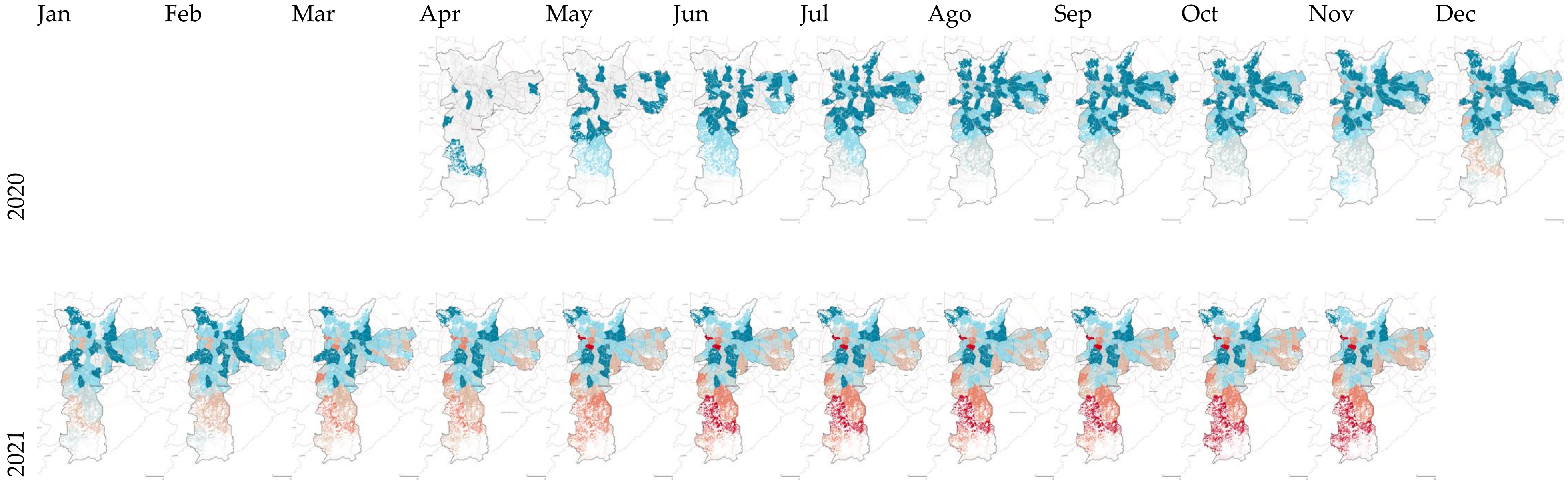
1. Dates before 02.02.2020 or after 30.11.2021, or before/after each data set limit (e.g. before January and after August 2020 for the first file in the above list).
2. Records missing georeferencing (census tract reference), including the values: missing (nan), 0, 9 (code for unknown), or references outside the SP metropolitan region.
3. Records missing the information on case outcome (identified in the 'classificacaoFinalModificada' field.

The clean-up resulted in 1,948,601 valid cases. We then filled-in missing dates (with the value 0 for cases and deaths) in Python using achieving a complete timeline (the original data omitted dates with no cases or fatalities). Next, we aggregated results at the census district scale (n = 164 districts and 100 weeks), added population estimates for 2019 (from Costa & Margutti, 2015, the latest data set includes 2019 population estimates) and calculated the fatality rate for each week as:

$$acc\_deaths\_100k = acc\_deaths_{10.10.21} \,/\, (pop\_2019 \,/\, 100{,}000).$$

We exported the resulting data as a Geopackage. Using QGIS 3.22 Temporal Controller functionality (QGIS Association, 2022), we plotted the data per week, from 19.04.2020 (week when the first deaths took place) to 30.11.2021 (week of the last record).

Figure C-2. COVID-19 cumulative fatality ratio per 100,000 inhabitants.



C.8 Additional survival analysis with the Cox proportional hazard model

We implemented the Cox proportional hazard model to and log-rank tests to verify these results. The Cox Proportional Hazard Model is a survival regression model that is also often used in medical research (Cleves et al., 2008). The method includes regressing covariates (e.g. age, civil status, amount consumed of alcohol) against the duration of joining the study or onset of symptoms and the time before an event (e.g. time before death or the cure of a patient). The idea being that the hazard for an individual is a linear function of its characteristics (i.e. covariates) and the population-level hazard baseline. The model results in a hazard rate for one or more subgroups within a population, and the association with each covariate in relation to the baseline.

The Cox regression results at Table C-2 shows the results for the regression at the individual scale from the SP Health Department dataset (SP Municipal Health Department, 2022). We regressed duration of event (time between onset of symptoms and death) against the covariates coded as dummies when appropriate age. The covariates were age (no dummies, measured in years as informed by patient), sex (0 = undefined, 0 = male, 1 = female), race (0 = undefined, 0 = White, 2 = 'Parda', 3 = Black,4 = Yellow, 5 = Indigenous), and distance to city centre (no dummies, measured as the distance of the census tract of residence informed by the patient to the SP city hall building, the Palácio do Anhangabaú). The results show all effects are statistically significant (p-value smaller than 0.5%). Age has a small positive effect, while sex has a pronounced positive effect, 1.62 more frequent deaths among Women. Non-White ethnicities also have a small positive effect. Contrary to expectations, distance from the city centre has no effect.

Table C-2. Cox proportional hazard model results with microdata, from 02.2020 to 11.2021

				coef. bounds*		exp(coef.)				
	coef.	**exp(coef.)**	**coef. SD**	**lower**	**upper**	**lower**	**upper**	**z**	**p**	**-log2(p)**
age	0.01	1.01	0.00	0.01	0.01	1.01	1.01	46.39	<0.005	inf
sex	0.48	1.62	0.04	0.40	0.57	1.49	1.76	11.33	<0.005	96.40
race	0.07	1.07	0.02	0.03	0.11	1.03	1.12	3.17	<0.005	9.38
dist. centre	0.00	1.00	0.00	0.00	0.00	1.00	1.00	11.19	<0.005	94.10

We adopted a confidence level of 95% for the analysis. *Coefficient and exp(coefficient) bounds are 5% (lower) and 95% (upper).

The Cox regression results for the cases aggregated by census district and classified by their region in SP are in Table C-3. We recoded regions as dummy variables (i.e. central region = 1, inner periphery = 2, and outer periphery = 3) and excluded other covariates. The results show a statistically significant positive coefficient with the increase of distance from the centre, that is from central to outer periphery (0.05 coefficient, with p-value smaller than 0.5%). The low p-value allows the rejection of the null-hypothesis (all fatalities happen in the same way) with a 95% confidence level. The 0.05 coefficient means that for every region beyond the central, there is an increase of 5% in mortality of the population. In other words, the farther from the centre, the more likely an individual is to die from COVID-19 in the period of analysis.

Table C-3. Cox proportional hazard model results with district data, from 02.2020 to 11.2021.

				coef. bounds*		**exp(coef.)**				
	coef.	**exp(coef.)**	**coef. SD**	**lower**	**upper**	**lower**	**upper**	**z**	**p**	**-log2(p)**
Rings**										
1 – 3	0.05	1.05	0.02	0.02	0.08	1.02	1.09	3.03	<0.005	8.66

**The rings from Figure 5-3 are coded as dummies for the analysis as follows: 1 = central region, 2 = inner-periphery, 3 = outer-periphery.

APPENDIX D LIST OF THE INTERVIEWED STAKEHOLDERS

Table D-1 presents a list of the interviewed stakeholders, organized by the date of interview.

Table D-1. List of the interviewed stakeholders for the COVIDGI project.

Name	**Institution**	**Position**	**Interview date**
Ernesto Galindo	Applied Economy Institute (IPEA)	Planning and research expert	09.12.2021
Abel Escovedo	Federal District Architects Union	Director of Union Matters, 2020-2022	16.12.2021
Orla Canavan & Jacopo Margutti	Red Cross Netherlands, 510 Initiative	Strategic product design lead & Humanitarian Data Scientist	16.12.2021
Prof. Dr. Ricardo Dagnino	Federal University of Rio Grande do Sul	Professor, Geography Department	21.12.2021
Claudia C Soares & Ana Ribeiro Neves	Terroá Institute	Project coordinator & Project assistant	22.03.2022
Ygor Santos Melo	Teto Brasil	National Communities Coordinator	30.03.2022

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Without my co-authors this research would not be as lively or insightful. Cleiton Chiarel, Júlio Vargas, Jürgen Scheffran, Katharina Heider, Laszlo Steinwärder, Miguel Rodriguez Lopez, Muhammad Mobeen, Vitor Pessoa, and Yechennan Peng helped carry the load and co-created all the contributions presented here. I thrived in the interaction with them and cherish it in all sincerity.

Being a researcher from the Global South in Hamburg proved challenging. Going through a pandemic increased that challenge at the same time it brought new opportunities. My origin provides the clarity to see the privileges I carry that shielded me from so much suffering others had to face in these times. I must also thank the German Academic Exchange Service (DAAD) for their unwavering support. I acknowledge the responsibility of being a DAAD scholar and the privilege to pursue research with such security. I extend my gratitude towards my colleagues and the management team at the School of Integrated Climate and Earth System Sciences (SICSS) and the Research Group Climate Change and Security (CLISEC). The Hamburg Research Academy and MIN Faculty were also instrumental in shaping the researcher I am today.

Early in the COVID-19 pandemic, I was fortunate to join the *Urbanistas contra o Corona* (Urbanists against Corona) network in Brazil. It was thanks to our collective work that Miguel, and I later successfully applied for the Volkswagen Stiftung 'Corona Crisis and Beyond' grant. I thank you for your companionship and understanding the toll COVID-19 would have on our unequal country. Thanks to the Volkswagen Stiftung grant, I was fortunate to promote German-Brazilian collaboration and research in the COVIDGI Project. I must thank all project members for their trust, understanding, and patience with me. You taught me fundamental lessons that shaped the multidimensional approach in this research. In COVIDGI, I also had the opportunity to interview wonderful social, research, and government stakeholders that generously donated their wisdom to our research.

Finally, I thank my family. Jussara, Leonardo, and Janaína you were with me every step of the way. Argileu will be missed but I know his wisdom still lives in me. Karine, we walk this world *zusammen*.

Thank you all.

EIDESSTATTLICHE ERKLÄRUNG

Hiermit erkläre ich, dass die vorliegende Dissertationsschrift selbst verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

I hereby declare upon oath that I have written the present dissertation independently and have not used further resources and aids than those stated.

Hamburg, den 29.11.2022 Alexandre Pereira Santos