Assessing vulnerability and resilience to extreme events with computational models

ASSESSING URBAN VULNERABILITY AND RESILIENCE TO EXTREME EVENTS WITH COMPUTATIONAL MODELS

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Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology,
by the authority of the Rector Magnificus, Prof. dr. ir. T. H. J. J. van der Hagen,
chair of the Board for Doctorates
to be defended publicly on Tuesday 4 March 2025 at 10:00 o'clock

by

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Keywords: urban, vulnerability, resilience, behaviour, computational modelling, extreme events, heat, pandemic, uncertainty

Front & Back: Oleg Apsalyamov x Mikhail Sirenko

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Let's go. In and out. Twenty minutes adventure.

Rick Sanchez

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SUMMARY

Humanity has always faced extreme events that pose significant challenges due to their unpredictability and substantial impact. While, in the past, these events were relatively rare, recently, the frequency, intensity, and geographic spread of extreme events have increased dramatically, driven by factors like climate change and globalisation. The European heatwaves of 2022, 2023, and 2024, for instance, demonstrated how climate-driven extremes can severely impact modern societies, with tens of thousands of heat-related deaths. Likewise, the COVID-19 pandemic revealed the vulnerabilities in global preparedness for health crises, causing severe economic impacts and widespread social disruption. Both phenomena underscore the urgent need for enhanced resilience and preparedness in the face of increasingly frequent and intense extreme events.

Cities are the centres of gravity for extreme events. Heatwaves disproportionately affect urban areas due to factors such as the urban heat island effect, which results from the concentration of heat-absorbing materials like concrete and asphalt in cities. Socioeconomic inequalities and the concentration of vulnerable populations, such as the elderly, low-income households, and those with pre-existing health conditions, further exacerbate the consequences of heatwaves in urban settings. Similarly, the rapid spread of the COVID-19 pandemic has been especially pronounced in cities, where people typically have more social contacts. Increased mobility and interconnectedness facilitate the transmission of the virus, as evidenced by the rapid surge of cases in cities. The disparities in access to healthcare and the prevalence of comorbidities among vulnerable populations in cities can further heighten the adverse effects of future pandemics.

The two central concepts of this thesis that help us understand the impact of extreme events are vulnerability and resilience. Vulnerability is the susceptibility of a system to damage when exposed to hazards. Often, vulnerability is seen as a combination of three key components: exposure, sensitivity, and adaptive capacity. Exposure relates to the elements within a system that could be affected, sensitivity denotes how much a system is impacted, and adaptive capacity is the ability to adjust to minimise damages. For example, in the context of climate change, vulnerability can manifest through the extent to which certain populations are exposed to a heatwave, how sensitive they are based on their sociodemographic characteristics and how well they can cope or adapt to escape the heat.

Resilience complements vulnerability by focusing on how systems respond to shocks. While vulnerability highlights where a system may fracture under pressure, resilience points to the system's strengths and capabilities to recover or adapt after a disruption. As such, resilience is not simply the opposite of vulnerability but a broader, connected concept emphasising recovery, adaptation, and transformation.

Both concepts have often been employed to understand how well our systems are prepared to handle disruptions and crises, especially in the context of climatic shocks and stresses. However, when they occur in cities, extreme events generate new types of problems and, thus, may require new assessment models.

Traditional approaches to urban vulnerability and resilience assessment typically involve the use of indicators, proxies, or composite indices, which are estimated either spatially (e.g., through the creation of vulnerability maps) or temporally (e.g., by tracing resilience trajectories). While widely adopted for preparing cities for extreme events, these approaches have several limitations. First, they rely on models that fail to capture the dynamic nature across urban systems, particularly the variations that occur across both spatial and temporal scales. Furthermore, even though it has been previously shown that resilience and vulnerability are connected, these models use the concepts of vulnerability and resilience as completely separated without considering how they interact. Finally, despite empirical evidence, they often overlook citizen behaviour as a driver of vulnerability and resilience.

Building on the increasing importance of understanding vulnerability and resilience in urban environments, particularly in the face of recent and future extreme events, this dissertation addresses the primary research question:

Main RQ: *How can we account for the spatial-temporal heterogeneity of cities in urban vulnerability and resilience assessment models for extreme events?*

To address this question, we formulate three sub-questions, each targeting a specific dimension of urban vulnerability and resilience and their relationships. The dissertation uses case studies of the three largest Dutch cities — The Hague, Rotterdam, and Amsterdam — and focuses on two extreme events: the 2019 European heatwave and the COVID-19 pandemic. By employing a computational approach that integrates data science, spatial analytics, and simulation modelling, the dissertation offers an in-depth exploration of how these cities respond to and recover from extreme events, capturing the spatial and temporal nuances of their vulnerability and resilience dynamics.

The dissertation's second chapter examines the concept of vulnerability and whether it is *static* in line with how vulnerability maps portray it. The corresponding sub-question is:

RQ1: *How does urban vulnerability differ spatio-temporally?*

We study anonymised ambulance calls — a proxy for *general* vulnerability — in The Hague, Rotterdam, and Amsterdam. The calls are allocated to cells in a grid with, for each cell, open socio-economic data and built environment data, as well as data on places of interest (POI). Using spatial analytics, time-series clustering and regression analysis, we search for spatio-temporal patterns and for attributes that best explain these patterns. We found that urban vulnerability is not static. It exhibits significant spatial-temporal variability or *rhythms of risk*, influenced by the daily rhythms of city life and the characteristics of each district's urban and social fabric.

The third chapter of this dissertation explores the relationship between vulnerability and resilience to heatwaves. Often, it is assumed that the most vulnerable areas of a city are also the least resilient. This chapter explores whether and, if so, how far this assumption holds true. The research sub-question posed is:

RQ2: *What are the relationships between vulnerability and resilience at the urban scale?*

We study the 2019 European heatwave, which significantly impacted Dutch cities on July 22, 2019, to examine these dynamics. To assess vulnerability, we use a conventional set of indicators, including factors such as age, health, and built environment characteristics like the urban heat island (UHI) effect, and analyse these using dimensionality reduction techniques. Resilience is measured by the change in the number of ambulance calls during the heatwave. By applying both statistical and spatial analysis methods, we aim to discover the *direction* of vulnerability-resilience relations in different areas: more-less (negative correlation), more-more (positive correlation), or less-less (positive correlation). We find that relationships between urban vulnerability and resilience are non-linear, context-specific, and driven by citizen adaptive behaviour. Citizens' adaptive behaviour, in this case, is moving to cooler areas and, therefore, escaping the heat. However, this behaviour can result in overcrowding and increase vulnerability in unexpected places, like parks and beaches. As a result, we get *less vulnerable, less resilient* type of relationships.

The dissertation's fourth chapter moves beyond analysing the current state of urban systems by examining the potential effects of policy interventions on vulnerability and resilience. The research question guiding this chapter is:

RQ3: *What is the impact of policy interventions on the vulnerability or resilience of various urban districts?.*

The shock used in this chapter is the spread of the COVID-19 virus, which we simulate in the districts of The Hague, the Netherlands. In this chapter, we leverage a wide array of datasets to go beyond the typical approach of generating a *synthetic population* — a standard input for agent-based models. Instead, we create a *synthetic city*, which incorporates not only a simulated population but also their spatio-temporally allocated routines, the built environment, and local businesses. Using the generated synthetic city as input for a large-scale agent-based model, we evaluate the effects of several policy interventions on the vulnerability and resilience of two representative urban districts, and analyse how these interventions influence the populations. We find that non-contextualised interventions can lead to unintended consequences and heighten vulnerability in unexpected urban areas - they *flip the risks*. The model illustrates the dangers of applying uniform interventions across diverse urban contexts and highlights the importance of considering each district's unique characteristics to avoid maladaptation.

The dissertation's contribution is a multi-dimensional and context-sensitive approach to assessing urban vulnerability and resilience. It integrates spatio-temporal analysis, citizen behaviour, and the diverse fabric of urban and social systems to better capture the dynamic and context-dependent nature of urban risks. By leveraging data science, spatial analytics, and agent-based modelling, the research moves beyond common static approaches and offers a more dynamic assessment of vulnerabilities and resilience to extreme events. Taken together, the studies present a methodology that not only tracks how vulnerability and resilience evolve across time and space but also simulates the impact of interventions and identifies potential maladaptive outcomes. Ultimately, it provides a more nuanced and spatial equity-oriented methodology for researchers, urban planners, and policymakers to assess, understand, and enhance urban resilience in the face of extreme events.

Future research could explore how vulnerability and resilience manifest across different cities and under various shocks. Another study area could examine whether additional vulnerability and resilience metrics complement each other or create trade-offs. For example, green infrastructure may enhance resilience to heat waves but can also lead to gentrification, displacing low-income residents and increasing social inequality. Future studies could scale up from district-level analyses to entire cities, using insights from smaller areas to inform city-wide strategies. Increasing citizen participation is another important research avenue. By involving community members directly in research and decision-making, cities could achieve more equitable outcomes. Residents could offer valuable insights on effective interventions and specific vulnerabilities, leading to solutions that better address local needs.

In conclusion, understanding urban vulnerability and resilience as dynamic, interconnected phenomena is crucial for designing effective policy interventions in the face of extreme events. By accounting for spatio-temporal heterogeneity and citizen behaviour, this dissertation provides a more nuanced and operational approach to assessing and enhancing urban resilience, paving the way for more targeted and equitable urban planning.

Samenvatting

De mensheid heeft altijd te maken gehad met extreme gebeurtenissen die aanzienlijke uitdagingen met zich meebrengen vanwege hun onvoorspelbaarheid en grote impact. Terwijl deze gebeurtenissen in het verleden relatief zeldzaam waren, is de frequentie, intensiteit en geografische spreiding van extreme gebeurtenissen de laatste tijd dramatisch toegenomen, gedreven door factoren zoals klimaatverandering en globalisering. De Europese hittegolven van 2022, 2023 en 2024 bijvoorbeeld, hebben aangetoond hoe door het klimaat gedreven extremen moderne samenlevingen ernstig kunnen treffen, met tienduizenden hittegerelateerde doden. Evenzo toonde de COVID-19-pandemie de kwetsbaarheden in de wereldwijde paraatheid voor gezondheidscrises aan, wat leidde tot ernstige economische gevolgen en wijdverspreide sociale ontwrichting. Beide verschijnselen benadrukken de dringende noodzaak om de veerkracht en paraatheid te verbeteren in het licht van steeds frequentere en intensere extreme gebeurtenissen.

Steden zijn de zwaartepunten voor extreme gebeurtenissen. Hittegolven treffen stedelijke gebieden onevenredig zwaar vanwege factoren zoals het stedelijk hitte-eilandeffect, dat ontstaat door de concentratie van warmteabsorberende materialen zoals beton en asfalt in steden. Sociaaleconomische ongelijkheden en de concentratie van kwetsbare bevolkingsgroepen, zoals ouderen, huishoudens met een laag inkomen en mensen met bestaande gezondheidsproblemen, verergeren de gevolgen van hittegolven in stedelijke omgevingen verder. Evenzo heeft de snelle verspreiding van de COVID-19-pandemie zich vooral in steden voorgedaan, waar mensen doorgaans meer sociale contacten hebben. Toegenomen mobiliteit en onderlinge verbondenheid vergemakkelijken de verspreiding van het virus, zoals blijkt uit de snelle stijging van het aantal gevallen in steden. De ongelijkheden in toegang tot gezondheidszorg en de prevalentie van comorbiditeiten onder kwetsbare bevolkingsgroepen in steden kunnen de negatieve effecten van toekomstige pandemieën verder vergroten.

De twee centrale concepten van dit proefschrift die ons helpen de impact van extreme gebeurtenissen te begrijpen, zijn kwetsbaarheid en veerkracht. Kwetsbaarheid is de gevoeligheid van een systeem voor schade wanneer het wordt blootgesteld aan gevaren. Vaak wordt kwetsbaarheid gezien als een combinatie van drie belangrijke componenten: blootstelling, gevoeligheid en aanpassingsvermogen. Blootstelling heeft betrekking op de elementen binnen een systeem die getroffen kunnen worden, gevoeligheid duidt op de mate waarin een systeem wordt beïnvloed, en aanpassingsvermogen is het vermogen om zich aan te passen om schade te minimaliseren. In de context van klimaatverandering kan kwetsbaarheid zich bijvoorbeeld manifesteren door de mate waarin bepaalde bevolkingsgroepen worden blootgesteld aan een hittegolf, hoe gevoelig ze zijn op basis van hun sociaaldemografische kenmerken en hoe goed ze in staat zijn om met de hitte om te gaan of zich eraan aan te passen.

Veerkracht vult kwetsbaarheid aan door te focussen op hoe systemen reageren op schokken. Terwijl kwetsbaarheid benadrukt waar een systeem kan breken onder druk,

wijst veerkracht op de sterke punten en capaciteiten van het systeem om te herstellen of zich aan te passen na een verstoring. Zo is veerkracht niet simpelweg het tegenovergestelde van kwetsbaarheid, maar een breder, verbonden concept dat de nadruk legt op herstel, aanpassing en transformatie.

Beide concepten worden vaak gebruikt om te begrijpen hoe goed onze systemen zijn voorbereid op het omgaan met verstoringen en crises, vooral in de context van klimatologische schokken en stressfactoren. Echter, wanneer ze zich voordoen in steden, genereren extreme gebeurtenissen nieuwe soorten problemen en kunnen daarom nieuwe beoordelingsmodellen vereisen.

Traditionele benaderingen voor de beoordeling van stedelijke kwetsbaarheid en veerkracht omvatten doorgaans het gebruik van indicatoren, proxy's of samengestelde indices, die ofwel ruimtelijk (bijv. door de creatie van kwetsbaarheidskaarten) ofwel temporeel worden geschat (bijv. door veerkrachttrajecten te volgen). Hoewel deze benaderingen breed worden toegepast om steden voor te bereiden op extreme gebeurtenissen, hebben ze verschillende beperkingen. Ten eerste vertrouwen ze op modellen die de dynamische aard van stedelijke systemen niet vastleggen, met name de variaties die zich voordoen op zowel ruimtelijke als temporele schalen. Bovendien, hoewel eerder is aangetoond dat veerkracht en kwetsbaarheid met elkaar verbonden zijn, gebruiken deze modellen de concepten van kwetsbaarheid en veerkracht als volledig gescheiden, zonder rekening te houden met hoe ze op elkaar inwerken. Ten slotte negeren ze, ondanks empirisch bewijs, vaak het gedrag van burgers als een drijvende kracht achter kwetsbaarheid en veerkracht.

In navolging van het toenemende belang van het begrijpen van kwetsbaarheid en veerkracht in stedelijke omgevingen, met name in het licht van recente en toekomstige extreme gebeurtenissen, behandelt dit proefschrift de primaire onderzoeksvraag:

Hoofdvraag: *Hoe kunnen we rekening houden met de ruimtelijk-temporele heterogeniteit van steden in modellen voor de beoordeling van stedelijke kwetsbaarheid en veerkracht bij extreme gebeurtenissen?*

Om deze vraag te beantwoorden, formuleren we drie deelvragen, die elk gericht zijn op een specifieke dimensie van stedelijke kwetsbaarheid en veerkracht en hun onderlinge relaties. Het proefschrift maakt gebruik van casestudies van de drie grootste Nederlandse steden — Den Haag, Rotterdam en Amsterdam — en richt zich op twee extreme gebeurtenissen: de Europese hittegolf van 2019 en de COVID-19-pandemie. Door gebruik te maken van een computationele benadering die datascience, ruimtelijke analyse en simulatiemodellering integreert, biedt het proefschrift een diepgaande verkenning van hoe deze steden reageren op en herstellen van extreme gebeurtenissen, waarbij de ruimtelijke en temporele nuances van hun kwetsbaarheids- en veerkrachtdynamiek worden vastgelegd.

Het tweede hoofdstuk van het proefschrift onderzoekt het concept kwetsbaarheid en of het *statisch* is, in lijn met hoe kwetsbaarheidskaarten het weergeven. De bijbehorende deelvraag is:

Onderzoeksvraag 1: *Hoe verschilt stedelijke kwetsbaarheid ruimtelijk-temporeel?*

We bestuderen geanonimiseerde ambulanceoproepen — een proxy voor *algemene* kwetsbaarheid — in Den Haag, Rotterdam en Amsterdam. De oproepen worden toegewezen aan cellen in een raster met voor elke cel open sociaaleconomische data en data over de gebouwde omgeving, evenals gegevens over Points of Interest (POI). Met behulp van ruimtelijke analyses, tijdreeksclustering en regressieanalyse zoeken we naar ruimtelijk-temporele patronen en naar attributen die deze patronen het best verklaren. Stedelijke kwetsbaarheid bleek niet statisch te zijn. Het vertoont aanzienlijke ruimtelijk-temporele variabiliteit, ofwel *ritmes van risico*, beïnvloed door de dagelijkse ritmes van het stadsleven en de kenmerken van de stedelijke en sociale structuur van elk district.

Het derde hoofdstuk van dit proefschrift onderzoekt de relatie tussen kwetsbaarheid en veerkracht bij hittegolven. Vaak wordt aangenomen dat de meest kwetsbare gebieden van een stad ook het minst veerkrachtig zijn. Dit hoofdstuk onderzoekt of, en zo ja in hoeverre, deze aanname waar is. De onderzoeksvraag die hierbij wordt gesteld is:

Onderzoeksvraag 2: *Wat zijn de relaties tussen kwetsbaarheid en veerkracht op stedelijke schaal?*

We bestuderen de Europese hittegolf van 2019, die Nederlandse steden aanzienlijk trof op 22 juli 2019, om deze dynamiek te onderzoeken. Om kwetsbaarheid te beoordelen, gebruiken we een conventionele set van indicatoren, waaronder factoren zoals leeftijd, gezondheid en kenmerken van de gebouwde omgeving, zoals het stedelijke hitte-eilandeffect (UHI), en analyseren we deze met behulp van technieken voor dimensiereductie. Veerkracht wordt gemeten door de verandering in het aantal ambulanceoproepen tijdens de hittegolf. Door zowel statistische als ruimtelijke analysemethoden toe te passen, proberen we de *richting* van kwetsbaarheids-veerkrachtrelaties in verschillende gebieden te ontdekken: meer-minder (negatieve correlatie), meer-meer (positieve correlatie), of minder-minder (positieve correlatie). We constateren dat de relaties tussen stedelijke kwetsbaarheid en veerkracht niet-lineair zijn, contextspecifiek, en worden gedreven door adaptief gedrag van burgers. In dit geval betreft het adaptieve gedrag van burgers het verplaatsen naar koelere gebieden, en dus ontsnappen aan de hitte. Dit gedrag kan echter leiden tot overbevolking en de kwetsbaarheid vergroten in onverwachte plaatsen, zoals parken en stranden. Hierdoor ontstaan *minder kwetsbare, minder veerkrachtige* relaties.

Het vierde hoofdstuk van het proefschrift gaat verder dan de analyse van de huidige staat van stedelijke systemen door de potentiële effecten van beleidsinterventies op kwetsbaarheid en veerkracht te onderzoeken. De onderzoeksvraag die centraal staat in dit hoofdstuk is:

Onderzoeksvraag 3: *Wat is de impact van beleidsinterventies op de kwetsbaarheid en/of veerkracht van verschillende stedelijke districten?*.

De schok die in dit hoofdstuk wordt gebruikt, is de verspreiding van het COVID-19-virus, dat we simuleren in de wijken van Den Haag, Nederland. In dit hoofdstuk maken we gebruik van een breed scala aan datasets om verder te gaan dan de typische benadering van het genereren van een *synthetische populatie* — een standaardinvoer voor agentgebaseerde modellen. In plaats daarvan creëren we een *synthetische stad*, die niet alleen een gesimuleerde bevolking omvat, maar ook hun ruimtelijk-temporeel toegewezen routines, de gebouwde omgeving en lokale bedrijven. Door de gegenereerde synthetische stad als invoer voor een grootschalig agentgebaseerd model te gebruiken, evalueren we de effecten van verschillende beleidsinterventies op de kwetsbaarheid en veerkracht van twee representatieve stedelijke wijken, en analyseren we hoe deze interventies de bevolkingen beïnvloeden. We constateren dat niet-gecontextualiseerde interventies kunnen leiden tot onbedoelde gevolgen en dat de kwetsbaarheid kunnen vergroten in onverwachte stedelijke gebieden — ze *kantelen de risico's*. Het model illustreert de gevaren van het toepassen van uniforme interventies in diverse stedelijke contexten en benadrukt het belang van het in overweging nemen van de unieke kenmerken van elk district om maladaptatie te voorkomen.

De bijdrage van het proefschrift is een multidimensionale en contextgevoelige benadering voor het beoordelen van stedelijke kwetsbaarheid en veerkracht. Het integreert ruimtelijk-temporele analyse, burgergedrag en het diverse weefsel van stedelijke en sociale systemen om de dynamische en contextafhankelijke aard van stedelijke risico's beter vast te leggen. Door gebruik te maken van datascience, ruimtelijke analyse en agentgebaseerde modellering gaat het onderzoek verder dan de gangbare statische benaderingen en biedt het een dynamischere beoordeling van kwetsbaarheden en veerkracht voor extreme gebeurtenissen. Gezien als geheel, presenteert het proefschrift een methode die niet alleen bijhoudt hoe kwetsbaarheid en veerkracht zich ontwikkelen in tijd en ruimte, maar ook de impact van interventies simuleert en mogelijke maladaptieve uitkomsten identificeert. Uiteindelijk biedt het een meer genuanceerde en op ruimtelijke rechtvaardigheid gerichte methodologie voor onderzoekers, stadsplanners en beleidsmakers om stedelijke veerkracht te beoordelen, te begrijpen en te verbeteren in het licht van extreme gebeurtenissen.

Toekomstig onderzoek zou kunnen verkennen hoe kwetsbaarheid en veerkracht zich manifesteren in verschillende steden en onder diverse schokken. Een ander onderzoeksgebied zou kunnen onderzoeken of aanvullende kwetsbaarheids- en veerkrachtstatistieken elkaar aanvullen of juist afwegingen creëren. Zo kan groene infrastructuur de veerkracht tegen hittegolven vergroten, maar ook leiden tot gentrificatie, waardoor laaginkomensbewoners worden verdrongen en sociale ongelijkheid toeneemt. Toekomstige studies kunnen opschalen van wijkanalyses naar volledige steden, waarbij inzichten uit kleinere gebieden worden gebruikt om strategieën voor de hele stad te informeren. Het vergroten van burgerparticipatie is een andere belangrijke onderzoekslijn. Door gemeenschapsleden rechtstreeks te betrekken bij onderzoek en besluitvorming, kunnen steden meer rechtvaardige uitkomsten bereiken. Bewoners kunnen waardevolle inzichten bieden over effectieve interventies en specifieke kwetsbaarheden, wat leidt tot oplossingen die beter inspelen op lokale behoeften.

Concluderend is het begrijpen van stedelijke kwetsbaarheid en veerkracht als dynamische, onderling verbonden fenomenen cruciaal voor het ontwerpen van effectieve beleidsinterventies in het licht van extreme gebeurtenissen. Door rekening te houden met ruimtelijk-temporele heterogeniteit en burgergedrag biedt dit proefschrift een meer genuanceerde en operationele benadering voor het beoordelen en verbeteren van stedelijke veerkracht, en effent het de weg voor meer gerichte en rechtvaardige stadsplanning.

1

INTRODUCTION

This chapter outlines the central themes of this research: extreme events, vulnerability and resilience, and assessment models. It identifies the research gap, formulates the main research question, and introduces the sub-questions that will be explored in the main chapters of the dissertation.

1.1. CONTEXT AND RATIONALE

Throughout history, humanity has encountered many types of events that are both rare and extreme in nature, each posing unique challenges due to their unpredictable nature and significant impacts. *Rare events* can be characterised by their low probability of occurrence, often making them difficult to predict and analyse (J. Li et al., 2023). Rare events can have a mild to severe impact depending on the specific circumstances. On the other hand, *extreme events* are distinguished primarily by their intensity or magnitude rather than how rare they are (Broska et al., 2020). Although these events can also be infrequent, the emphasis is placed on the severity of their consequences. Extreme events often result in significant disruption, damage, or loss, posing challenges for individuals, communities, and countries.

In recent decades, the **frequency**, **intensity**, and **geographic distribution** of extreme events have shifted dramatically, driven by factors such as climate change and globalisation (Calvin et al., 2023). In 2022, Europe experienced the deadliest meteorological event of the year with the European heatwaves, which resulted in at least 61,672 heat-related deaths (Ballester et al., 2023). In 2023, heat caused 47,000 deaths across Europe (Gallo et al., 2024). The frequency of such heatwaves is expected to rise (Y. Gao et al., 2023). The Netherlands, a country that is historically not used to extreme heat, has faced six heatwaves since 2006. One of the most recent ones, The July 2019 European heatwave, lasted only six days, but the temperature in many parts of the country surpassed historical maximums. For instance, a new record of 40.7°C was recorded at the Gilze-Rijen weather station near Breda. According to Statistics Netherlands (2019), the 2019 heatwave caused at least 400 extra deaths in the Netherlands. These events exemplify a

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broader trend: regions once considered safe from extreme heat now face these threats regularly.

Although humanity has faced pandemics before, the scale and impact of COVID-19 caught modern societies largely unprepared. On March 11, 2020, the WHO declared COVID-19 a global pandemic, and already two weeks later, on March 27, 2020, every European country had at least one case. Antarctica was the last continent to report a COVID-19 case in December 2020. According to the World Bank, the global GDP in 2020 fell by 5.2% due to COVID-19. However, its potential mid- and long-term impacts remain to be fully understood (Aaditya & Rahul, 2023; Bianchi et al., 2023; Mohamed et al., 2022). Like heatwaves, epidemics are expected to increase in frequency and impact in the coming years (Marani et al., 2021).

The geographical distribution of extreme events is crucial for understanding their impacts and for developing appropriate mitigation strategies (Ayanlade et al., 2022; Walsh et al., 2020). Heatwaves, for instance, disproportionately affect urban areas due to factors such as the urban heat island effect, which results from the concentration of heat-absorbing materials like concrete and asphalt in cities (Iungman et al., 2024; Peng et al., 2024). This effect can lead to significantly higher temperatures in urban environments than in surrounding rural areas. Additionally, socioeconomic inequalities and the concentration of vulnerable populations, such as the elderly, low-income households, and those with pre-existing health conditions, further exacerbate the consequences of heatwaves in urban settings (M. Chen et al., 2023; McDonald et al., 2024).

Similarly, the rapid spread of pandemics, such as COVID-19, has been especially pronounced in cities, where people typically have a high number of social contacts (Kato & Takizawa, 2022; Stier et al., 2021). Increased mobility and **interconnectedness** facilitate the transmission of the virus, as evidenced by the rapid surge of cases in cities such as New York during the early stages of the pandemic (Fu & Zhai, 2021; Lamb et al., 2021). The disparities in access to healthcare and the prevalence of comorbidities among vulnerable populations in these urban settings further heightened the adverse effects of the pandemic (R. Li & Huang, 2023; Nicoletti et al., 2023).

As extreme events become more intense, frequent, and geographically widespread, we must develop effective responses to keep populations safe. This will require an understanding of what makes cities vulnerable, what builds resilience, and which changes are necessary to current frameworks and assessment models to provide more nuanced insights into urban resilience, guiding urban planning and ensuring that vulnerable populations are better protected in the face of future crises.

1.2. KEY CONCEPTS

VULNERABILITY: WHERE DOES THE SYSTEM GET FRACTURED?

Vulnerability refers to the susceptibility of a system to experience damage or adverse effects when exposed to shocks or stressors. The concept of vulnerability is multifaceted, and its operationalisation varies depending on the type of shock or stress and the system of interest. In climate science, the IPCC (2007) deconstructs vulnerability into three primary components: *exposure*, *sensitivity*, and *adaptive capacity* (Figure 1.1). Exposure refers to the presence of people, livelihoods, environmental services, and resources that could be negatively affected. Sensitivity is the degree to which a system is affected, either adversely or beneficially, by climate variability or change. Adaptive capacity is defined as the ability of a system to adjust to climate change, to moderate potential damages, to take advantage of opportunities, or to cope with the consequences IPCC (2007).

In the context of heatwaves, exposure, sensitivity, and adaptive capacity dominate the scholarship and define how different populations are affected (Szagri et al., 2023). When applied to urban areas, the city itself becomes the system of interest, with vulnerability defined by the interplay between residents and the built environment under heat stress (Ahmed et al., 2023; Srinivas, 2020). Wilhelmi and Hayden (2010) identify various factors linked to these components: exposure is determined by the distribution of heat within the city, sensitivity is defined by socio-demographic variables, and adaptive capacity depends on social capital.

For example, elderly populations (those aged 65 and older) are typically more physically sensitive to extreme heat. At the same time, exposure may be heightened for individuals living or working in areas affected by the Urban Heat Island effect (UHI), where poor air circulation prevents cooling. Adaptive capacity, meanwhile, can be represented by a person's social support network; those with a strong network may receive aid during extreme events, reducing their vulnerability. Conversely, individuals with limited social connections may struggle to cope, increasing their vulnerability.

The vulnerability framework defined by (IPCC, 2007) can be similar when applied to epidemics, where exposure, sensitivity, and adaptive capacity remain crucial factors. Vulnerability during an epidemic is often measured with a social vulnerability index — a composite metric aiming to capture the overall vulnerability of various populations (Kawlra & Sakamoto, 2023). For instance, during the COVID-19 pandemic, sensitivity was higher among older adults and those with pre-existing health conditions (Tatar et al., 2023).

In terms of exposure, frequent social contacts, visits to specific types of places of interest (POI), and reliance on public transport played key roles in the pandemic. For example, higher exposure levels were observed in locations like grocery stores or public transit hubs, where social distancing was difficult to maintain (Liu et al., 2022; Oraby et al., 2021; Tapiador et al., 2024). Meanwhile, adaptive capacity was influenced by factors such as the ability to work from home, which reduced exposure for some, while frontline workers faced heightened risk due to their essential roles.

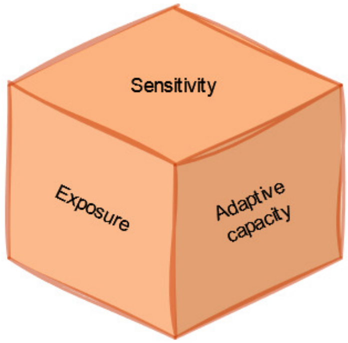

Figure 1.1: A visual representation of vulnerability as a meta-attribute of an urban system.

RESILIENCE: JUST THE FLIP-SIDE OF VULNERABILITY?

Resilience generally refers to a system's ability to recover from a shock, making it a valuable property when facing extreme events (Robertson et al., 2021). Theoretically, the advantages of resilience — or what is sometimes called *general* resilience — span multiple domains, allowing systems to respond effectively to various types of extreme events (Steinmann, 2024). For instance, redundancy is one of the key attributes of a resilient system (Krishnan et al., 2023). Whether applied to a supply chain (e.g., multiple food storage facilities) or a healthcare system (e.g., available hospital beds), redundancy can provide benefits during various crises, from hurricanes to tsunamis.

In practice, however, resilience research often focuses on a specific system and type of extreme event. In the urban domain, resilience is often understood as a city's capacity to *recover*, *adapt*, and *transform* in response to shocks (Chelleri et al., 2015). Though resilience is sometimes framed as the opposite of vulnerability (Buyukozkan et al., 2022), it is more accurately described as a connected and complementary concept (Engle, 2011), as shown in Figure 1.2.

Despite the growing interest in urban resilience, scholars debate how to define and measure it (Meerow et al., 2016). These debates reflect the complexity of urban systems and the wide-ranging impacts that shocks can have on multiple subsystems. For example, while residents feel the immediate effects of a heatwave, it can also disrupt critical infrastructures like energy and transport. Urban systems are highly interconnected, meaning that disruptions in one system often trigger cascading effects in others (Buyukozkan et al., 2022; Zaidi & Pelling, 2015).

Resilience research often divides a city into functional subsystems — such as energy, transport, or ecology — and assigns indicators to assess how well each subsystem can respond, recover, adapt, or transform. In urban heat resilience, much of the focus has been on the role of green and blue infrastructure (e.g., greenery and water bodies) in mitigating the effects of heat (Aram et al., 2020; Iungman et al., 2023). In epidemic resilience, X. Chen and Quan (2021), for example, proposes studying four key subsystems of a city: the economy, ecology, infrastructure, and the social system and how they recover. For each subsystem, the authors suggest using aggregated indicators like GDP (economy), green space (ecology), hospital availability (infrastructure), and population density (social system) to measure resilience.

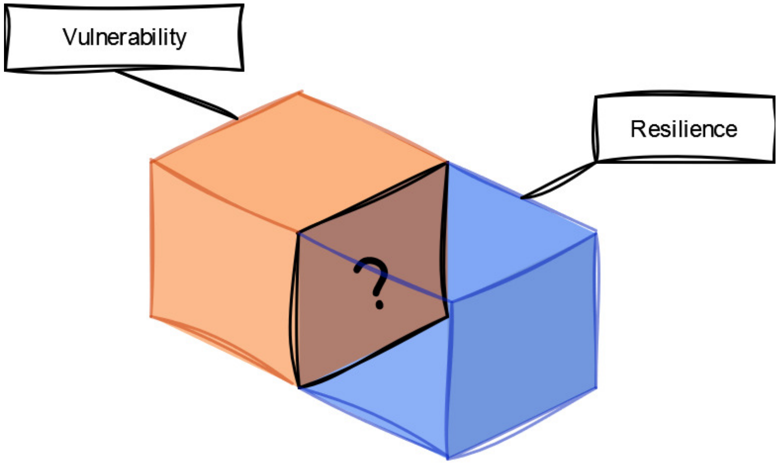

Figure 1.2: Conceptualising relations between vulnerability and resilience via a shared attribute.

1.3. VULNERABILITY, RESILIENCE, SPATIAL EQUITY AND THE LACK THEREOF

Modern cities are **heterogeneous** and full of **inequalities**. During extreme events, these inequalities become especially pronounced (Kalocsányiová et al., 2023). For instance, previous research found significant variations in COVID-19 rates among households of different races or ethnicities, income levels and household sizes. Similarly, McDonald et al. (2024) highlight the differences in urban tree cover, accessibility of green spaces and the potential impact of greenery on mitigating extreme heat. Such variations can also be observed in urban resilience. Champlin et al. (2023) argue that urban districts respond differently to the COVID-19 pandemic due to factors defining their resilience capacities (e.g., citizens' age and access to infrastructures). Jones (2019) summarises this phenomenon by stating: "Resilience isn't the same for all."

With the growing body of literature highlighting the unequal distribution of vulnerability and resilience to extreme events over the population in a city (M. Chen et al., 2023; Gaynor & Wilson, 2020; IFRC, 2023), there is a pressing need to redesign the assessment models to account for inequalities of modern cities. One approach is through the lens of *spatial equity*. Spatial equity refers to the fair and just distribution of resources, services, and opportunities across different geographical areas or spaces (Talen & Anselin, 1998), with the goal of ensuring that all individuals and communities have equal access to what they need to thrive, regardless of their location.

Numerous elements of urban systems are vulnerable to heatwaves and epidemics (Stolte et al., 2024). This research's primary focus is the vulnerability and resilience of individuals and communities. While scholars tend to distinguish and focus on a specific subsystem of a city, for example, transport, infrastructure, or governance, this study zooms into individuals and communities which are part of and interact with the city's many subsystems. In this way, the research focus is similar to Lefebvre (2003) with "*The urban is first and foremost the inhabitants, not the containers*".

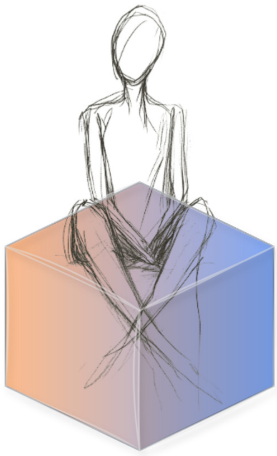

Figure 1.3: Placing the focus on individuals and communities in exploring urban vulnerability and resilience to extreme events.

1.4. ASSESSING URBAN VULNERABILITY AND RESILIENCE

Vulnerability and resilience assessments are often quantitative, producing a specific metric (Reckien, 2018). The exact metric depends on how the system of interest is defined, the type of shock or stress involved, and the key performance indicators. In the climate change domain, vulnerability assessments are frequently **spatial**, as exposure to hazards can vary greatly depending on location. These assessments aim to create a single metric to characterise how vulnerable a particular area is. For instance, when assessing heatwave vulnerability, some countries are more exposed than others (S. Gao et al., 2024).

Resilience assessments, on the other hand, are more often **temporal**, conceptualising resilience as a process. These assessments seek to understand how a system recovers after a shock. For example, Ivanov (2022) examines how global supply chains bounced back after the COVID-19 pandemic.

Assessing urban vulnerability to heatwaves typically results in an *urban vulnerability map* (Wolf et al., 2015). This map displays a Heat Vulnerability Index (HVI), which measures how vulnerable a system or set of subsystems is to heatwaves. The HVI consists of multiple indicators that address various aspects of the urban system. For instance, energy systems might be evaluated based on power grid stability, while transportation systems could be assessed for their susceptibility to disruptions such as road or rail buckling. Similarly, in the context of epidemics, scholars develop vulnerability indices using a collection of indicators or proxies to visualise vulnerability across geographical regions (Mishra et al., 2020). Importantly, these metrics are often static, evaluating only the system's current state and lacking the capacity to assess how policy interventions might improve the system's future performance.

Urban resilience assessments frequently produce *resilience trajectories*, which map out how a system recovers over time. Defining these trajectories involves specifying both the system, the metric of interest and how it would change under a shock. Recently, there have been calls to make resilience assessments more spatially focused and **granular**, both in terms of space and time (Haraguchi et al., 2022). Cariolet et al. (2019) argue "(2), very few studies have been applied at city scale." Further, while urban processes are dynamic, most resilience assessments focus on timescales of weeks or months, with few looking at days or hours (Buyukozkan et al., 2022).

A simulation model (Wang et al., 2020; Zhang et al., 2023) offers an alternative to the metrics approach to assess vulnerability and resilience. This approach is particularly useful when dealing with dynamic systems such as cities as it allows us to simulate how an urban system changes over time. Next, simulation models allow us to move beyond *descriptive* analyses and **assess the impact of interventions** to enhance resilience or reduce vulnerability, thereby shifting to a *prescriptive* focus. Commonly used simulation model types for this purpose are agent-based models (ABM), discrete-event simulations (DES), and system dynamics (SD) (Falagara Sigala et al., 2022). Regardless of the specific model type, the objective is to capture the behaviour of the urban system's essential components over time due to the extreme event in question.

The COVID-19 epidemic boosted the development and use of ABMs centred around citizen behaviour to understand the spread of the virus and design policy interventions (Lorig et al., 2021). Although citizen behaviour is also crucial during heatwaves (Kondo et al., 2021), there are only a limited number of ABMs designed to assess impacts over time and inform policy decisions in this context, with such scenarios more frequently being addressed using the map-based approach previously described (Wolf et al., 2015).

1.5. IDENTIFYING THE RESEARCH GAP AND FORMULATING RESEARCH QUESTIONS

To summarise, extreme events such as heatwaves and pandemics are becoming increasingly frequent and intense, often occurring either in regions that have not traditionally experienced them or becoming global. The interconnectedness of modern societies exacerbates the impact of these events. In particular, urban areas are emerging as critical epicentres of such extreme events due to their role in attracting populations, concentrated infrastructure, and existing and/or increasing social inequalities. Despite vulnerability and resilience being central to understanding the impacts of extreme events, there are still significant challenges in assessing these concepts, particularly on the urban scale. Computational models, both metric-based and simulation-based, are promising tools to evaluate vulnerability and resilience across urban populations. Still, current approaches often fail to capture the complexities and disparities within cities.

Metric-based vulnerability and resilience maps can be useful (Wolf et al., 2015). However, they are typically *static*: even though urban life is highly dynamic, the change in the values of the underlying variables is not reflected in the maps. In the review by Niu et al. (2021), the authors report that most studies do not assess the temporal dimension of an external shock. Recent studies in urban analytics advocate using a more granular examination of vulnerability, considering spatial and temporal dynamics (Champlin et al., 2023; Quagliarini et al., 2023). Similarly, urban resilience scholars argue for the inclusion of human mobility into urban resilience assessments to be able to assess the dynamic nature of urban life (Haraguchi et al., 2022). Moreover, some research still employs methods that ignore differences in area size, shape, or population, thus neglecting the modifiable areal unit problem (MAUP) (Jiao et al., 2024). MAUP occurs when the results of spatial analysis change based on the size or shape of the areas studied, potentially leading to imprecise assessments of vulnerability or resilience. For instance, the review by Haraguchi et al. (2022) demonstrates that urban resilience research spans multiple spatial scales but is often constrained by the availability of data rather than by the ideal spatial resolutions required.

By considering temporal dynamics and embracing more granular spatial units, assessments can more accurately reflect the dynamic nature of urban environments and the diverse experiences of different communities. This approach can help to ensure that urban planning and policy interventions are more equitable and effectively targeted. In this dissertation, we begin by questioning the prevailing assumption that urban vulnerability, although typically mapped spatially, remains static over time. *This leads to our first research question:*

RQ1: *How does urban vulnerability differ spatio-temporally?*

Although the concepts of vulnerability and resilience are widely recognised to be connected (Kelman, 2018), the question remains: how are they related? The relationships between vulnerability and resilience are critical in both academic research and practical application. Despite their interconnected nature, some practitioners treat them as diametrically opposed (Buyukozkan et al., 2022), a perspective that can simplify otherwise complex interactions (Jabareen, 2013). To bring this discussion to the next level, there is a need for empirical, data-driven research that thoroughly examines these relationships within the spatio-temporal dimensions of urban life (Haraguchi et al., 2022; Jones et al., 2021). *This consideration brings us to our second research question:*

RQ2: *What are the relationships between vulnerability and resilience at the urban scale?*

Finally, there is a notable gap in understanding the behavioural responses of affected individuals to extreme events (Kabisch et al., 2021) and thus in translating this emergent behaviour into a computational model. For example, during a heatwave, residents in urban heat islands (UHIs) might seek relief by visiting parks, thus exhibiting adaptive behaviours that alleviate the heat's immediate pressures (Iungman et al., 2023). Similarly, research reports significant variations in the behavioural response to COVID-19 policies (Tintori et al., 2020). Behavioural responses might also vary between different groups of people in cities (e.g., differing by age, income, level of education, household size, or ethnicity), where these groups are often clustered in certain neighbourhoods.

Importantly, this behavioural richness can only be explored with models allowing for heterogeneity. A complicating factor for the exploration of extreme events is that they often have no precedent (in the recent past), and as a result, data is lacking, especially on a highly granular level. In such a case, employing deep uncertainty methods and exploratory modelling can be used to explore the implications of deeply uncertain variables (Bankes et al., 2013; Stanton & Roelich, 2021), such as agent-based models (ABMs). *This leads us to the third research question:*

RQ3: *What is the impact of policy interventions on the vulnerability or resilience of various urban districts?*

Synthesising these issues, it becomes clear that a multi-dimensional approach is needed to account for the spatial-temporal heterogeneity of cities when assessing vulnerability and resilience. *Therefore, the main research question guiding this study is:*

Main RQ: *How can we account for the spatial-temporal heterogeneity of cities in urban vulnerability and resilience assessment models for extreme events?*

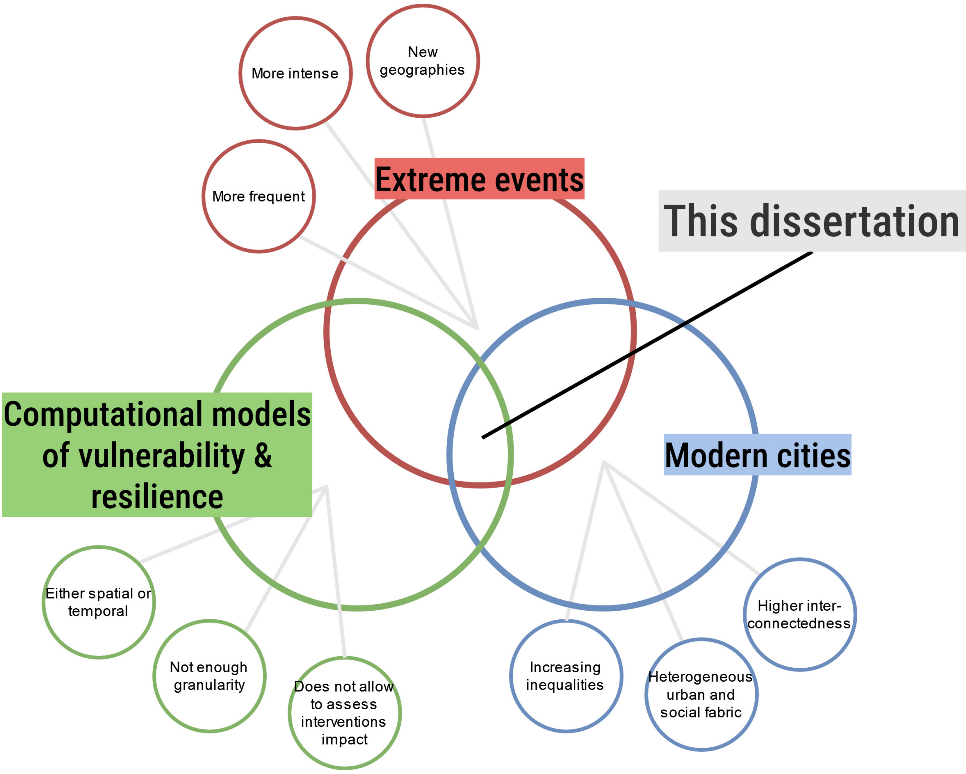

Figure 1.4: Visualising the research focus of this dissertation.

1.6. RESEARCH METHOD AND OUTLINE

This dissertation addresses specific research gaps at the intersection of urban vulnerability and resilience and extreme events — heatwaves and epidemics — and computational modelling. Focusing on case studies of the three largest Dutch cities — The Hague, Rotterdam, and Amsterdam — it examines two extreme events: the 2019 European heatwave and the COVID-19 pandemic. By employing a computational approach that integrates data science, spatial analytics, and simulation modelling, the research aims to enhance the understanding of urban vulnerability and resilience in the face of extreme events. Each chapter addresses a specific research question, contributing to a comprehensive understanding of the complex dynamics between vulnerability and resilience and collectively answering the main research question.

Following the introduction, the second chapter investigates whether vulnerability is indeed *static* as traditionally portrayed by vulnerability maps. To address **RQ1**, we study anonymised ambulance calls — a proxy for *general* vulnerability — in The Hague, Rotterdam, and Amsterdam. These calls are distributed over a grid enriched with open socio-demographic and economic data, built environment characteristics, and points of interest (POI). Using spatial analytics, time-series clustering, and regression analysis, we search for spatio-temporal patterns and identify attributes that best explain these patterns.

The third chapter delves into the relationship between vulnerability and resilience in the context of heatwaves, addressing **RQ2**. The central hypothesis examines whether the "more vulnerable, less resilient" paradigm holds true at the urban scale. We assess these dynamics using the 2019 European heatwave — which significantly impacted Dutch cities on July 22, 2019. Vulnerability is evaluated using a conventional set of indicators, including factors such as age, health status, and built environment characteristics like the urban heat island (UHI) effect, analysed through dimensionality reduction techniques. Resilience is measured by the change in the number of ambulance calls during the heatwave. By applying statistical and spatial analysis methods, we aim to uncover the *direction* of vulnerability-resilience relationships in different areas: more-less (negative correlation), more-more (positive correlation), or less-less (positive correlation).

Moving beyond the analysis of urban systems in their *current* state, the fourth chapter examines the potential effects of policy interventions on vulnerability and resilience, addressing **RQ3**. The shock investigated in this chapter is the spread of the COVID-19 virus, which we simulate in the districts of The Hague. As a methodology, we select agent-based modelling (ABM). The ABM allows us to simulate the individual behaviours of agents-citizens within an urban environment with a high resolution. This approach helps to overcome potential artefacts that can arise from using aggregate entities of a lower resolution, e.g., districts. Leveraging a wide array of datasets, we go beyond the typical approach of generating a *synthetic population* — a standard input for agent-based models — and instead create a *synthetic city*. This synthetic city incorporates not only a simulated population but also their spatio-temporally allocated routines within the city's built environment and a variety of POI. Using this as input into a large-scale agent-based model, we evaluate the effects of several policy interventions on the vulnerability and resilience of two representative urban districts, analysing how these interventions influence the populations.

The final chapter synthesises the findings from the individual studies. It discusses the limitations of the research and offers recommendations for further research, aiming to contribute to developing more accurate and dynamic models that can better inform urban planning and policy-making in the face of extreme events.

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The rhythm of risk: Exploring spatio-temporal patterns of urban vulnerability with ambulance calls data

Published as Sirenko, M., Comes, T., & Verbraeck, A. (2024). The rhythm of risk: Exploring spatio-temporal patterns of urban vulnerability with ambulance calls data. *Environment and Planning B: Urban Analytics and City Science*, DOI:23998083241272095.

Abstract

Urban vulnerability is affected by changing patterns of hazards due to climate change, increasing inequalities, rapid urban growth and inadequate infrastructure. While we have a relatively good understanding of how urban vulnerability changes in space, we know relatively little about the temporal dynamics of urban vulnerability. This paper presents a framework to assess urban vulnerability over time and space to address this gap. We apply the framework to Amsterdam, Rotterdam, and The Hague, the Netherlands. Using high-resolution, anonymised ambulance calls and socioeconomic, built environment, and proximity data, we identify three temporal patterns: 'Midday Peaks', 'Early Birds', and 'All-Day All-Night'. Each pattern represents a unique rhythm of risk arising from the interaction of people with diverse demographic and socioeconomic backgrounds and the temporal flow of their daily activities within various urban environments. Our findings also highlight the polycentric nature of modern Dutch cities, where similar rhythms emerge in areas with varying population densities. Through these case studies, we demonstrate that our framework uncovers the spatio-temporal dynamics of urban vulnerability. These insights suggest that a more nuanced approach is necessary for assessing urban vulnerability and enhancing preparedness efforts.

2.1. INTRODUCTION

In 2023, Europe, parts of North America, and Asia experienced one of the hottest summers ever recorded. At the same time, flash floods and earthquakes rattled cities worldwide. According to the United Nations Human Settlements Programme (UN-Habitat, 2022), climate change, rapid urban growth, increasing spatial inequalities, and pressures of migration and conflict have exacerbated urban vulnerabilities. While the need to better analyse and reduce vulnerabilities is broadly recognised (UNISDR, 2015), rapidly growing and highly dynamic urban areas pose challenges to vulnerability assessment.

Modern cities are complex. This complexity is both spatial, with city centres packed with more places of interest compared to quieter outer residential areas, and temporal, as the ebb and flow of urban life create distinct rhythms. These rhythms are a product of the dynamic interplay between live-work patterns, transportation, and visits to various places of interest, driving the health and safety in urban environments (Brelsford et al., 2022; R. Verma et al., 2021).

Assessing urban vulnerability, therefore, demands an approach that integrates spatial and temporal heterogeneity. Traditional vulnerability assessments, focusing on spatial inequalities, often miss the temporal layer – even though behavioural rhythms, such as commuting or shopping patterns, significantly influence urban dynamics. This point is further illustrated by studies like Curiel et al. (2021), which found that crime and road accidents in Mexico City shared similar temporal patterns influenced by the area's economic activities.

Our investigation aims to understand whether vulnerability in urban spaces adheres to these rhythmic patterns. We hypothesise that by closely examining human behaviour, especially routine activities intrinsically connected to places of interest, we can unveil the complex spatio-temporal variations in urban vulnerability. This approach aligns with recent advancements in urban analytics, which advocate for a more granular examination of vulnerability, considering spatial and temporal dynamics (Champlin et al., 2023; Haraguchi et al., 2022; Quagliarini et al., 2023).

Vulnerability scholars have developed frameworks ranging from generic models (IPCC, 2014) to conceptual approaches that encompass various (urban) systems contributing to and compromising vulnerability (Garfias Royo et al., 2023; Kyprianou et al., 2022). Some have operationalised these frameworks using data (Alabbad et al., 2023; Sun et al., 2020). Given the plethora of vulnerability assessments, there are increasing calls for empirically grounded measurements (Jones et al., 2021). Moving forward, Fekete (2019) and Ho et al. (2019) highlight the need for validation of indicators, indexes and proxies. To address this gap, we use ambulance call data as a proxy to empirically measure urban vulnerability. The rationale is straightforward yet profound: ambulance calls, triggered by a range of urban incidents, offer a real-time snapshot of where and when a city's fabric shows signs of stress or failure: medical emergencies, public safety incidents, etcetera (for more information see A). This approach addresses the spatial and temporal dimensions of vulnerability, providing a multidimensional view of urban dynamics.

By blending vulnerability theory with advances in citizen behaviour and urban analytics, this paper aims to achieve a twofold objective. First, it aims to develop an analytical framework for assessing urban vulnerability across spatial and temporal dimensions. Subsequently, the paper illustrates the application of this framework by investigating the following questions:

1. How does urban vulnerability change across space and time?
2. Are there vulnerability rhythms - identifiable patterns to these changes?
3. What elements of the urban ecosystem primarily shape these vulnerability rhythms?

We utilise open data on ambulance calls from the 112 emergency network for three Dutch cities, Amsterdam, The Hague and Rotterdam, as a proxy for urban vulnerability. This data has a high resolution: the call location as a latitude and longitude pair and the time of the call with a minute precision. We aggregate it over 24 hours to generate "daily rhythms" connected to each grid cell and identify rhythms similar in shape. We further dissect it with a one-square-kilometre spatial grid of socio-demographic, built environment and infrastructure attributes and search for attributes of the urban ecosystem that best explain the resulting rhythms.

2.2. Background

Urban life follows rhythms

An urban environment is polyrhythmic, consisting of nested fast-changing behavioural rhythms resulting from live-work patterns (Brelsford et al., 2022), transport (R. Verma et al., 2021) or visits to different places of interest (POI) (Betancourt et al., 2023). Consequently, the rhythms of human behaviour also drive urban vulnerability. For instance, Curiel et al. (2021) explored crime and road accidents in Mexico City. The authors found that crime and road accidents have similar patterns, with valleys overnight and peaks during the evening.

However, what is not clear is whether the evolution of vulnerability follows similar rhythms over space and time. We hypothesise that by analysing human behaviour, specifically routine activities connected to places of interest, we can better understand the spatio-temporal variations in urban vulnerability. As a city comes to life, its residents embark on their daily activities, whether work, school, or leisure. These rhythms stem from many factors, including an individual's age and socio-economic status, their living location, destinations, and the accessibility of various amenities. Our objective is to examine if the patterns of urban vulnerability mirror these behavioural rhythms.

A framework to analyse urban vulnerability

Vulnerability generally refers to the susceptibility of a system to experience damage or adverse effects when exposed to hazards or stressors. Urban vulnerability refers to the potential of a given population, urban space, or infrastructure to be affected by adverse circumstances (Srinivas, 2020). Urban vulnerability assessment is often based on exposure, sensitivity and adaptive capacity (IPCC, 2007). Conventionally, urban vulnerability assessments utilise exposure data (e.g. the presence of a heat island in a particular district) and geographically allocated census data to assess the sensitivity and adaptive capacity (e.g. poor or above 65 y.o.) to a shock or stress (e.g. a heatwave) (Wolf et al., 2015).

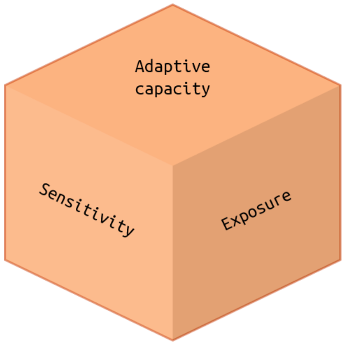

Figure 2.1: A visual representation of vulnerability as a meta-attribute of an urban system.

Recently, an increasing number of studies have stressed the importance of measuring vulnerability as a spatio-temporal phenomenon, especially in light of COVID-19 (see, e.g., (Huang et al., 2021; R. Li & Huang, 2023)). These studies include exposure, sensitivity and adaptive capacity. For instance, Fu and Zhai (2021) examines relations between conventional static social vulnerability and social-distancing behaviours during the COVID-19 pandemic. They found that citizens' behaviour differs over space and time, and, therefore, the spatio-temporal dimension of social vulnerability becomes critical when designing policies. From the exposure side, Chen and Quan (2021) shows how heat exposure varies over the mega-city of Beijing: the core functional area has the highest exposure risk, which decreases outward. Remarkably, the exposure hotspot shifts overnight, demonstrating spatio-temporal variability. Arguably, some of the shifts in vulnerability stem from population movements. However, a recent review on human mobility found that dynamic mobility and movement data are not conventionally part of vulnerability assessments (Haraguchi et al., 2022). In sum, urban vulnerability is a spatio-temporal meta-attribute of a city (Figure 2.2). Therefore, it is crucial to understand its dynamics over space and time.

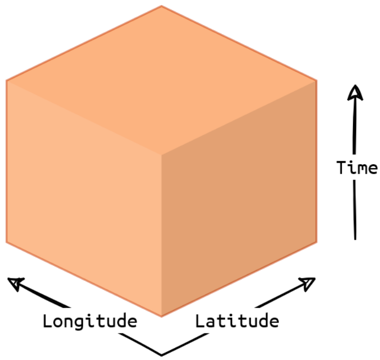

Figure 2.2: Urban vulnerability as a spatio-temporal cube.

Vulnerability assessments have traditionally leaned on socio-economic and district or block-level census data. The emergence of smart cities and advances in urban analytics now allow for a more granular examination of vulnerability in both space and time. Several authors have demonstrated the value of moving towards higher resolutions, both spatially and temporally. For instance, Renner et al. (2018) found that incorporating daily and seasonal fluctuations in people's mobility reveals vulnerability hotspots. R. Li and Huang (2023) argues for the analysis on a finer spatial scale of how socio-economic attributes differ within a city. Champlin et al. (2023) point at the differences in behaviour across various social groups and districts. Quagliarini et al. (2023) highlight the hourly and daily variations in how citizens and visitors use different open spaces. Yin et al. (2020) demonstrates that the ambient air temperature has a significant variability over a day and other areas of a city, thus highlighting how exposure to extreme temperatures may differ. While all these studies start to address behavioural patterns or exposure dynamics, what is missing is a vulnerability assessment that is designed to capture the dynamic and multi-rhythmic nature of our cities at a high spatial *and* temporal resolution.

A PROXY FOR IDENTIFYING WHERE AND WHEN THE URBAN ECOSYSTEM GETS FRACTURED

Conventionally, vulnerability assessments use a composite indicator. While such an approach was found helpful by some (Wolf et al., 2015), one of its most prominent problems is the lack of "ground truth" to validate it. Given the variability of indicator-based vulnerability assessments (e.g. Birkmann et al. (2022)), it is unclear whether postulated and aggregated indicators represent a high or low vulnerability (Copeland et al., 2020). Following the calls for more empirically grounded measurements of vulnerability and resilience (Jones et al., 2021), we use a reverse approach where we first define a proxy to measure urban vulnerability empirically.

The proxy has three requirements: it must have high spatial and temporal resolutions and help reveal when and where an urban system exposes its vulnerability and gets fractured. We propose the number of ambulance calls as a proxy to create insights into urban vulnerability. Our motivation is as follows. When a vulnerable system encounters a situation that exposes its weaknesses, it is more likely to experience a failure or an accident, resulting in an ambulance call. People call an ambulance, but when they do so, they are in a certain location for a particular activity. Therefore, we hypothesise that fluctuations in the number of ambulance calls over space and time will correspond to urban rhythms, particularly daily routines. We expect ambulance calls will allow us to understand the sensitivity, exposure, and adaptive capacity at a high spatial granularity and gain better insights into where and when the urban system is vulnerable.

Several recent studies utilised ambulance call data to study vulnerability. Seong et al. (2023) found that the number of heat-related ambulance calls in the Austin and Travis County areas of Texas is higher in neighbourhoods with more elderly or more people receiving social benefits. D. Li et al. (2022) demonstrated the connection between historical redlining, exposure to extreme heat and subsequent emergency department visits. The authors found that exposure (land surface temperature) and sensitivity (e.g., old, low-income, etc.) vary over space and may result in more emergency department visits.

Certainly, the number of ambulance calls is not the sole proxy to measure urban vulnerability. Raška et al. (2020) states that any indicator-based vulnerability assessment will capture only a fraction of the "true" vulnerability. That is, this study does not propose "the" proxy but instead proposes an example, which is spatio-temporal and has a high resolution. Later, it can be combined with other proxies, illuminating different aspects of the urban system.

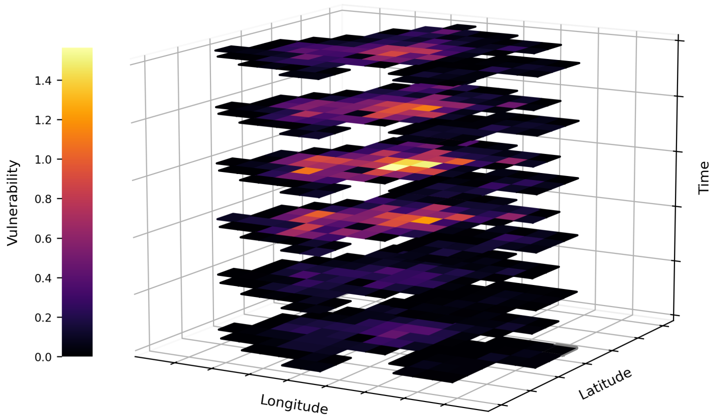

Figure 2.3: A visual representation of the spatio-temporal variance in the chosen proxy: the number of ambulance calls.

2.3. METHODOLOGY

STUDY AREA

We analyse the three largest municipalities of the Netherlands. Given the focus of the paper on urban vulnerability, we follow a pragmatic approach and use the administrative definition and official boundaries of the municipalities of Amsterdam, Rotterdam, and The Hague, with populations of 918,117, 663,900, and 562,839, respectively, in 2023 (CBS, 2023), to demonstrate the application of our approach. These municipalities are often referred to as cities, but they are also part of larger metropolitan areas—Amsterdam Metropolitan Region, Haaglanden, and Rotterdam-The Hague Metropolitan Region, respectively. These metropolitan regions consist of various municipalities. Planning policies in the Netherlands have focused on establishing compact cities (instead of the urban sprawl typical for many cities in the US) with strong cores and ample opportunity for the different municipalities to develop their own spatial visions and development plans (Claassens et al., 2020). Therefore, in the Netherlands, each municipality functions independently and relies on its own infrastructure, municipal services, and unique identity. By focusing on the municipalities (Amsterdam, Rotterdam, The Hague) rather than on the larger agglomerations or metropolitan areas, we can better study the high-paced life and potential vulnerabilities specific to cities. This approach also facilitates comparisons across cities by excluding potential differences in the surrounding satellite municipalities.

DATA

In our study, we utilised two open and freely accessible data sets. The first is "Kaart van 500 meter bij 500 meter met statistieken" provided by Statistics Netherlands (CBS), which offers 2019 data on socio-economic factors, the built environment, and proximity with a spatial resolution of 500 by 500 meters. The second is the anonymised ambulance call data from the Dutch P2000 network, managed by 112-nederland.nl. This dataset spans 2017-2020 and includes ambulance call records with spatial details pinpointing 4- and 6-digit postal codes.

AMBULANCE CALLS

P2000 is an open network and a part of the Dutch C2000 alarm network maintained by The Dutch Ministry of Justice and Security. Amongst others, this network registers ambulance calls. Importantly, the calls are anonymous and do not have information about who called and the reason for the call. It has, however, a 4 or 6-digit postcode as a latitude and longitude pair with the middle point of the street where it was made.

We aim to analyse a *typical weekday* - an average across three autumn seasons and five weekdays. Let $a_{i,j}(t)$ be the number of ambulance calls made from coordinate *(i, j)* at time t. For each year, we constrain t by 1 September and 30 November, and the coordinate pairs *(i, j)* are constrained by the municipal borders of the case cities.

Autumn is chosen as it is most representative of normal urban activity in Dutch cities, featuring regular work and school schedules without major holidays or events (T. Verma et al., 2021). Unlike December, spring, and summer, autumn lacks significant external disruptions, allowing focus on resident-driven dynamics. Additionally, autumn avoids seasonal health impacts like the flu prevalent in January and February (Statistics Netherlands, 2019). We exclude weekends due to intercity travel complicating within-city pattern analysis and lower call volumes (e.g., 87-weekday calls vs 32-weekend calls in The Hague). See the Supplementary materials for more details.

Next, we have three grids consisting of cells of 1 km^2 for each case city G. Let g_k denote a grid cell k where $k \in [1, K]$ and K is the total number of grid cells of the three cities (equal to 775). To connect the calls and the grid cells, we count each $a_{i,j}(t)$ to the corresponding grid cell g_k.

For creating a typical weekday, we first aggregate calls into six equal periods T: 00:00-04:00, 04:00-08:00, 08:00-12:00, 12:00-16:00, 16:00-20:00, and 20:00-00:00. It is quite common to smooth the data to analyse temporal patterns (Prieto Curiel, 2023). However, in our case, we work with data of high spatial granularity, which leads to relatively small grid cell sizes and limits the volume of data per grid cell. By aggregating data into four-hour bins, we aim to identify and reason about the urban routines and patterns more effectively. Smaller time bins might introduce noise and obscure meaningful patterns, especially in grid cells with fewer observations.

Next, we average all calls made during the weekdays in each grid cell g_k over each period t in T.

We thus obtain a matrix A of size $N \times T$. N is the number of grid cells where the number of ambulance calls is more than 0 in any period t. In our case, $N = 528$. T is the number of daytime periods, equal to 6. The values $A_{i,j}$ represent the average number of ambulance calls made in the grid cell g_i at the period T_l, where l is one of the 6 time periods. Table 2.1 shows a snapshot of the resulting matrix A for three grid cells. See more

Day time Grid cell	0-4	4-8	8-12	12-16	16-20	20-0
1	0.02	0.00	0.28	0.03	0.03	0.11
5	0.00	0.00	0.03	0.00	0.00	0.02
6	0.06	0.03	0.48	0.22	0.14	0.17

Table 2.1: Typical weekday across three grid cells. The rows are grid cells, and the columns are daytime periods. The value is the average number of ambulance calls from this grid cell during this period.

Importantly, the number of ambulance calls increases with higher population density (see Section 4.1). Our objective, however, is to understand the temporal dynamics of vulnerability. Instead of analysing the number of calls per resident of a grid cell (static), we are interested in rhythms emerging from the changes in population over time. This distinction is critical because footfall and traffic are dynamic phenomena that fluctuate throughout the day. These rhythms may directly affect the number of incidents and, consequently, the number of ambulance calls. To address these dynamic patterns, we used Z-normalisation (with a mean of 0 and a standard deviation of 1). This method allows us to capture the rhythms of incident occurrences while the raw data represents volumes (see Figure S4). Analysing these rhythms helps us to uncover the polycentric nature of Dutch cities.

URBAN ECOSYSTEM

The CBS's "Kaart van 500 meter bij 500 meter met statistieken" dataset, updated annually, provides detailed spatial data on the Netherlands. It includes 134 features in socioeconomic, built environment, and proximity categories. Our focused analysis of 2019 data for The Hague, Rotterdam, and Amsterdam leverages 31 key features from this dataset; see Table 2.2. Importantly, the distance to the city centre (the last feature of the proximity list) is measured to the busiest historical areas: Grote Markt in The Hague, the square in front of Koninklijk Paleis in Amsterdam, and the middle of the Centrum district in Rotterdam. While this feature set may not capture all possible nuances of urban vulnerability, it allows us to identify features that can meaningfully contribute to understanding these patterns, grounded in scientific literature and practical for policy-makers.

Socio-economic	Built environment	Proximity, km
0-15 y.o.	% Owner-occupied houses	Shopping
15-25 y.o.	% Rented houses	Cafe & restaurant
25-45 y.o.		Entertainment, arts & culture
45-65 y.o.		Childcare
65+ y.o.		Primary education
% Dutch		Secondary & higher education
% Western		National or provincial road
% Non-western		Train station
One-person household		GP 9-17
Multi-person household w/o kids		Hospital 9-17
Single-parent household		Hospital 24h
Multi-person household w kids		Pharmacy
% Low-income household		GP station 24h
% High-income household		Distance to the city centre
Residents receiving social benefits		

Table 2.2: Selected features of interest in three categories from the CBS data set. Socio-demographic features and built environment features are percentages or real numbers. Proximity is the distance in km by road to the closest amenity of a particular type.

Methods

Our goal is to identify the rhythms of vulnerability and identify the factors that explain these rhythms. We do this in two steps. First, we analyse the number of calls temporally and spatially via a hotspot analysis. Second, we cluster the previously constructed typical weekday time series. We finish with the search for attributes that best explain the clusters with an exploratory data analysis.

Hotspot analysis with the Local Indicator of Spatial Autocorrelation (LISA)

The Local Indicator of Spatial Autocorrelation (LISA) is one of the key techniques in urban analytics for revealing local spatial patterns within datasets (Anselin, 1995). Rooted in the Local Moran's I statistic, LISA identifies spatial clusters and outliers, categorising them into four significant associations: high-high (hotspots), low-low (coldspots), high-low, and low-high. By capturing these nuanced spatial relationships, LISA offers insights into areas of concentrated phenomena - in our case, the number of ambulance calls. We use an open-source Python package, PySAL (Rey & Anselin, 2007), to create LISA cluster maps for each of the 3 case cities.

Time series clustering

Clustering techniques are essential for finding hidden structures and patterns when analysing time series data. Various methods include Dynamic Time Warping (DTW), K-means clustering, spectral clustering, etcetera. Steinmann et al. (2020) analysed the performance of various algorithms and found that agglomerative clustering scores relatively high when dealing with time series of complex shapes. We use its implementation from the Python package EMA Workbench (Kwakkel, 2017). We aim to cluster typical weekdays constructed from the number of ambulance calls recorded in a specific grid cell.

2.4. RESULTS

IDENTIFYING HOTSPOTS: DAILY PEAKS AND MULTIPLE CENTRES

Temporally, an apparent trend emerges across all cities (Figure 2.4): ambulance calls are sparse during the night, reaching the minimum between 04:00 and 05:00 in the morning. Subsequently, there is an increase, peaking at 12:00 for The Hague and 13:00 for Rotterdam and Amsterdam. This peak then tapers off gradually as the day progresses towards midnight. This pattern mirrors typical human activity rhythms, with nocturnal lulls and daytime peaks reflecting our daily routines and habits.

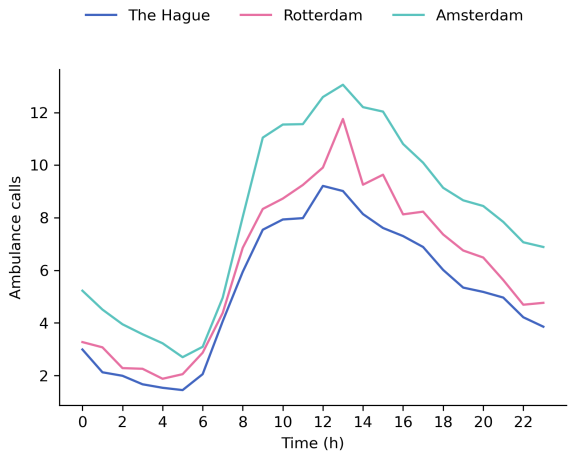

Figure 2.4: Number of ambulance calls recorded during a typical weekday from 00:00 until 23:59 in three Dutch cities: The Hague, Rotterdam and Amsterdam.

Spatially, the city centres of the three cities register the highest number of calls (left panel of Figure 2.5). In The Hague, the pattern is straightforward: the central four grid cells record most calls, with numbers tapering off to form concentric rings as one moves outward. Rotterdam, bisected by a river, has two central hubs where calls peak. Adjacent areas to these hubs show slightly fewer calls, with the numbers decreasing further as one moves away. Amsterdam's city centre, characterised by its network of canals, divides into distinct "rings".

The Local Indicator of Spatial Association (LISA) cluster map supports our hypothesis, pinpointing city centres as hotspots. However, not all peripheral residential areas are characterised as cold spots. Each of the three cities also presents spatial outliers, with grid cells labelled low-high and high-low.

2

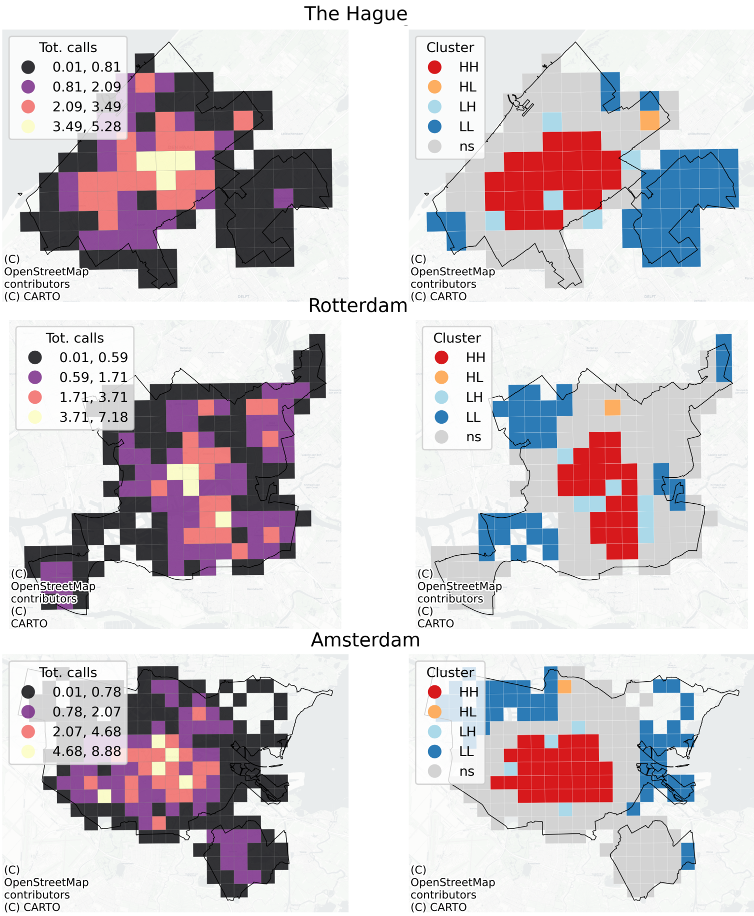

Figure 2.5: Comparative visualisation of emergency healthcare needs in three Dutch cities — The Hague, Rotterdam, and Amsterdam—during a typical weekday. The left panels feature choropleth maps representing the total number of ambulance calls, while the right panels display Local Indicators of Spatial Association (LISA) cluster maps. Data covers a 24-hour cycle. Read legend labels as HH - high-high, HL - high-low, LH - low-high, LL - low-low, ns - not significant. Each grid cell is 1 km × 1 km.

SIX DISTINCT DAILY PATTERNS

Our primary interest now lies in analysing the call patterns. A pattern is the typical daily shape of call activity in a grid cell. We hypothesise that even though the number of calls might vary, the shape representing the pattern could remain consistent across the grid cells in all cities. We identified six distinct patterns that can be classified into three main groups (Figure 2.6).

The first group, "Midday Peaks", comprises the two most dominant clusters (0 and 1) and accounts for 48% of the total number of clustered grid cells. These clusters have a major peak during the 12:00 - 16:00 window. Cluster 1 displays a minor peak (can be observed as a spike of multiple grey lines) from 8:00 to 12:00. Cluster 0 has a more complex shape with multiple secondary peaks from 00:00 to 04:00 as well as from 04:00 to 08:00 and from 16:00 to 20:00.

The second group, "Early Birds", which encompasses 30% of the data, consists of Clusters 2 and 3. Both clusters primarily peak from 8:00 to 12:00, then see a decline in calls. Cluster 2 experiences a more gradual decrease, while Cluster 3's decline is more pronounced. A few grid cells in Cluster 2 show fluctuations between 12:00 and 16:00 and again from 16:00 to 20:00. Similarly, grid cells in Cluster 3 also display variations, particularly in the 20:00 - 00:00 period.

The third group, "All-Day All-Night", represents 22% of the grid cells, Clusters 4 ("All-Day Active") and 5 ("Daytime-Nighttime"), both of which maintain a relatively high volume of calls throughout the day. Cluster 4 peaks between 8:00 and 12:00 and then maintains a consistent call volume until midnight. In contrast, Cluster 5, although more volatile, shows a variance between its 8:00-12:00 values and the subsequent periods. Nonetheless, its average suggests a relatively stable overall call volume. Remarkably, it spikes more during nighttime: 20:00-24:00 and 00:00-04:00.

To summarise, we found six distinct patterns of urban vulnerability that can be grouped into three categories.

An analysis of the clusters' geographical distribution offers insight into a potential explanation of vulnerability patterns. Cluster 0, the most dominant cluster, predominantly appears in the city centres or "Central Business District". These areas experience increased foot traffic during working hours (12:00 - 16:00), primarily due to a higher concentration of shops and leisure amenities, leading to a greater number of calls during this period. Remarkably, individual grid cells labelled as Cluster 0 can also be found outside the centres, for instance, southwest of The Hague and Rotterdam. This finding suggests similar activities are happening in these smaller secondary centres, which often operate autonomously. Cluster 1 ("Inner-City Periphery") often surrounds Cluster 0 but tends to be located farther away from the city centre.

Clusters 2 and 3 are predominantly in the "Outer Residential" areas. These clusters peak from 04:00 to 08:00. One possible explanation for such a distribution is that calls from these clusters might be related to incidents coinciding with the start of daily human activities, such as commuting to work. These clusters sometimes overlap with Clusters 0 and 1 in outlying residential districts or smaller secondary city centres.

Clusters 4 and 5, forming the last group of "Urban Core", frequently overlap with Clusters 0 or 1 and are primarily found in the city centre. These clusters have a relatively stable number of calls throughout the day, suggesting these areas are the busiest parts of the cities with consistent footfall, activities, and corresponding incidents. The late-night activity spikes observed in Cluster 5 may suggest the presence of leisure amenities in the area.

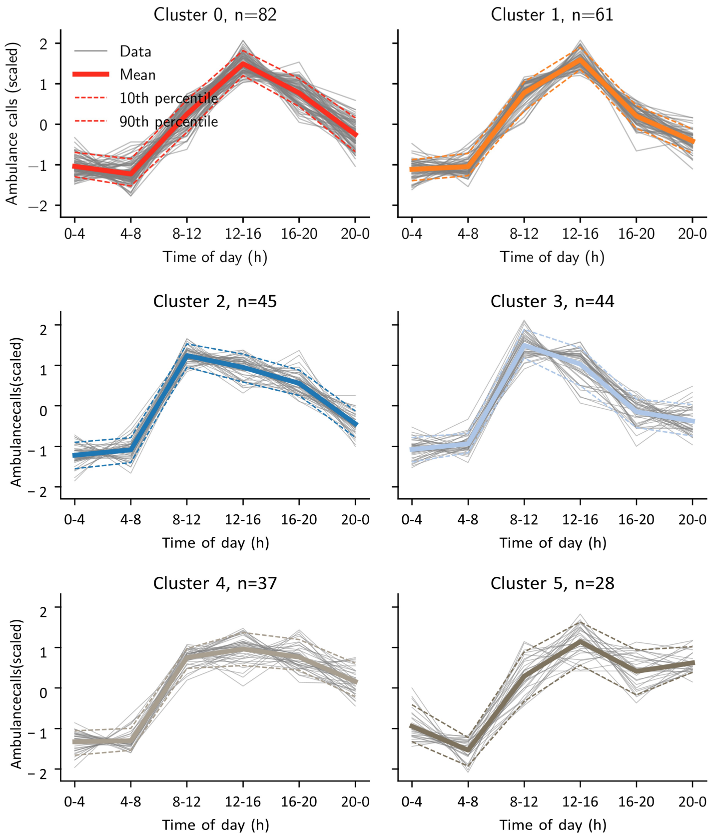

Figure 2.6: Temporal patterns of ambulance calls for the top six cluster labels (0-5) across three Dutch cities—The Hague, Rotterdam, and Amsterdam. Each plot represents one of the cluster labels, where "n" in the title indicates the number of grid cells associated with that label. The x-axis denotes the time of day, while the y-axis displays the number of ambulance calls, standardised using Z-normalisation. The plots include the scaled data, mean values, and the 10th and 90th percentiles to capture the range of variability.

The spatial distribution of clusters reveals a multifaceted pattern (Figure 2.7). While mirroring traditional urban zoning with a generally concentric layout, it also highlights the complexity and polycentric nature of modern Dutch cities. In The Hague, the concentric layout is slightly more pronounced, with a distinct yet gradual transition from the city centre, characterised by Clusters 0, 1, 4, and 5, to the outer residential areas represented by Clusters 2 and 3. In contrast, in Rotterdam and Amsterdam, the pattern is more varied, with different cluster types interspersed throughout the city. Additionally, we observe a complete mix of all cluster types in the more remote parts of these cities. This indicates a polycentric trend, where distinct districts operate independently, suggesting that modern Dutch cities can be described as a conglomerate of smaller cities within a city.

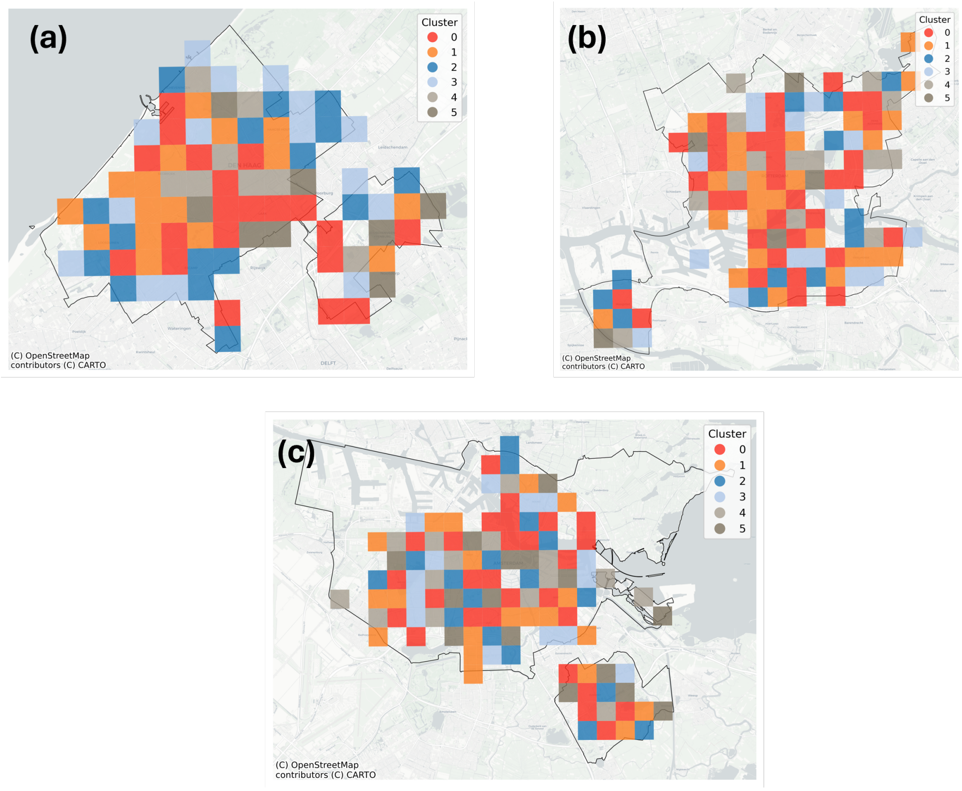

Figure 2.7: Spatial distribution of temporal clusters of ambulance call patterns in The Hague, Rotterdam, and Amsterdam (panels a, b, and c, respectively).

EXPLAINING THE PATTERNS

We can partly attribute temporal vulnerability patterns to conventional zoning. The remaining complexity, however, requires us to zoom in and search for features that could explain them better.

We start by testing a hypothesis of whether the population of a grid cell can explain the number of ambulance calls made during a typical weekday. There is a strong correlation between population and calls, as indicated by Spearman's rank correlation coefficient of 0.89 and Kendall's tau of 0.70. Thus, population serves as a reasonably good predictor. However, it is notable that there are outlier grid cells in each city where the number of calls is not adequately explained solely by the population. While the average number of calls made during a typical weekday per 10,000 residents equals 2.16, the data has a significant variance of 160. The total number of grid cells falling below Q1 of 10% or above Q3 of 90% in terms of the number of registered calls is approximately 20% (89 out of 465). For example, two grid cells in the city centre of The Hague report 5 and 6 calls. The same applies to another part of The Hague, near the national highway. The number of calls there exceeds the mean and equals 5, 6 and even 30 calls. Moreover, such a deviation from the mean expands when we zoom into the number of calls made during a specific time interval. It is, therefore, promising to explore the relations between other elements of the urban fabric and the identified six patterns of urban vulnerability.

Each cluster represents a complex urban fabric, encompassing socio-demographics and economics, the built environment, and business landscapes. Notably, while each grid cell within these clusters displays a mixture of attributes, no single attribute is exclusively unique to any one cell.

Figure 2.8 illustrates the median values for two sets of features. The process of preparing this figure involves several steps. We first normalise the values by the number of residents in each grid cell. Note that normalisation is only applied to socio-demographic features (panel a), not to proximity features (panel b). Next, we scale these normalised values between 0 and 1 across all grid cells. This scaling highlights the relative differences, making the highest and lowest values stand out. Consequently, the values are relative, representing the highest and lowest values within the city. Finally, we group the grid cells by their cluster labels and calculate the median. We use the median instead of the mean to account for the skewness in the data. In panel a, '1' indicates the grid cells with the highest share of specific socio-demographics, while in panel b, '0' represents the grid cell closest to the amenity and '1' the farthest. This method highlights the relative distribution compared to other grid cells within the cities. Our analysis reveals that, despite some outliers with very high or low values, the median differences across clusters for most indicators are limited, indicating the polycentric and compact nature of Dutch cities (Claassens et al., 2020).

Panel a visualises attributes of three categories: socio-demographic (age, household structure, ethnic background), socio-economic (income and social benefits), and built environment (the share of rented houses in a grid cell). The figure highlights both shared features and those that are unique to each. For instance, all clusters share a similar proportion of residents aged 0-15 and 15-25 years, as well as a mix of 1-person and multi-person households, both with and without children. This sets the stage for us to delve deeper into the unique attributes of each cluster.

Cluster 0 is distinguished by a higher proportion of non-Western residents, single-parent, and low-income households. This cluster's residents are, relative to other clusters, more likely to receive social benefits and live in rented housing. In contrast, Cluster 1 is characterised by a very balanced demographic composition. The standout feature here is the ethnic background of its residents, who are predominantly non-Western, similar to Cluster 0. However, Cluster 1 notably has fewer single-parent households and rented homes, marking a clear distinction from Cluster 0.

Clusters 2 and 3 exhibit similarities in their demographic makeup, with a higher concentration of residents aged 45-65 and over 65. These clusters have the fewest residents in the 25-45 age group. Yet, there are notable differences: Cluster 3 has a smaller percentage of single-parent and low-income households compared to Cluster 2 and fewer rented houses.

Clusters 4 and 5 share similarities in their age demographics, with the highest percentage of residents aged 24-45, indicating a younger population. However, they differ in other aspects. Cluster 4's residents predominantly have non-Western backgrounds and include more low-income households and rented homes. In contrast, Cluster 5 primarily consists of Western residents, with fewer low-income households and rented properties.

Additionally, Cluster 5 has the lowest proportion of residents receiving social benefits.

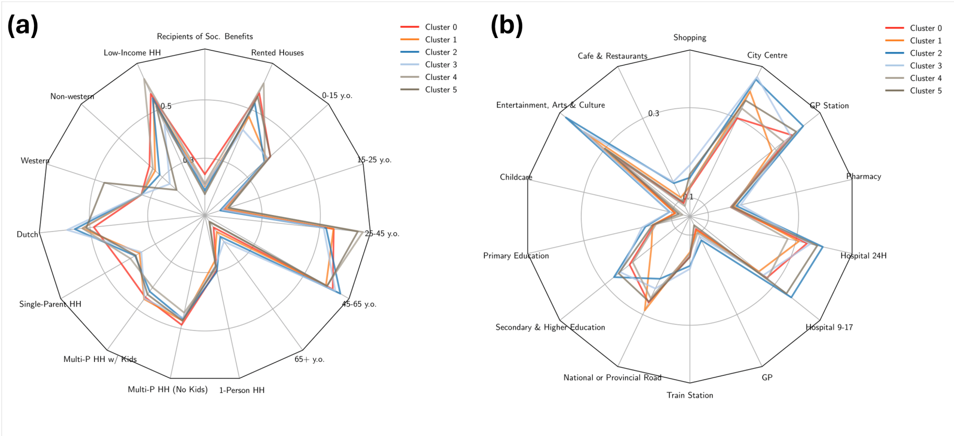

Figure 2.8: Median values for the socio-economic and built environment (panel a) and distance to amenities attributes (panel b) of grid cells across the three case cities. The socio-demographic attributes are normalised by the number of residents in each cell. Next, both feature sets have been further standardised between 0 and 1 to ensure comparability. Finally, the median is calculated over the grouped by cluster label grid cell values.

Panel b in Figure 2.8 displays another aspect of the urban fabric: proximity or distance to amenities. Note that the values of this panel are only scaled between 0 and 1 and were not normalised by population. In total, it visualises six categories: health, transport, education, going out, shopping and distance to the city centre. It is worth noticing that all analysed cells have relatively high access to multiple amenity categories.

Cluster 0 cells, positioned closer to the City Centre, benefit from greater access to Shopping, Cafe & Restaurants, and Entertainment, Arts & Culture. These cells are typically further from National or Provincial Roads. Areas with such an amenity composition are often called "Central Business Districts." Indeed, a higher concentration of Cluster 0 cells is found in the geographical centres of case cities like The Hague's Centrum district, Centrum and Noord in Rotterdam, and Centrum and Zuid districts in Amsterdam. This trend, however, extends beyond these conventional models. Cluster 0 cells are also present in other city parts, such as southeast of The Hague and Rotterdam While these areas may not be identical in amenity count, their proximity to amenities could potentially generate similar urban vulnerability patterns.

Cluster 1 has balanced access amenities for shopping and going out. However, it has a lower distance to a specific subcategory of the latest: Entertainment, Arts & Culture venues. Like Cluster 0, it is also generally further from National or Provincial Roads. Cluster 1 cells have enhanced access to Secondary & Higher education, hospitals, and general practitioners. Considering its composition and spatial distribution, Cluster 1 can be identified as an Inner-City Periphery. These cells are often located around Cluster 0 but are typically slightly further from the city centre.

Clusters 2 and 3 are characterised by their distance from the City Centre, resembling suburban and outer residential areas and have lower access to going-out amenities. Cluster 2, however, is closer to national or provincial roads but has less access to hospitals than Cluster 3.

Cluster 4 shares similarities with Cluster 0 in terms of composition. It is close to the city centre and has high access to going out amenities. Notably, Cluster 4 cells also have better access to hospitals and GPs.

The final cluster, Cluster 5, often located near the city centre, has balanced access to central business amenities. Its distinguishing feature is high access to Entertainment, Arts & Culture. However, it has lower access to education, transport, and health amenities.

Each of the three cities embodies a complex picture of vulnerability, characterised by six distinct patterns. These patterns of vulnerability fluctuate throughout the day, influenced by various factors of the urban fabric: time of day, location, residents, activities, and the amenities where these activities take place.

Patterns 2 and 3 are more pronounced in the early hours, reflecting the vulnerability that dominates during morning routines. Patterns 0 and 1 become more evident in the afternoon, aligning with the rhythms of urban life in central business districts. Patterns 4 and 5, on the other hand, present a persistent vulnerability throughout the day, indicative of areas with unique demographic or infrastructural characteristics.

While these vulnerability patterns often mirror conventional urban zones — for instance, pattern 0 peaks around noon in central business districts, and outer residential areas see heightened vulnerability between 8:00 and 12:00, coinciding with work commutes — there are deviations. These deviating patterns can emerge in other parts of the city, revealing a polycentric nature in modern Dutch urban landscapes. This suggests multiple "centres" where similar resident behaviours and vulnerabilities are echoed, invalidating traditional city zoning concepts.

Delving deeper, the presence of vulnerable populations in specific areas requires more attention and response. For example, unusual spikes in vulnerability within cluster 0 during night hours might signal emergency needs within vulnerable households. Clusters 2 and 3, predominantly residential areas with a high concentration of families, are situated away from city centres yet near national or provincial roads. ‘This geographic positioning makes these clusters particularly vulnerable during the morning rush hours. In contrast, clusters 4 and 5 are located in the urban core and are abundant with amenities catering to social and leisure activities. This results in a more consistent pattern of vulnerability, reflecting the vibrant, ongoing urban life in these areas. This highlights the complex interplay between amenities, human behaviour, and vulnerability patterns.

2.5. DISCUSSION AND CONCLUSIONS

INTERPRETATION OF RESULTS

We confirm that urban vulnerability arises from spatial-temporal dynamics. Spatially, city centres are hotspots for ambulance calls, likely due to high population densities and elevated human activities. The Hague shows a concentric pattern, while Rotterdam and Amsterdam exhibit polycentric trends, indicating modern cities as networks of interacting sub-cities with nested vulnerabilities. Temporally, ambulance call patterns mirror the circadian rhythm of city life, with peak periods aligning with human activity cycles.

We identified six distinct patterns of urban vulnerability, which can be grouped into three main categories: "Midday Peaks," "Early Birds," and "All-Day All-Night." This classification echoes the inherent rhythms of urban life, shaped by demographic and economic characteristics, infrastructural elements, and human activities. The "Midday Peaks" clusters, predominant in central business districts, highlight a crucial aspect of urban life where the convergence of commercial activities, high population density, and human interaction culminates in a pronounced vulnerability during midday hours. This is a clear deviation from traditional vulnerability models that often overlook the temporal aspect, assuming a uniform vulnerability throughout the day. In contrast, the "Early Birds" clusters show a surge in vulnerability in the early hours, most likely tied to morning commutes and the start of the workday. This pattern is particularly significant in outer residential areas, suggesting a shift in vulnerability from the city centre to suburban areas as the day progresses. Finally, the "All-Day All-Night" clusters, maintaining high levels of calls throughout the day, suggest areas with a continuous interplay of various factors contributing to vulnerability. These could be regions with mixed-use development, a blend of residential and commercial spaces, or areas with nightlife activities, indicating a non-traditional urban rhythm. These findings extend the current understanding of urban vulnerability, traditionally focused on static, spatial aspects, by integrating the temporal dimension, which reflects the dynamic nature of city life.

This research also confirms a polycentric trend in modern Dutch cities, indicating that distinct districts function similarly, essentially making these cities a conglomeration of "smaller cities" within a larger urban area. From a vulnerability perspective, this suggests that similar patterns of vulnerability are evident not only in, for example, city centres but also in outer residential areas, albeit at a reduced scale, as indicated by a lower number of ambulance calls. Such insights are crucial for urban planners and policymakers, who may need to consider these varying dynamics when addressing the needs and potential policy interventions in different parts of the city.

Our findings suggest that emergency services, such as ambulances, can optimise their resources by focusing on specific clusters during their peak vulnerability times. For instance, increasing the presence of emergency services in "Midday Peaks" areas during 12:00 - 16:00 could enhance response times and potentially reduce the impact of emergencies. The distinct patterns of vulnerability identified in our study could guide the design and development of urban infrastructure. For areas classified under "Early Birds," for example, enhancing road safety measures and public transport facilities during morning hours could mitigate vulnerability associated with commuting. Similarly, in "All-Day All-Night" clusters, where there is a continuous pattern of vulnerability, urban design can focus on creating safer, well-lit, and easily accessible public spaces.

Limitations and further directions

Our study is exploratory and has several limitations. First, it must be noted that an ambulance call cannot fully capture complex phenomena of risk, exposure and vulnerability. The reliance on ambulance call data, while innovative, does not capture the entire spectrum of urban vulnerability. This data type predominantly reflects emergency health-related incidents, potentially overlooking other aspects of urban vulnerability, such as crime or non-emergency health issues. Future research could benefit from incorporating additional data sources, such as police reports or health service usage data, to provide a more comprehensive view of urban vulnerability. While the proposed proxy has limitations as any other proxy used to assess the vulnerability or resilience of an urban system Haraguchi et al. (2022), it is critical to use a variety of data to overcome methodological challenges.

Our study is designed to allow others to expand on our initial approach and add other data sets, e.g., related to social, environmental, or economic vulnerability. In addition, we hope that our approach will be tested in other contexts and settings, going beyond the case studies that we presented here to test the generalisability of the patterns we identified.

Another set of limitations pertains to the spatio-temporal granularity of our analysis. We currently delineate cities using municipal boundaries, which may not fully capture the extent of the vulnerability, as it does not stop at these borders. By integrating additional data sources, such as intercity mobility, we can stress-test our findings and better understand the vulnerability introduced by city visitors. Moreover, conducting the analysis on a finer temporal scale, such as 1-hour intervals, would be possible with more observations. This approach would facilitate the development of more targeted interventions.

We are also aware that not all citizens may call an ambulance, even when they are in great need. However, the accessibility of ambulance services in the Netherlands is relatively high. Transferring this proxy to other countries will require extra effort due to the healthcare differences and accessibility.

Conclusion

Our research has put forward an analytical framework to analyse urban vulnerability as a spatio-temporal phenomenon, previously mainly studied as spatial or temporal. At the core of our framework is the number of ambulance calls as a proxy for where an urban system gets fractured. We apply this framework to the three biggest Dutch cities and find that urban vulnerability changes across space and time, challenging traditional notions of static, spatially focused assessments.

These findings offer a more nuanced understanding of modern cities from the vulnerability perspective, depicting vulnerability not as a static phenomenon but as a dynamic one that varies across space and time. This enriched perspective has implications for urban planning and policy-making. Emergency services and planners, therefore, need to adopt strategies that are tailored to the unique temporal and spatial characteristics of different urban areas.

While our data spans three full years, as with any system, there might be inconsistency in reporting or registering. To minimise the impact, we aggregate the data over years, months and days and study the averages instead of absolute values.

2.6. Data & code availability

The data used for the analysis is available at https://doi.org/10.4121/468af1da-4e27-4d9d-9f80-5d60aa5ccb0d. The code used to perform the analysis is available at https://github.com/mikhailsirenko/rhythm-of-risk.

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3

More vulnerable, less resilient? Insights into the spatial-temporal dynamics of vulnerability, resilience and adaptive capacity from the 2019 European heatwave

By Mikhail Sirenko, Alexander Verbraeck & Tina Comes, under review in *npj Urban Sustainability*.

Abstract

Urban resilience and vulnerability are key concepts for sustainable development in our cities. While most research describes how resilience and vulnerability are linked theoretically, there is a lack of data-driven empirical studies that examine and contextualise their interdependencies in time and space. This study explores the spatio-temporal relationship between resilience and vulnerability during the 2019 European heatwave in the three largest Dutch cities: The Hague, Rotterdam and Amsterdam. Our spatio-temporal analysis reveals a nuanced and highly contextualised relationship between districts' vulnerability profiles and their resilience to heatwaves. First, we identify vulnerability profiles based on demographic, socioeconomic, and health factors. Even though the three case study cities may seem similar, we see significant differences in underlying factors determining vulnerability, confirming the need for contextualised vulnerability assessments. Second, contrary to conventional wisdom, our analysis reveals both negative

(more vulnerable, less resilient) and positive (more vulnerable, more resilient) relationships between vulnerability and resilience depending on the time of the day. This finding suggests that relationships are more complex and influenced by citizens' adaptive behaviours by the underlying social and urban fabric. This research highlights the critical role of tailored, dynamic urban planning and response strategies. We argue to move towards an integrated and contextualised assessment of urban resilience and vulnerability.

3.1. Introduction

In 2023, the world experienced its hottest summer on record, with July being the hottest month ever documented (Perkins-Kirkpatrick et al., 2024). The preceding year, Europe faced several heatwaves, resulting in 61,762 heat-related deaths (Ballester et al., 2023). The Netherlands, a country not traditionally used to extreme temperatures, has experienced six heatwaves since 2018. The 2019 heatwave alone led to an excess of 400 deaths (Statistics Netherlands, 2019). These heatwaves serve as critical stress tests for urban areas, amplifying existing vulnerabilities and challenging the adaptive capacities of urban systems (Chen et al., 2023; McDonald et al., 2024). Prior research highlights a rise in health emergencies during heatwaves exacerbated by the Urban Heat Island (UHI) effect, which intensifies local temperatures (Seong et al., 2023), as well as by structural inequalities (Li et al., 2022).

Urban resilience is essential for sustainable urban development, and understanding urban vulnerability is a prerequisite for achieving it (Krishnan et al., 2024; Simpson et al., 2023). Assessing urban vulnerability to extreme heat involves identifying the susceptibility of city systems to adverse effects from climate stressors like heatwaves, influenced by factors such as socio-economic conditions, infrastructure, and population health (Szagri et al., 2023). Urban resilience is often measured as the capacity of these systems to recover from, adapt or transform under such shocks (Chelleri et al., 2015). A better understanding of the intricate relationship between vulnerability and resilience allows us to make urban systems that are better capable of withstanding future climatic challenges.

Although theoretical frameworks on urban vulnerability and resilience are established (Jabareen, 2013; Krueger et al., 2022; Sharifi, 2023), there is a significant gap in empirical, data-driven research that thoroughly examines these relationships within the spatio-temporal dimensions of urban life Haraguchi et al. (2022) and Jones et al. (2021). Due to the lack of high-resolution spatio-temporal data, such assessments are often conducted at the country or regional level (Hu et al., 2020; Ke et al., 2023). However, the specific impacts of heatwaves vary significantly across different urban areas due to differing social, economic, and physical characteristics of these areas and their populations.

This study addresses the aforementioned gap by presenting a detailed analytical framework that dissects the spatio-temporal dynamics of urban resilience and vulnerability to heatwaves. The 2019 European heatwave serves as the backdrop for our study, a critical event that tested urban infrastructures and health systems of European cities (Ma et al., 2020). Our research focuses on the three largest Dutch cities: The Hague, Rotterdam, and Amsterdam. It offers a nuanced exploration of how different times of the day influence the interplay between districts' urban vulnerability and resilience.

We analyse open data on ambulance calls and employ Non-Negative Matrix Factorization (NMF) to assess heat vulnerability across urban districts. Our study seeks to answer two main research questions: 1) How do temporal patterns of ambulance calls relate to heatwave conditions across different urban and social fabrics? 2) What spatial patterns of vulnerability can be discerned within these cities, and how do they affect their resilience to heatwaves? Previous research has established a connection between heatwaves and an increase in ambulance calls, making them a useful proxy for assessing urban resilience (Mathes et al., 2017; Seong et al., 2023; Zhan et al., 2018). Our vulnerability assessment is informed by conventional vulnerability mapping techniques (Wolf et al., 2015) and enhanced by applying NMF (Wang & Zhang, 2013), a robust dimensionality reduction technique. By combining socio-demographic, economic, health, UHI effect, temperature, and ambulance call data, we analyse urban vulnerability and resilience, thereby contributing valuable insights to the discourse on urban sustainability and climate adaptation strategies.

3.2. RESULTS

TEMPORAL PATTERNS OF HEAT RESILIENCE

We start by analysing the temporal variability of health impact at the urban scale. During the heatwave week (22-28 July 2019), the number of ambulance calls across all three cities: The Hague, Rotterdam and Amsterdam- experienced a significant increase, rising by 20% above the 2019 summer weekly average over the heatwave period. The hottest day on record was particularly striking. On July 25, 2019, temperatures spiked beyond 40°C. The temperature rise correlated with a significant increase in ambulance calls: 41% in The Hague, 31% in Rotterdam, and 27% in Amsterdam, compared to an average summer day of 2019.

Even though the increase in ambulance calls confirms the important health impacts of heatwaves, there is a significant variation in the underlying temporal patterns across cities. As expected, there is a positive correlation between higher temperature and an increase in the number of calls with $\rho = 0.3$ for The Hague and $\rho = 0.25$ for Amsterdam. The relationship in Rotterdam $\rho = 0.06$ appears more complex, indicating a delay in response between temperature increase and rise in calls.

During the hottest day, Thursday, 25 July, both The Hague and Rotterdam experienced a large spike in calls—up to 100% more than on a regular non-heatwave summer day—during the 12:00-16:00 and 16:00-20:00 intervals. In contrast, Amsterdam saw a smaller increase of 58% during the same time frame. Yet, Amsterdam's call volume peaked at 106% more than normal two days later, on Saturday, 27 July, between 08:00 and 12:00. In part, this may be related to citizens' capacity to handle the heat, which depletes over time or is caused by the gradual heating up of the built environment.

Across all cities, the highest average increase observed was 24% in The Hague during the noon interval (12:00-16:00), closely followed by increases during the night (00:00-04:00), and evening periods, with percentages ranging from 21% to 23%. Rotterdam mirrored this pattern, with its peak average increases at noon and evening (20:00-00:00) times. Amsterdam differed, showing its highest average increase of 30% in the early evening, with relatively consistent increases throughout the day and a notable absence of increase at night. This leads us to:

Proposition 1A: Variability in the social and urban fabric and corresponding vulnerabilities lead to different temporal resilience patterns throughout the day.

Proposition 1B: Buffer capacities decouple exposure to heat from vulnerability.

This proposition implies that adaptive capacity is driven by behavioural and urban differences.

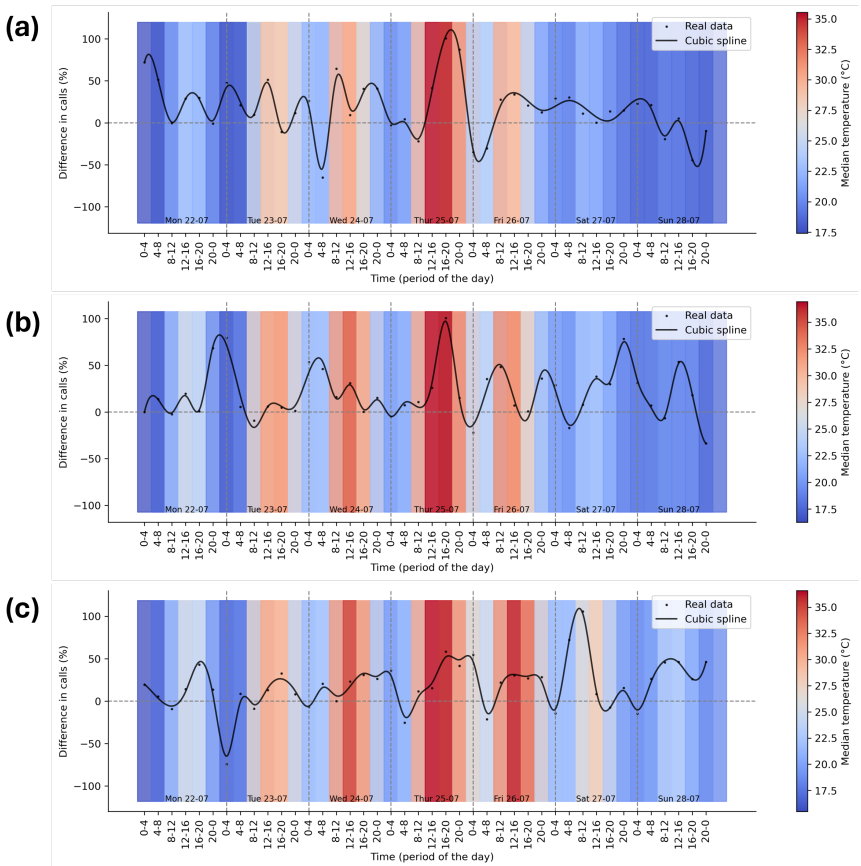

Figure 3.1: Difference in call volume over time compared with median temperature during the 2019 European heatwave from Monday, July 22 to Sunday, July 28. The three panels represent data for different cities: (a) The Hague, (b) Rotterdam, and (c) Amsterdam. Each graph shows the percentage difference in the number of calls (black line) compared to the average number of calls over a typical week. The graphs contain real data points as well as a cubic spline fit. The background gradient indicates the median temperature in Celsius, transitioning from cooler temperatures (blue) to warmer temperatures (red). The period of the day is segmented into 4-hour intervals.

SPATIAL PATTERNS OF HEAT VULNERABILITY

To understand the spatial patterns of heat vulnerability, we apply Non-Negative Matrix Factorization (NMF) to the district features of each city separately. Figure 3.2 visualises the resulting components matrices. Panels (a), (b), and (c) represent The Hague, Rotterdam and Amsterdam. The case cities can be viewed as a combination of at least four vulnerability profiles, each with a unique share of features that define vulnerability.

see **??** for more details.

For all three cities, profile 0 has the highest contribution of features that could potentially increase heatwave vulnerability. Yet, what drives vulnerability is different across the three cities.

Districts of profile 0 in The Hague show the highest contribution of children 0-14 years old, single-person households and households with children (including single parents) and people with lower education and income. Demographic, socio-economic, as well as health-related features, indicate lower adaptive capacity of families with young children in the city. From the exposure side, profile 0 districts have a significantly higher presence of the UHI effect. Remarkably, people 65+ years old, commonly referred to as vulnerable to heatwaves, do not prominently feature here. Rotterdam's districts of profile 0 have a similar structure despite a higher share of 65+ people, while low and medium education features have a similar presence in the profile. Health-related features are becoming less pronounced in Rotterdam's profile 0. In contrast, Amsterdam's profile 0 contains mostly people in the 45-64 and 65+ age groups, without children, predominantly of low education and income. We also see high values for severely limited due to health and mobility issues. In addition, we see the highest contribution of exposure (UHI) across all profiles.

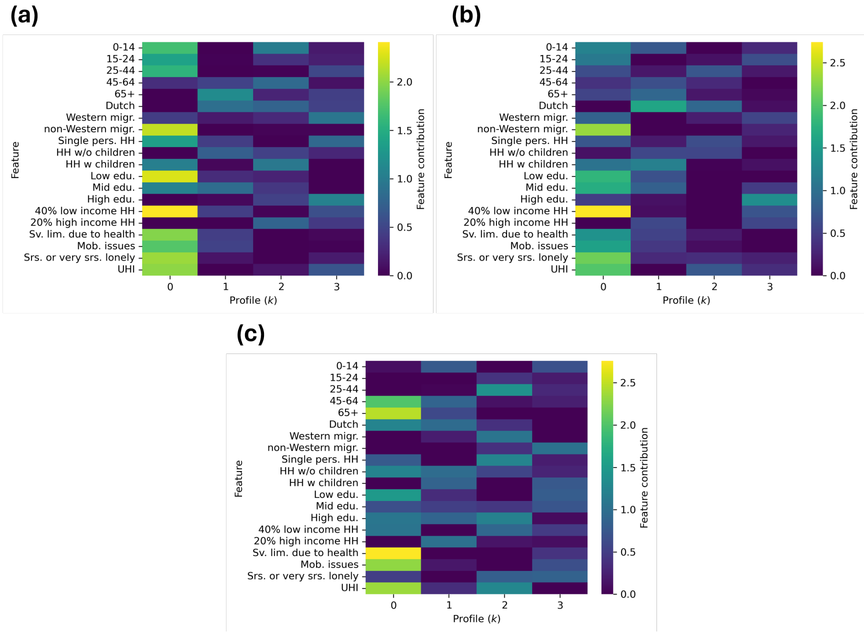

Figure 3.2: Feature contribution generated by Non-negative Matrix Factorization (NMF) for assessing heatwave vulnerability across districts in The Hague, Rotterdam, and Amsterdam. Panels (a), (b), and (c) correspond to each city, respectively. The heatmaps visualise the contribution of various vulnerability indicators to four distinct vulnerability profiles identified by NMF. The colour gradient transitions from blue to yellow to signify the increasing magnitude of contribution, thereby illustrating the differential impact of each feature on the vulnerability profiles within the urban districts. The abbreviation HH stands for the household, and UHI for urban heat island.

Geographically, in The Hague, we observe the highest concentration of the most vulnerable districts (Profile 0) in the southeast and the city centre, leading to high segregation and clear-cut differences in this vulnerability profile. For Rotterdam, profile 0 dominates in the south and also several districts in the city centre, indicating that vulnerability is more dispersed through most of the city, besides the outskirts in the west and north. Amsterdam is characterised by a few pockets of vulnerability scattered across the city.

A recent review on the heatwave vulnerability in the Netherlands has found mixed evidence, stating that elderly, socially deprived or poor households may be the most vulnerable to heatwaves (Ahmed et al., 2023). Similarly, high population density has been associated with higher heat exposure (Szagri et al., 2023).

Our findings draw a more nuanced picture, highlighting the interplay between various features of the urban and social fabrics and what makes a city and its districts vulnerable or not. This is true even though our three case cities may seem very similar at first glance, as they are all located in the same social-political-environmental context. While in the literature, contextualisation has been discussed in the context of global vulnerability and resilience assessment (Birkmann, 2007), which is typically based on a single indicator, our findings show how localised and sensitive environmental vulnerability is.

This leads us to

> **Proposition 2:** Contextualisation and adjustment of vulnerability to the social and urban fabric are crucial, even if the cities are embedded in the same context and region.

This finding stresses the importance of place and space and implies that vulnerability and resilience metrics need to be *contextualised hyperlocally*. There is no single factor or variable nor a standard set of variables that can adequately measure urban heat vulnerability.

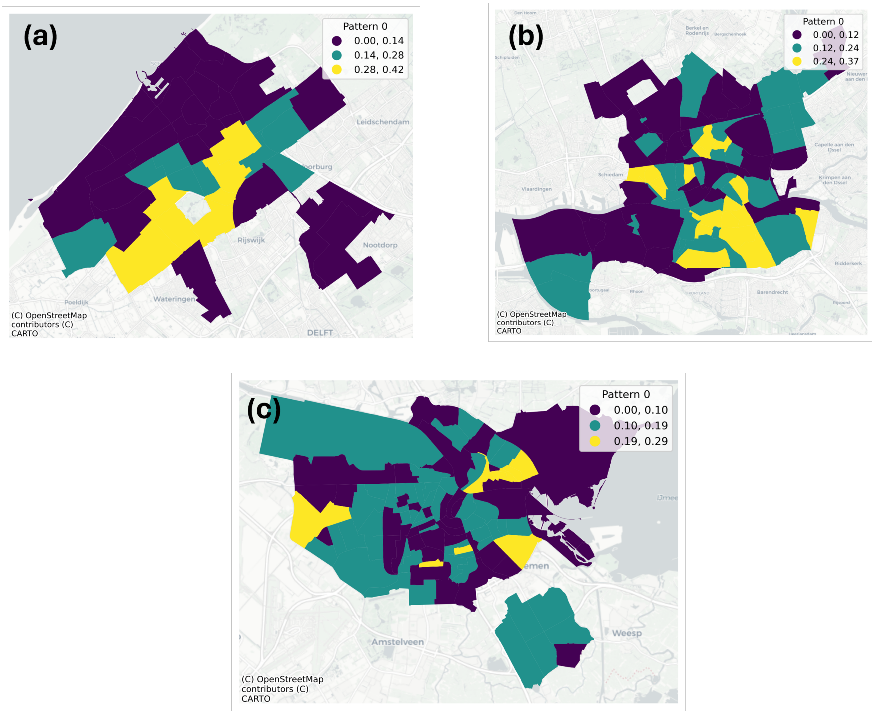

Figure 3.3: Spatial distribution of vulnerability Profile 0 as derived from the basis matrix W of Non-negative Matrix Factorization (NMF), illustrated across districts in The Hague, Rotterdam, and Amsterdam (panels a, b, and c, respectively). Each choropleth map categorises the districts into three distinct classes based on the intensity of Profile 0's presence, visually representing how this particular vulnerability profile spread throughout the cities.

ON THE INTERPLAY OF VULNERABILITY AND RESILIENCE

ON THE INTERACTION OF VULNERABILITY AND RESILIENCE

Overall, there is a strong correlation between the number of ambulance calls and the identified vulnerability profiles, indicating a relation between resilience and vulnerability features.

Table 3.1 presents the Spearman's rank correlation between identified vulnerability profiles and three key indicators: the total number of calls made during an average summer week, the total number of calls made during a heatwave week, and the difference in the number of ambulance calls during a heatwave compared to the average weekly calls in summer (referred to as resilience). Across all three cities and the indicators of interest, the Spearman's rank correlation ranges from -0.28 to 0.5. This range suggests that certain features can significantly influence the number of ambulance calls.

The Hague presents a distinct picture, with profile 0 districts showing a strong positive correlation for all three indicators, underscoring the high vulnerability of the profile. Profiles 1 and 2 reveal negative or no correlations, although to varying degrees, indicating a potential for resilience or lower vulnerability. Remarkably, profile 3 districts have strong negative correlations across all three indicators. The last suggests a significant decrease in ambulance calls during heatwaves. This implies that the heatwaves in The Hague further amplify existing vulnerability profiles, shifting calls even more to the most vulnerable (and away from the least vulnerable) districts.

In Rotterdam, profile 0 again shows a strong positive correlation but only for the average and heatwave week calls. Correlation coefficients for the difference are slightly lower. Profile 1 areas display a unique pattern, with a slight positive correlation during the heatwave, suggesting varying impacts or responses compared to other profiles. This indicates that in Rotterdam, profile 1 (characterised by households with children) is also vulnerable and that heat vulnerability in Rotterdam is a broader phenomenon than in the other cities. Profile 3 in Rotterdam shows negative correlations, indicating potentially effective responses to heatwaves, confirming the findings for The Hague.

Amsterdam's analysis also confirms that profile 0 areas show a strong positive correlation across the board, highlighting a potential lack of resilience. Interestingly, profile 1 (high-income, highly educated households) demonstrates a shift towards negative correlations, suggesting that areas under this profile might exhibit resilience that allows them to drastically flip the profile during heatwaves. Profile 2 areas, conversely, show a mixed response with a slight increase in call frequencies during heatwaves, whereas profile 3 maintains a neutral stance with minimal fluctuations in call volumes. This leads us to

> **Proposition 3:** Heatwaves amplify existing vulnerabilities and social disparities.

We clearly show how resilience varies across vulnerability profiles and how the recent heat wave applied this difference. This is especially prominent for the profiles of highly educated and high-income residents: they show high levels of resilience, which flips the overall trend.

City	Profile	Total calls during avg. week	Total calls during heatwave week	Diff. in calls between heatwave - avg. week
The Hague	0	0.50	0.48	0.16
	1	-0.15	-0.17	-0.02
	2	-0.26	-0.20	-0.01
	3	-0.25	-0.28	-0.25
Rotterdam	0	0.42	0.35	0.10
	1	0.07	0.13	0.09
	2	-0.28	-0.24	-0.07
	3	0.05	0.00	-0.12
Amsterdam	0	0.24	0.32	0.27
	1	0.08	-0.01	-0.17
	2	-0.21	-0.16	0.04
	3	0.05	0.05	-0.00

Table 3.1: Spearman's correlation coefficients between urban vulnerability profiles and the total number of calls made during the average summer week and heatwave week and the difference in calls between the heatwave week and average summer weeks in The Hague, Rotterdam and Amsterdam. The coolwarm color palette is used to visualize the strength and direction of the correlations, spanning from red for positive correlations to blue for negative correlations. Deeper shades indicate stronger relationships, while lighter shades reflect more moderate correlations

3

TEMPORAL PATTERNS IN THE RESILIENCE-VULNERABILITY INTERACTION

Temperatures, as well as citizen behaviour, change over time. Therefore, we investigate the temporal patterns in the interaction of urban vulnerability and resilience to heatwaves.

Figure 3.4 visualises relations between vulnerability and resilience by time of day. The x-axis represents vulnerability, the y-axis represents resilience, and every point is a district (see Section 4.3 for a complete description of the analytical framework). The box text reports Spearman's correlation coefficient for each period. The bivariate colour scheme navigates the relations, with red in the bottom right corner for the most vulnerable and blue in the upper left corner for the most resilient. Thus, if a district (point) is in the upper part of the scatterplot, this district is resilient. Conversely, if a district is in the far right part of the plot, it is vulnerable. Note that while resilience varies across time of the day, vulnerability is static. Thus, every point (district) will always have the same position on the x-axis; only its position on the y-axis will change.

Conventional wisdom suggests that higher vulnerability is associated with lower resilience. Therefore, we expect to see a negative correlation between these two. Positive correlations suggest the opposite: higher vulnerability is associated with higher resilience. Interestingly, correlations "flip" across all cities, suggesting that the relationship between heatwave vulnerability and resilience changes over time.

Our analysis shows that - despite lower temperatures with respect to the daily maximum - the most difficult periods are night and early morning for all cities, with the highest number of districts demonstrating low resilience. This could be potentially explained by the fact that the heat accumulated during the day often persists at night, meaning that residents and infrastructure do not have enough time to cool down and recover (Torralba et al., 2024).

When comparing cities, The Hague had the highest number of districts demonstrating low resilience (27) during the 2019 European heatwave. Rotterdam and Amsterdam share the same number of 13.

The Hague's correlations range from -0.37 to +0.25 across different times of the day. Notably, the strongest negative correlation of -0.37 occurs in the 20:00 - 00:00 time frame, suggesting that in The Hague, districts with higher vulnerability see relatively few ambulance calls during heatwaves at night and in the early morning (until 8:00). Surprisingly, during the day, the correlation is positive with the highest values in the late afternoon, suggesting that during the hottest hours, higher vulnerability is associated with higher resilience and fewer calls. This finding suggests high adaptive capacity despite a significant urban heat island effect for the 0 profile.

The correlations for Rotterdam show a similar pattern, yet with less pronounced values (between -0.12 to + 0.13). We find the strongest negative correlation of -0.12 during the night hours (00:00 - 04:00). This finding suggests that Rotterdam districts, while having "more" vulnerability attributes, have experienced smaller differences in ambulance calls than The Hague's districts.

Amsterdam also demonstrates significant variations in correlations throughout the day from -0.16 to 0.19. The temporal pattern, however, is different from the patterns in the other two cities. Importantly, we find *negative* correlations during the hottest periods of the day (12:00-20:00). In other words, in Amsterdam, hotter temperatures lead to a loss of resilience in highly vulnerable districts. The correlation turns positive in the evening (20:00-0:00) when the city starts cooling again.

This shift of the temporal pattern points us to the hidden dynamics driving vulnerability. While in Amsterdam, profile 0 is characterised by people with limited mobility in the 65+ age group, in Rotterdam and The Hague, relatively young people and families with children form the most vulnerable profile. Our temporal analysis shows that these groups may be able to adapt during the hottest hours, possibly by moving to cooler parts of the city. Yet at night, when they might return to their homes and neighbourhoods, high vulnerability leads to more ambulance calls, even though the temperatures go down.

These findings show a clear and distinct change in vulnerability-resilience relationships. Surprisingly, this is not merely driven by the changing temperatures throughout the day, but we find indications that behaviour, adaptation and coping capacity play a crucial role. This leads us to

> **Proposition 4:** Adaptive behaviour transforms urban dynamics and leads to changes in vulnerability and resilience relationships over time.

To effectively assess resilience and vulnerability, it is essential to use *dynamic* measurements and analysis tools that recognise adaptive behaviour and coping capacity rather than relying solely on static metrics based on geographical boundaries. Additionally, understanding the fundamental factors contributing to people's vulnerability in different cities is crucial for explaining the arising dissimilarities.

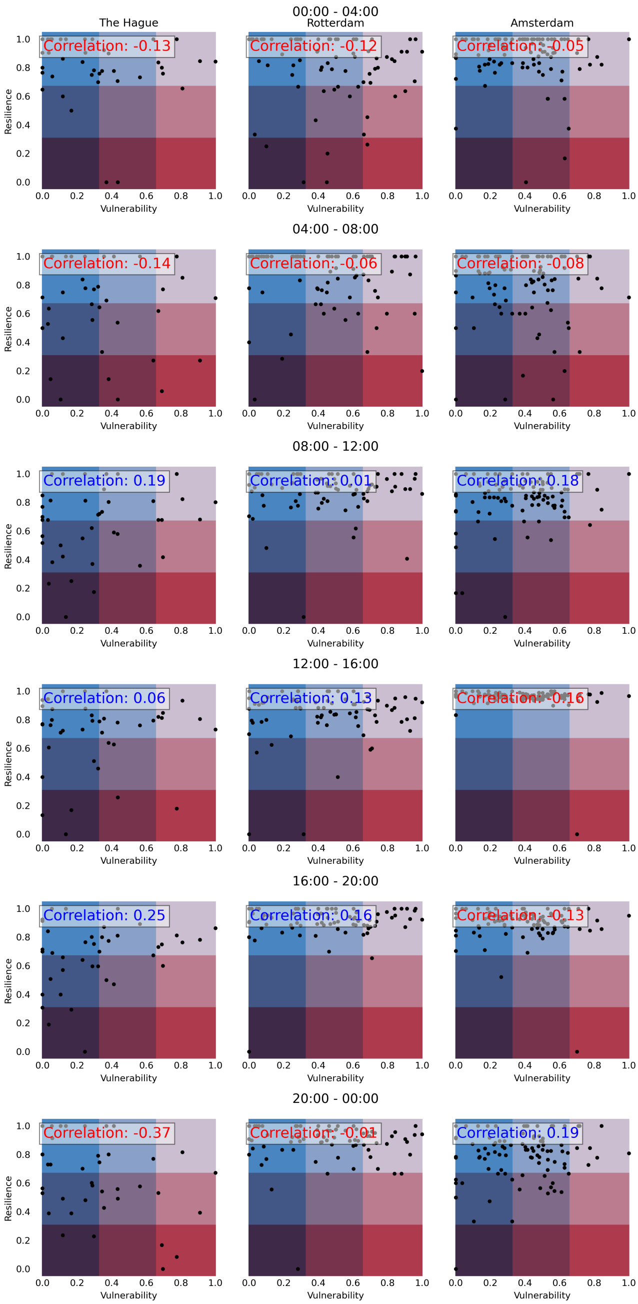

Figure 3.4: Scatter plots illustrating the relationships between urban vulnerability and resilience to heatwaves across different periods for The Hague, Rotterdam, and Amsterdam. Each column represents a city, while each row corresponds to a specific time period. Spearman's correlation coefficients indicate the strength and direction of the relationships, revealing temporal variations in vulnerability and resilience. The bivariate colour scheme in the background highlights the type of relationship between vulnerability and resilience, with a gradient ranging from blue (low vulnerability and high resilience) to red (high vulnerability and low resilience), visually emphasizing areas with different combinations of vulnerability and resilience.

3

Spatial-temporal patterns in the resilience-vulnerability interaction

To better understand the relationship between vulnerability and resilience in space and over time, we look at the individual quadrants and the districts that belong to them. Specifically, we are interested in understanding the emergence of the following phenomena:

1. High vulnerability (> 0.66), high resilience (> 0.66) (high-high quadrant 3C in Figure 3.5).
2. High vulnerability (>0.66), low resilience (< 0.33) (high-low quadrant 3A in Figure 3.5),
3. Low vulnerability (< 0.33), low resilience (<0.33) (low-low quadrant 1A in Figure 3.5),

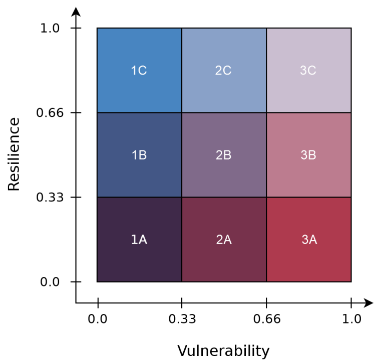

Figure 3.5: Quadrant analysis of vulnerability-resilience relationships categorising the data into nine distinct groups. This classification allows us to identify districts with varying levels of vulnerability and resilience, such as high vulnerability and high resilience (3C), high vulnerability and low resilience (3A), and low vulnerability and low resilience (1A), among other combinations.

By investigating the 3C high-high quadrant, we can understand how many highly vulnerable districts are also highly resilient, indicating cases of effective adaptation. On average, across all time periods, the high-high quadrant contains 5 out of 40 (12.5%) of The Hague's districts, 18 out of 76 (23.5%) of Rotterdam's and 7 out of 97 (7.6%) Amsterdam's districts. Note that not all of the districts are highly vulnerable, and if we calculate a fraction of the number of districts in the 3C quadrant to the number of vulnerable districts, we get the following: 71.4% for The Hague, 89.7% for Rotterdam, and 91.7% for Amsterdam. Thus, the number of highly vulnerable districts that are also resilient is the highest for Amsterdam and the lowest for The Hague.

Recall that we conceptualise vulnerability as a spatial attribute, which does not change over time (a common approach in the literature on heat vulnerability (Ahmed et al., 2023)). However, resilience does: the total number of the most vulnerable districts remains constant. Thus, while a district has a constant high vulnerability, it may lose its resilience, which was in place during the day and becomes fragile at night. That is, for

The Hague, the number of vulnerable districts that are also resilient becomes the lowest during the late evening (20:00 - 0:00) with 28.6% and early morning (04:00 - 08:00) with 57.5%. A similar pattern applies to Rotterdam; the number drops to 80% and 75% at night (0:00 - 04:00) and early morning. Amsterdam demonstrates more complex behaviour, with the highest number of vulnerable districts being resilient at night and late evening, which goes down to 87.5% during the rest of the day.

The 3A high-low quadrant aims to capture a more conventional idea that being highly vulnerable could imply being less resilient. The high-low districts are the most critical since these areas demonstrate a lack of adaptation and have clear signs of being highly vulnerable. As we previously have seen, the majority of highly vulnerable districts demonstrate high resilience; however, some of them lose their resilience at specific times during the day. On average, across all time periods, The Hague has five unique districts with high vulnerability and low resilience, Rotterdam has two, and Amsterdam has one. Importantly, Rotterdam has more districts (a total of 9) that demonstrate medium resilience (quadrant 3B). Overall, The Hague seems to have the highest number of highly vulnerable districts with low resilience.

Remarkably, districts with high vulnerability show low resilience only during specific periods of the day: at night when the accumulated heat strikes particularly vulnerable populations or areas with a lot of human activity and traffic. For The Hague at 04:00 - 08:00, these are the Schildersbuurt and Leyenburg residential districts with high concentrations of vulnerable individuals. Or, again, in The Hague, from 12:00 - to 16:00, it is the Groente- en Fruitmarkt district, which, on the one hand, has vulnerable individuals but, on the other hand, is neighbouring the largest market of the city.

The 1A low-low quadrant contradicts conventional wisdom - why would districts with low vulnerability demonstrate low resilience? Districts of this category are of particular interest since they have a higher chance of being overlooked: they lack the conventional vulnerability features but also demonstrated low resilience via an increase in the number of ambulance calls during the heatwave. Looking at the bigger picture, all three cities have many districts in this category across all periods: 9 for The Hague, 6 for Rotterdam and 4 for Amsterdam. While the urban fabric of these districts is quite diverse, they form at least three categories: beaches, coastal areas and parks, proximity to highways, and industrial areas.

Beaches and coastal areas are popular during hot summer, especially in The Hague (Scheveningen, Kijkduin en Ockenburgh). Similar considerations apply to the "green and blue districts" (Zorgvliet in The Hague, Blijdorpsepolder in Rotterdam, and Houthavens, Willemshaven in Amsterdam). What makes these districts less resilient may, therefore, be their attractiveness to people from more vulnerable districts, especially during the hottest hours of the day. While green and blue spaces have been widely advocated to combat the urban heat island effect (Gunawardena et al., 2017), they surprisingly become "hotspots" in our study. The lack of resilience in these districts compensates for the relatively high resilience of highly vulnerable districts during the day. This leads to

> **Proposition 5:** Driven by citizen adaptive behaviour, green and blue areas become the hotspots of low resilience during a heatwave.

This finding also corroborates our hypothesis on the crucial role of adaptive behaviour, whereby people move to cooler areas during the day. Thus, having blue and green infrastructure "somewhere" in the city might not benefit vulnerable individuals living in a UHI. It provides them with benefits by reducing their exposure, but only during a chunk of the day. There is a need to "spread out" and extend these infrastructures to the areas that need them the most.

Other districts that show low resilience are those near highways (e.g., Hoornwijk in The Hague). Increased traffic of people entering or leaving the city, especially on busy beach days, increases risk. In addition, industrial districts show low resilience (Nieuw Mathenesse in Rotterdam). Here, the presence of industrial sites and the lack of established community services and social networks may lead to lower resilience during the day, particularly since workers may be restricted in their adaptive behaviour and cannot move to cool areas during working hours.

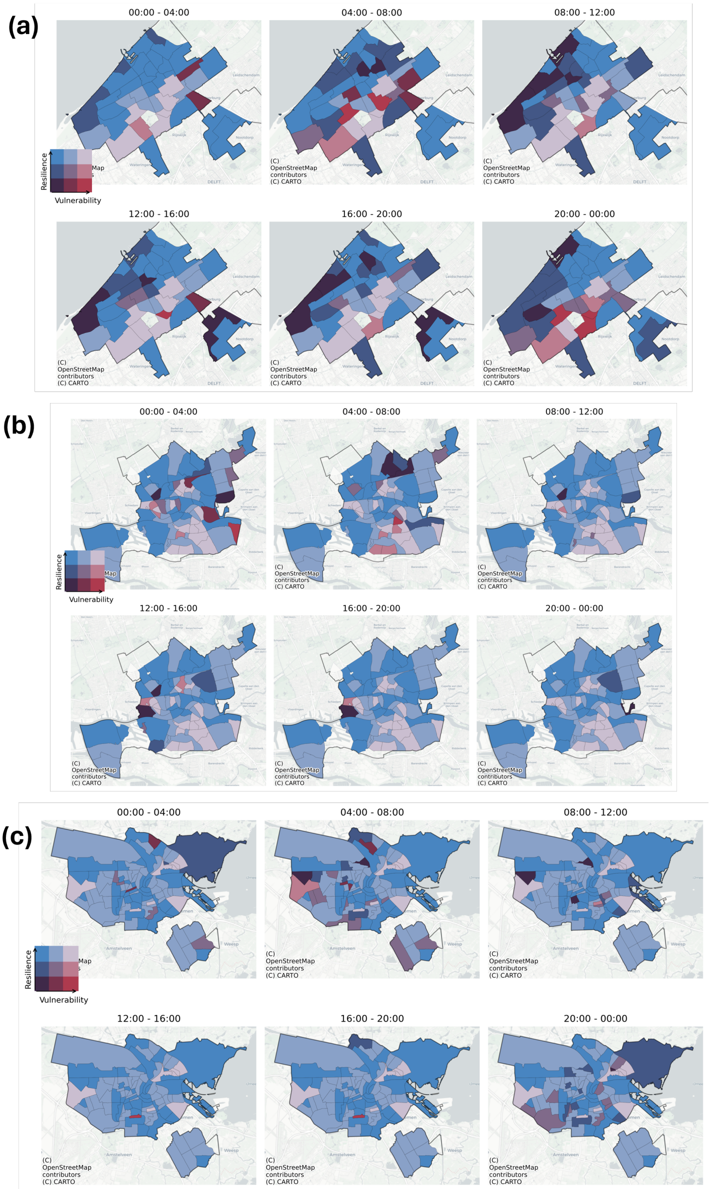

Figure 3.6: Bivariate choropleth maps showing the spatial relationships between urban vulnerability and resilience to heatwaves over different periods in the districts of The Hague (panel a), Rotterdam (panel b), and Amsterdam (panel c). Each map highlights how varying levels of vulnerability and resilience intersect, providing insights into how different districts cope with heat shock across time, with colour gradients representing the intensity of these interactions.

3.3. DISCUSSION

Our exploration of the spatial-temporal dynamics of vulnerability and resilience resulted in six propositions, which we split into groups. Three of these propositions (1B, 2, 5) point to the relationship between vulnerability and resilience and the role of citizen adaptive behaviour as a key factor in explaining the dynamic relationship between these two concepts. The other three propositions (1A, 3, 4) refer to the hazard and its implications.

HEATWAVES AMPLIFY SOCIAL DISPARITIES, YET CITIZEN ADAPTATION CHANGES VULNERABILITY AND RESILIENCE PATTERNS

Our findings indicate that resilience and vulnerability to heatwaves is a phenomenon that is deeply embedded in time and space and dependent on the underlying social and urban fabric. This is reflected in our three heatwave-related propositions (H1-H3) as indicated in Table 3.2.

Concept	Proposition
Time	**H1.** Buffer capacities decouple exposure to heat from vulnerability.
Social/Urban Fabric	**H2.** Heatwaves amplify existing vulnerabilities and social disparities.
Space	**H3.** Driven by citizen adaptive behaviour, green and blue areas become the hotspots of low resilience during a heatwave.

Table 3.2: Overview of propositions on heatwaves

For the temporal dimension (proposition H1), we observe that the number of calls can be somewhat decoupled from the greatest exposure to heat. The Hague experienced the highest increases in ambulance calls during peak temperature periods, suggesting that its urban fabric and social fabric are more vulnerable to immediate heat shock. In contrast, Rotterdam's delayed response indicates a more complex interplay between temperature and health impacts, possibly due to better initial coping mechanisms or delayed recognition of heat-related issues (Guo, 2017). Amsterdam's unique pattern of delayed peak ambulance calls further underscores the importance of considering local behaviours and urban characteristics in resilience planning. In part, this may be related to citizens' capacity to handle the heat, which depletes over time or is caused by the gradual heating up of the built environment. Additionally, the movement of people could play a role — while it may be possible to avoid unfavourable conditions during the day, vulnerable populations might return home at night, leading to unexpected resilience patterns. This suggests that adaptive capacity for heatwaves includes a temporal dimension, challenging the conventional view of it as a static component related to abilities like ventilating buildings or using shades (Hatvani-Kovacs et al., 2016).

Our findings on the impact of heatwaves on urban and social fabric (proposition H2) support the broader disaster literature, demonstrating that crises disproportionately impact the most socially disadvantaged groups. This trend is evident in the context of this study on heatwaves. where districts with lower income, lower education, and health issues experienced the most significant increases in ambulance calls. Similar patterns have been observed in other crises, such as the COVID-19 pandemic (Gaynor & Wilson, 2020) or natural disasters such as floods (Gunawardena et al., 2017; Tate et al., 2021). Consequently, we reaffirm the need to address the distributional and equity impacts of heatwaves and other disasters, drawing on findings from previous research. This highlights the importance of enhancing resilience and preparedness (De Bruijn et al., 2022).

In terms of space (proposition H3), we found that green and blue areas, typically considered as mitigators of urban heat (Gunawardena et al., 2017; McDonald et al., 2024), can become hotspots of low resilience during heatwaves (Figure 3.7). Districts with beaches, parks, and other recreational areas showed increased ambulance calls, likely due to the influx of people seeking relief from the heat. This pattern was especially prominent in The Hague's coastal districts and Amsterdam's green spaces. This implies that response to heatwaves must also consider that places less exposed to heat will become attractors for vulnerable populations and temporarily have to handle an increase in demand. Furthermore, propositions H1 and H3 combined (time and space) help in understanding the '*inconsistencies*' and intricate relationships underlying heat vulnerability indicators, as identified (Hatvani-Kovacs et al., 2016; He et al., 2019).

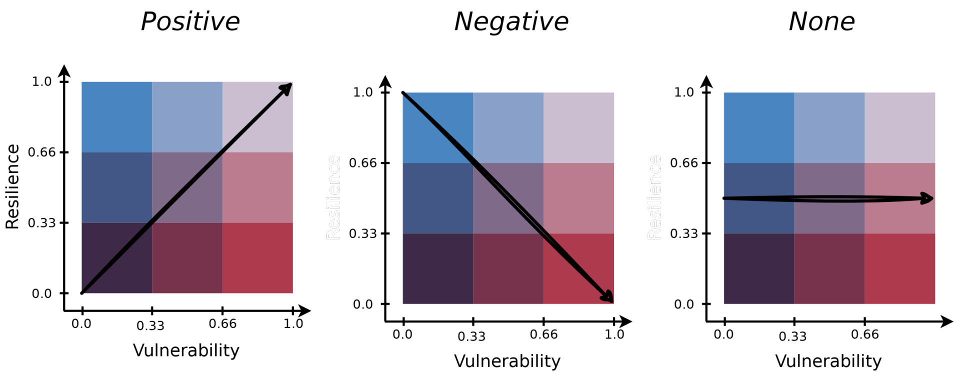

Figure 3.7: Conceptual model illustrating three types of relationships between vulnerability and resilience: positive (higher vulnerability, higher resilience), negative (higher vulnerability, lower resilience), and no relationships.

In conclusion, we have shown that non-linear relations between vulnerability and resilience for heatwaves go in both directions: the more vulnerable, the less resilient (negative), as well as the more vulnerable, the more resilient (positive) (Figure 3.7). These relations, however, depend on two factors: the time of the day and the underlying urban and social fabric forming adaptive capacity. Given the limited resources of healthcare providers, it is critical to understand how resilience and, potentially, vulnerability fluctuate over the course of the day. Additionally, our analysis reveals several cases of low vulnerability and low resilience. All these points indicate that several requirements for assessing urban resilience and vulnerability must be integrated to better understand urban dynamics.

Measuring urban vulnerability and resilience locally in time and space

The second set of propositions highlights the implications for urban vulnerability and resilience metrics (M1-M3) (see Table 3.3). Our findings highlight the need for localised strategies targeted to the spatial, temporal, urban and social contexts. Therefore, there is a need for metrics that are tailored to the unique vulnerability, resilience and their shared attribute - adaptive capacity, of each city's dynamic profile and context.

Requirement	Proposition
Dynamic Metrics	**M1** Variability in social and urban fabric and corresponding vulnerabilities lead to different temporal resilience patterns throughout the day.
Hyper-Contextualised Metrics	**M2** Contextualisation and adjustment of vulnerability to the social and urban fabric are crucial, even if the cities are embedded in the same context and region.
Measuring Adaptation	**M3** Adaptive behaviour transforms urban dynamics and leads to a change in vulnerability and resilience relationship over time.

Table 3.3: Overview of propositions related to measuring urban resilience and vulnerability.

The most vulnerable districts in each study city are characterised by different demographic, socioeconomic and health features. Therefore, proposition M1 emphasises the importance of contextualising vulnerability assessments to account for each city's specific social and urban fabrics. While it has been argued that there is a need for contextualised and multi-scalar approaches (Cáceres et al., 2024; Hufschmidt, 2011), there is still a widespread push for unified 'global' vulnerability metrics to compare different regions, countries or cities (Birkmann et al., 2022). Our results show that these standardised vulnerability metrics may fail to capture local nuances, leading to ineffective or misdirected interventions, even if the context seems very similar. Therefore, we argue that there is a need for hyper-localised vulnerability and resilience assessments that identify the unique characteristics of each urban area.

The temporal analysis of resilience patterns revealed that citizen adaptive behaviour significantly influences the relationship between vulnerability and resilience (see Figure 3.8). For instance, in The Hague, the highest ambulance call volumes were observed in the evening, suggesting that citizens might adapt during the hottest parts of the day but suffer from heat stress later. These observations highlight the dynamic nature of vulnerability and resilience (M2), driven by behavioural adaptations (M3). Some of these considerations were previously theoretically discussed, e.g. by de Boer et al. (2016) and Matyas and Pelling (2015), yet here we provide empirical evidence and formulate propositions that can be tested in other contexts.

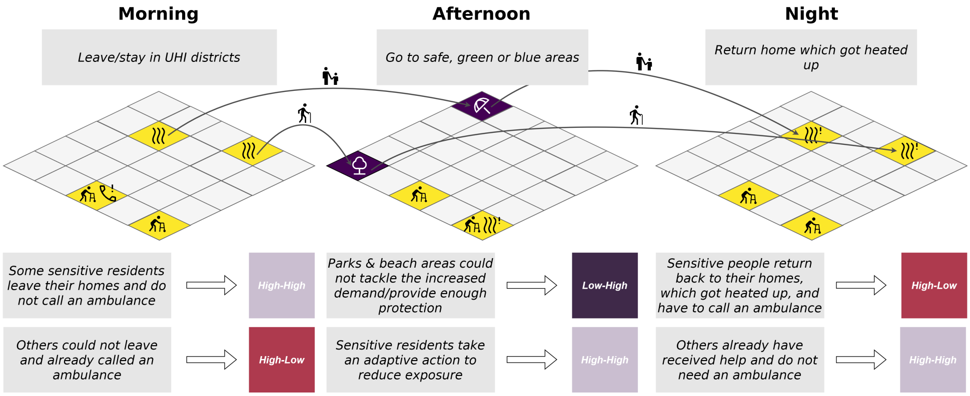

Figure 3.8: Diagram depicting the dynamic changes in behaviour among vulnerable citizens and the resultant shifts in resilience. This figure highlights how adaptive behaviours during heatwaves can alter vulnerability and resilience landscapes within urban settings over relatively short periods of time. Grid cell colour labels, along with classifications such as "high-high", "high-low", and "low-high" represent the relationship between vulnerability and resilience.

Even though the need to include temporal aspects in both vulnerability and resilience aspects is increasingly recognised (see, e.g., Hufschmidt (2011)), highly dynamic vulnerability assessments are currently primarily conducted for fast-moving systems such as transport (Cats & Jenelius, 2014). In urban systems, there is often the underlying assumption that change is slow, and therefore, also resilience and vulnerability metrics follow a similar pace of annual updates (Krishnan et al., 2024). Yet, here, we show drastic changes in vulnerability and resilience landscapes in the course of a single day, driven by citizens' adaptive behaviour under variations in exposure. Therefore, urban resilience assessments should aim for metrics that capture changes in highly dynamic environments attuned to behavioural shifts, especially in fast-paced crisis responses under resource constraints.

Figure 3.8 highlights the rapid pace of urban change driven by citizens' behavioural adaptation. The figure suggests that resilience and vulnerability are properties that arise from the interaction of exposure and sensitivity (moderated via the built environment and social characteristics) and emergent behavioural patterns. These findings also have implications for the ongoing debate between 'objective' and 'subjective' approaches for resilience and vulnerability assessments (Jones, 2019). We argue that *because* resilience emerges from an interaction of 'objective' factors like features in space (see, e.g., Cariolet et al. (2019) for a review) and 'subjective' actions and interactions (as, e.g., in (Champlin et al., 2023)), there is a need for more integrative metrics that consolidates objective and subjective elements.

Figure 3.9 illustrates our proposed conceptual framework. Here, resilience and vulnerability are measured hyper-locally in space, and the different layers of the cube represent the changes of both aspects over time, driven by citizens' adaptive behaviour and exposure changes. This framework allows us to discern the 'objective', static and generic aspects of urban vulnerability that do not change over time (e.g., UHI) from the 'subjective' aspects that change depending on the emergent system properties (e.g., citizen adaptive behaviour).

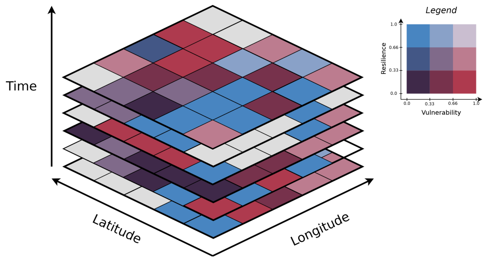

Figure 3.9: Proposed conceptual framework for assessing the co-evolution of vulnerability and resilience in urban areas over time and space, represented as a spatio-temporal cube. Each grid cell depicts a specific area in a city with a unique urban and social fabric, while the stacked surfaces correspond to different time intervals. Colours indicate the bi-variate relationships between resilience and vulnerability, capturing both static and dynamic aspects influenced by adaptive behaviours and environmental changes.

In sum, this study is exploratory in nature and provides the first empirical insights into the state and relationships between urban vulnerability and resilience. We present propositions to spark academic discussions regarding the specific hazard (heatwave) and the debate on measuring resilience. We hope our propositions will be further tested in other locations and contexts. Given the many methods and approaches developed to measure urban resilience, we are aware that our choices for the scope and context present several limitations.

First, as in any empirical study, the granularity and scope of the data used are crucial. Following the calls for responsible data in the smart city (Matheus et al., 2020), we use only openly available socio-demographic, health data and built environment data (see Section 4.2). While these data sets are widely used in research, they may not fully capture the nuances of vulnerability (Stolte et al., 2024). Incorporating additional environmental factors, such as humidity can futher help to stress-test the relations between vulnerability and resilience (Torralba et al., 2024). Furthermore, adding occupation data, could provide a more comprehensive understanding of the impact of heatwaves on people working in open spaces, such as construction workers or garbage collectors, who are known to be at risk. Moreover, including behavioural data, possibly obtained through map-based surveys (Champlin et al., 2023) or anonymised mobility tracking (Yabe et al., 2024), could enhance the spatio-temporal assessment of vulnerability.

Furthermore, the methodology for operationalising urban vulnerability also has its limitations. Non-Negative Matrix Factorization (NMF), while less sensitive to hyperparameters than techniques like Principal Component Analysis (PCA), requires making choices that can affect the outcomes. Exploring different hyperparameter values and their effects on vulnerability profiles would be valuable for validating and extending our findings. Additionally, the conventional approach to vulnerability assessment, which focuses on identifying the "most vulnerable" districts, may overlook areas with fewer or less severe vulnerabilities. Our study aims to reveal relationships between urban vulnerability and resilience rather than conduct the most comprehensive vulnerability assessment. Finally, the proxy for resilience—the percentage difference in ambulance calls—may not fully capture the complexity of adaptive measures taken by citizens and healthcare providers. The high accessibility of ambulance services in the Netherlands supports our approach, but applying this proxy in other countries will require adjustments to account for differences in healthcare accessibility.

Overall, our findings underscore the importance of contextualising vulnerability assessments and developing dynamic resilience metrics that account for spatio-temporal variations and citizens' adaptive behaviour. By focusing on the unique characteristics and needs of each city's districts, policymakers and urban planners can create more effective and equitable strategies to enhance resilience against heatwaves. Future research should continue to explore the behavioural dynamics driving resilience and develop tools to better capture these variations in urban vulnerability and resilience assessments.

3.4. METHODS

STUDY PERIOD AND AREA

The modern history of the heatwaves in the Netherlands counts five exceptional cases: the heatwaves of 2006, 2010, and 2018, the July 2019 European heatwave and August 2020. The July 2019 European heatwave lasted only six days, from July 22 to July 28, but the temperature in many parts of the country renewed historical maximums. For instance, a new record in 39.2°C was recorded at the Gilze-Rijen weather station near Breda. This heatwave claimed at least 400 extra deaths (Statistics Netherlands, 2019). Official statistics point out that the rise in mortality was unequal among different age groups. According to the data for the 2006, 2018 and 2019 heatwaves, increases in mortality were the highest among people of two age groups: 65-79 and over 80 years old. CBS also reported that the impact of at least two heatwaves was unequal geographically. In 2006, the south of the country (North Brabant, Limburg) was affected the most, whereas in 2019, it was the east (Overijssel, Gelderland, Flevoland). It is important to note that mortality is not the only way to measure the damage made by heatwaves. Besides the fatal outcomes, extreme heat may significantly worsen a person's health but keep him or her alive. Mortality numbers indicate the importance of the problem but do not cover the broad range of health consequences that could be captured with the use of ambulance call data.

We study the three largest Dutch cities delineated by the official municipal boundaries: The Hague, Rotterdam and Amsterdam, with a total population of 537,833, 644,618 and 862,965 and an area of 98,12, 132,08 and 219,3 km^2 on January 1 2019. All three cities can be characterised as extremely urbanised, meaning that they have an average density of 2,500 or more addresses per km^2 and have strong UHI effect (Wandl & Van der Hoeven, 2013, 2015, 2018). The cities are also known for being segregated. Among the three, The Hague has the highest segregation index of 34%. Amsterdam has a segregation index of 30% and Rotterdam of 25%. The segregation index here is a percentage of people with a non-western migration background who would have to move to achieve an even distribution within a municipality. The index varies from 0 - ultimately even distribution to 100, meaning complete segregation. This index was proposed by Kennisplatform Inclusief Samenleven (KIS) and is used by Dutch municipalities. A high population density, UHI, and diverse urban and social fabric make these cities useful exemplars for studying the relations between vulnerability and resilience to heatwaves.

Data sources

Our study utilises five open data sets to study the impact of the 2019 European heatwave on the population of the 3 biggest Dutch cities: The Hague, Rotterdam and Amsterdam, namely socio-demographic and economic, health, UHI effect, temperature and ambulance calls. Note that we focus on the corresponding municipalities, not the larger metropolitan areas, as the ones with a higher population and built environment density, footfall, and traffic. The unit of the analysis is a district, as sociodemographic, health, and ambulance call data are available only at this spatial scale.

3

Socio-demographic and economics

We use an open data set "Key figures for districts and neighbourhoods 2019" (Kerncijfers wijken en buurten 2019 in Dutch) provided by Statistics Netherlands and available to download at https://www.cbs.nl/nl-nl/maatwerk/2019/31/kerncijfers-wijken-en-buurten-2019. This data set reports yearly changes across various socio-demographic and socio-economic variables such as age group, ethnicity, family composition, income, etc. The data is provided at district and neighbourhood scales for each Dutch municipality. Thus, individual privacy is preserved, and no individual resident can be traced back using this data set.

Health and lifestyle

We utilise data highlighting another aspect of the social fabric at the district scale: a data set on residents' health from "Health and lifestyle per neighbourhood, district and municipality" (Gezondheid en leefstijl per buurt, wijk en gemeente in Dutch). This data set results from a national survey conducted in 2016 jointly by The National Institute for Public Health and the Environment (RIVM) and Statistics Netherlands and is available for download at https://buurtatlas.vzinfo.nl/#home. The data set contains information about the fraction of residents experiencing certain health problems: mobility issues, prolonged sickness, etc. This data set contains only the aggregates and does not report individual responses.

Urban Heat Island effect

The Urban Heat Island (UHI) data is available at the Climate Impact Atlas https://www.klimaateffectatlas.nl/en/ and provided by Atlas Natural Capital https://www.atlasnatuurlijkkapitaal.nl/. The data set reports the UHI effect in °C as an average air temperature difference between the urban and surrounding rural areas. The UHI is calculated based on population density, wind speed, and amount of green, blue and pavement (read more about the methodology at https://www.atlasnatuurlijkkapitaal.nl/stedelijk-hitte-eiland-effect-uhi-in-nederland). The data set is a raster file, and to align it with our analysis, we aggregate it over the district shapefiles and take the median over the resulting values.

Ambulance calls

P2000 is part of the Dutch C2000 alarm network. The network uses the FLEX protocol developed by Motorola and uses emergency pagers as information receivers. P2000 is an open network with information publicly available via multiple websites, which enthusiasts run, e.g., https://www.p2000-online.net and https://alarmeringen.nl. For this study, we contacted the owners of https://112-nederland.nl and requested a data dump from 2019. The Dutch Ministry of Justice and Security maintains the network. One specific type of message that this network registers is for ambulances. Notably, the calls are anonymous and do not have information about who called and the reason for the call. It may, however, have a 4 or 6-digit postcode and a timestamp. In this case, a call has a pair of coordinates - the middle point of the street where it was made.

TEMPERATURE

To collect temperature data, we use an API from the Dark Sky - a multi-platform app and service aimed at providing accurate and up-to-date weather information. Note that as of 2023, the Dark Skye API is no longer accessible since it was acquired by Apple in early 2020. While there are many other ways to get temperature data, Dark Sky API provides conventional access to its data. It operates with the aggregated measurements of many weather data sources such as the German Meteorological Office, EUMETNET, etcetera. The data we collected contains hourly temperature measurements of The Hague, Rotterdam and Amsterdam for the heatwave period.

ANALYTICAL FRAMEWORK

A BRIEF OVERVIEW

This study uses open data to explore the link between vulnerability and resilience to heatwaves in 3 cities. We conceptualise vulnerability in a rather conventional way in line with the previous studies as a meta-attribute of the system that experiences shock and consists of three sub-attributes: sensitivity, exposure, and adaptive capacity (Szagri et al., 2023). To operationalise each sub-attribute, we connect them with a set of related variables (Reckien, 2018). For example, to capture residents' sensitivity to heat, we use a variable that represents how many of them have serious health issues (Wilhelmi & Hayden, 2010). The final step in assessing vulnerability is the construction of a *vulnerability profile* - a unique combination of variables dominating a district via dimensionality reduction technique Non-negative Matrix Factorization (NMF).

Similarly to vulnerability, we conceptualise resilience as a meta-attribute out of recovery, adaptation and transformation (Meerow et al., 2016). The operationalisation involves identifying the corresponding variables that capture the system's capacity to respond to the shock. For example, in case of a heatwave, a citizen living in UHI may decide to go to a park and, therefore, avoid the excessive pressure created by the heat, demonstrating adaptive capacity. The impact of the heatwave spans across multiple temporal scales, which, in turn, can be loosely associated with resilience sub-attributes: short (recovery-adaptation), mid (adaptation-transformation) and long-term (transformation) (Chelleri et al., 2015). For instance, a change in human behaviour (going to the park) can be considered an example of a short-term impact and captured with adaptive capacity. The mid and long-term may include training vulnerable individuals and changes in the built environment. While all of these are important, in this study, we aim to unpack the short-term impacts of the heatwave and how it manifests through the changes in human behaviour and adaptive capacity. To measure adaptive capacity, we use the spatio-temporal excess in the number of ambulance calls made during the heatwave.

We conceptualise the link between vulnerability and resilience via adaptive capacity, which is present in both vulnerability and resilience, in line with what was proposed by Engle (2011). On a higher level, most of the researchers consider vulnerability and resilience related (Sharifi, 2023). Going further, some state that resilience is not "just the flip side of vulnerability" (Haraguchi et al., 2022), while others do consider it to be simply the opposite (Patel et al., 2020), and a few have tried to go beyond and explicitly understand how they are related (Bergstrand et al., 2015). To operationalise these relations, we zoom into the connection between a). the distribution of the most vulnerable, represented by the vulnerability profile of a city district, as they manifest vulnerability most prominently, and b). the difference between the number of ambulance calls as it demonstrates the immediate response and potential adaptive reaction of the lack thereof.

Vulnerability as a function of socio-demographic, economic, health and built environment

Vulnerability is the degree to which a system is susceptible to and unable to cope with the adverse effects of climate stressors (IPCC, 2007). The concept of vulnerability is multifaceted, and its operationalisation varies depending on the type of shock or stress and the system of interest. In climate change, vulnerability is often deconstructed into three primary components: exposure, sensitivity, and adaptive capacity. Exposure refers to the presence of people, livelihoods, environmental services, and resources that could be negatively affected. Sensitivity is the degree to which a system is affected, either adversely or beneficially, by climate variability or change. Adaptive capacity is defined as the ability of a system to adjust to climate change, to moderate potential damages, to take advantage of opportunities, or to cope with the consequences.

In the study of heatwaves, these three components dominate the discussion, highlighting how they interact to affect populations differently (Szagri et al., 2023). When the focus shifts to urban areas from rather a general concept of heatwave vulnerability, the system of interest becomes the city itself, encompassing the interplay between the residents and their interactions with the built environment under heat stress conditions (Ahmed et al., 2023). However, it is important to acknowledge that no vulnerability assessment is complete and comprehensive (Heesen et al., 2014). There will always be some features that some stakeholders might find missing, underscoring the inherent limitations of such assessments. Additionally, the effectiveness of a data-driven vulnerability assessment is always constrained by the availability of relevant data. As such, the goal of these assessments is not necessarily to achieve perfection but rather to minimise inaccuracies and biases.

Further elaborating on the methods used to measure urban vulnerability, we aim to cover only the key types of features as highlighted in the recent review by Szagri et al. (2023), which are found across various studies. This selective approach helps focus on the most critical aspects contributing to urban vulnerability. Table 3.4 lists the features selected to capture urban vulnerability to heatwaves. Note that this table is not meant to be exhaustive, and incorporating additional variables like humidity might enhance the assessment (Torralba et al., 2024).

Notably, all features, except for Urban Heat Island (UHI) effects, are represented in percentage terms relative to the total population—for example, the percentage of individuals aged 0-14 reflects the proportion of this age group in the total population of the district. This methodological choice highlights how demographic and environmental characteristics are considered in relation to the overall urban population, thereby providing a clearer picture of the areas and groups most at risk during heatwaves.

Category	Feature	Source
Age group	0-14 15-24 25-44 45-64 65+	Statistics Netherlands
Ethnicity	Dutch Western migration background Non-Western migration background	
Household composition	Single person household Household without children Household with children (incl. single-parent)	
Education	Low education Mid education High education	
Income	40% low income household 20% high income household	
Health	Seriously limited due to health issues Mobility issues Serious or very seriously lonely	RIVM
Built environment	Urban Heat Island effect	

Table 3.4: Selected features to characterise urban vulnerability to heatwaves.

Measuring urban vulnerability to heatwaves involves various methodologies, each with inherent limitations (Diaz-Sarachaga & Jato-Espino, 2020). In this study, we combine socio-demographic, economic, health and behavioural data and variables related to the built environment to gauge vulnerability at the district scale. This approach helps identify geographical areas where certain patterns—such as significant populations of the elderly or low-income groups—are more susceptible to heatwaves (Wilhelmi & Hayden, 2010). However, the measurement is complicated because the same features can correspond to two or three sub-attributes since they are also "meta" to a certain extent.

There is no clear "cut" that should be treated as sensitivity, exposure or adaptive capacity. For example, gender typically belongs to sensitivity due to underlying health-related status, but when we look at it more broadly, in combination with household composition, it becomes a part of adaptive capacity. Female-headed single-parent households might be unable to leave their homes due to a need to care for their children or elderly.

Principal Component Analysis (PCA) has been widely used to operationalise vulnerability assessment. Szagri et al. (2023) found that approximately 35% of research on heat vulnerability employs PCA to analyse and synthesise diverse vulnerability factors into principal components. Recent research has extended this approach by integrating novel data sources and advanced computational techniques to enhance the robustness of vulnerability assessments (Reckien, 2018).

To further quantify urban heat vulnerability in this study, we employ Non-negative Matrix Factorization (NMF), implemented using the scikit-learn Python package (Pedregosa et al., 2011). NMF is a statistical method used to decompose multivariate data by reducing the dimensionality of the original dataset into interpretable parts under the constraint that all involved data points (and thus components) must be non-negative (Wang & Zhang, 2013). This characteristic makes NMF particularly suited for data that naturally does not support negative values, such as physical quantities or counts.

NMF is not as common as PCA in the field of vulnerability assessment. However, NMF has several pros that would make this method extremely useful for such tasks. One of the strongest advantages of NMF is its ability to produce "components", commonly denoted as W and H matrices, that have a clear interpretation. When analysing urban vulnerability, NMF not only helps to identify patterns with factorization of the input matrix V, but thanks to its inherent clustering property, it provides clusters in the data corresponding to specific socio-demographic or environmental factors contributing to vulnerability. Unlike other dimensionality reduction techniques that might produce abstract components, NMF provides a part-based representation where each component can be distinctly associated with physical or meaningful features of the dataset. This aspect can be particularly useful in urban settings, where understanding the contribution of different elements (like infrastructure or population density) to heat vulnerability is crucial.

As with any unsupervised learning algorithm, one of the key parameters is the number of components, and there is no definite answer to how it must be selected. While it is important to aim at the high or low values of the selected metrics, e.g., reconstruction error, another aspect that must be preserved is the interpretability of the results. Here, we are guided by both - optimising for metrics and, most importantly, keeping the results interpretable. The task is complicated because we have 3 case cities, and the optimal number of components might be different given various social factors. However, all three cities have high levels of segregation, which is reflected not only in the segregation index but also in other attributes such as income, health etc. In theory, this fact (high levels of segregation) can simplify the interpretation of resulting component matrices.

Thus, our pipeline looks as follows. We prepare the input data matrix V of $n \times m$ size, where n is the number of observations (districts) and m is the number of features. The matrix is individually prepared from the five data sets listed in 3.4 for each city. We scale the features between 0 and 1 since the input must be positive and pass it to the

NMF. We run the method with various numbers of components from 2 to 10 to search for the number that gives us the lowest reconstruction error along the most interpretable W and H matrices, which, in our case, equals 4. Finally, we look at the vectors of H matrix and the "weights" of their features - "vulnerability profiles". If the vector has a high contribution of features like, for example, 65+, mobility issues, and low income, we treat it as more vulnerable than the one with fewer features.

RESILIENCE AS A DIFFERENCE IN AMBULANCE CALLS

Generally speaking, resilience is the ability to recover from a shock. In urban studies, resilience can be conceptualised as the ability of a city to recover, adapt, and transform in response to various shocks (Chelleri et al., 2015). This meta-attribute is crucial for understanding how urban areas can withstand and change following adverse events. However, defining and measuring urban resilience is challenging due to the intricate and interconnected nature of city systems (Buyukozkan et al., 2022). Urban resilience sparks considerable debate among scholars (Meerow et al., 2016), who offer a plethora of definitions and perspectives, reflecting the complexity of the urban systems and the broad impacts of shocks that affect multiple subsystems. For instance, the effect of heatwaves is immediately felt by residents and also disrupts infrastructure systems like energy and transport, which are interconnected; impacts in one can trigger cascading effects in others (Zaidi & Pelling, 2015).

Research into urban resilience, particularly regarding heat resilience, often focuses on the role of green and blue infrastructure in mitigating the effects of heat (Aram et al., 2020; Iungman et al., 2023). However, there is a notable gap in understanding the behavioural responses of affected individuals (Kabisch et al., 2021). For example, during a heatwave, residents in urban heat islands (UHIs) might seek relief by visiting parks, thus exhibiting adaptive behaviours that alleviate the heat's immediate pressures. Such individual decisions highlight the system's adaptive capacity—a key component of resilience.

Furthermore, the impacts of heatwaves and other urban shocks can span multiple temporal scales, which align with different aspects of resilience: short-term (recovery and adaptation), mid-term (adaptation and transformation), and long-term (transformation) (Chelleri et al., 2015). In the short term, adaptive behaviours, such as utilising green spaces, represent immediate responses. Over the mid- and long-term, strategies might include training vulnerable populations and altering the built environment to cope better with future shocks.

Resilience can be assessed using various methodologies: a single proxy, a set of indicators, or a composite index (Cariolet et al., 2019; Diaz-Sarachaga & Jato-Espino, 2020). Each approach has its limitations and, much like assessments of vulnerability, captures only a fraction of the true resilience of a system (Raška et al., 2020). This echoes the broader challenge in resilience studies: balancing the utility of these assessments with their inherent incompleteness, aiming to provide actionable insights rather than definitive answers (Haraguchi et al., 2022). As noted in the literature, embracing the diversity of viewpoints on resilience may enrich our understanding, though it also poses challenges in harmonising these perspectives into coherent policy actions.

We propose to measure resilience as spatio-temporal excess in ambulance calls during a heatwave, offering a concrete example of how urban systems react to extreme temperatures in terms of the health and safety of the residents. Previous research has found a connection between increased calls and heatwaves (Graham et al., 2016; Kue & Dyer, 2013; Seong et al., 2023; Zhan et al., 2018). Moreover, ambulance calls can be more informative than mortality data since it allows us to understand morbidity (Mathes et al., 2017). However, what is missing is how the adaptation of citizens' behaviour (adaptive capacity) results in a change in the number of calls. Notably, this change must be tracked with high-resolution data to be interpretable.

Table 3.5 presents a snapshot of how the ambulance call data looks like. Our hypothesis is as follows. In a country like the Netherlands, where healthcare, including emergency services, is accessible to most of the population, the fewer the calls, the better. If, during the heatwave, a certain district shows more ambulance calls than the average, it has low resilience. While no ambulance calls are perhaps impossible, overall, the city aims to minimise this number.

Date	Time	Message
2017-01-01	00:00:13	P 1 GEBOUWBRAND Van Heuven Goedhartlaan 2-8 UTR...
2017-01-01	00:00:37	A1 Goudsbloemlaan 71-79 DHG 2565CP : 15101 Ritn...
2017-01-01	00:00:39	Prio 1 Noord Ringdijk - N207 20,1 MDT Wegvervoe...

Table 3.5: Three sample records from the P2000 network. Each record has at least three attributes: the date and time when the record was registered in the system and the message. The message may have a 4 or 6-digit postal code as in record 2: "2565CP" and other information.

More specifically, we aim to compare the total number of ambulance calls made during the heatwave from the 22 to the 28 of July - a full week from Monday until Sunday, with the "average week," The average week here is an average of all summer weeks of 2019, excluding the heatwave week. Note that the averaging is happening by hour. Thus, we add the number of calls made during 0:00 on Monday, for example, 3 June, to those made during 0:00 on Monday, 10 June and so on. Next, the averaging is happening by the district.

Let $C_{d,h,w}$ represent the number of ambulance calls in district d, at hour h, during week w. Then, the heatwave week calls are:

$$H_{d,h} = C_{d,h,\text{heatwave}}$$

This represents the number of calls during the heatwave at hour h in district d. Next, for non-heatwave summer weeks, let us denote this set of weeks as W), the average number of calls at hour h in district d is calculated as:

$$A_{d,h} = \frac{1}{|W|} \sum_{w \in W} C_{d,h,w}$$

where $|W|$ is the total number of weeks in the set W.

To compare the ambulance call rates during the heatwave to a typical summer week, calculate the percentage difference for each district d and hour h, using the following formula:

$$\%\Delta_{d,h} = \left(\frac{H_{d,h} - A_{d,h}}{A_{d,h}}\right) \times 100$$

This formula calculates the percentage by which calls during the heatwave exceed or fall below the average calls for the same hour in the same district.

Several pros and cons emerge when evaluating the efficacy of using ambulance call data as a proxy for measuring urban resilience. Firstly, this proxy, characterised by its spatio-temporal granularity and high resolution, provides a detailed snapshot of urban responses to heatwaves and similar crises. It allows for a focused analysis of how residents react under stress by utilising emergency services, indicating their immediate adaptive capacity.

However, there are limitations to relying solely on this approach. The difference in ambulance calls, while informative, do not comprehensively represent urban resilience. They might lead to overconfidence in citizens' resilience if interpreted in isolation. The data depend heavily on the assumption that residents have equal access to and willingness to use emergency services. In contexts like Dutch cities, where healthcare services are readily accessible and affordable, this assumption may hold true. Yet, applying this proxy to cities with different healthcare systems and levels of accessibility could lead to skewed results and require careful adaptation and additional contextual proxies.

Additionally, the complexity of urban systems makes relying on a single proxy problematic. Cities are dynamic entities with multiple interacting components, and resilience cannot be fully captured through one-dimensional metrics. Therefore, while ambulance call data can be a useful component of a broader set of indicators, it should be integrated with other proxies that illuminate different aspects of the urban resilience landscape. This integration can provide a more robust and nuanced understanding of how cities cope with and adapt to various shocks.

ANALYSING RELATIONS BETWEEN VULNERABILITY AND RESILIENCE

Vulnerability and resilience are integral concepts in understanding how systems respond to external shocks (Krueger et al., 2022). Vulnerability reveals how susceptible a system is to disruptions, illustrating its potential weak points (Salas & Yepes, 2018). Conversely, resilience provides insights into a system's ability to recover, adapt and transform under these shocks, highlighting its strengths in maintaining functionality under stress (Chelleri et al., 2015). Although these concepts are connected (Kelman, 2018), the question remains: how are they related? This relation is critical in both academic research and practical application. Despite their interconnected nature, some practitioners may treat them as diametrically opposed (Buyukozkan et al., 2022), a perspective that can simplify complex interactions (Jabareen, 2013).

In addressing these concepts, this study builds on the framework proposed by (Engle, 2011), who articulated that vulnerability and resilience are interconnected through adaptive capacity. Applied to an urban system, this linkage suggests that the ability of citizens to adapt in response to stimuli is a critical bridge between how vulnerable it is and how resilient it can be.

Building upon the notion of adaptive capacity, our previous discussions have highlighted its value in studying immediate responses to heatwaves. For instance, adaptive capacity provides a useful lens to examine how citizens react to a heatwave, particularly in terms of health and safety outcomes. This approach allows us to capture real-time responses and adjustments, which are crucial for building systemic resilience.

Our methodology for exploring these dynamics involves a comparison between district-level vulnerability and resilience. We define vulnerability through an index comprising five categories of variables that represent different aspects contributing to a district's susceptibility to heatwaves. Resilience, on the other hand, is quantified through the percentage difference in the number of ambulance calls during the heatwave, assuming that fewer calls indicate higher resilience. Specifically, we focus on the relative concentration of the most vulnerable profile within each district—a profile characterized by possessing the highest number of vulnerability-contributing features.

Finally, our analysis aims to test the hypothesis that districts with higher levels of vulnerability exhibit lower resilience. This hypothesis posits a negative correlation between vulnerability and resilience, suggesting that an increase in one typically results in a decrease in the other. By exploring this relationship, we aim to contribute to a more nuanced understanding of how vulnerability and resilience interact within urban districts during heatwave conditions, thereby providing insights into effective strategies for enhancing urban resilience.

3.5. Data & code availability

The data used for the analysis is available at https://doi.org/10.4121/9d0700b5-cfd8-44a7-a5fd-68cb0c86e8a9. The code used to perform the analysis is available at https://github.com/mikhailsirenko/more-vulnerable-less-resilient.

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4

Flipping risks: On urban maladaptation in times of epidemics

By Mikhail Sirenko, Alexander Verbraeck & Tina Comes, under review in *Scientific Reports*.

Abstract

Epidemics are long-lasting and transboundary crises that challenge traditional approaches. Given the complexity and interconnectedness of modern cities, interventions can lead to unintended consequences, i.e., maladaptation. Although adaptation is central to resilience, crisis management remains focused on short-term response in sector-specific crises, leaving a gap in understanding urban (mal-)adaptation. This study examines the impacts of uniform interventions across diverse urban districts, assessing interventions' role in fostering adaptation or maladaptation. We use the COVID-19 pandemic in The Hague, Netherlands, as a case study, employing a large-scale agent-based model. We find that without intervention, the high social contact city centre becomes an infection hotspot due to the transient population it attracts. Conversely, the outer residential district, with fewer amenities, experiences infections primarily among its residents. A uniform lockdown policy significantly reduces infections in the city centre by limiting mobility and social interactions but inadvertently increases risk in the outer residential district. Based on a conceptualisation of urban adaptation in an index, we conclude that un-contextualised uniform interventions can lead to maladaptation, highlighting the unintended consequences of one-size-fits-all interventions. Our results underscore the importance of context-specific crisis response strategies to ensure spatial equity and address the heterogeneous nature of modern cities.

4.1. INTRODUCTION

Driven by climate change and biodiversity loss, epidemics are expected to take an increasing toll in the coming years (Marani et al., 2021), leading to longer-term crises that transcend traditional geographical and sectorial boundaries (Comes et al., 2022). Crisis management literature, which traditionally has focused on sector-specific and short-term crises, must now adapt to these challenges.

Conventionally, crises and disasters are studied at two spatial scales: global or national studies and case studies at the individual or organisational level. Global and national reports, such as the IFRC's World Disaster Report (IFRC, 2023), UNDRR's Global Assessment Report on Disaster Risk Reduction (UNDRR, 2023), and the World Risk Report by Bündnis Entwicklung Hilft and IFHV (2023), offer valuable insights for country comparison and international advocacy. Yet, they often lack the nuanced understanding of *across* and *within* countries, which are needed for effective local responses. At the local level, case studies (Canlas & Karpudewan, 2020; Vega, 2018) ensure participation, contextualisation, and engagement but struggle with generalisability due to the subjective role of the researcher and the reliance on relatively few cases. Although some researchers have proposed combining qualitative and quantitative methods (Baharmand et al., 2022), there remains a need for generalisable, data-driven approaches that offer both contextualisation and high spatial granularity.

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Crisis management traditionally follows a cycle of mitigating, preparing, responding, and recovering (Comes et al., 2022). Despite the recognised importance of adaptation in crisis response, it often remains implicit under the broader categories of sensemaking and decision-making (Weick, 1993). Meanwhile, disaster resilience literature emphasises the capacity of individuals, communities, organisations, or systems to adapt and respond, highlighting significant barriers to effective adaptation, especially under stress (Champlin et al., 2023; Paulus et al., 2024). Complex human adaptive behaviours can result in unplanned outcomes or maladaptation, where some social groups may follow the rules while others resist (Duque-Calvache et al., 2021; Tintori et al., 2020).

Maladaptation, a concept from climate change literature, refers to interventions that inadvertently worsen situations (Schipper, 2020). Similarly, epidemic control measures can have unintended consequences, such as amplifying inequalities and undermining climate resilience (Ahmed et al., 2020; Nundy et al., 2021). According to Schipper (2020), maladaptation is an action that results in an increased vulnerability through inaction or a maladaptive outcome of the strategies that were initially set out to help adapt. While adaptive responses have shown benefits in various epidemics like influenza (Chowell et al., 2009) and COVID-19 (Dewi et al., 2020; Neufeld et al., 2020), uniform country-scale interventions may not account for the diverse urban and social fabrics that influence adaptive behaviour. Although such interventions may appear fair by applying the same measures to all, they often benefit only a subset of the population.

The centres of gravity for epidemics and other climate crises are modern cities, which are increasingly heterogeneous (Brelsford et al., 2017). Due to segregation and socioeconomic inequalities, two adjacent districts within the same city can be widely different (Nicoletti et al., 2023), making crisis management increasingly complex. Socioeconomic inequalities and the concentration of vulnerable populations, such as the elderly or low-income households or those with pre-existing health conditions, can further exacerbate the consequences of climatic shocks as well as infectious diseases in urban settings (M. Chen et al., 2023; Kalocsányiová et al., 2023; McDonald et al., 2024).

Computational models have demonstrated their usefulness in crisis response (Altay & Green, 2006). While traditionally, optimisation models have dominated during the COVID-19 pandemic, the focus has increasingly shifted towards simulation models (Lorig et al., 2021). However, the spatial scale these models use is critical: country, region, city or district within the city. As indicated by (Iwanaga et al., 2022), the choice of the "right" scale plays a critical role in the interpretability of the underlying processes. Virus spread is driven by human mobility (Kato & Takizawa, 2022), contacts between humans (Zhang et al., 2016), or, more generally, human behaviour (Van Den Broek-Altenburg & Atherly, 2021). Therefore, behaviour and the locations of that behaviour must be at the core of models analysing the impact of interventions (L. Liu et al., 2022).

The aim of this research is threefold. First, we showcase how the maladaptation concept by (Schipper, 2020) unfolds under the urban crisis response, focusing on citizen adaptive behaviour across different environments. Second, we develop a large-scale agent-based model, a full-scale replica of a city, to serve as a sandbox for testing various interventions based on the work of (Zhang et al., 2016). Finally, we develop an urban adaptation index and use the model to examine whether the common interventions to combat the epidemic would result in maladaptation at the urban scale. As the case study, we use the COVID-19 pandemic in one of the most populous yet diverse cities of the Netherlands - The Hague.

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4.2. RESULTS

CENTRUM VS OUTER RESIDENTIAL: EQUAL ACCESS BUT UNEQUAL DISTRIBUTION OF ESSENTIAL SERVICES

The Hague, the third most populous city in the Netherlands, presents a diverse urban landscape with varying patterns of service distribution and citizen behaviour across its districts. Our analysis focuses on two exemplary but distinct districts: Centrum, located in the city centre, and Ypenburg, an affluent outer residential district (Figure 4.1). Despite having comparable population sizes and areas, these districts exhibit different urban and social characteristics.

We find that Centrum, with a population of 21,643 residents over two km^2, and Ypenburg, with 26,833 residents over five km^2, both have relatively high access to essential services such as grocery shops. The median distance to the closest supermarket is 0.3 km Centrum and 1.1 km Ypenburg. Centrum has a higher percentage of elderly residents, a significant proportion of individuals with chronic health conditions, and a larger segment with low income and low educational attainment. Conversely, Ypenburg has a population with fewer chronic health conditions and psychological distress, higher income, and higher educational attainment.

The Hague's Centrum district serves as a hub of activity, hosting a significant proportion of the city's amenities. With 2,440 amenities (2019 data; 17% of the city's total), Centrum has 113 amenities per 1,000 residents, significantly higher than Ypenburg's 292 amenities (2% of the total) or 11 per 1,000 residents. This uneven distribution extends to essential services such as supermarkets, where Centrum has ten compared to Ypenburg's one. This centralisation of services in Centrum is arguably designed to cater not only to its residents but also to the transient population, visitors and tourists passing through the city centre.

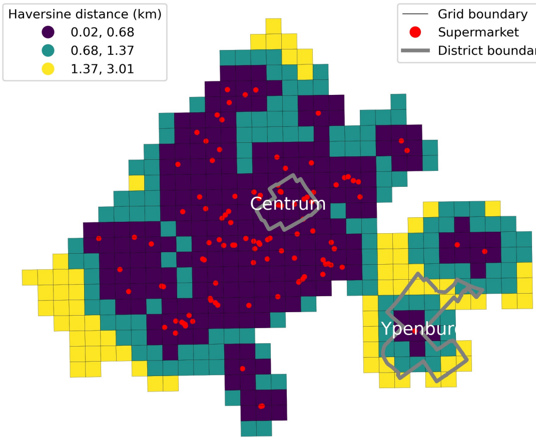

Figure 4.1: Spatial distribution of supermarkets and proximity analysis in study districts: Centrum and Ypenburg. The map displays the distribution of supermarkets (red dots) within the Centrum and Ypenburg districts, delineated by grey lines. The grid cells are colour-coded based on the Haversine distance to the nearest supermarket, with purple (0.02-0.68 km), green (0.68-1.37 km), and yellow (1.37-3.01 km) representing increasing distances. Grid boundaries are shown in black, highlighting the spatial extent of the analysis area. Spatial distribution and proximity analysis of supermarkets in the Centrum and Ypenburg districts. The map visualizes supermarket locations (red dots) within district boundaries (grey lines) and color-coded grid cells representing Haversine distances to the nearest supermarket: purple (0.02–0.68 km), green (0.68–1.37 km), and yellow (1.37–3.01 km). Black grid boundaries delineate the analysis extent. Data source: OpenStreetMap.

Previous research has found that the behaviour of citizens in terms of transportation and shopping habits is an important driver of the spread of a virus (Guo et al., 2022; Tapiador et al., 2024). We see that before the pandemic, a significant proportion of grocery shopping trips by residents of highly urbanised areas in the Netherlands were made by bicycle or on foot (49%), with the remainder split between car (37%) and public transport (13%). The median distances travelled for groceries are 0.6 km on foot, 1.5 km by bicycle, and 5 km by car. These distances indicate that most shopping activities occur within where the resident is: either to be home but also work or recreation, forming trip-chaining.

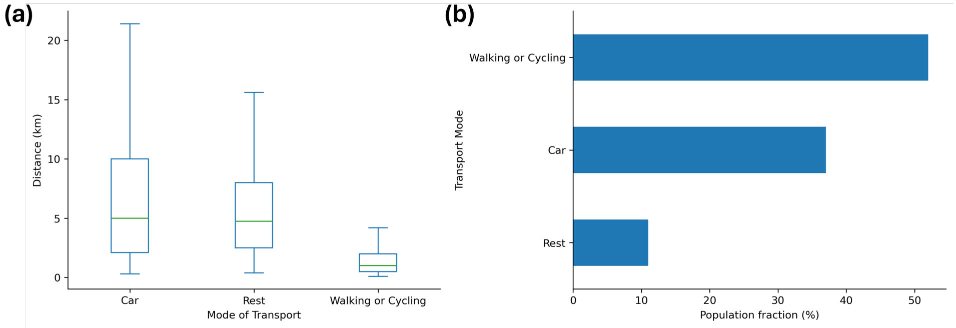

Figure 4.2: Travel distance by mode of transport (panel a) and preferred mode of transport for grocery shopping (panel b). Panel a illustrates the median distances travelled for groceries by car, walking and cycling, and the rest of the transport modes (e.g., train, tram or scooter), while panel b shows what population fraction prefers which mode of transport for grocery shopping.

Another important aspect of the virus spread is how much time is spent with potentially infected individuals in indoor spaces (Atamer Balkan et al., 2024). The median time spent on grocery shopping is 30 minutes, typically involving one visit per week (44%).

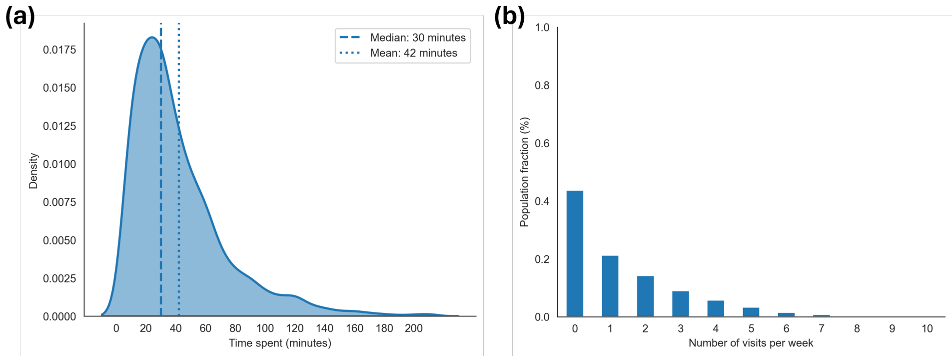

Figure 4.3: Probability density function of the time spent (panel a) and number of visits (panel b) for grocery shopping. Panel a shows the median time residents spend on grocery shopping per visit, while panel b depicts the frequency of grocery shopping trips per week. Zero number of weekly visits for grocery shopping implies that other household members do the shopping.

Given the two districts' very different urban and social fabric, we hypothesise that the adaptation to government interventions during COVID-19 will also differ. Understanding adaptive citizen behaviour in these districts is key to analysing potential maladaptation.

THE CITY CENTRE IS A HOTSPOT UNDER A NO-RESPONSE SCENARIO

Few countries worldwide have approached the COVID-19 pandemic without imposing any restrictions on their populations (Åslund, 2020; Ludvigsson, 2023). Figure 4.4 visualises the potential consequences of such a no-restriction approach within urban districts for The Hague. In this scenario, the city does not implement any measures to control the spread of the virus. Thus, we assume that citizens would continue their daily routines, businesses and services remain open, and other activities remain unchanged. This "business-as-usual" approach leads to a rapid spread of the virus (see Supplementary Information for the temporal progression of the virus). In both districts, the spread peaks at around 25 days. Following this peak, the number of infections declines as most of the population is infected and subsequently recovers.

Panel a in Figure 4.4 captures a snapshot on day 25 of the simulation. This visualisation uses lines to connect the residences of agents with the locations within their district where they contracted the virus. Red lines indicate that the infected agent was a visitor to the district, while blue lines denote infections occurring within the agent's district of residence. Despite the similar number of residents in both districts, the patterns of virus spread exhibit striking differences. The central district, characterised by its numerous amenities and attractions, becomes an infection hub. People from across the city travel to the central district for work, leisure, and shopping. During these visits, some individuals contract the virus and then return to their home districts, potentially spreading the infection to household members.

Panel b demonstrates an almost opposite cumulative trend in the proportion of infections in the two study districts at the end of the model run. In the central district, most infections (65%) occur among visitors, further driving the spread of the virus in their home districts, while only 35% of infections involve the district's residents. This is because the central district's work locations, amenities, and other attractions draw numerous visitors, who then become vectors for the virus. In contrast, the outer residential district shows a reverse trend. Ypenburg, with fewer work locations, amenities, and attractions, is less frequently visited by outsiders. Consequently, social interactions primarily occur among residents. As a result, the majority of infections (78%) in Ypenburg are among its residents, while only 22% of infections involve visitors.

In summary, an inaction scenario or "no response" strategy makes the city centre a hotspot for the virus. From this central area, the virus spreads quickly to other districts, making it crucial to address the outbreak at its source to prevent a citywide epidemic. Additionally, the lack of a response exacerbates the vulnerability of Centrum residents, who are already at risk due to a combination of socioeconomic and health factors. Their increased exposure to interactions with visitors from other districts further heightens their exposure, vulnerability, and the corresponding risk of infection.

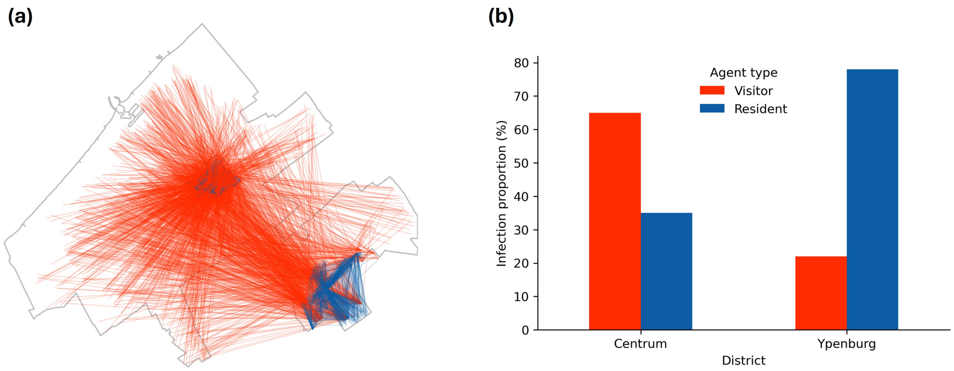

Figure 4.4: The impact of inaction on the spread of the virus. Panel a visualises the infections in Centrum and Ypenburg on day 25 of the simulation, using lines to connect the residences of agents with the locations where they contracted the virus. Red lines indicate that the infected agent was a visitor to the district, while blue lines denote infections occurring within the agent's district of residence. Panel b depicts the proportion of infections involving residents versus visitors in both districts at the end of the simulation. The proportions are calculated as the number of infections by each agent type divided by the total number of infections in the respective district.

MALADAPTATION AND FLIPPED RISK FROM THE CITY CENTRE TO THE PERIPHERY

During the pandemic, the Netherlands has implemented several interventions to combat the pandemic (Van Den Broek-Altenburg & Atherly, 2021). All interventions were the same for the entire country. Only a few countries, e.g. Vietnam, tried to consider the difference in the spread of the virus at the urban and community scale, as opposed to the country scale, which resulted in district lockdowns.

Figure 4.5 illustrates the potential impact of a "hard lockdown." This intervention involves closing schools, childcare centres, bars, and restaurants and extending to cultural and recreational amenities and non-essential shops. Essential services such as supermarkets, hospitals, police, and fire stations remain operational. The motivation behind such a combination of measure is as follows. The Netherlands' initial response to the pandemic did not occur immediately at the onset of the pandemic. The first COVID-19 case was reported on 27 February 2020, but stringent measures were not introduced until 15 March 2020. On this date, the government mandated closing schools, childcare facilities, bars, and restaurants. Despite these efforts, the infection rates continued to rise. Importantly, these policies were applied uniformly across the country without accounting for variations in vulnerability, behavioural patterns or social contact rates. Thus, by extending the types of amenities that must be closed, we wanted to explore whether these measures would slow down the virus spread (More on the various combinations of measures that we have tested and their effectiveness can be found in Sirenko et al. (2020) or Sirenko et al. (2022)).

The primary benefit of the hard lockdown is a significant delay in the spread of infections (see Supplementary Information). With the hard lockdown, the peak of infections was delayed to around 90 days as opposed to 25 days under the no-response scenario. This delay 'flattens the curve' and provides more time for healthcare systems to prepare and respond.

In the central district, our simulation shows that infections dropped significantly under the hard lockdown compared to inaction: from 24,138 to 2,967 (a drop of 88%). With the hard lockdown, the number of visitors infected decreased substantially (from 72% to 23%), indicating that reducing mobility and social interactions in densely populated areas can effectively mitigate the spread of the virus.

Conversely, in the outer residential district of Ypenburg, where social interactions were less frequent under inaction, and the population density is lower, the simulation shows that while the number of infections decreased in the absolute sense, the reduction was less pronounced compared to the central district: from 26,072 to 22,060 infections (a drop of 15%). The number of infections by the district's residents actually *increased* (91%) in comparison to the "no response" strategy (72%).

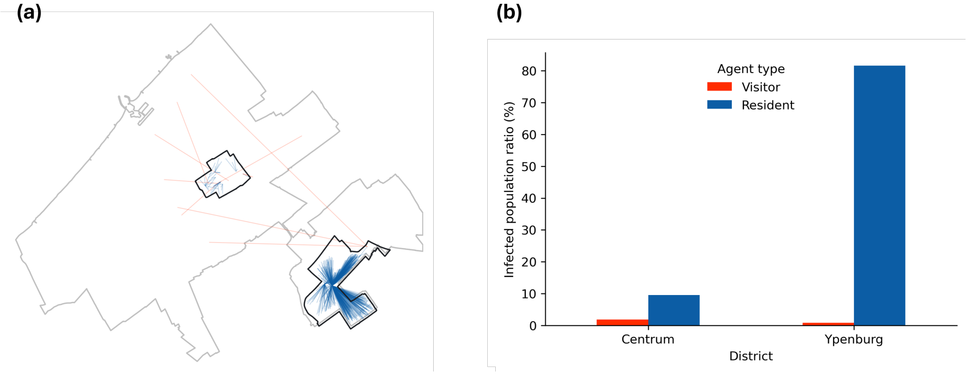

Figure 4.5: The impact of a hard lockdown on the spread of the virus. Panel a shows the number of infections in Centrum and Ypenburg on day 90 of the simulation, using lines to connect the residences of agents with the locations where they contracted the virus. Red lines indicate that the infected agent was a visitor to the district, while blue lines denote infections occurring within the agent's district of residence. Panel b depicts the infected population ratios. The ratios represent the fractions of infections among residents and visitors at a given time relative to the district's population.

To understand this pattern, we need to examine the role of the essential services that remained open: supermarkets. Figure 4.6 shows the infections by agent and location type: supermarkets versus agent homes. The figure reveals that supermarkets are pivotal in the transmission chain. Individuals adapt their behaviour and do not visit any other location anymore. Additionally, the trip chaining stops: no more shopping on the go or close to the workplaces. As a result, individuals are more likely to get infected during their supermarket visits and subsequently spread the virus within their homes. This pattern is especially pronounced in Ypenburg, which has a higher overall number of infections compared to Centrum, indicating that supermarkets are crucial in both districts. However, due to the limited number of supermarkets serving Ypenburg residents, these locations become infection hotspots. According to our findings, the hard lockdown alters daily routines, making supermarkets the primary place where people, except for essential workers, interact with others. On the urban scale, supermarkets have served as transmission hubs for the virus, similar to airports' role on a national and international level (Silva & Ribeiro, 2023).

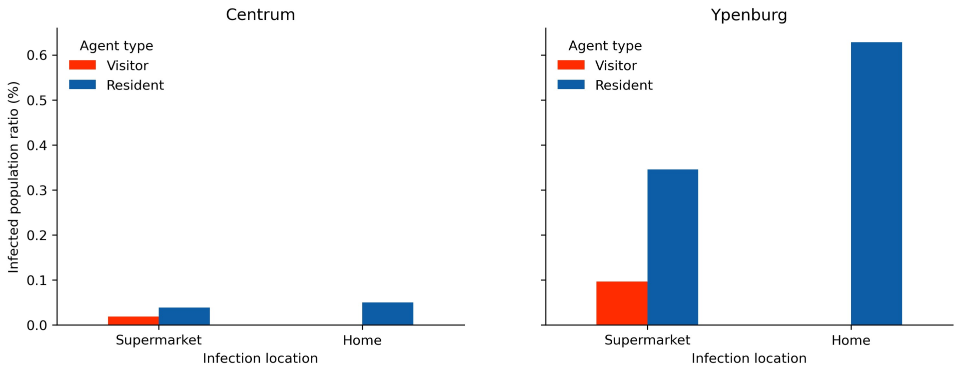

Figure 4.6: Infected population ratio by location type in central and outer residential districts under hard lockdown. The left panel visualises the ratio of infections contracted at supermarkets versus those at agents' homes in Centrum. The right panel shows the same comparison for Ypenburg. These ratios indicate the proportion of infections occurring at supermarkets and homes among residents and visitors, normalised to the district's population size.

To analyse if and in how far urban adaptation and maladaptation occurred, we introduce a metric for assessing the effectiveness of adaptation measures. The metric compares impact under inaction with impact given an adaptive intervention α at a location λ.

$$\text{Urban Adaptation Index}_{\alpha,\lambda} = \frac{\text{Impact with measure } \alpha \text{ at location } \lambda}{\text{Impact without measures at location } \lambda}$$

If the UAI is below 1, α is considered effective (adaptation). Conversely, if the UAI is above 1, the α is considered ineffective or harmful (maladaptation). This approach provides a quantitative approach to evaluate whether specific interventions reduce or exacerbate district risk.

In our case study, we compare the number of infections under the lockdown to those without any measures. We apply this method to the Centrum and Ypenburg districts. The infection numbers with and without measures are as follows: Infections in Centrum with measures are 2,967, and without measures are 24,138. In Ypenburg, infections with measures are 22,060, and without measures are 26,072.

Calculating the UAI for Centrum, we get:

$$\text{UAI}_{\text{Hard Lockdown, Centrum}} = \frac{2,967}{24,138} \approx 0.123$$

For Ypenburg, the UAI is:

$$\text{UAI}_{\text{Hard Lockdown, Ypenburg}} = \frac{22,060}{26,072} \approx 0.846$$

We can further zoom into the UAI of various urban locations λ in the different districts. Table 4.1 provides the results for three types of locations: district supermarkets, agents' homes, and other types of locations (schools, bars & restaurants, etc.). We find that supermarkets in both districts experienced a significant increase in infections, reflected in a high UAI - or maladaptation - pushing infections into supermarkets. Clearly, Ypenburg shows the highest UAI, suggesting a strong maladaptive outcome. Homes in Ypenburg also showed a high UAI, indicating second-order effects and increased vulnerability.

District	Location Type	UAI
Ypenburg	Supermarket	3.009
	Home	1.964
	Other	0.054
Centrum	Supermarket	1.337
	Home	0.423
	Other	0.029

Table 4.1: Urban Adaptation Index (UAI) by Location Type and District

In conclusion, applying uniform interventions across diverse urban districts can lead to maladaptation. In the case of The Hague, the Netherlands, our model shows that the uniform approach did not account for the higher risk of transmission in the outer residential areas which have fewer shopping facilities. By not tailoring interventions to different districts' specific needs and conditions, the measures were less effective in some areas and potentially over-restrictive in others.

4.3. DISCUSSION

This study examines urban maladaptation during the COVID-19 pandemic, focusing on the impact of un-contextualised uniform interventions on the city with diverse urban and social fabrics and citizens' adaptive behaviour. Our analysis uses a simulation model of a city focusing on two exemplary districts in The Hague: Centrum, located in the city centre, and Ypenburg, an outer residential area. Despite comparable high access to essential services, their uneven capacity distribution leads to varying adaptive behaviours and health outcomes. The no-response strategy exacerbates existing vulnerabilities, particularly among city centre residents. Centrum, characterised by a high density of work locations, amenities, and attractions, becomes an infection hotspot as it attracts visitors throughout the city. Conversely, Ypenburg, with its limited work locations and amenities, sees the virus spread mainly among its residents rather than visitors to the district. Imposing a country-wide lockdown on a city flips the risks in urban districts: the uniform intervention turns the outer residential district into a hotspot. This shift occurs as residents adjust their behaviour, stopping trip chaining and thereby cutting the number of social interactions in the city centre, lowering infection rates there. In Centrum, residents have a higher essential service capacity and can choose among various supermarkets that will be much less busy given the absence of visitors, effectively reducing infection risk. However, in Ypenburg, the limited number of supermarkets becomes overcrowded due to restricted travel, leading to outbreaks nearly as severe as those seen without any response.

Our findings align with previous research on COVID-19, which reports a significant difference in how a virus spreads within cities (Mena & Aburto, 2022; Plümper & Neumayer, 2020). More specifically, virus spread is highly dependent on the types of places people visit (Kato & Takizawa, 2022; L. Liu et al., 2022). Recent studies have highlighted the opportunities for 15-minute cities to be pandemic-proof (Allam et al., 2022; Khavarian-Garmsir et al., 2023). Here, the crucial idea is that equal access is decisive in reducing infections (Guzman et al., 2024). Others have argued for response diversity (Falagara Sigala et al., 2022; Walker et al., 2023), by which having access to a range of options reduces the risk.

What we have found, however, is that local capacity may play a more significant role than accessibility in case of an epidemic. While, in principle, the citizens of Ypenburg *can* still have access to a wide range of essential services and supermarkets across (and beyond) the city, behavioural routines and patterns drive them to choose the closest option. This aligns with Staw's Threat Rigidity theory (Staw et al., 1981), which stresses that individuals often respond in rigid, habitual ways in a crisis. This rigidity led to ineffective responses, intensifying a potential risk for information management within organisations (Plotnick et al., 2009). Here, we can expand this finding to the emergent maladaptive behaviour of people in a city. Having a higher *local capacity* tailored to the needs of the surrounding population can thus be beneficial in reducing the burden in case of a crisis. Remarkably, redundancy and buffer capacity are well-known in the crisis and resilience literature (Nowell et al., 2017).

Previous studies established a link between a country's policy response and the number of positive cases (Capano et al., 2022; Dewi et al., 2020). There is evidence for similar maladaptation issues where centralised uniform measures increased vulnerability in already at-risk areas and social groups (Elers et al., 2021; Perry et al., 2021), thereby raising the questions of spatial equity and urban inequalities. While a uniform policy might be perceived as fair since the same set of rules applies to everyone, in reality, it ignores any potential issues at the district scale. For a policy to be equitable, it must ensure that everyone receives the support they need. However, when an intervention is applied uniformly to each resident of the country—making it equal by default—this condition is not met. Multiple research efforts indicated a need for more targeted policy interventions (Neufeld et al., 2020); however, few studies discuss the differences that appear due to the complex interactions emerging at the urban scale (L. Liu et al., 2022). While there is enough empirical evidence highlighting how epidemics and crises, in general, disproportionately affect already vulnerable individuals (J. T. Chen & Krieger, 2021), here we stress the importance of interventions centred around the questions of spatial equity (Talen & Anselin, 1998) that currently manifests in idea of a 15-minute city (Khavarian-Garmsir et al., 2023). Crucially, we expand the core ideas of access and accessibility by capacity, central to the urban resilience literature (Feliciotti et al., 2016).

We stress that the adaptive behaviour that arises as a response to a crisis or intervention is tightly connected to the underlying urban and social fabric and may exhibit patterns of threat rigidity, leading to maladaptive behaviour that then flips the risks. Interventions must also consider a potential adaptive behaviour, which is in part based on citizens' risk perception (Guo et al., 2022). Previous research found a link between the types of urban streets and COVID-19 risk perception (Hou et al., 2024). Here, we hypothesise that a similar connection might exist between the types of urban districts and COVID-19 risk. Thus, to address a crisis effectively and design a robust policy that would withstand scenarios with various magnitudes or behavioural responses (e.g., more infectious viruses, lower compliance to the interventions, etc.), one must consider existing urban inequalities and how these can be mediated.

We argue for integrating adaptation into the crisis management cycle by introducing principles of spatial equity, particularly in urban settings where inequalities are more pronounced (Figure 4.7). This begins with conducting more equitable risk assessments during the mitigation and prevention phases, ensuring that all urban populations are considered and their vulnerabilities are not exacerbated. These assessments should identify and address systemic inequalities that often leave marginalised communities disproportionately exposed to risks. During the preparedness phase, it is crucial to consider the broader social, economic, and environmental contexts that arise from existing urban inequalities. This means developing preparedness plans that are not only technically sound but also socially inclusive, taking into account the unique needs and capacities of different urban neighbourhoods. Incorporating spatial equity principles into the response phase involves developing flexible strategies that adapt to changing conditions and behavioural responses while ensuring equitable resource allocation. This approach helps prevent the reinforcement of existing inequalities, flipping the risks from one area to another and promoting a more unified and effective crisis response. Finally, the recovery phase should emphasise lessons learned from various social groups' behavioural responses and system vulnerabilities, focusing on addressing these disparities to build a more resilient urban environment. Recovery efforts should prioritise rebuilding in ways that enhance long-term resilience for all communities, ensuring that no group is left behind.

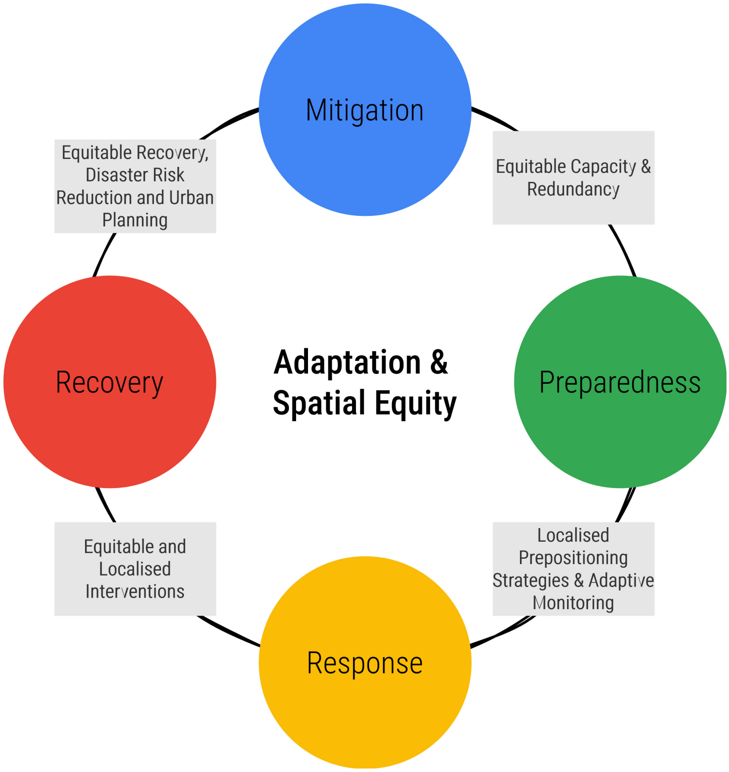

Figure 4.7: Adaptation and spatial equity-oriented crisis management cycle. The diagram illustrates the four critical stages — Mitigation, Preparedness, Response, and Recovery — each guided by the proposed principles that could foster successful adaptation and promote spatial equity throughout the crisis management process.

Our research is exploratory and has several limitations. First and foremost, any model is always an abstraction and a reduction of reality (Thompson & Smith, 2019). Thus, multiple elements and processes are aggregated or simplified. In the model, we limit ourselves to citizens, their behaviour, and the businesses and services they use. Previous research has demonstrated that these components are critical for understanding the disease's spread (Kalocsányiová et al., 2023; L. Liu et al., 2022; Van Den Broek-Altenburg & Atherly, 2021). Therefore, the model can be further refined by incorporating additional submodels that are considered essential for different research objectives. Second, we focus on the first wave of the pandemic when the residents' response is rather uniform. Further into the pandemic, we have observed much more complex response patterns, e.g., "pandemic fatigue" (MacIntyre et al., 2021; Petherick et al., 2021). Given the district's characteristics and the crisis phase, further work can be centred around incorporating other types of adaptive behaviour into the model.

In conclusion, our study reveals that uniform, un-contextualised intervention during a pandemic may lead to maladaptation in urban districts. While the uniform lockdown reduces infections in a central district, it inadvertently increases vulnerabilities in outer residential areas due to limited service capacity. These findings highlight the importance of designing adaptive, flexible, and context-specific interventions that consider the unique characteristics of different urban areas. By doing so, policymakers can enhance the resilience of cities to future epidemics and other crises, ensuring more equitable outcomes for all residents.

4.4. METHODS

INTRODUCTION TO THE MODEL

The purpose of the model is to evaluate the impact of different interventions on the spread of the COVID-19 virus throughout urban districts. The basic idea is that to understand how an airborne virus spreads, we must simulate human behaviour at the individual level and interactions among people in cities at a high spatio-temporal resolution (Zhang et al., 2016). Specifically, the model addresses the following question: What is the impact of inaction (no response) and a hard lockdown on the two exemplar districts, central and outer residential? The model comprises four submodels: *person*, *location*, *activity*, and *disease*. The latter consists of *transmission* and *progression* submodels. To consider our model realistic enough for its purpose, we derive patterns in daily citizen activities that form weekly routines, spatially allocated socio-demographics and built environments and places of interest from existing data. We base the epidemiological submodel on peer-reviewed literature and available empirical data.

The model includes the following entities: person and location. A person entity models a resident of a city of a certain age. Each person is associated with a household of one of four types: *single* (one agent), *couple without children* (two agents), *couple with children* (more than two agents) and *single-parent* (two or more agents). Importantly, a household is not an entity but a person's attribute. People are part of one of 11 social groups (student, pensioner, etc.) based on age and other factors. Each person has sets of activities (schedules) they perform on weekdays and weekends at different locations. Depending on a person's social group, they have different activities (study, shopping, etc.) to perform and, therefore, various schedules. Assuming all family members stay together, all persons belonging to the same household are placed in a single location of *home* type. Finally, a person has a *disease phase*, e.g. susceptible, exposed, etc., defined in line with the corresponding progression model.

The location entity models residential objects or homes (an apartment or a house) and non-residential objects or places of interest (POI). Each object has a pair of coordinates, an area in m2, and if it is a POI, it has a category and a subcategory: education category and school subcategory, shopping category and supermarket subcategory, etc. A POI can be indoors or outdoors, such as in a park.

As for spatial and temporal scales, the model is spatially and temporally explicit and has high resolution. Persons and locations have a set of latitude and longitude pairs; therefore, the model reports back the outcomes on the building scale (opposite to the district or neighbourhood scale). However, we aggregate the outcomes on the district scale due to the nature of open anonymised input data, which we used to generate a synthetic population.

The model does not have the agent-based model (ABM) timestep concept. It follows discrete-event formalism, and we can examine a phenomenon or count attributes at a specific moment. For example, instead of checking every 10 minutes the number of person agents in a supermarket, we count the number only when an agent comes or leaves. However, for simplicity's sake, we collect and aggregate model outcomes by hour. As for the extent, the model represents a single city: The Hague, the Netherlands. By default, there are no incoming and outgoing persons from and to other cities. Thus, the model is a *closed system*.

The most important processes of the model, which are repeated every hour, are the movement of person agents between various locations and their potential infection. Each person has two sets of daily schedules: one for weekdays and one for weekends. A schedule is a combination of routine activities repeatedly executed by an agent over a day. The total number of available activities is 11. For example, sleep at home, travel by public transport, work at a university, shop at the supermarket, travel by foot, and sleep at home. Each activity has a start time, end time and location where it must be executed. The schedules differ by social group. A student agent has a different set of schedules from a pensioner. This process results in the following: multiple agents happen to simultaneously carry out an activity at the same location of a certain floor area. If there is an infectious agent among them, the susceptible agents present may also get infected.

The most important design concept of the model is the spatially and temporally explicit heterogeneous behaviour of agents. Person agents are heterogeneous to an extent and form 11 social groups, each with an associated set of weekday and weekend schedules. The model is spatially explicit, and each agent has a home and the schedules, along with the mode of transport and destination of each activity. For example, an agent of a student social group lives in a district called Centrum and has an activity to do in the evening: Meeting with others. The model is designed to first sample the activity's start time, which in turn depends on how long the previous activities lasted. Next, the model samples the type of location: a bar or restaurant or a cafe. Finally, depending on where the agent lives and other attributes (transport), it will sample the exact location and how the agent will get there. Such a design allows us to generate realistic enough dynamics of modern urban areas.

The key process in the model is how the virus spreads. The intuition behind this process is as follows. We integrate the viral load progression within an infected person over time with the likelihood of transmitting the virus to others in closed spaces. The amount of virus (viral load) a person carries changes over time, peaking and then declining, which directly impacts their contagiousness. We translate this understanding into a probability of transmission, factoring in the effectiveness of masks, the duration of exposure between individuals, and adherence to social distancing measures.

MODELLING CITIZEN BEHAVIOUR

The unique behaviour of each individual citizen collectively forms discernible patterns, often referred to as urban routines (Champlin et al., 2023). These behaviours are not only temporal (e.g., sleeping at night and working during the day) but also spatial, as people typically perform daily activities, like grocery shopping, in nearby locations, thus forming a *social contact*. Previous research highlighted the importance of social contacts in various places of interest (POI) (L. Liu et al., 2022). Thus, by modelling urban routines and assigning them to citizens of various social groups and then situating these activities in specific spaces, we aim to simulate the virus's spread dynamics. The process of modelling urban routines involves four main steps: creating a synthetic population, defining locations, modelling activities, and integrating these components in time and space.

Creating a synthetic population

The foundation of any data-driven agent-based model is the creation of a synthetic population (Zhou et al., 2022), forming the *people* submodel. Methods for generating this population vary (Chapuis et al., 2022), with some relying on microdata for accuracy and precision and others using more aggregate or open data due to privacy concerns or data availability, as is the case in the Netherlands.

Following the methodology proposed by Ge et al. (2014), we utilise open data to generate households and individuals through a stepwise decision-tree approach informed by aggregate statistics. This results in a population distributed by district, with attributes such as household structure, size, and age. We further specify this synthetic population by categorising individuals into social groups (students, workers, unemployed, and pensioners) based on age and district-level statistics.

Defining locations

Businesses and corresponding places of interest (POI) are essential for city life and disease spread (L. Liu et al., 2022), forming the *locations* submodel. We integrate POI data from OpenStreetMap (OSM) with municipal data from the Municipality of The Hague https://denhaag.incijfers.nl/, detailing the number of businesses by type and their respective employee counts. Previous studies have demonstrated OSM's utility in crises, particularly in large cities like The Hague (Gebremedhin et al., 2020).

To further refine our model, we derive POI area information using land registry data from https://www.kadaster.nl/zakelijk/registraties/basisregistraties/bag, which provides type-specific area measurements in square meters. Residential locations for agents are also included in this submodel, resulting in a dataset with spatially allocated residential and non-residential POIs of various types associated with specific areas and employee numbers.

Modelling activities

Citizen behaviour is captured through urban routines, which form the *activity* submodel. We utilize the Time Use Survey (TUS) in the Netherlands (Roeters, 2019), where respondents from different social groups record their activities in 10- intervals over a week. This data creates a weekly calendar detailing sleep, work, study and other activities. These schedules inform the activities of agents from each social group, specifying the day and duration of each activity.

Integrating components

The final step involves connecting the submodels in time and space. First, we link people and locations. The synthetic population generates agents with sociodemographic attributes, each associated with an urban district and forming a household. Households are randomly allocated to residential locations within districts, ensuring that each household holds only one home. Students and workers are then assigned to study and workplaces, filling the corresponding POIs until capacity is reached. Next, we connect activities to locations. Since the TUS does not specify activity locations, we utilise the 2019 Dutch National Travel survey to estimate average travel distances to various amenities, ensuring realistic activity placement.

DISEASE TRANSMISSION AND PROGRESSION

The *disease* submodel in our agent-based model consists of two primary components: the *transmission* model and the *progression* model. The transmission model captures the process by which an infected agent can transmit the virus to a non-infected agent within a closed space. The progression model describes how the disease progresses in an infected agent based on age and COVID-19-specific factors. Together, these models simulate the spread of COVID-19 within a city.

TRANSMISSION MODEL: DISTANCE-BASED INFECTION

One of the key challenges in modelling disease transmission is accurately representing how the virus spreads in a closed environment. This task is complicated by numerous uncertainties, including factors related to droplet transmission, types of activities, and environmental conditions. While previous work, such as (Li et al., 2022), has addressed some of these issues, their models are often difficult to scale to the level of an entire city.

To address this, we extend the work of (Stroud et al., 2007) by incorporating the newly available epidemiological insights (e.g., development of viral load over time, etc.). At the core of our transmission submodel is the infection probability, which we define as follows:

$$p_{i,j} = 1 - e^{-\sum_{j=1}^{M_k} (1-\mu)^2 \times P_j(d) \times t_{i,j} \times \sigma(\max(\Delta(A_k, N_k), \psi)) \times \alpha}$$

where:

- M_k represents the number of infected individuals in the k-th location,
- μ is a factor representing mask effectiveness,
- $P_j(d)$ is the transmission probability of the infected person j at d days since infection,
- $t_{i,j}$ is the time that person i and person j spent together,
- σ accounts for the distance between individuals,
- Δ is the average distance between people,
- A_k is the area of the k-th location,
- N_k is the total number of people in the k-th location,
- ψ is a factor representing social distancing and
- α is a calibration factor.

PROGRESSION MODEL: A MODIFIED SEIRD

Once an infection event occurs between a susceptible and an infected agent, the susceptible agent may become infected, depending on the probability defined by the transmission model. Following infection, the agent transitions through various states (compartments) as the disease progresses, such as from infected to hospitalized or recovered.

We employ a modified SEIRD (Susceptible-Exposed-Infected-Recovered-Dead) model (Menda et al., 2021). This model does not consider reinfection (Figure 4.8), which is particularly suited for our study's focus on the first wave of the pandemic over a short-term period of 90-120 days.

A key feature of our modified SEIRD model is the distinction between symptomatic and asymptomatic infections (Nishiura et al., 2020). This distinction is crucial because symptomatic agents are assumed to alter their behaviour by staying at home, while asymptomatic agents continue their routines, potentially spreading the virus further.

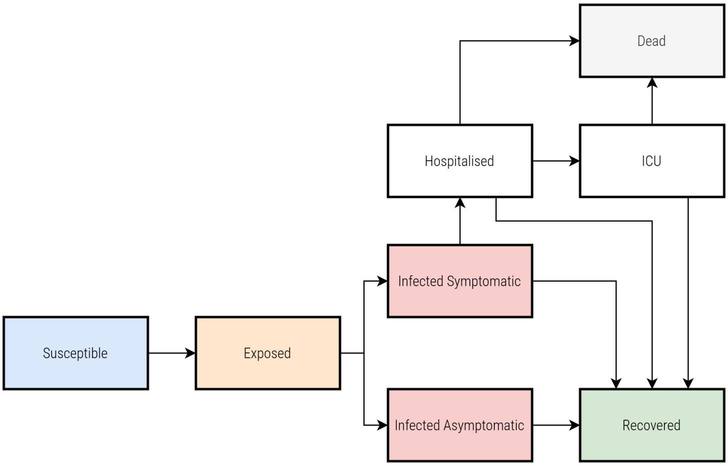

Figure 4.8: A modified SEIRD model that accounts for asymptomatic infection.

Detailed explanations of each component can be found in the Supplementary Materials.

INTERVENTION MEASURES AND THE IMPACT ON CITIZEN BEHAVIOUR

The primary objective of this study is to examine the impact of uniform interventions on citizen behaviour and corresponding (mal)adaptation at the urban scale. To achieve this, we explore two distinct scenarios: (1) inaction or no response, which serves as the baseline, and (2) a hard lockdown, under which all amenities are closed except for essential services such as supermarkets.

In the no-response scenario, agents follow their original schedules based on the Time Use Survey (TUS) with no alterations. However, in the hard lockdown scenario, significant changes occur in agents' schedules. Firstly, agents stopped activities related to the amenities that were closed. For instance, students no longer attend school, and the time they would have spent elsewhere is now spent at home with other household members.

Secondly, some activities change location. Previously, multiple agent types engaged in trip-chaining, performing shopping activities close to their workplaces or schools. With travel for these needs no longer necessary, agents now prefer to shop at the nearest supermarket. This redistribution of shopping activities in space could potentially influence the spread of the disease.

EXPERIMENTAL SETUP AND OUTPUT ANALYSIS

We initialise the model using parameters corresponding to the Alpha variant of COVID-19 and 100 infected agents randomly drawn from a synthetic population. Both the algorithm for generating the synthetic population and the simulation model itself utilise iterated random seeds to capture stochastic variability. We run the simulation 10 times each over a 120-day period and report the averaged outcomes.

Although the model generates a wide array of outputs, our analysis focuses on the spatial dynamics of disease transmission. Specifically, we examine the locations and districts where infections occur, as well as the districts of infected agents' residences. For clarity, we present a representative visualisation from one simulation instance, noting that the overall patterns remain consistent across runs.

We recognise that a comprehensive sensitivity analysis (SA) (Edeling et al., 2021) would significantly enhance the robustness of the model's outcomes. Additionally, our primary focus is on the spatial-temporal dimension of an ABM, which introduces additional complexity to the SA. In this context, our work serves as a call for the development of new methods capable of handling more realistic ABM representations of modern cities (Raimbault et al., 2019).

ON VALIDITY OF THE MODEL AND ITS OUTCOMES

In this study, we adopt an exploratory modelling framework for policy analysis (Bankes et al., 2013). Unlike traditional simulation models that strive for precise predictions under fixed assumptions, our approach explores a range of outcomes under uncertainty to identify robust policies across plausible futures. Early in the COVID-19 pandemic, uncertainties regarding virus characteristics, behavioural responses, and intervention impacts would make it impossible to employ a traditional modelling approach (Q. Liu & Cao, 2022; Swallow et al., 2022).

On top of these uncertainties, one may question the internal validity of our model, particularly the choices made in its design. We do not claim to create a comprehensive digital twin of the city; rather, our aim is to build a "good enough" model that captures the *key* mechanisms of disease spread across urban districts with diverse built environments, social fabrics, and amenities (see Appendix C for further details).

A critical mechanism we model is shopping behaviour, which empirical evidence suggests was indispensable during the pandemic's first month. At that time, in-person shopping was the norm, as online options were limited and e-retailers struggled to manage demand. To capture this behaviour, we relied on the Time Use Survey 2016 (Roeters, 2019) and the Dutch National Travel Survey (ODiN 2019). Our analysis indicates that while the frequency and duration of shopping trips vary, overall patterns, such as transport mode and travel distance, remain consistent across socio-economic groups. Although adaptive behaviours emerged after the first wave, our model primarily reflects early dynamics.

Transitioning to model validation, we note that simulation models are typically assessed through historical validation and fit-for-purpose (Dam et al., 2013). For unprecedented events like COVID-19, historical validation is less relevant. Therefore, our model's validity should be assessed through its ability to serve its intended purpose. Moreover, most COVID-19 models have operated on short time horizons (approximately one month) or must integrate critical elements, such as the physics of transmission and behavioural responses, to be predictive (Rahmandad et al., 2022). The issue of equifinality (Williams et al., 2020), where multiple models can yield similar outcomes, further complicates validation based solely on historical data.

Ultimately, our model is designed to explore disease dynamics within representative urban neighbourhoods by simulating individual interactions to avoid scaling artefacts common in many ABMs (Manson et al., 2020). Our findings, which align with empirical evidence on crowding and the role of spatial and social inequalities, aim to inform both local policymakers by identifying potential hotspots and national decision-makers by highlighting between and within city variations.

4.5. DATA & CODE AVAILABILITY

The data used for the analysis is available at https://doi.org/10.4121/33c01ff0-d3af-4293-8690-339bbca2bb37. The code used to perform the analysis is available at https://github.com/mikhailsirenko/flipping-risks. The agent-based model can be found at https://github.com/averbraeck/medlabs and https://github.com/averbraeck/medlabs-heros.

4.6. STUDY FUNDING

This study was done as part of the Health Emergency in Interconnected Systems (HERoS) project. HERoS is a Horizon 2020 project funded under the "SC1-PHE-CORONAVIRUS-2020 – Advancing knowledge for the clinical and public health response to the 2019-nCoV epidemic" call. The HERoS project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101003606. For more information about the project, please see https://www.heros-project.eu/.

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5

Discussion

The main chapters of this dissertation present three studies that collectively aim to "Assess Urban Vulnerability and Resilience to Extreme Events through Computational Models." While some findings are unique to individual studies, others consistently reappear. This chapter first provides an overview of each study's findings and synthesises them across the common themes. Second, it acknowledges limitations, sketches avenues for future research, and formulates concluding statements.

5.1. Key findings from individual studies

Study 1: Rhythm of Risk

The second chapter of this dissertation explored whether urban vulnerability exhibits not only spatial variability — as commonly portrayed — but also spatio-temporal variability. Moreover, we aimed to identify common patterns or *rhythms* shared by various parts of major Dutch cities and to find factors that could explain them. We utilised ambulance calls as a proxy for *general* urban vulnerability and applied a combination of spatial analytics, time-series clustering, and regression analysis. Formally, we examined three sub-questions: 1) whether it is possible to distinguish temporal patterns in vulnerability, 2) whether the identified patterns vary over space, and 3) what elements of the urban and social fabric can explain these patterns and their difference in space and time.

A clear finding was that urban vulnerability is inherently dynamic, shaped by the daily rhythms of city life. Our analysis identified three distinct patterns of vulnerability that shift based on the time of day and the characteristics of each district's urban and social fabric.

For instance, the "Midday Peaks" pattern emerges in central business districts, where commercial activity, higher population density, and increased human interaction lead to heightened vulnerability during midday hours. In contrast, the "Early Birds" pattern shows an increase in vulnerability during the early hours, likely associated with morning commutes and the start of the workday. This pattern is particularly pronounced in outer residential areas, indicating a shift in vulnerability from suburban areas to the city centre as the day progresses. Lastly, the "All-Day All-Night" pattern exhibits consistently high levels of vulnerability throughout the day, suggesting a continuous interplay between mixed-use developments and locations with active nightlife.

These findings challenge static models of urban vulnerability and underscore the importance of considering spatial *and* temporal dynamics in vulnerability assessments. Our research demonstrates that urban vulnerability varies across different areas and, over time, is shaped by the urban and social fabric and the behaviour of citizens.

Interestingly, while the volume of ambulance calls varies by area — with city centres typically seeing the highest numbers — the patterns behind these calls can be similar across different locations. For example, the "Midday Peaks" pattern, driven by elevated business activities, appears not only in the city centre but also in some outer residential districts. This reveals that modern Dutch cities are increasingly polycentric, with multiple areas sharing similar rhythms despite differing in size.

STUDY 2: MORE VULNERABLE, LESS RESILIENT?

In this study, we explored the relationship between urban vulnerability and resilience during the 2019 European heatwave, focusing on districts within The Hague, Rotterdam, and Amsterdam. Our central hypothesis is whether the commonly held "more vulnerable, less resilient" holds true at the urban scale.

To assess citizens' vulnerability to heatwaves, we utilise data on socio-demographics, health, and built environment characteristics. We employed a dimensionality reduction technique - non-negative matrix factorisation - to synthesise this multifaceted data into a vulnerability index. As a proxy for resilience, we used the excess in the number of ambulance calls during the heatwave period, assuming that higher call volumes indicate lower resilience. Through statistical and spatial analyses, we examined the relationships between urban vulnerability and resilience, leading us to formulate several propositions about their interplay and the implications for assessing vulnerability and resilience in urban settings.

First, our findings confirm that urban resilience is dynamic and varies over time. During the heatwave, ambulance calls increased significantly across all three cities, with the peak occurring on July 25, 2019, when temperatures exceeded 40°C. Specifically, The Hague experienced a 41% increase in calls, Rotterdam 31%, and Amsterdam 27%. These increases highlight the immediate pressure on emergency services during extreme heat events.

When we increased the temporal granularity of our analysis from daily to hourly intervals, we observed pronounced variations both over time and between cities. On the hottest day, Thursday, July 25, The Hague and Rotterdam experienced substantial spikes in ambulance calls—up to 100% more than on a regular non-heatwave summer day—during the afternoon and early evening hours (12:00–16:00 and 16:00–20:00). In contrast, Amsterdam saw a smaller increase of 58% during the same time frame. Interestingly, Amsterdam's call volume peaked two days later, on Saturday, July 27, between 08:00 and 12:00, with a 106% increase over normal levels. This delay suggests that factors other than immediate temperature peaks, such as accumulated heat stress or various populations, may influence resilience.

Secondly, the differing demographic and socioeconomic profiles of districts in The

Hague, Rotterdam, and Amsterdam underscore the need to contextualise vulnerability spatially. In The Hague, districts most affected by the urban heat island (UHI) effect are characterised by families with young children, single-parent households, and lower education and income levels, but not a significant elderly population. Similar districts in Rotterdam have a higher proportion of older residents but exhibit less pronounced health issues. In contrast, Amsterdam's vulnerable districts primarily consist of older adults without children, low education and income levels, significant health and mobility limitations, and the highest UHI exposure. These distinctions demonstrate that vulnerability manifests differently in each city, emphasising the importance of spatial context in understanding and addressing urban vulnerability.

Our analysis revealed that the relationship between urban vulnerability and resilience is complex and multi-directional. We found that it can manifest in several ways: (1) more vulnerable, less resilient, aligning with a more conventional view; (2) more vulnerable, more resilient, demonstrating a potential case of successful adaptation; and (3) less vulnerable, less resilient, which suggests hidden vulnerabilities or insufficient adaptive capacities.

Adaptive behaviour plays a critical role in shaping this relationship. For example, citizens moving to cooler areas during the hottest parts of the day significantly influence the observed resilience of different districts. This spatially embedded adaptive behaviour can alter the distribution of vulnerability and resilience across the urban landscape.

Although blue and green spaces are often cited in the literature as effective solutions to mitigate heatwaves, our findings suggest a more nuanced reality. Districts with recreational areas, such as the beaches of The Hague and parks in Rotterdam, experienced increased ambulance calls during the heatwave — likely due to the influx of people seeking relief from the heat. This phenomenon indicates that areas typically considered safe and less vulnerable can become hotspots under extreme conditions, as the concentration of people raises the potential for heat-related incidents.

Conversely, areas with the most vulnerable residents demonstrate higher resilience because fewer of them remain there during peak heat periods, having relocated to cooler areas. In this sense, these areas exhibit resilience during the daytime as a result of adaptive behaviour, highlighting the importance of mobility and access to cooler environments in coping with extreme heat.

STUDY 3: FLIPPING RISKS

In the third study, we aimed to understand the impact of policy interventions on the vulnerability and resilience of different urban districts during the COVID-19 pandemic. Our primary objective, focusing on two districts in The Hague, was to assess the impact of non-contextualised interventions that were uniformly designed at the national level.

The methodology used in this study was agent-based modelling (ABM). Leveraging a wide array of datasets, we created a *synthetic city* that allows not only simulating a population but also incorporates the agents' spatio-temporally allocated routines within the city's built environment and various points of interest (POIs). Using this synthetic city as input into a large-scale ABM of The Hague, we evaluated the effects of non-pharmaceutical interventions, i.e., POI closures, on the vulnerability and resilience of two exemplar but distinct urban districts: in the city centre and outer-residential, analysing how these interventions influence the populations and the spread of the virus.

Our findings demonstrate that while many studies on urban resilience focus on access and accessibility of infrastructures or urban services, the varying capacity of essential services plays a crucial role. Although both districts have high accessibility to essential urban services, i.e. supermarkets, they differ in capacity and spatial distribution. The central district, with its higher density of amenities and essential services, caters to both residents and a transient population. In contrast, the outer residential district, though more affluent, has fewer amenities.

In a *no-response scenario* — one with no restrictions or governmental interventions — the central district becomes a major infection hub due to its numerous amenities and attractions that draw people from across the city. The virus spreads quickly within the central district, with visitors contracting the virus and subsequently spreading it to other districts. This elevates the overall risk and turns the city centre into a hotspot.

However, implementing a *non-contextualised* lockdown measure flips the risk to the outer residential district. Such an intervention significantly reduces risk in the central district by limiting mobility and social interactions. At the same time, it has unintended consequences in the outer residential district. Residents are forced to shop in fewer local supermarkets that lack the capacity to accommodate the larger groups who would normally shop in the city centre. These supermarkets become major infection hubs. As a result, while the intervention effectively limits risk in the central part of the city, it inadvertently increases risk in the outer residential areas, demonstrating a case of maladaptation.

These findings highlight the importance of contextualising policy interventions to account for urban heterogeneity. Uniform policies may not be effective across different urban districts and can lead to unintended negative consequences and shift the risk from one district to another. Policymakers should consider the unique characteristics and capacities of each district to design interventions that enhance resilience without inadvertently increasing vulnerability elsewhere.

5.2. SYNTHESIS ACROSS THE STUDIES

Urban vulnerability and resilience are dynamic, fluctuating over both time and space. Our general vulnerability study demonstrated that vulnerability forms distinct spatio-temporal patterns — what we refer to as *rhythms of risk* — within the urban environment. The heatwave study highlighted how certain urban districts experience peaks in vulnerability during specific times of the day, such as midday when temperatures are highest, and how resilience varied accordingly. Similarly, during the COVID-19 pandemic, the shifting nature of vulnerabilities was evident as infection hotspots moved from the central to the outer residential areas due to policy interventions that altered people's movement patterns. Understanding these **spatio-temporal dynamics is crucial** for designing interventions that are effective at the right times and in the right places.

Vulnerability and resilience are **interconnected**. In the heatwaves study, we observed that these relationships are multi-directional. This finding challenges the conventional paradigm of *more vulnerable, less resilient*, urging us to explore hidden vulnerabilities and insufficient adaptive capacities more carefully. Recognising this complexity allows for a more nuanced understanding of urban risks and how they can be mitigated.

Urban inequalities greatly influence how vulnerability and resilience manifest across different urban areas. Areas with citizens of lower income, education, and health issues have constantly high levels of risk throughout the day, while more wealthy areas have elevated levels of risk only during certain parts of the day. During the heatwave, some districts with higher levels of vulnerability also demonstrated lower resilience, highlighting a lack of adaptive capacities among the citizens. In the pandemic study, the contrasting urban fabrics determined how the virus spread and how residents could protect themselves. Districts with a higher density of amenities and services could more easily adapt to the policy-imposed changes, whereas those with fewer facilities faced challenges in managing increased local demand. Effective urban planning **must consider these urban inequalities** ensuring that all residents have the resources and infrastructure needed to respond to extreme events.

People's behaviour plays a significant role in shaping urban vulnerability and resilience. Under normal circumstances, citizens' routines define vulnerability. During heatwaves, these behaviours are adaptive, such as seeking cooler areas — like parks or beaches — which can mitigate some risks but may also lead to unintended consequences, such as overcrowding, potentially exacerbating other risks. In the context of the COVID-19 pandemic, changes in shopping patterns due to lockdown restrictions created new risks, particularly in areas with fewer amenities. When residents of the outer residential districts stopped travelling to the city centre, they began overcrowding local supermarkets that lacked the capacity to handle the increased demand, turning these locations into new infection hotspots. Recognising and anticipating these **behavioral responses is essential** for managing crises in urban areas more effectively.

Computational models are essential for operationalising the abstract and complex concepts of urban vulnerability and resilience. In the heatwave study, with the use of empirical data, we **discovered** that relationships between vulnerability and resilience to heatwaves are not one-sided but multi-directional. In the pandemic study, an ABM **enabled** us to identify the potential maladaptive outcomes before they occurred. When used in combination—first, metric-based assessments to understand the baseline, and second, an ABM to provide deeper insights into interventions—these tools can significantly enhance urban planning and crisis management. By integrating these computational models, cities can better prepare for and respond to extreme events.

A one-size-fits-all approach to assessing urban vulnerability and resilience is inadequate. Each urban area has unique characteristics that must be considered to ensure effective interventions. For national and city governments, this means policies must be tailored to the specific contexts of different urban districts. The heatwave study advocates for context-sensitive approaches, while the pandemic study illustrates the risks of applying uniform interventions across diverse urban settings. When policy interventions fail to account for the diverse urban fabrics and corresponding inequalities inherent in modern cities, they can lead to maladaptive outcomes. To prevent such outcomes, **assessments, as well as policies, must be contextualised** and designed with an understanding of the diverse capacities and vulnerabilities within urban populations.

However, while contextualising assessments and policies is essential, it presents significant challenges. Tailoring interventions can extend the policy development cycle, delaying implementation at times when an immediate response is crucial, like in the case of the pandemic. Implementing different rules in neighbouring areas may also lead to perceptions of unfairness, potentially undermining public acceptance and compliance. Moreover, managing and monitoring diverse policies requires substantial administrative capacity and resources, raising feasibility concerns. To address these issues, it is crucial to find a balance by establishing overarching objectives with flexibility for local adaptation. Deciding the appropriate level of contextualisation is vital; while individual tailoring is impractical, focusing on community or district levels where common vulnerabilities exist may offer a more feasible and effective approach.

The synthesis of findings from these studies underscores the importance of a multidimensional approach to assessing urban vulnerability and resilience (Figure 5.1). By considering spatio-temporal dynamics, citizen behaviour, urban inequalities, and the need for context-specific interventions, policymakers and planners can develop strategies that enhance resilience and avoid maladaptation. Computational models play a critical role in this process, making it possible to operationalise complex concepts and ensure that interventions are both effective and equitable.

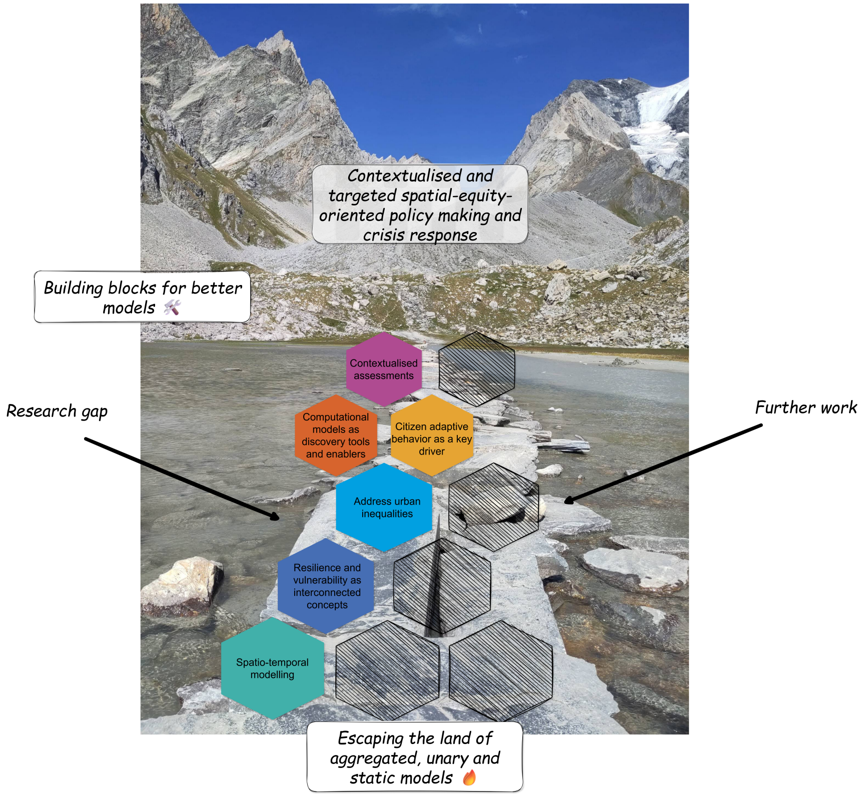

Figure 5.1: Stepping stones for better urban vulnerability and resilience assessments.

5

5.3. LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

As with any research on the socio-technical-environmental system of a city, several limitations must be acknowledged to understand the scope and applicability of its findings. While presenting challenges, these limitations also offer valuable opportunities for further exploration.

LIMITATIONS

Firstly, the reliance on ambulance calls as a proxy for general vulnerability or an excess in the number of calls for urban heat resilience used in the first two studies, while useful, has its constraints. Ambulance calls may not capture all aspects of vulnerability/resilience, particularly in areas where other factors, such as social networks or informal support systems, play a significant role. Future research could explore additional facets of urban resilience and vulnerability by using different indicators, indices, and proxies to provide a complementary assessment. Additionally, one may explore how those additional metrics interact and whether there are trade-offs across the different resilience dimensions.

Second, it is important to acknowledge that no vulnerability and resilience assessment is complete and comprehensive. There will always be some features that some stakeholders might find missing, underscoring the inherent limitations of such assessments. Additionally, the effectiveness of data-driven assessments is inherently constrained by the availability, quality and resolution of relevant data. In particular, open data sources, while valuable, may have limitations in coverage, granularity, or timeliness. Without having the data allowing for differentiating between various social groups within the city one might not be able to conduct an assessment.

Finally, it is important to note that the studies conducted were all based within the same geographical area. This common geography may limit the generalisability of the findings to other regions with different climates, urban infrastructures, or socio-economic conditions. The unique characteristics of a single locale—such as its specific environmental challenges, cultural norms, and governance structures—can significantly influence both vulnerability and resilience to extreme events. Therefore, the insights gained might not fully capture the complexities present in other urban settings.

DIRECTIONS FOR FURTHER RESEARCH

This research focused on the immediate individual response to extreme events and the adaptive and coping capacity citizens exhibit. Other aspects of resilience that are more relevant for longer-term transition to sustainable cities - such as transformative capacity - remain unexplored. Future studies could address these gaps by integrating richer datasets or employing mixed-methods approaches that combine quantitative and qualitative data, which would be particularly beneficial in situations where quantitative data alone is unavailable or inappropriate.

Furthermore, one can explore how the results of district-level analysis scale up to the city and, therefore, contribute to an important debate on upscaling and downscaling. Importantly, previous research already indicated that scaling could cause all sorts of artefacts. Thus, one should avoid assuming that a model made at a district scale could be multiplied a certain number of times is equal to a model of a city. Instead, one might think about making a high-resolution model of a region and explore the types of relations between its cities, districts and neighbourhoods. The generalisability of the results to scales should be approached with caution and requires some guidance, as urban areas are highly heterogeneous, and findings at different scales may vary.

Additionally, the research employed specific computational models with set hyperparameters, which could influence the results. For instance, a wide body of studies on heat vulnerability relies on dimensionality reduction techniques with hyperparameters like solver, loss function, etc. Future research could experiment with varying hyperparameters or apply alternative models to test the robustness of the findings.

Future research should consider exploring multiple and diverse geographical contexts to determine whether the observed patterns in vulnerability and resilience and their relationships hold true elsewhere. Expanding the geographical scope would enhance the robustness of the findings and contribute to a more comprehensive understanding of urban vulnerability and resilience on a global scale.

Finally, involving citizens and policy-makers throughout the research cycle, from data collection to developing and implementing interventions, could enhance the relevance and acceptance of measures, leading to effective and equitable outcomes.

6

CONCLUSION

6.1. RESEARCH QUESTIONS & ANSWERS

This dissertation set out to address the following central question:

Main RQ: *How can we account for the spatial-temporal heterogeneity of cities in urban vulnerability and resilience assessment models for extreme events?*

To tackle this rather broad challenge, we broke it down into three interrelated sub-questions:

RQ1: *How does urban vulnerability differ spatio-temporally?*

RQ2: *What are the relationships between vulnerability and resilience at the urban scale?*

RQ3: *What is the impact of policy interventions on the vulnerability or resilience of various urban districts?*

Our findings across three studies provide coherent and nuanced answers to these questions. **For RQ1**, our analysis of ambulance call data across major Dutch cities revealed that vulnerability is not static but follows distinct daily "rhythms of risk." **For RQ2**, the study of heatwave impacts demonstrated that the relationship between vulnerability and resilience is complex and multi-directional. While conventional wisdom might suggest that higher vulnerability leads to lower resilience, our findings indicate that this relationship can also be reversed or more nuanced. **For RQ3**, our agent-based modelling of COVID-19 interventions in The Hague demonstrated that uniform, non-contextualised policies can lead to unintended consequences for the vulnerability and resilience of populations across different urban districts.

Taken together, these studies illustrate that modern cities are inherently heterogeneous, both in their physical layouts and in the lived experiences of their inhabitants. Extreme events, whether heatwaves or pandemics, do not impact cities uniformly but rather in ways that reflect underlying spatio-temporal dynamics and underlying socio-economic inequalities. We advocate for a shift away from static, one-size-fits-all approaches toward assessments and policies that embrace the four-dimensional reality of urban life, where space, time, individual behaviour, and social inequalities interact.

6.2. CONCLUDING REMARKS

Modern cities are complex and increasingly characterised by inequality and segregation. Individuals and communities do not simply exist in two dimensions, as some vulnerability maps and resilience trajectories suggest; their experiences unfold across four dimensions — space and time. Each person carries their own vulnerabilities and resilience, shaped by where they live and the specific circumstances they encounter.

Just as we are not flat, static beings, the challenges we face, such as extreme heat or pandemics, also vary dynamically across time and space. For instance, temperatures during a heatwave can fluctuate dramatically throughout the day and differ significantly between a concrete jungle and a nearby park. Similarly, the spread of a pandemic evolves over days, weeks, and months, affecting different areas of a city in diverse ways.

If we fail to consider these variations, we risk overlooking critical aspects of urban life - it is like observing a city without the right lenses. But if we focus on those four dimensions, we gain a sharper understanding. By examining vulnerability and resilience as interconnected spatio-temporal phenomena, we can unlock a deeper understanding of how cities function during extreme events. This approach enhances our comprehension and opens up opportunities to design more effective, targeted interventions that address the unique needs of different urban areas.

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Supplementary Materials to Rhythm of Risk

Methodology

Data overview

P2000 is part of the Dutch C2000 alarm network. The network uses the FLEX protocol developed by Motorola and uses emergency pagers as information receivers. P2000 is an open network with information publicly available via multiple websites, which enthusiasts run. The Dutch Ministry of Justice and Security maintains the network. One specific type of message that this network registers is for ambulances. Notably, the calls are anonymous and do not have information about who called and the reason for the call. It may, however, have a 4 or 6-digit postcode. In this case, a call has a pair of coordinates - the middle point of the street where it was made.

Date	Time	Message
2017-01-01	00:00:13	P 1 GEBOUWBRAND Van Heuven Goedhartlaan 2-8 UTR...
2017-01-01	00:00:37	A1 Goudsbloemlaan 71-79 DHG 2565CP : 15101 Ritn...
2017-01-01	00:00:39	Prio 1 Noord Ringdijk - N207 20,1 MDT Wegvervoe...

Table A.1: Three sample records from the P2000 network. Each record has at least three attributes: the date and time when the record was registered in the system and the message. The message may have a 4 or 6-digit postal code as in record 2: "2565CP" and other information.

There are at least five generic categories for ambulance calls:

1. Medical or psychiatric emergencies and pre-existing medical conditions.
2. Trauma and injuries. This could be due to falls, motor vehicle or bicycle accidents, sports injuries, workplace accidents, burns, and other forms of physical trauma.

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3. Public safety incidents.

4. Environmental exposure.

Data gathering

You can download "Kaart van 500 meter bij 500 meter met statistieken" (Kaart met statistieken) by CBS from the following page https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data. The "Geographishe data" webpage has links to various spatial data sets. Note that the data is regularly updated, and a data set for 2019 downloaded on 1 January 2023 could differ from the one downloaded on 1 September. The updated data sets, however, usually note what was changed.

Dutch P2000 is an open network; everyone can connect and collect messages. Multiple platforms put the preprocessed messages online: https://www.p2000-online.net/ https://alarmeringen.nl/. For this study, we contacted the owners of https://112-nederland.nl/ and requested a data dump from 2017-2020.

The number of ambulance calls registered in the P2000 system increases with a higher population. The average number of ambulance calls over 2017-2019 was equal to 89,068 for Amsterdam, 69,321 for Rotterdam and 58,780 for The Hague.

From the temporal perspective, we analyse data from 2017 until 2020.

Data preparation

The gridded data (Kaart met statistieken) from CBS covers the whole of the Netherlands. The first step to preparing it is simply limiting it to the boundaries of a city of interest. For example, panel a of Figure A.1 demonstrates how the result for The Hague will look like:

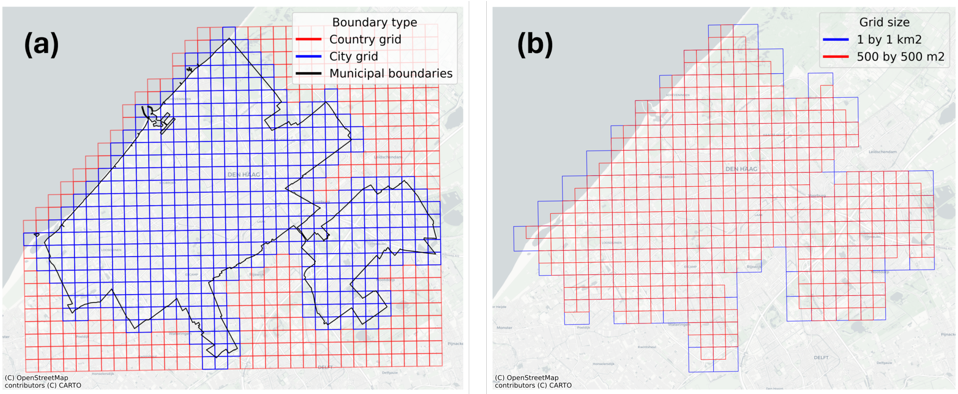

Figure A.1: Grid manipulations. Panel a visualises selecting The Hague's grid from the country's grid via spatial join. The red grid represents a part of the country's grid, the blue grid is its subset for The Hague, and the black line displays the city's municipal boundaries. Panel b shows how two grids are overlaid. On the bottom is the blue one of 1 by 1 km2 resolution, and on the top is the red one of 500 by 500 m2. Most of the red cells have four blue cells in them.

The next step is upscaling the grid from 500 by 500 m2 to 1 by 1 km2 resolution and

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aggregating the data from each grid cell (see panel b of A.1). Note that while aggregating, we sum the values of the smaller grid cells to create the value of the larger grid cell. Such a step is necessary for the further analysis. At the later stage, we assign ambulance calls to each grid cell, and if the grid cell size is too small, we cannot identify the patterns. Let us retake The Hague as an example. The initial grid has 441 grid cells, and the new one has 128.

The CBS dataset comprises 31 features across three categories as detailed in Table A.2. It is important to acknowledge that this set is not exhaustive and only partially captures the nuances of urban vulnerability. Our objective, however, is not to provide a comprehensive explanation of vulnerability patterns but rather to identify a subset of features that could meaningfully contribute to understanding these patterns, are grounded in scholarly literature, and are practical for policy-makers to utilise.

Socio-economic	Built environment	Proximity, km
0-15 y.o.	% Owner-occupied houses	Shopping
15-25 y.o.	% Rented houses	Cafe & restaurant
25-45 y.o.		Entertainment, arts & culture
45-65 y.o.		Childcare
65+ y.o.		Primary education
% Dutch		Secondary & higher education
% Western		National or provincial road
% Non-western		Train station
One-person household		GP 9-17
Multi-person household w/o kids		Hospital 9-17
Single-parent household		Hospital 24h
Multi-person household w kids		Pharmacy
% Low-income household		GP station 24h
% High-income household		Distance to the city centre
Residents receiving social benefits		

Table A.2: Selected features of interest in three categories from the CBS data set. Socio-demographic features and built environment features are percentages or real numbers. Proximity is the distance in km by road to the closest amenity of a particular type.

Note that 5 of them, namely "Shopping", "Cafe & restaurants", "Entertainment, arts & culture", "Childcare", and "HAVO, VWO and VMBO", are aggregations over the initially separate features. For example, the distance feature "Shopping" is a median across the initial set of features: "Big supermarket" and "Regular shops."

The initial dataset consisted of P2000 call data for various Dutch cities. For this study, we specifically focused on calls made from The Hague, Rotterdam, and Amsterdam. Some did not have latitude and longitude pairs; these were excluded from our analysis.

From the temporal perspective, we analyse data from 2017 until 2020. We focus on the three autumn months: September, October and November. The choice to focus on the autumn season, specifically from September to November, is informed by multiple factors. Previous research indicates that autumn is most representative of "normal" urban activity in Dutch cities (Verma et al., 2021). This period is characterised by regular work and school schedules without the disruption of major holidays or events. In the

Dutch context, Autumn does not include significant public holidays, reducing variability in daily routines and allowing for a more consistent analysis of urban dynamics.

We identified calls of two types: calls made by citizens from within the city and calls initiated by professionals in institutions such as hospitals or police stations. Given our study's aim to explore urban vulnerability in a general context, we opted to exclude the latter, as they represented a significant portion of the dataset but did not align with our focus. Moreover, some of these professional calls involve transporting individuals who are not in an emergency state, and the available data do not allow us to distinguish the specific reasons behind each call.

Our analysis was further narrowed down to calls made during the autumn season, specifically from September 1st to November 31st. We focused on weekdays to construct a representative "typical weekday". This was achieved by averaging the data across three autumn seasons and five weekdays, providing a consistent baseline for our study.

We focus on the autumn season (September to November) because it best represents “normal” urban activity (Verma et al., 2021). During this period, regular work and school schedules prevail without disruption from major holidays or events, ensuring consistent daily routines. Unlike December's Christmas activities or the tourist influx and festivals of spring and summer, autumn's relative quiet means that resident activities primarily drive observed patterns, offering clearer insights into urban dynamics.

In addition to the above reasons, health trends also influence our data selection. January and February are characterised by higher incidences of flu, which can disproportionately affect ambulance call volumes and skew the analysis (Statistics Netherlands, 2019). In the case of the Netherlands, a person would first call a general practitioner (GP); in severe cases, as in 2019, they might call an ambulance. By choosing autumn, we avoid these seasonal health impacts and focus on a period that represents normal health and activity patterns.

We have chosen to focus exclusively on weekdays to capture the typical daily activities of residents. Weekends in Dutch cities often involve considerable intercity travel for leisure and social activities, which complicates the analysis of within-city patterns. Without an origin-destination matrix, it becomes challenging to account for the movement of visitors, which could skew the data.

Furthermore, the volume of ambulance calls differs significantly between weekdays and weekends. For example, in The Hague, the average number of calls on weekdays is 87, compared to 32 on weekends. Similar patterns are observed in Amsterdam and Rotterdam, with weekend calls comprising approximately 13% of the weekly total. By focusing on weekdays, we ensure our analysis is based on a higher and more consistent volume of calls, reflecting the core activities and vulnerabilities of the resident population.

City	Weekday Mean	Weekend Mean	Percentage Left Out
The Hague	87.37	32.28	13%
Rotterdam	103.32	37.39	13%
Amsterdam	134.35	51.85	13%

Table A.3: Comparison of the average number of autumn ambulance calls made during the weekdays and weekends across the case cities.

The choice to study only the weekday data has several implications. First, the analysis may provide an incomplete representation of urban dynamics. Weekends often exhibit different patterns of activity compared to weekdays, influenced by leisure activities, social events, and tourism. By excluding weekends, the analysis might miss these variations, potentially leading to a skewed understanding of resident behaviour and urban dynamics. Additionally, certain health-related incidents, such as sports or social gatherings injuries, might be more prevalent on weekends. Ignoring these could skew the analysis of health trends and understanding public health needs.

The next data preparation phase involves grouping the calls into time slots throughout the day: 0-4, 4-8, 8-12, 12-16, 16-20, and 20-24 hours. These calls were then allocated to corresponding grid cells across the cities. Such a binning serves as an alternative to smoothing (Prieto Curiel, 2023) but has several implications.

Firstly, using hourly aggregates presents challenges due to the low number of observations in many grid cells. The case cities, unlike larger metropolitan areas, have fewer ambulance calls per hour, especially in residential areas. This sparsity can lead to significant variability and noise, making it difficult to discern meaningful patterns. Low-density data can result in fragmented and erratic visualisations that do not accurately reflect underlying urban dynamics.

Secondly, aggregating data into four-hour bins mitigates this issue by smoothing out temporal distribution. This increases the number of observations per bin, reducing random fluctuations and enhancing the reliability of detected patterns. The four-hour bins also align with typical human activity cycles, such as morning, afternoon, evening, and night, providing a meaningful context for interpreting the data.

In summary, while finer temporal aggregation offers more detail, it risks over-fragmenting the data in smaller cities. Four-hour bins balance granularity and interpretability, ensuring that observed patterns are statistically robust and contextually relevant.

In cases where certain grid cells registered an exceptionally low number of calls, we applied an interquartile range (IQR) filter, specifically using the first quartile (Q1) as a threshold to exclude these cells.

To ensure that we could reliably identify consistent patterns in the call data, we excluded grid cells with an exceptionally low number of calls. Specifically, we applied an interquartile range (IQR) filter using the first quartile (Q1) as a threshold. Although it is possible that areas with very few calls might indicate low vulnerability and/or high resilience, their sparse data do not provide sufficient information to form robust patterns in our analysis.

Finally, the data were standardised by scaling to a mean of 0 and a standard deviation of 1. This normalisation was a preparatory step for subsequent clustering analysis.

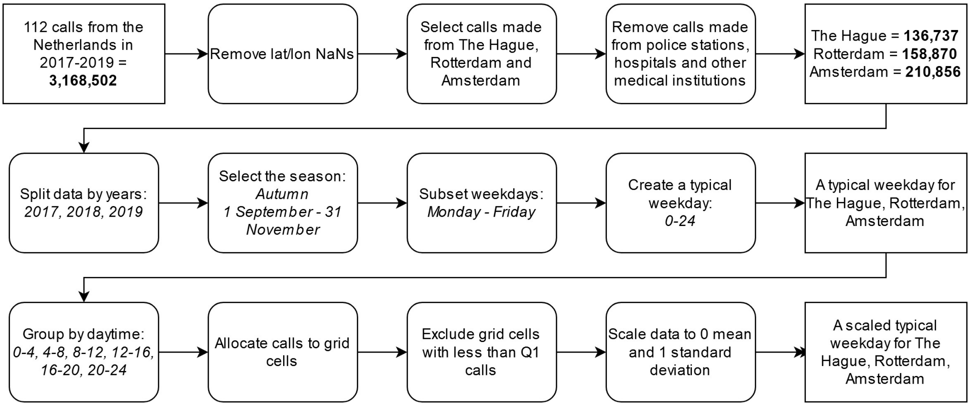

Figure A.2: An overview of data preparation steps applied to P2000 data. The resulting number of calls on a typical weekday after the preparation is 125.01 for The Hague, 142.61 for Rotterdam, and 192.23 for Amsterdam

Instead of raw counts, we aim to analyse *typical weekday* - an average across three autumn seasons and five weekdays. Let us denote by $a_{i,j}(t)$ a number of ambulance calls made from a place with coordinates i, j at a time t. For each year, we constrain t by 1 September and 31 November and the coordinates i and j are constrained by the municipal borders of the case cities.

Next to it, we have three grids of 1 km2 for each case city G. Let us denote by g_k a grid cell k where $k \in [1, K]$ and K is the total number of grid cells over three cities and equals 775. To connect the calls and the grid cells, we place each $a_{i,j}(t)$ to the corresponding grid cell g_k.

Now, let us create a typical weekday. We first aggregate calls by six equal periods T: 00:00-04:00, 04:00-08:00, 08:00-12:00, 12:00-16:00, 16:00-20:00, and 20:00-00:00. We assume that these periods sufficiently cover multiple aspects of urban life. For example, during 04:00-08:00, early commuters start their journey to work, students go to universities and colleges slightly later, from 08:00-12:00, etcetera. Next, we average all the calls made during the weekdays in each grid cell g_k over each time period t in T.

As a result, we have a matrix A of N by T size. N is the number of grid cells where the number of ambulance calls is more than 0 in any period t. In our case, $N = 528$. T is the number of daytime periods equal to 6. The values $A_{i,j}$ represent the average number of ambulance calls made in the grid cell g_i at the period T_l, where l is one of the 6 time periods. Table A.4 shows a snapshot of the resulting matrix A for three grid cells. Figure A.3 gives us a visual interpretation of the temporal information from Table A.4 and the grid G.

Day time Grid cell	0-4	4-8	8-12	12-16	16-20	20-0
1	0.015385	0.000000	0.276923	0.030769	0.030769	0.107692
5	0.000000	0.000000	0.030769	0.000000	0.000000	0.015385
6	0.061538	0.030769	0.476923	0.215385	0.138462	0.169231

Table A.4: Typical weekday across three grid cells. The rows are grid cells, and the columns are daytime periods. The value is the average number of ambulance calls from this grid cell during this period.

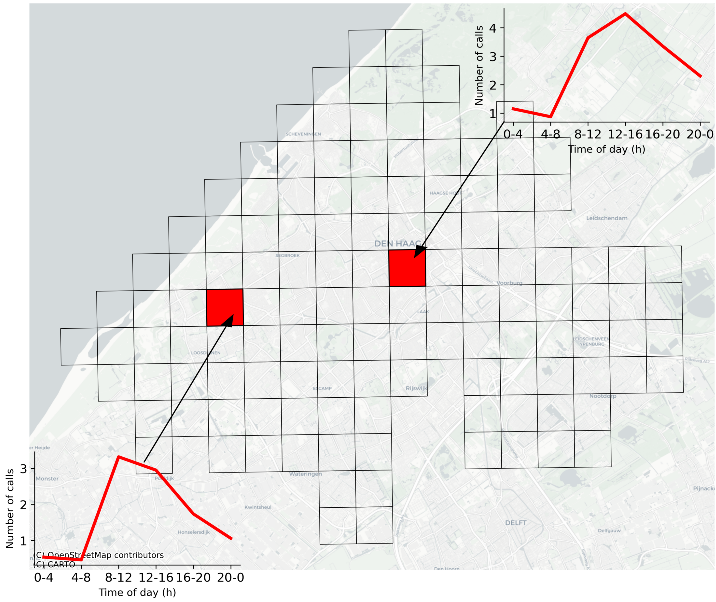

Figure A.3: Typical weekday of two example grid cells in The Hague. The graphs show the average number of ambulance calls from these grid cells over six daytime periods.

Note that we apply Z-normalisation to the grid cell calls. Z-normalisation is a statistical technique used to standardise data by converting it into a distribution with a mean of zero and a standard deviation of one. This transformation allows for the comparison of different datasets on a common scale, irrespective of their original units or magnitudes. The formula for Z-normalisation is as follows:

$$Z = \frac{X - \mu}{\sigma}$$

where Z is the Z-score, X is the original data point, μ is the mean of the dataset, σ is the standard deviation of the dataset.

The primary reason for employing Z-normalisation in our analysis is to capture the dynamic nature of urban environments. Footfall and traffic patterns in cities are inherently fluctuating, influenced by various factors such as time of day, day of the week, and special events. These fluctuations impact the number of incidents that require ambulance services. By scaling the data, we can identify and analyse these temporal patterns, or "rhythms," which would be obscured if we only considered static population-normalised figures.

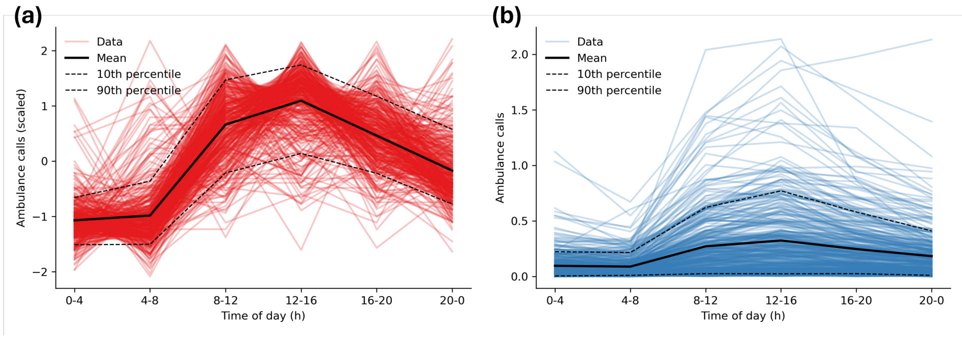

Figure A.4: Scaled ("rhythms") vs raw ("volumes") ambulance calls over a typical weekday in the panel a and b, respectively. The values of panel a were derived by applying standardisation using Z-normalisation. The plots include the scaled data, mean values, and the 10th and 90th percentiles to capture the range of variability.

Clustering performance metrics

Evaluating the performance of a clustering algorithm in the absence of ground truth data is a challenge. A common approach is to use clustering metrics. However, given the strengths and weaknesses of each metric, adopting a multi-metric approach is generally more robust and reliable.

Figure A.5 and Table A.5 present three key metrics: the Silhouette Score, Calinski-Harabasz Score, and Davies-Bouldin Index (Caliński & JA, 1974; Davies & Bouldin, 1979; Rousseeuw, 1987), across varying numbers of clusters.

In a complex socio-technical-environmental system such as a city, it is crucial not to depend solely on these metrics for cluster validation but to supervise it with domain knowledge and visual inspection. In this case, we benefit from the fact that cities exhibit a high degree of socio-economic segregation (see, for example, (Meijers et al., 2014)). Consequently, we would expect similar patterns to emerge in neighbouring districts. Additionally, the practical relevance of the clusters must be considered, particularly in terms of their size. Clusters with an extremely low number of observations, for instance, may not provide meaningful insights.

Consequently, opting for only 2 clusters was deemed insufficient for our analysis. Instead, we selected a 16-cluster solution, a decision supported by peaks in both the Calinski-Harabasz and Silhouette Scores. This choice ensures that our clusters are not only statistically significant but also substantively meaningful, containing a sufficient number of observations to draw reliable conclusions about the socio-technical-environmental dynamics within the studied urban areas.

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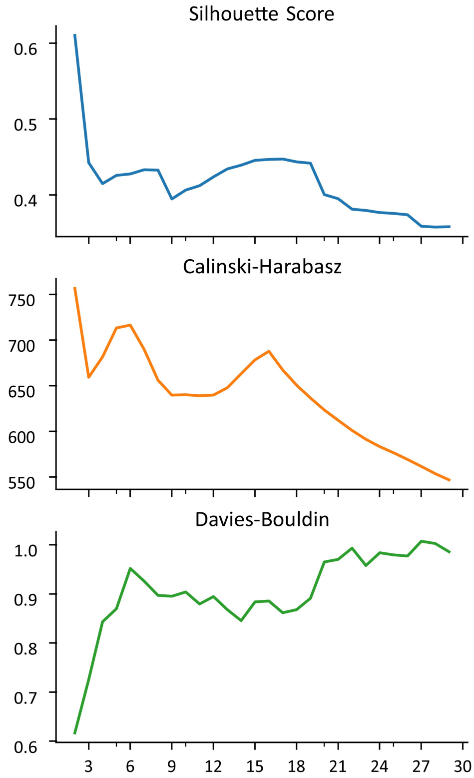

Figure A.5: Comparative analysis of agglomerative clustering performance using three key metrics: Silhouette Score, Calinski-Harabasz Index, and Davies-Bouldin Index. Each metric is plotted against the number of clusters (x-axis) and its corresponding value (y-axis) across a range from 2 to 30 clusters.

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N clusters	Silhouette Score	Calinski-Harabasz	Davies-Bouldin
2	0.61	757	0.62
3	0.44	659	0.73
4	0.41	682	0.84
5	0.43	713	0.87
6	0.43	716	0.95
7	0.43	690	0.93
8	0.43	656	0.90
9	0.39	640	0.90
10	0.41	640	0.90
11	0.41	639	0.88
12	0.42	640	0.89
13	0.43	648	0.87
14	0.44	663	0.85
15	0.45	678	0.88
16	0.45	688	0.89
17	0.45	667	0.86
18	0.44	651	0.87
19	0.44	637	0.89
20	0.40	623	0.97
21	0.39	612	0.97
22	0.38	601	0.99
23	0.38	591	0.96
24	0.38	583	0.98
25	0.38	577	0.98
26	0.37	569	0.98
27	0.36	562	1.01
28	0.36	554	1.00
29	0.36	547	0.99

Table A.5: Performance evaluation of agglomerative clustering across cluster counts ranging from 2 to 30, using three key metrics: Silhouette Score, Calinski-Harabasz Index, and Davies-Bouldin Index. Color intensity represents the metric value, with brighter shades indicating lower values.

Results

Hostspots of urban vulnerability in time and space

While the data across the years indicates a stable trend in the number of calls, there is a mild difference between the years (Table A.6). Notably, the higher the city's population, the more ambulance calls are recorded on average.

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		The Hague	Rotterdam	Amsterdam
	2017	121	140	204
Mean	2018	120	137	183
	2019	121	151	179
	2017	18	21	27
Standard Deviation	2018	17	17	19
	2019	15	19	20
	2017	36	59	87
Minimum	2018	81	91	146
	2019	77	104	139
	2017	162	181	270
Maximum	2018	162	168	232
	2019	170	207	238

Table A.6: Statistical summary of daily ambulance calls in autumn seasons for The Hague, Rotterdam, and Amsterdam from 2017 to 2019: mean, standard deviation, minimum, and maximum values.

When categorising the calls into six distinct time periods as illustrated in Figure A.6, a consistent trend emerges: there are fewer calls overnight, a surge during the afternoon, followed by a gradual decline leading up to midnight.

Examining the spatial distribution of ambulance calls during specific time frames reveals shifting patterns in areas with the highest call frequencies. In The Hague, during the early hours of 04:00 - 08:00, the zone with the highest call density is spread out, reaching beyond the city centre. However, by the time frame of 12:00-16:00, this pattern narrows considerably, with the city centre's three grid cells accounting for the majority of calls. As the day progresses, the high-call-density zone broadens, only to constrict back to a few central grid cells by midnight. Amsterdam exhibits a similar trend, with a more localised hotspot during nighttime hours that disperses throughout the day. Rotterdam, however, presents a slight anomaly. Its most condensed call hotspot appears during the 20:00 - 00:00 window, just before midnight. A plausible explanation for this pattern is that it aligns with the onset of human activities, such as commuting back home or engaging in nightlife.

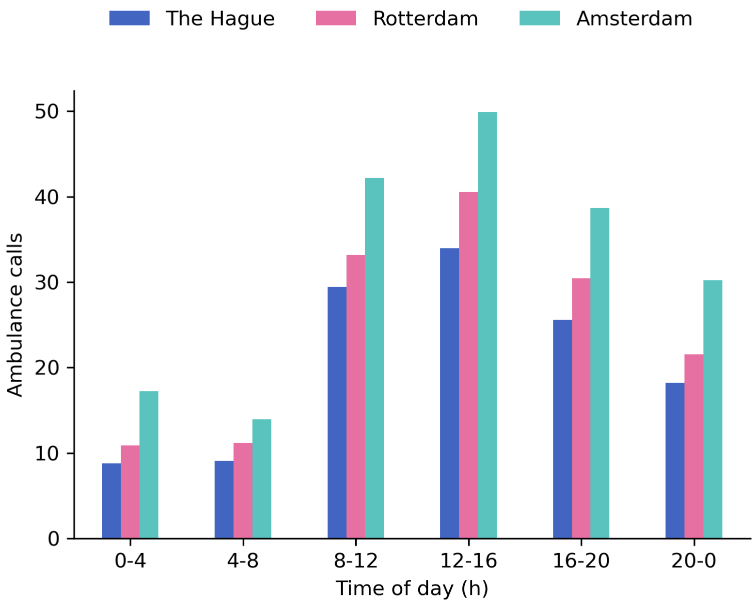

Figure A.6: Average number of ambulance calls during a typical weekday, segmented into six time periods (0-4, 4-8, 8-12, 12-16, 16-20, 20-24 hours), in three Dutch cities: The Hague, Rotterdam Amsterdam.

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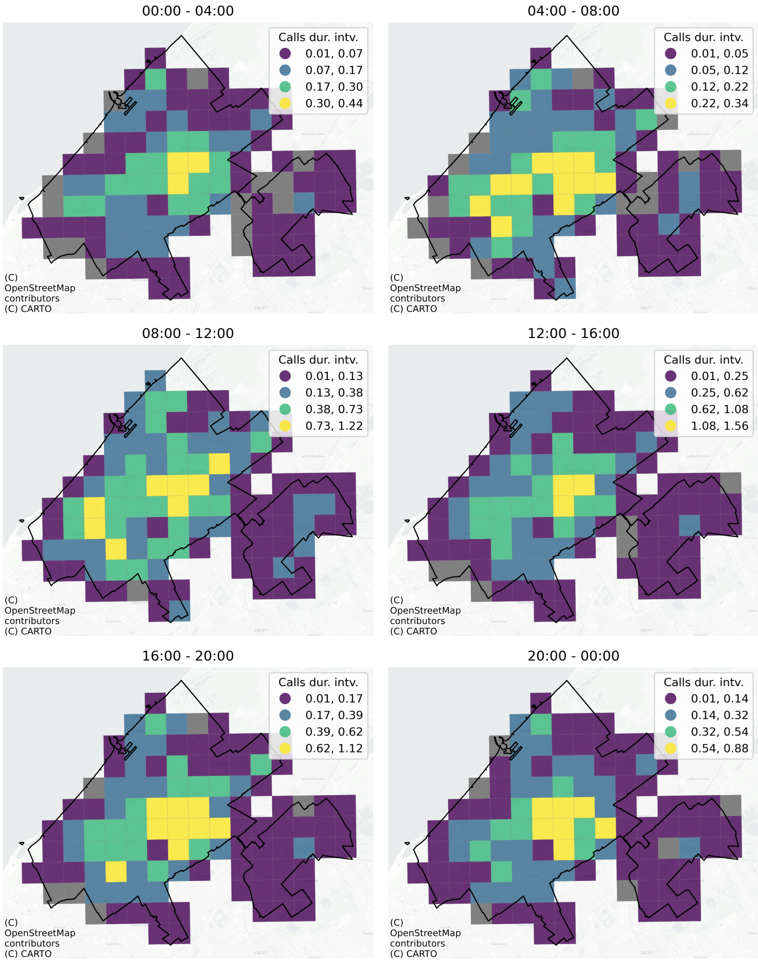

Figure A.7: A series of six choropleth maps illustrating the distribution of ambulance calls in The Hague during a typical weekday. The maps are segmented into six time periods (0-4, 4-8, 8-12, 12-16, 16-20, 20-24 hours).

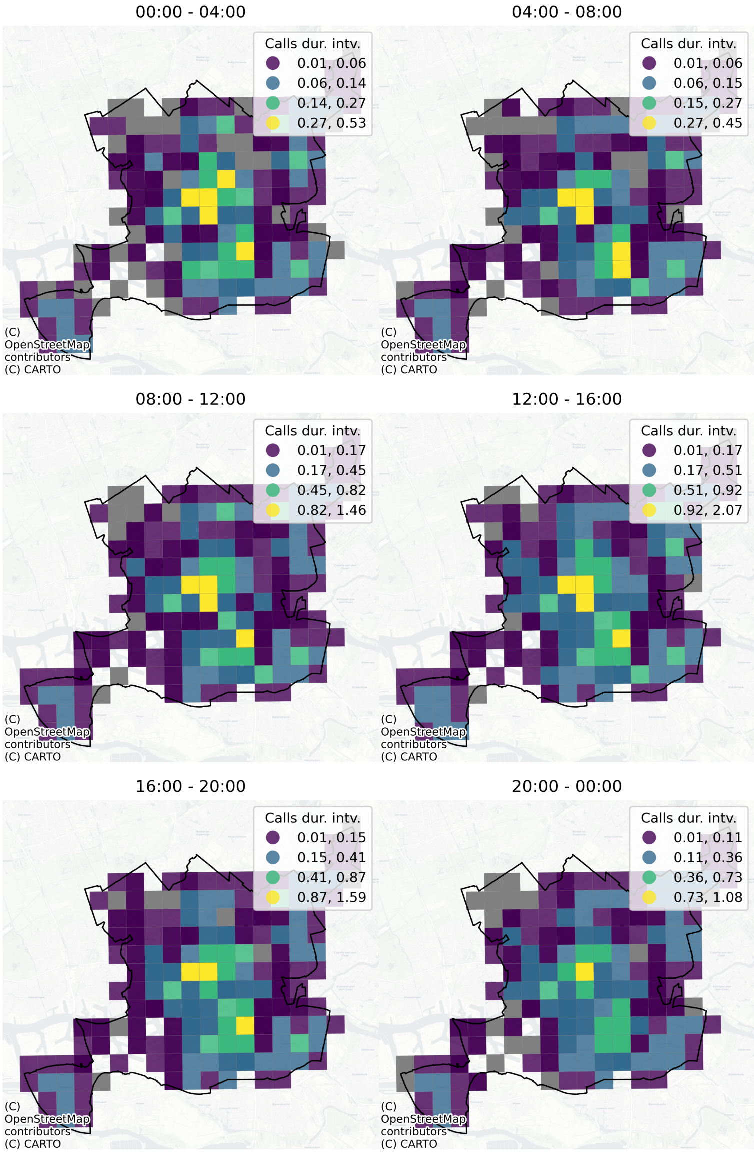

Figure A.8: A series of six choropleth maps illustrating the distribution of ambulance calls in Rotterdam during a typical weekday. The maps are segmented into six time periods (0-4, 4-8, 8-12, 12-16, 16-20, 20-24 hours).

Figure A.9: A series of six choropleth maps illustrating the distribution of ambulance calls in Amsterdam during a typical weekday. The maps are segmented into six time periods (0-4, 4-8, 8-12, 12-16, 16-20, 20-24 hours).

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B

Supplementary Materials to Flipping Risks

Epidemiological submodel

The epidemiological submodel of the agent-based model used in Chapter 4 consists of 2 submodels: *progression* (or compartmental) and *transmission*. Let us discuss each of them in detail in the corresponding subsections.

Progression model

The modified SEIRD model accounts for symptomatic and asymptomatic infections (B.1). It also has Hospitalised and ICU states that help plan hospital and ICU capacities.

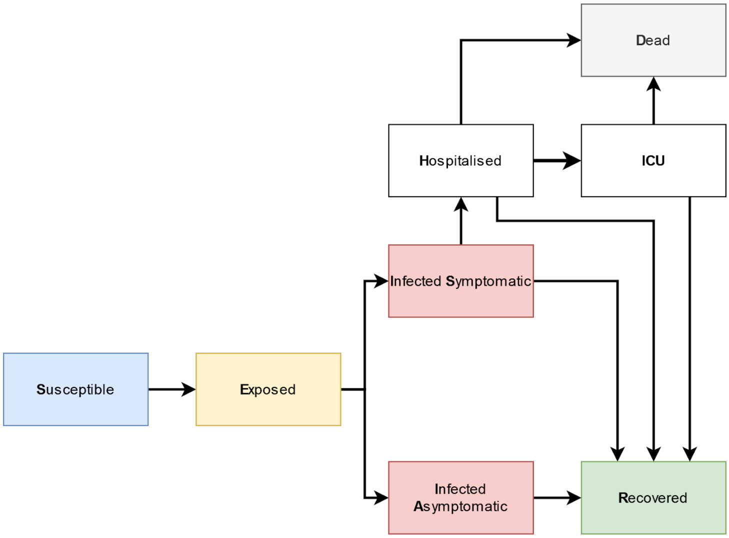

Figure B.1: The modified SEIRD Susceptible-Exposed-Infected-Recovered-Deceased submodel.

The main difficulty of any progression model is the specification of its transition rates. Put simply, how many people will move from, e.g., Infected-Symptomatic to Hospitalised, and how long will they stay in the latter? The infection model defines the transition from Exposed to Infected-Symptomatic or Infected-Asymptomatic, and the progression model can help to describe the "social" or "behavioural" aspect of the disease. Whether or not a person will go to a hospital depends not only on the virus's epidemiology but also on other social and behavioural factors. For example, a person can go to a hospital for testing after the clinical disease period is over because of the necessity to work or other reasons.

In the current model implementation, we use the same days to transition between the compartments across all age groups due to the lack of reliable data for the Netherlands (Table B.1). Here and further, TPDF(a, b, c) stands for probability density distribution of Triangular distribution with a lower limit a, upper limit b and mode c, where a < b and a <= c <= b.

From / To	Hospitalised	ICU	Dead	Recovered
Infected-Asymptomatic	-	-	-	TPDF(12,16,20)
Infected-Symptomatic	TPDF(7,9,11)	-	-	TPDF(12,16,20)
Hospitalised	-	TPDF(1,3,5)	TPDF(1,3,5)	TPDF(11,13,15)
ICU	-	-	TPDF(2,4,6)	TPDF(28,30,32)

Table B.1: Number of days needed for transitioning from one compartment to another.

The data from the National Institute for Public Health and the Environment (RIVM) allowed us to construct and specify transition probabilities for various age groups (RIVM, 2021).

From	To	Age group								
		0-19	*20-29*	*30-39*	*40-49*	*50-59*	*60-69*	*70-79*	*80-89*	*90+*
Symp.	Hosp.	0.02153	0.01648	0.05044	0.11142	0.20593	0.44038	0.60867	0.32301	0.12687
Hosp.	ICU	0.00152	0.00245	0.00921	0.02614	0.05829	0.14674	0.15508	0.01647	0
Hosp.	Dead					0				
ICU	Dead	0	0	0	0	0.01452	0.08393	0.39731	0.63002	0.67882

Table B.2: Transition probabilities between compartments for different age groups.

DISTANCE-BASED INFECTION MODEL

To model infections in the ABM, we propose a *distance-based infection model* (DBIM). This model takes into account an extensive set of parameters, including non-pharmaceutical interventions (NPIs), social distancing and mask use. As a base, we use the work of (Stroud et al., 2007).

The viral load $v(t)$ is a function of time t in days since infection (Kissler et al., 2021). It depends on the latent period L, the incubation period I, the clinical disease period C, and the viral load peak v_{max} in log10 copies per mL (B.2).

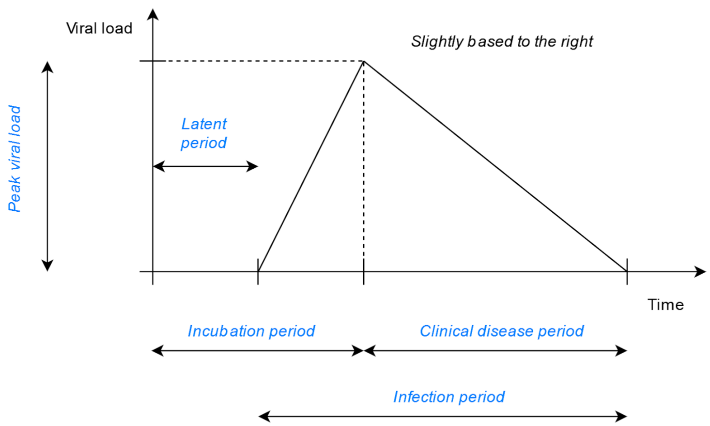

Figure B.2: A theoretical model of the viral load changes over time.

These are epidemiological parameters and they differ by variant. Here is a set of parameters for the alpha variant $L = 2$, $I = 3.4$, $C = 6.2$, and $v(t)$ is defined as:

$$\begin{cases} v(t) = v_{max} \cdot \frac{t-L}{I-L} & \text{if } t \geq L \text{ and } t < I \\ v(t) = v_{max} \cdot \frac{I+C-t}{C} & \text{if } t \geq I \text{ and } t < I+C \\ v(t) = 0 & \text{else} \end{cases}$$

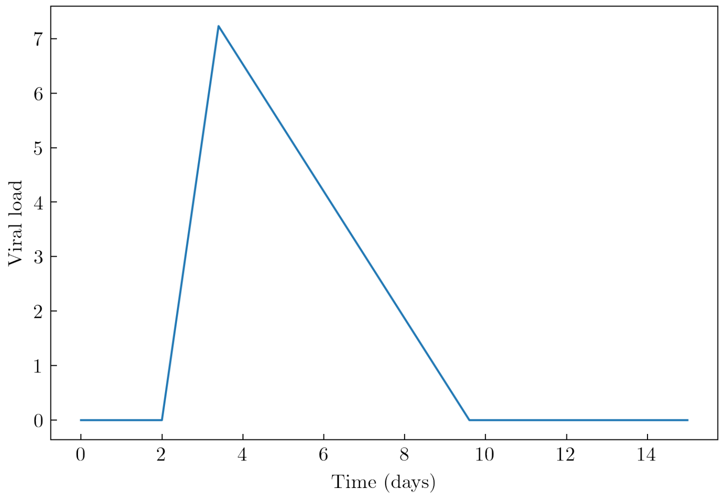

Figure B.3: Development of the viral load of the alpha variant over time.

Second, we have to convert the viral load into what we call transmission probability $P(t)$. $P(t)$ captures how likely an infected person can transmit a virus to a susceptible person in close contact (0 m distance between people). $P(t)$ must be dependent on time: we need to know how long the close contact lasts to estimate $P(t)$ correctly. For now, let us loosen this dependency. Relations between transmission probability and viral load are sigmoid-like:

$$P(t) = \frac{1}{1 + e^{-k \times (v_t - v_0)}},$$

where k is the transmission rate, v_t is the viral load at time t, and v_0 is the reference viral load. After calibration:

$$k = 2.294, \quad v_0 = 4.0.$$

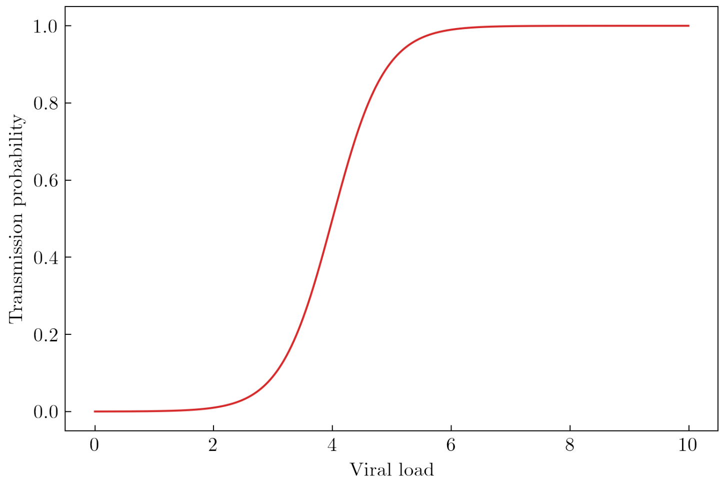

Figure B.4: Relations between viral load and transmission probability.

Then, the transmission probability over time becomes:

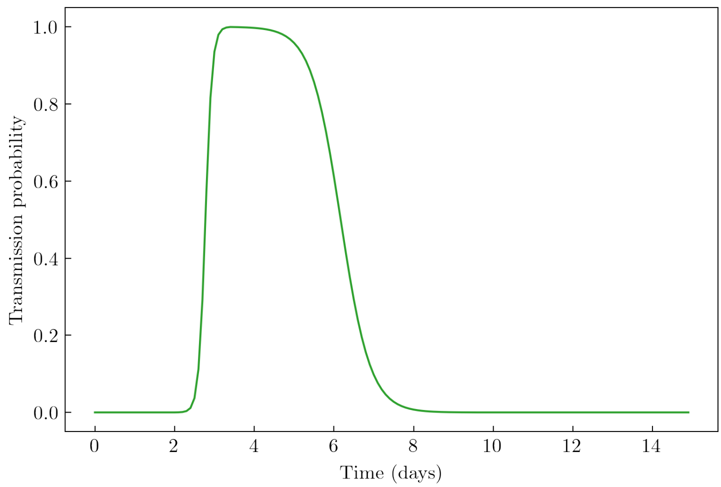

Figure B.5: Development of transmission probability over time.

Finally, we formulate the infection probability $p_{i,j}$ between a susceptible person i and an infected person j is given by:

$$p_{i,j} = 1 - e^{-\sum_{j=1}^{M_k} (1-\mu)^2 \times P_j(d) \times t_{i,j} \times \sigma(\max(\Delta(A_k, N_k), \psi)) \times \alpha}, \tag{B.1}$$

where:

- μ is the mask effectiveness

- $P_j(d)$ is the transmission probability of person j at day d
- $t_{i,j}$ is the time spent together
- $\Delta(A_k, N_k)$ is the distance factor
- ψ is the social distancing factor
- α is the calibration factor

To calculate the average distance, we use a simple formula:

$$\Delta = \sqrt{\frac{A}{N}}$$

Social distancing ψ spreads people apart. Here, ψ is the distance after which there is no infection. Let us assume that there is no infection after 3 metres. If we use a corresponding policy, then we compute $\sigma(\psi)$, and not $\sigma(A, N)$.

To define a factor describing relations between distance and transmission probability, we come up with a simple theoretical model:

$$1 - \frac{1}{1 + \exp(-3 \times (\max(\Delta(A_k, N_k), \psi) - 1.5))}$$

Given the following setup:

$$\psi = 0, \quad A_k \in [1, 100], \quad N_k = 5,$$

it converts to:

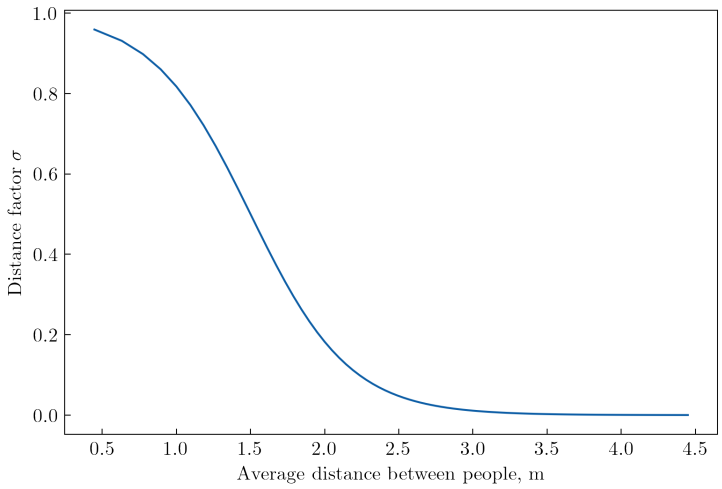

Figure B.6: Relations between average distance and distance factor σ.

Importantly, the current version of the formula has to be calibrated with the use of σ.

To verify the model, we do a series of experiments with the following set of parameters (B.3).

Parameter	**Symbol**	**Value**
Number of infected people in the room	M	1
Mask effectiveness	μ	1
Days since infection of the infected person	d	3.4
Time spent together	$t_{i,j}$	8
Room area	A	25
Number of people in the room	N	7
Social distancing	ψ	1
Calibration factor	α	0.025

Table B.3: Experimental setup for model verification.

Figure B.7 presents the set of graphs of the model verification process.

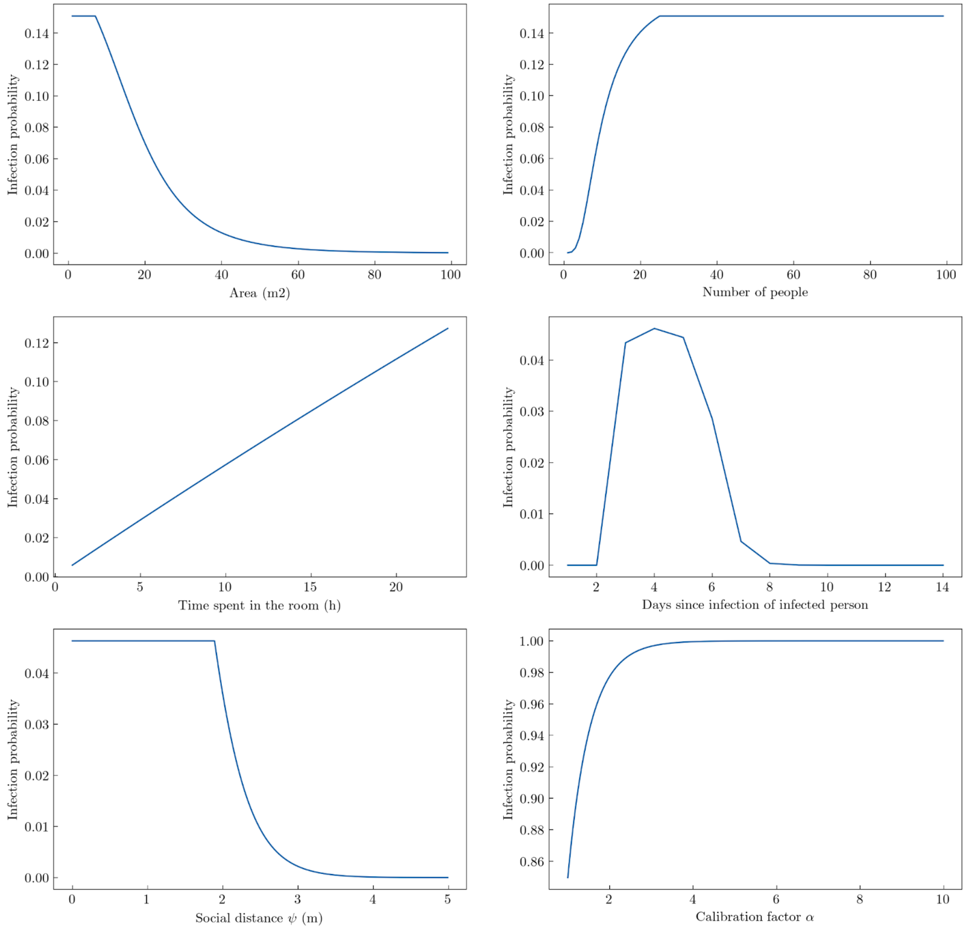

Figure B.7: Experiments with infection probability $p_{i,j}$.

Table B.4 enlists all parameters-constants used in the epidemiological model:

Parameter	Symbol	Value
Latent period	L	2
Incubation period	I	3.4
Clinical disease period	C	6.2
Peak viral load	$v_{\max}$	7.23
Reference viral load	v_0	4
Transmission rate	k	2.294
The factor for social distancing	ψ	1
Calibration factor	α	0.025

Table B.4: Parameters-constants of epidemiological submodel.

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C

Making Good Enough Models of Cities: A Beginners Guide

Presumably Catchy Introduction

Urban analytics and city science are booming. The number of articles that begin with "By 2050, the number of people living in cities…" is getting out of hand. And you are also interested. Cool, cool, cool.

Want to be one of those who is creating computational models of cities? Fields like urban analytics, city science, urban data science, and GIS are all involved. These models can take many forms, whether visualising how heat is distributed over a city or network models examining the impact of traffic or urban resources.

And why do they make these models? Including the studies described in Chapters 2, 3 and 4? The goal is to extract useful knowledge from these models and contribute to better decision-making. For example, together with Alexander Verbraeck, Tina Comes, and others (see the full lists here and here), we made a simulation model of a city called HERoS that can be used to understand how the virus spread on the city scale and what can be done to tackle it. Another example, with my colleagues Leonardo Nicoletti and Trivik Verma, we developed CityAccessMap.com, which was used to introduce a new indicator for SDG 11. Beyond utility, modelling cities is fascinating since you can reveal some hidden patterns.

You might ask: how do I do any of this stuff? Oh well, here we go. This tutorial is not about modelling an entire city—an overly ambitious exercise. Instead, we'll model a specific problem a city faces. Creating a "generic" city model might be fun, but real modelling requires making tough decisions about what to include and leave out. Everything is connected, sure, but for now, we'll focus on modelling a specific problem and be brave about what we exclude.

Warning! This guide will offer some basic steps. It's not meant to be comprehensive but a starting point. Moreover, it's not meant to be complete but rather an invitation to look into something that could become an MSc course. The most recent version of this tutorial can be found at https://github.com/mikhailsirenko/good-enough-models-of-cities.

WHAT'S A GOOD ENOUGH MODEL?

First, let's have a talk about the *good enough* model, using different bird nests as metaphors to illustrate our point. What do I mean by "good enough"? Incomplete? Something deeply profound and lacking depth to be representative of the phenomena of interest? Just like a pigeon nest (Figure C.1)? Or "we ran out of funding, and that's what we are" kind of model? Nope.

Figure C.1: Pigeons making nests be like. Credits go to oranke_dino on Reddit.

A good enough model of a city is a model that is *sufficient* to generate *useful* insight. Sounds simple? However, let's unpack what sufficiency and usefulness in this context stand for.

With any complex system, a modeller has to make (hard) choices about what to include or exclude. In the context of cities, this decision-making process becomes particularly pronounced due to their inherent complexity and dynamic nature. Even a simple question, such as where the city ends, requires quite some thought. Should we set the model to be limited to official administrative borders, or should we also add surrounding areas where people live but commute into the city for work, effectively acting as its citizens? So, "sufficient" relates to the level of detail and the complexity of the model we aim to create.

For instance, consider a city where certain neighbourhoods are disproportionately affected by heatwaves due to factors like urban heat island effect (UHI), lack of green spaces, or socioeconomic disparities. If we exclude these factors from our model, we may miss essential dynamics affecting citizens' health outcomes. On the other hand, too much detail — such as modelling every building's materials — can make the model heavier than needed and difficult to interpret.

Contrary to the trend of developing digital twins of cities — which aim for exhaustive and highly detailed representations of every building, street, and infrastructure component — the concept of a "good enough" model acknowledges that any model we create is incomplete. Moreover, cities can be modelled from various perspectives, each emphasising different aspects such as transportation, energy consumption, social interactions, or environmental impact. By default, a model cannot capture every facet of the urban environment.

Consider the nests of sociable weavers, which are complex structures housing hundreds of birds (Figure C.2). While impressive, such complexity is not our goal in modelling cities. Instead, we want to ask meaningful questions and seek empirical evidence to validate our modelling choices, ensuring that the model remains manageable and focused. By doing so, we avoid overcomplicating the model, which can lead to confusion, increased computational requirements, and difficulties in interpreting the results.

Figure C.2: Sociable weavers' nests are wild. Credits go to Wikipedia. The photo was taken by Harald Süpfle and licensed under CC-BY-SA-2.5. Read more here.

Additionally, constructing a model of a city is a modular process. We can learn from software development methodologies, such as rapid prototyping and the "fail fast" philosophy. These approaches emphasise building iterative versions of a product, learning from each iteration, and making necessary adjustments quickly. Applying this to city modelling will allow us to develop models incrementally, testing and refining them as we progress. By starting with a simple model and gradually adding complexity, we can identify which components contribute most significantly to the insights we seek. (It is almost like inherently designing your modelling process for sensitivity analysis!)

For example, we might begin by modelling the UHI using basic parameters like air temperature and land surface characteristics. Then, we could incorporate additional factors such as vegetation cover, building materials, population density, or energy consumption patterns. At each stage, we assess whether the added complexity enhances our understanding of how heat waves impact the city or whether it unnecessarily complicates the model without providing significant benefits.

But what defines "useful" in the context of a model? Ultimately, usefulness is determined by you, the modeller, or the end-users for whom the model is intended. If the model generates insights that stakeholders find meaningful and actionable, then "your job is done here". For example, suppose a municipality lacks information about which neighbourhoods require more attention during heatwaves. If your model identifies these vulnerable areas and provides guidance for resource allocation, it is sufficient and useful.

Our aim is to achieve something similar to the nest of the great reed warbler (Figure C.3): a structure that is simple yet complete, fulfilling its intended purpose without unnecessary complexity.

Figure C.3: The great reed warbler builds nests look good enough. Credits to Wikipedia. Image uploaded by Wikinoby commonswiki under CC-BY-SA-3.0 Uported license. Read more here.

In summary, a "good enough" model balances simplicity, complexity, sufficiency, and manageability. "Perfectly balanced...". It involves making thoughtful decisions about what to include based on the goals of the model and the needs of its users.

Step 1: Define What to Model — A City or a Problem?

Before diving into modelling, it's crucial to identify the specific issue you want to address or ask an interesting question. Are you interested in the overall dynamics of a city, or are you focusing on a particular problem within the urban environment? This guide will concentrate on modelling a problem rather than attempting to model an entire city. Questions to consider:

1. What is the issue you're trying to address?
2. What kind of understanding is currently missing?
3. What questions do you hope your model will answer?

Task 1: Identify the Problem and Write It Down
Begin by writing down the problem you want to address. This initial definition might evolve as you deepen your understanding or find out that there is no data, but it's essential to start somewhere. Your problem statement can be a straightforward declaration or formulated as a question. For example:

- *Heatwaves are causing significant health issues in urban areas.*
- *How effective are the measures that could mitigate the impact of heatwaves in cities?*

Defining the problem will guide your subsequent steps, including the selection of data, modelling approach, and analysis techniques.

Step 2: Make a Conceptual Model

With your problem defined, developing A CONCEPTUAL MODEL is next. It sounds scary and tough, but we'll use some tricks to help us out. Long story short: identify **the key** components and relationships that are relevant only **to your** issue. And that's the first trick: we'll have to define the system's boundaries and make a hard but necessary decision about what to leave out.

There are at least two approaches (ideally combined in a loop) to developing a conceptual model:

Start with Theory or Get Ready for a Reading Challenge

You heard it right. You'll need to dive into existing literature to understand the theoretical underpinnings of your problem. Huh. The good news is the more you read, the easier it is. So, get ready to conduct a literature review to explore recent papers, books, and studies related to your topic. This will help you:

- Identify key variables and factors influencing the problem.

- Understand established relationships and mechanisms.
- Sheds a bit of light on previous modelling efforts and methodologies.

Example: If you're studying the impact of heat on citizens' health, you might search for keywords like "urban heat," "city temperature," "public health," "heatwaves," "emergency services," and "behavioural responses to heat." Starting broad and then narrowing your focus can help you capture a comprehensive picture of the issue.

A useful technique is to imagine your problem as a black box with inputs, outputs, and internal structures. For instance, in the heat example:

- Inputs: Environmental heat levels, activation of policy interventions (e.g., heat action plans).
- Internal Structure: Urban infrastructure, population demographics, behavioural responses.
- Outputs: Reported mortality and morbidity rates due to heat.

Or, if you're familiar with it, consider drawing a systems diagram (read more in a truly amazing book Policy Analysis of Multi-Actor Systems by Enserink et al. (2023)), which can help visualise these components and their interconnections.

Task 2.1: Conduct a Literature Review and Draw a Conceptual Model of Your Problem

1. Research articles, reports, and data sources relevant to your problem.
2. Identify key variables, factors, and relationships.
3. Create a visual representation (e.g., a diagram) of your conceptual model.

START WITH DATA AKA MESS AROUND AND FIND OUT

Alternatively, you can begin by messing around with available data formally known as *exploratory data analysis* (EDA). Many institutions and organizations provide open-access datasets. I won't go over them; if you're reading this, you can search for information online. I would say that try exploring the websites of cities: e.g., Barcelona, The Hague, Helsinki. Large organisations typically (but not always) provide data on the country scale.

When starting with data:

- Search datasets relevant to your problem.
- Look for variables that might influence or explain the issue.
- Conduct exploratory data analysis to uncover patterns and relationships.

Example: In the heat scenario, you might gather data on temperature variations across different districts, socio-demographic information, healthcare access, and energy usage. Analysing this data could reveal correlations between temperature and population density, income levels, or health outcomes.

Another tip! Want to save yourself a ton of time? Use Cookiecutter Data Science for your EDA. I cannot stress enough how easier your life would be if you started with a structured approach for any of your data science projects. Ok, I'll try. A LOT!

Task 2.2: Find Data and List Variables

1. Identify and collect datasets that could inform your problem.
2. List the variables that are relevant.
3. Analyse the data to discover patterns and relationships.

Special Considerations When Modeling Cities

Think Modular

Cities can be broken down into building blocks (e.g., roads, buildings, utilities). Recognising these modules helps structure your model. For example:

- Roads are used by people and vehicles to move around the city.
- Energy system powers public infrastructure like libraries, hospitals, and schools.

Running out of ideas? Try to play any city simulator, even on your phone. Look at what are the building blocks the game offers and think whether these are relevant to your problem.

Urban Dynamics, which is Spatio-Temporal

Urban environments are dynamic. People use roads to move around, energy consumption fluctuates, and services operate on schedules. Your model should account for these dynamic interactions.

As a result, urban phenomena often vary across space and time. While visualising data on a map is helpful, remember that processes change over time. Search for spatio-temporal data and, in the worst-case scenario, complement spatial with temporal data.

Urban Inequalities

Modern cities often have disparities in income, access to services, and environmental quality. Be cautious when interpreting correlations between inequalities and the phenomena you're studying. Ensure that your analysis accounts for confounding factors.

When to Stop Adding Complexity

Aim for a "good enough" model to address your problem without unnecessary complexity. Starting simple allows you to focus on core elements and understand fundamental relationships. You can always add complexity later as needed. Initially, limit yourself to:

- A manageable number of core elements or datasets (e.g., five).

- A few key connections between variables.

WORKING ALONE OR WITH OTHERS

While working alone is OK, working with others can significantly enrich your model by bringing in different perspectives and expertise. Modelling is an exercise that is always done from someone's "perspective". That's why participatory modelling is considered to be more effective than when no stakeholders evolved.

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STEP 3: SELECT THE MODEL TYPE

Now that you have a conceptual model and some initial understanding of your problem, it's time to choose the appropriate modelling approach. The model type you select should align with the nature of your problem, the data available, and the insights you aim to generate.

As the old cliche goes, "It is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail." (The Law of the Instrument). Therefore, it's important to be open to different modelling techniques rather than forcing your problem into a familiar framework. On the other hand, you are faced with a dilemma: either learn multiple tools or restrict yourself to solving problems that fit within the capabilities of your current tool. It's important not to be overly rigid here — there's value in stepping outside the conventional uses of a tool and applying it to new challenges. However, be careful. Read Russell Ackoff's "On the Mismatch Between Systems and Their Models" before diving into the complexities of tool selection.

Here are some common model types used in urban modelling:

SIMULATION MODELS

- Agent-Based Models (ABM): Simulate the actions and interactions of autonomous agents (e.g., individuals, households, vehicles) to assess their effects on the system as a whole. Useful for modelling complex behaviours, emergent phenomena, and heterogeneous populations.

- System Dynamics Models (SD): Use stocks, flows, feedback loops, and time delays to understand the behaviour of complex systems over time. Ideal for studying aggregate trends, policies, and long-term dynamics.

- Discrete Event Simulation (DES): Model the system as a sequence of events in time, suitable for systems where changes occur at discrete points (e.g., public transport schedules, emergency response).

STATISTICAL MODELS

- Regression and Correlation: Identify patterns and relationships between variables. Useful for predicting outcomes and understanding influencing factors.

- Clustering and Dimensionality Reduction: Use algorithms to find patterns.

- Time-Series: Analyse data points collected or recorded at specific time intervals to identify trends and seasonal variations.

Indicators and Indices
Create composite measures to represent complex phenomena (e.g., livability index, heat vulnerability index). Relatively easy to make and interpret, familiar to policy-makers and practitioners.

Network Models
Focus on the relationships and interactions between entities, such as transportation and social networks. Analyse flows, connectivity, centrality, and vulnerability within networks.

Geographic Information System (GIS)-Based Models
Utilise GIS to analyse spatial data and visualise results on maps. Good for spatial analysis, location-based modelling, and integrating various spatial datasets.

How to Select the Appropriate Model Type
Here are some factors to consider when choosing your model:

1. Nature of the Problem:
   - Is the problem dynamic or static?
   - Does it involve individual entities or aggregate behaviour?
   - Are spatial or temporal aspects critical?
2. Data Availability:
   - Do you have detailed micro-level data or aggregate data?
   - Is the data quantitative, qualitative, or both?
3. Desired Insights:
   - Are you interested in predicting future states, exploring scenarios, or understanding underlying mechanisms?
   - Do you need to visualise spatial patterns?
4. Complexity and Resources:
   - What is the acceptable level of complexity?
   - What are your computational resources and time constraints?
   - What is your expertise with different modelling techniques?

Here are some examples:

- If you are studying how individual behaviours contribute to virus spread, an ABM might be appropriate.

- If you want to understand how different policies affect overall virus spread in a city over time, an SD model could be suitable.

- For analysing the spatial distribution of heat vulnerability across a city, a GIS-Based Model with statistical analysis may be the best approach.

Note that further in the tutorial, we'll focus on a few models to make this tutorial more tangible and not turn it into a book: simulation (mainly ABM), statistical and indicator-based.

STEP 4: COLLECT AND PREPARE DATA

Data is the foundation of your model. Collecting and preparing data involves sourcing relevant datasets, ensuring their quality, and formatting them for use in your modelling tools. As the saying goes, "Garbage in, garbage out." The quality of your data directly affects the reliability of your model's outputs. Sometimes, the data you need might not be available or might not match your initial expectations. Be prepared to revisit your conceptual model or adjust your problem statement based on the data you can obtain.

There is plenty of information about collecting and preparing the data. Overall, you'll have to familiarise yourself with the platforms that store the data you want. As we previously discussed, these are most likely the ones run by cities. Data preparation-wise, here is a great tutorial entitled "Build a Reproducible and Maintainable Data Science Project" by Khuyen Tran. Some of the tools described here (e.g., Great Expectations or Pandera) can be quite useful for data preparation/preprocessing.

Task 4: Collect and Prepare Data

1. **Data Collection**:
   - Identify and download the datasets relevant to your model.
   - Ensure you have permission to use the data.
2. **Data Preparation**:
   - Clean and preprocess the data.
   - Document your data sources and any changes made.
3. **Revisit Conceptual Model** (if necessary):
   - Assess whether the data collected supports your conceptual model.
   - Modify your model or problem statement if required.

STEP 5: MAKE THE MODEL

Now comes the exciting part — building your model! This step involves translating your conceptual model into a computational one using appropriate tools and techniques.

Since there are plenty of excellent tutorials on building different types of models, I'm exempted from going into details regarding each of them here! Hooray! For example, Agent-Based Modelling of Socio-Technical Systems or the tutorials provided by the GAMA Platform. However, let's go over the steps that are common regardless of the model type you've selected:

1. **Choose the Right Tools**:
   - For ABMs, consider platforms like Mesa, GAMA, or PYDSOL.
   - For statistical models, programming languages like Python (with libraries such as pandas, scikit-learn) or R are commonly used.
   - For GIS-based models, open-source tools like QGIS are very useful.
2. **Translate the Conceptual Model**:
   - Define the variables, parameters, and equations that represent the relationships in your conceptual model.
   - For simulation models, code the behaviours, rules, and interactions of agents or system components.

Since you're modelling a complex system that is likely to involve a significant amount of uncertainty, addressing uncertainty is not that easy. People even have dedicated Twitter accounts for that! Consider using decision-making under deep uncertainty (DMDU) methods. You can read more about it DMDU Society.

Lastly, remember the key principles we discussed in the previous steps: **aim for good enough**, **be modular**, **think spatio-temporally**, **account for inequalities**, and **work with others**.

Task 5: Build Your Model

1. **Set Up the Development Environment**:
   - Install and configure the necessary software and tools.
2. **Implement the Model**:
   - Translate your conceptual model into code or a computational framework.
   - Ensure that your code is well-organised and documented.
3. **Test the Model Iteratively**:
   - Run the model with test data or parameters.
   - Debug and refine as needed.

Step 6: Analyse and Visualise Results

Analysing the results of an already-built model can be a lot of fun. This step involves puzzling over outputs, performing further analysis, and presenting your findings in an accessible manner (data storytelling!).

Depending on your model type and objectives, your analysis may include statistical analysis to ensure that the type of relations you've found hold true, sensitivity analysis to identify which factors most significantly affect the outcomes, spatial analysis using GIS tools to examine patterns and relationships, and temporal analysis to observe how variables change over time.

Visualisation is key to understanding and communicating your findings. Create graphs and charts, but start simple with some pre-built libraries (e.g., matplotlib), but later explore mode advanced ways to visualise data, e.g., with Observable HQ. Similarly, make some simple maps that display spatial data and patterns, and later explore advanced topics, e.g., interactive storytelling by Mapbox. For dynamic models, animations or interactive dashboards such as Dash, Streamlit, or HoloViz can illustrate how the system evolves over time.

Presenting your results effectively requires careful consideration, especially when addressing non-experts. Surprisingly, simply throwing graphs at them doesn't work! Simplify complex data by using clear and straightforward visuals and focusing on the key message. Structure your presentation in a way that tells a coherent story. Use the audience language, avoid jargon at all costs and explain technical terms ONLY WHEN NECESSARY.

Task 6: Analyse and Visualise Your Model's Results

1. **Perform Data Analysis**:
   - Run statistical analyses relevant to your objectives.
   - Conduct scenario and sensitivity analyses as planned.
2. **Create Visualizations**:
   - Generate graphs, charts, and maps to represent your findings.
   - Ensure visuals are clear and effectively convey the intended message.
3. **Prepare to Communicate Results**:
   - Develop a narrative that explains your findings.
   - Consider the audience and tailor your presentation accordingly.

Step 7: Verify and Validate

Verification ensures that your model is correctly implemented, and validation is about whether it represents a real-world problem. As such, verification is more applicable to simulation models than to statistical or indicator-based models. Validation can be done for both.

What is it all about in a nutshell? Verification of a simulation means checking whether everything works as intended. For instance, you'll need to check all outcomes, the main and secondary ones. It is quite a tough process, but that's how you'll make sure that the model does not have any bugs. If the model is complex and has multiple submodels, first perform verification of its individual submodels, then take two or three interacting ones and check them, and so on, until you make sure that the main model outcomes are correct.

Next comes validation. And this one could be tricky. If you model a phenomenon that happened in the past, then you can perform historical validation. Historical validation is possible if past data exists, but it might not apply if your model addresses scenarios that haven't occurred. In such cases, you may consider using expert validation for the overall performance metrics of your model and use historical validation for individual components of your model. Some say the ultimate test of a model's validity is its usefulness.

Task 7: Verify and Validate Your Model

1. **Verification**:
    - Conduct thorough testing to ensure the model operates correctly.
2. **Validation**:
    - Compare model outputs with real-world data or expert expectations.
    - Document validation processes and findings.
3. **Refinement**:
    - Make necessary adjustments based on verification and validation results.

INSTEAD OF CONCLUSION

As we agreed in the beginning, it's not a comprehensive guide but just an attempt to compile into a set of meaningful steps supervised with tips. I didn't cover many topics here: open data, ethical implications, communicating models and their results, equifinality, but it also means there is so much to explore. Everyone would like to have that single piece of text, a tutorial, or a video that would be comprehensive but to be point, contain multiple examples, be deep and focused, and so on. Do you see where it's going? Yes, it doesn't exist, at least yet. I think it could be said that there are MSc-level courses. Or maybe a full-scale program? Nah, it is so much more fun to gather this knowledge from various sources. I hope you got the main idea and start making good enough models that will eventually evolve into something beautiful and useful, like in Figure C.4.

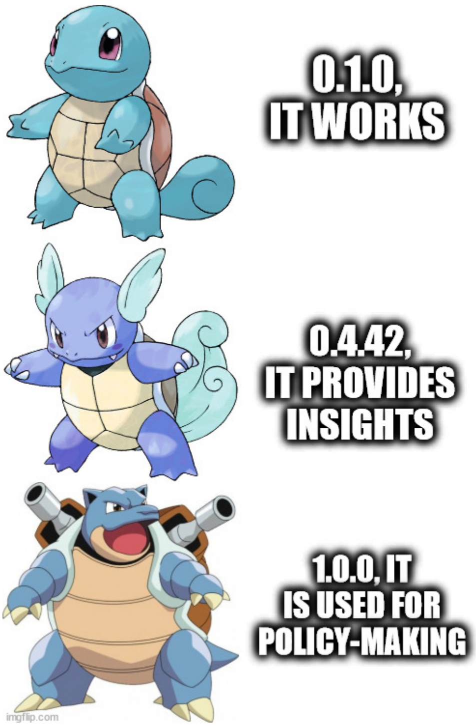

Figure C.4: Evolution of good enough models be like. Created by Mikhail Sirenko with imgflip.com and available at https://imgflip.com/i/954kvi.

ACKNOWLEDGEMENTS

The *butterfly effect* is fascinating but quite an abstract concept. Let's be honest: it is challenging, if not impossible, to pinpoint exact causes or trace the ripple effects of a single moment. However, when it comes to one's personal life, the effects of small interactions — a word, a meeting, or a friendship — are much easier to recognise and appreciate. These moments and connections shape the course of our lives in profound ways, even if we don't fully realise their impact until much later.

What follows is a list of people who have influenced my life. Some of them may not even realise they had any impact on me and might be surprised to find themselves mentioned here. Nevertheless, their contributions, whether big or small, have shaped who I am today.

To fully appreciate the interconnectedness of life, we must start at the **very beginning**. Why start so far back? Because **every interaction** and **every person** we've encountered add a layer to who we are now. Some would argue that yes, "but not everything is as impactful, basic principles of sensitivity analysis, bruh." I would reply, go and make a model of someone's life, chad, to prove me wrong, ok?

This task of listing these wonderful people, however, is not without its challenges. Inevitably, I may overlook someone, not out of forgetfulness but because the web of influence is so vast: everyone matters, and everything is connected. If you don't see your name here, know that your presence and influence are acknowledged in me, even if not explicitly mentioned.

First and foremost, I am deeply grateful to my mom for her indispensable support and my dad for bringing the challenges I had to solve.

My *academic journey* — Chapter One — began thanks to two remarkable mentors: Shumskaya Liliya Akramovna, whose challenging "Can you even do it?" pushed me toward mathematics, and Sibiryakova Valentina Aleksandrovna, for her patience and introduction me to the world of Pascal programming.

Chapter Two starts at the Faculty of Applied Mathematics and Cybernetics of Tomsk State University. Immense gratitude goes to Tarasenko Peter Felixovich for sharing his unique way of thinking and Tarasenko Felix Petrovich for showing me the world of systems analysis. I am particularly thankful to Dmitriyev Yuriy Glebovich for his exceptional leadership and to Zenkova Zhanna Nikolaevna for bringing warmth and humanity to teaching. Special thanks to my comrades Alexey, Dmitriy, and Andrey, with whom I shared laughter, dreams, and — most importantly — spectacular failures during exams.

I am also extremely grateful to Vasilev Nikolai, a great human being who has brought and keeps bringing people together not only to do sports but also to build themselves and the world around them. I am thankful to my friends who went with me through this journey: Dima, Egor, Denis, and Sergei.

The Dutch Chapter Three began with a single conversation. Bert Enserink introduced me to the EPA program during the Masters Event in 2014, and that brief chat set everything in motion. Sometimes, the smallest moments lead to the biggest adventures.

Fast forward to Chapter Four, August 2017, when I joined the EPA MSc program. First comes the **Midnight Team** (just made up the name — hope you're okay with it, boys!) — Ammar, Connor, Merih, Shajee, and Yubin — with whom I spent countless days and nights on the fifth floor, fueled by endless sweets. You're the best. (Did anyone escape diabetes?) The EPA program connected me with truly extraordinary minds: Alper, Ashwin, Gurvinder, Patrick, and Rizky, whose *insights* helped us to understand *what's actually going on*. You're amazing people. It was inspiring to meet the next generation of students — Irene, Jason, Jin, Leonardo, and Sahiti — and engage in spicy conversations. To Amir, Bramka, and David, then PhD students: I'm genuinely grateful for our collaboration and friendship.

The one only best version 2017 of the program wouldn't have been possible without these brilliant minds and personalities:

- Peter Bots, with his razor-sharp intellect and vast knowledge
- Bert Enserink, whose openness and unique management style united everyone
- Scott Cunningham, for his creativity and big heart
- Martin de Jong, for his willingness to open research to others
- Alexander Verbraeck, for making complex concepts accessible and delivering fantastic courses
- Erik Pruyt, for inspiring us to tackle only things that matter (with small models tho)
- Jan Kwakkel, for his unique perspective on coding, memes, and uncertainty
- Servaas Storm, for his outstanding sense of humor

A special thanks go to the security team of the Wijnhaven building, who placed their trust in the Midnight Team from day one. While we haven't all become professors (yet!) as they wished — who knows what the future holds?

A very special thank you goes to Olga for her help and support and for being with me since the very beginning of the journey.

Chapter Five materialised through Scott Cunningham's trust and support, Trivik Verma's open-minded approach and the beautiful challenges he brought, and Bartel Van de Walle's innovative leadership.

Chapter Six opened up thanks to Tina Comes' true leadership and support, alongside Alexander Verbraeck's great contributions. The HERoS project would not have been possible without Sahiti, Jin, Dan, Anmol, Fabio, Hidde, and Srijith. My gratitude extends to everyone involved, especially project lead Gyöngyi Kovács.

I'm grateful to all the master students who helped me grow: Pietrangelo, Jochem, Daan, Eva, Amerens, Hidde, Elias, and Annemeike. I hope you had as much fun as I did.

Special thanks to Raphael for his sense of humour, Carissa for her enthusiasm for learning and collaborating, Daniel for his principles and dedication, and Ylenia for her book recommendations and fresh perspectives on life. And, of course, Ankita, for showing me what life is truly about. Having someone to hang out with, even virtually, was invaluable during those COVID-19 days.

I cherish the memorable moments shared with colleagues Ali, Floris, Arka, Julien, Jen, and Su-Mae. Maybe we will hang out again sometime?

The seventh and final chapter of this journey — my dissertation — began rather with "Can I? Really?" and has now reached its conclusion. I'm deeply grateful to Patrick and Ankita for their support; they are wonderful friends. Some people indeed appear repeatedly in our story, and for good reason. Thank you, Tina Comes and Alexander Verbraeck, for your trust, ideas, and invaluable contribution to this dissertation. It has been a fascinating adventure that showed me what's possible when you try.

This journey would not have been possible without each and every one of you. I love you all.

Curriculum Vitæ

Mikhail Sirenko

11-01-1989	Born in Siberia.

Education

2005–2010	Specialist Degree Mathematical Methods in Economics & Econometrics Faculty of Applied Mathematics & Cybernetics Tomsk State University
2012–2016	Candidate of Science Studies Mathematical Modelling, Numerical Methods and Program Complexes Faculty of Applied Mathematics & Cybernetics Tomsk State University
2017–2019	Master of Science Engineering & Policy Analysis Faculty of Technology, Policy & Management Delft University of Technology

Experience

2023-present	Disaster Resilience Analyst @The World Bank
2023-2024	Researcher @Wageningen University & Research
2019-2024	Researcher @Delft University of Technology
2014-2016	Lecturer @Tomsk State University

List of Publications

20. Sirenko, M., Comes, T., & Verbraeck, A. (under review). Flipping risks: On urban maladaptation in times of epidemics. *Scientific Reports*.

19. Sirenko, M., Verbraeck, A., & Comes, T. (under review). More vulnerable, less resilient? Insights into the spatial-temporal dynamics of vulnerability, resilience and adaptive capacity from the 2019 European heatwave. *npj Urban Sustainability*.

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Supervision of Master's Students

9. **Annemieke Brouwer**, 2024, *Dynamic Adaptive Epidemic Control: A case study of anticipatory action to cholera outbreaks in Cameroon*, https://repository.tudelft.nl/record/uuid:4e5f58cb-3b0c-471e-a06b-680abcb51b2a

8. **Elias Bach**, 2022, *Social Media and Climate Change: Exploring the Effect of Climate-related Events on Online Discourse using Topic Modelling & Sentiment Analysis*, https://repository.tudelft.nl/record/uuid:6c94636f-2640-48d2-ab9e-f2cd81ae3b71

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6. **Hidde Bijlard**, 2022, *Open vs Micro; comparing different agent populations and their impacts: Assessing the differences between populations in epidemiological agent-based models*, https://repository.tudelft.nl/record/uuid:d0538346-2a89-47c9-9b3f-4b0e2e65028b

5. **Amerens Jongsma**, 2021, *Turning down the volume or taking away the mic. A study of COVID-19 vaccine-related misinformation on Dutch Twitter.*

4. **Eva Brink Carvalho**, 2021, *Food distribution during a COVID-19 outbreak in a refugee settlement: An Agent-Based Model approach taking into account queuing behavior uncertainty*, https://repository.tudelft.nl/record/uuid:0b7342ec-6faf-4a6b-896e-c723f65ee6b1

3. **Daan van Beek**, 2021, *Human behaviour and continuous food supply in a semi-permanent refugee settlement: An exploration of policies for a network of Food ATMs in interaction with uncertain beneficiary behaviour in the context of the Bidi Bidi refugee settlement in Uganda*, https://repository.tudelft.nl/record/uuid:b136b952-35b0-4c2d-9bf3-6361e0e92937

2. **Jochem Vlug**, 2020, *Impact of Migration and Urbanization on Cities: an Agent-Based Model on the effects of Migration on the city of The Hague*, https://repository.tudelft.nl/record/uuid:8e57837f-2651-4320-b08c-939e7cf5c149

1. **Pietrangelo De Biase**, 2020, *Sub-national Government Fiscal Sustainability: A Research on Fiscal Risks and Fiscal Federalism in Times of COVID-19*, https://repository.tudelft.nl/person/Person_33f98546-aeeb-4f28-a79e-b0f6c27b9dc1

Key Talks

21. **Annual Conference of the Society for Decision Making Under Deep Uncertainty (DMDU) 2023**
    Towards a 15-minute city under deep uncertainty
    Date: 29 October 2023
    Location: Delft, the Netherlands
    Audience: Conference audience

20. **International Conference on Resilient Systems (ICRS) 2023**
    The more vulnerable, the less resilient?
    Date: 27 June 2023
    Location: Mexico City, Mexico
    Audience: Conference audience

19. **Humanitarian Networks and Partnerships Weeks (HNPW) 2023**
    Simulation modelling in a data-scarce environment
    Date: 30 April 2023
    Location: Geneva, Switzerland
    Audience: Humanitarian workers, NGO representatives, government officials, and inter-governmental organizations

18. **Annual Conference of the Society for Decision Making Under Deep Uncertainty (DMDU) 2022**
    Not a silver bullet: Searching for lockdown alternatives in an artificial city
    Date: 9 November 2022
    Location: Mexico City, Mexico
    Audience: Conference audience

17. **World Urban Forum**
    How to avoid biases in vulnerability and resilience assessment
    Date: 30 June 2022
    Location: Katowice, Poland
    Audience: Urban planners, city officials, architects, NGOs, and community leaders

16. **First responders training session**
    A guide on COVID data and models
    Date: 21 June 2022
    Location: Amsterdam, the Netherlands
    Audience: Humanitarian workers and disaster response coordinators

15. **Deloitte**
    Deep uncertainty 101
    Date: 18 May 2021
    Location: Amsterdam, the Netherlands
    Audience: Business consultants, financial and data analysts

14. **Humanitarian Networks and Partnerships Weeks (HNPW) 2022**
Do we really need to violate people's privacy to build better models?
Date: 10 May 2022
Location: Geneva, Switzerland
Audience: Humanitarian workers, NGO representatives, government officials, and intergovernmental organizations

13. **The European Working Group on Humanitarian Operations (EURO-HOpe) mini-conference**
Behavioural Models in Epidemics
Date: 23 November 2021
Location: Helsinki, Finland
Audience: Conference audience

12. **European Commission**
Research to Policy Meeting: Behavioural Models in Epidemics
Date: 19 October 2021
Location: Online
Audience: EU policymakers, government officials, researchers, and experts

11. **International Conference on Urban Health (ICUH) 2021**
How the turntables: Estimating the impact of NPIs against COVID-19 in an artificial city
Date: 6 July 2021
Location: Online
Audience: Conference audience

10. **Leiden University Medical Center (LUMC)**
Simulating COVID-19 in the artificial city of The Hague under uncertainty
Date: 23 June 2021
Location: The Hague, the Netherlands
Audience: Medical professionals, researchers, and medical students

9. **Dutch Police**
Simulation modelling for decision-making: From complex problems with a high degree of uncertainty to an operationalisable insight
Date: 21 April 2021
Location: Online
Audience: Law enforcement officials and public safety experts

8. **Statistics Netherlands**
Simulating COVID-19 in the artificial city of The Hague
Date: 2 February 2021
Location: Online
Audience: Statisticians, government officials, and researchers

7. **OECD**
Resilient to extreme heat? A case study of 2019 European heatwave in the Netherlands
Date: 2 February 2021
Location: Online
Audience: International policymakers, economists, and researchers

6. **Veiligheidsregio Haaglanden**
Exploring The Hague's responses to COVID-19: A simulation model approach

Date: 21 January 2021
Location: Online
Audience: Regional safety and emergency management officials

5. **GGD Haaglanden**
Exploring The Hague's responses to COVID-19: A simulation model approach
Date: 18 January 2021
Location: Online
Audience: Public health officials

4. **Joint International Resilience Conference 2020**
Exploring responses to COVID-19 in an artificial city
Date: 11 November 2020
Location: Online
Audience: Conference audience

3. **The Hague Municipality**
Exploring The Hague's responses to COVID-19: A simulation model approach
Date: 9 November 2020
Location: Online
Audience: Local government officials

2. **International Conference on Environmental Modelling and Software (iEMSs) 2020**
Assessing Urban Vulnerability and Resilience: The Case of July 2019 European Heatwave
Date: 15 September 2020
Location: Online
Audience: Conference audience

1. **International Conference for Computational Social Science (IC2S2) 2020**
Assessing Urban Vulnerability and Resilience to Extreme Heat with Big Data and Machine Learning: The Case of July 2019 European Heatwave
Date: 19 July 2020
Location: Online
Audience: Conference audience