Integrating Risk Science and Urban Planning: Mitigating Hazards and Protecting Our Communities

by

Thomas McLeod Logan

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Industrial and Operations Engineering)
in the University of Michigan
2019

Doctoral Committee:

Professor Seth Guikema, Chair
Associate Professor Roger Flage, University of Stavanger
Assistant Professor Robert Goodspeed
Assistant Professor Joi Mondisa

Tom McLeod Logan
tomlogan@umich.edu
ORCID iD: 0000-0002-9209-3018

Dedication

My family and friends
You give me a life full of exploration and nature. You make me care about our world

Kia Kaha, Aotearoa

Acknowledgments

I will start by acknowledging my closest friends: Andrew Nisbet and Tim Williams. Incidentally, who are also both contributors to various chapters within this dissertation. Working with you is always a great pleasure; You are both exceptional scientists and I look forward to our next projects and adventures together.

Also thank you to my other close friends and housemates, who have made my time in Ann Arbor an absolute pleasure: Jeremiah, Tessa, Matti, Alex, Lauren, Adam, Matt, Emily, and others. A special thank you to Jer, Tessa, and Matti for your enthusiasm for adventures and general support over the past 12 months. On this note, I also want to thank the Southern Michigan Orienteering Club (SMOC), especially Barbara and Jens. Spending the weekends orienteering and adventuring racing in the Michigan outdoors makes me love life.

Thank you to my collaborators on the various projects that I have worked on. I thoroughly enjoy collaborating on projects and you provide joy, motivation and encouragement. Thank you all for your enthusiasm and guidance. I'm honored to have tackled these projects with you. A special thanks to Jeremy Bricker. Thanks for hosting me at Tohoku University and for your help with the tsunami modelling: that paper and the tour through the tsunami damaged area further opened my eyes to the challenges for hazard mitigation and adaptation. Thank you to Roger, Rob, and Joi for accepting the task of reviewing this dissertation; it would have been easier if I'd stuck to a single discipline - your insights and advice have been stellar. Also, I want to acknowledge the Michigan University-wide Sustainability and Environment (MUSE) initiative and the key people that have breathed life into it. I've learned a great deal about interdisciplinary collaboration and you've enhanced my research and perspective more than I can articulate.

Thank you to a range of staff at the University of Michigan. Notably Nicole Scholtz of the

Clark GIS library for the spatial data help; Andria Rose and Mariah Fiumara in the College of Engineering for helping improve graduate life; and Chris, Rod, Mint, and Rebekah in IOE for the vast array of things you've helped me with.

This work was funded by Fulbright New Zealand, the John R Templin Trust, the Johns Hopkins University's Dean Robert H. Roy Fellowship and Gordon Croft Fellowship, the University of Michigan's Rackham PreDoctoral Fellowship, and the US National Science Foundation (grant numbers CRISP-1638197 and SEES-1631409). This funding is gratefully acknowledged.

I also must acknowledge and thank the University of Canterbury, my alma mater. The education I received there was outstanding and I was completely prepared for taking on the world. Thank you to the faculty I interacted with there, I cannot wait to work with you all again in the near future.

Another huge thank you to my "senior" academic siblings: Andrea, Roshi, Allison, Gina, and Julie. I couldn't have asked for more incredible role models and although we weren't in the same place for long, your continued guidance and advice throughout was so helpful and so appreciated.

Finally, and certainly not least, I want to thank my advisor: the newly minted Professor Seth Guikema. It has been a thoroughly interesting and fun five years. We first met quite spontaneously while I was on holiday in Japan. This spontaneity is something we share and it has been fun to jump into various projects together. I recall replying to his invite to move university after a year with "sure, as long as you're not moving to the middle of [State redacted for political correctness - don't worry, it wasn't Michigan]." Thank you Seth for providing me the freedom in my research direction. I realize that this is a privilege and I am truly appreciative. This academic freedom has fed my curiosity about and passion for the world. Your mentorship has prepared me very well for my next adventure.

Table of Contents

List of Figures

List of Tables

List of Appendices

Abstract

The climate crisis is an unprecedented threat. We urgently need to design our infrastructure, economic, and agricultural systems and our communities to withstand hazards and reduce risk to address this threat. This dissertation contributes by exploring the potential of data-driven urban planning and through increasing our understanding of how risk and data science can be used to build the resilience of our communities.

Central to this thesis is the understanding that risk analysis (the assessment, characterization, communication, and management of risk, along with related policy) can enhance urban planning to better mitigate hazards and protect our communities. To improve risk analysis's efficacy for use in urban planning, there are a series of necessary advances to the science of risk (i.e., the knowledge, frameworks, and principles that underlie risk analysis). Each chapter of this dissertation contributes to these advances, including how we focus risk analysis for the betterment of people, how we leverage data science to understand the role of urban form in hazard mitigation, how we incorporate spatiotemporal and behavioral feedbacks into risk analysis, and how we capture resilience within the risk concept. The primary aims of the dissertation were to:

1. Explore the potential for risk science to be used to support urban planning
2. Advance methods and understanding of spatiotemporal risk analysis
3. Propose an operational approach to building the resilience of communities to hazards

The first chapter identifies how urban planning challenges can develop and motivate developments in risk science. I then advance approaches for conducting risk analysis that captures spatiotemporal and behavioral feedbacks using a coupled complex system model in the second chapter. The third chapter uses machine learning and spatial data to explore how urban characteristics are associated with high temperature, that could lead to higher risk. The next section, chapters four and five, focuses risk analysis on people. I propose that the focus of resilience

efforts be on the equitable provision of essential services, such as health care, food, and education. Specifically, we can measure how people's access to essential services changes due to a hazard and across demographic groups. The framework I propose can be used by decision makers before, during, and after a hazard to improve the social sustainability and reduce the long-term risk of a community. In the final two chapters I argue that we must explicitly consider the dimension of time in risk analysis and that this means that the pillars of resilience can be addressed within the concept of risk. This understanding, coupled with the other work within this dissertation, means that resilience, and resilience analysis, is well within the purview of modern risk analysis.

Chapter 1

Introduction: Opportunities for risk science in urban planning [1]

1.1 Introduction

Air pollution, chronic disease, natural disasters, urban sprawl, and climate change; these are examples of failures at the intersection of urban planning and risk science. Consider the horrific damage Hurricane Harvey wrought on Houston, Texas in 2017. This damage was severely exacerbated by inadequate integration of risk analysis and urban planning. This natural event was turned into a man-made disaster in part by the lack of zoning laws that, among other effects, lead to the concreting of the water catchment basins that previously acted as natural flood defenses [136]. This situation is clearly pertinent to risk analysis: the assessment, characterization, communication, and management of risk, along with related policy. Adequate integration of risk analysis into urban planning would mean that our cities and communities can be designed to reduce the consequences from such an event. While natural events may not be predictable, they can be anticipated, and the design of our cities and the capacity of our people and governments to respond significantly impacts whether a natural event becomes a disaster [217, 255]. Yet, astonishingly, "natural" disasters are considered a fact of life in today's cities. With climate change, population rise, and environmental degradation exacerbating the consequences of poor planning, we urgently need to improve how risk is incorporated into

[1] I intend to submit a modified version of this chapter as a perspective paper to the *Journal of Risk Analysis*.

urban planning practice.

Urban planning and risk analysis face related challenges. One challenge is that urban planning involves managing irreducible uncertainty as the effects of decisions span decades, if not centuries. For example, cities like Houston must decide if and how to prepare for hurricanes. The intensity and frequency of those hurricanes increasingly depends on climate change, which, in turn, depends on complex atmospheric reactions and human (in)action. Urban planning also requires managing interdependent, complex adaptive systems. These systems have spatiotemporal and nonlinear feedbacks that are often counter intuitive [119]. For example, seawalls not only damage neighboring coastline [28], but can also increase the long-term vulnerability of the towns they are intended to protect [56, 200]. Urban planning also requires communication of risk that is plausible to potentially partisan decision makers and justifiable to the public. These challenges are not limited to managing hazards. For instance, urban planning involves designing healthy cities to reduce people's incidence of chronic disease. Furthermore, increasing road capacity does not relieve traffic congestion, but rather induces more vehicle miles traveled [103]. Intuition-based decision making can therefore be either ineffectual or detrimental [119]. Clearly, we need to understand these complex causative pathways and evaluate the trade-offs between options. However, we often have little data and are unable to conduct controlled experiments. These challenges are pertinent to risk science, that is, these challenges force risk analysts to devise frameworks and advance the knowledge of the field in a way that supports risk analysts tackling a broad array of problems.

Risk science has foundational questions, questions common to a range of applications [24], that are also relevant to planning, for example [349]:

- Has the full spectrum of potential risks and benefits been identified and weighed?
- What are the risk tradeoffs or countervailing risks?
- How are potential risks and benefits distributed in the population?
- What broader social, economic, legal, and public policy issues should be considered?
- What are perceived risks and benefits and how do these compare to actual?
- What is the best way to communicate risk/benefit information?

Underlying all of these is uncertainty in both the occurrence of an event and its consequences. Collaborations to tackle these shared challenges would find promising synergies.

The time to integrate risk science with urban planning is overdue. Governments are increasingly realizing there is a climate emergency [38, 216, 228] that will require significant systemic changes to how society operates [168, 348]. The urban system must also undergo changes and there are calls for new urban design principles that are grounded in risk [96, 341]. However, these calls lack specifics on what risk is or how it can be leveraged. Additionally, relevant research calls are advocating further investigation into risk-related questions [105, 265, 271]. Examples we have identified where urban planning challenges that fall into foundational risk science issues include:

- Uncertainty
  - Exposure to natural events and increases in severity or frequency
  - Black swans[2] or unknown threats
  - Lack of or poor information related to systems studied such as the land-use or the fragility of structures
- Communication and perception
  - Scarcity of risk expertise in the relevant authorities
  - Limited trust, understanding, and confidence in risk analysis by elected officials and stakeholders
  - Psychological difficulties in how the people perceive hazards, which lead them to simply ignore or discount the potential for disaster [57], including:
    - The misconception that defensive structures have eliminated exposure [57, 108, 200]
    - The inability to perceive probabilities or the potential to become fatalistic.
- Systems and causality
  - Understanding how urban form affects residents' risk of disease or poor mental or physical health
  - Predicting the consequences of an event on a city
  - Extrapolating models to predict consequences from events exacerbated by climate change
- Societal risk and decision making
  - The externalization of costs because financial burden is often assumed through public investment in defensive measures or insurance programs [57, 272, 301].
  - Deciding when and how to respond to threats such as sea level rise
- Ethics

[2] a surprising extreme event relative to the present knowledge [13]

- Ensuring hazard protection is equitably distributed
- Insuring properties vulnerable to hazards

I argue that urban planning challenges, such as these, can motivate advances in foundational risk science. The challenges open numerous collaboration opportunities, data sets, focus groups, and case studies. Risk analysts can leverage these to advance risk analysis practices and research that is relevant to a variety of applications, thus furthering how we understand, assess, communicate, and manage risk [21].

This dissertation demonstrates some of these synergies and contributes to our understanding of risk and resilience, spatial and temporal risk, incorporating feed backs, and hazard mitigation. In this introduction I identify challenges in urban planning that provide impetus and opportunity for foundational advances in risk science. My primary goal is to motivate research at this interface that is both interdisciplinary and impactful.

The aims of the dissertation were to:

1. Explore the potential for risk science to be used to support urban planning

2. Advance methods and understanding of spatiotemporal risk analysis

3. Propose an operational approach to building the resilience of communities to hazards

In the remainder of this introductory chapter, I identify and elaborate on the opportunities of professionals in risk science to involve themselves in urban planning for the benefit of both fields. In doing so I discuss the contribution of the subsequent chapters. I conclude with an outline of the work included in this dissertation.

1.2 Opportunities

In this section, I present issues of foundational importance to risk science and describe how urban planning challenges motivate their receiving attention. These foundational risk issues were identified and described by risk scholars previously [15, 24]. My contribution is to discuss how each is relevant to urban planning. The knowledge gained from addressing these urban planning challenges would be relevant and influential for a range of other risk assessment and risk management applications. The urgency of preparing for global and societal change should motivate our dedication to these issues.

1.2.1 The concept versus measure of risk

Table 1.1: Definitions of risk from the urban planning and risk literature

Authors	Definition
Knight (1921), [181]	Risk is measurable uncertainty (therefore not uncertainty)
Mack (1971), [206]	**Risk**: two or more states of the world are possible and the assignment of the probability of each can be made with confidence. **Uncertainty**: cases where information is inadequate and observation disorderly.
Kasperson et al. (1985) [174]	threats to human beings and what they value
Cutter et al. (1996), [85]	Risk is the likelihood of occurrence (or probability) of a hazard. Risk has two domains: 1) potential sources of risk (industrial, flooding) and contextual nature of the risk (high consequence, low consequence) 2) simple probabilistic estimate based on frequency of occurrence
Deyle et al. (1998), [96]	Risk = magnitude x probability
Intergovernmental Panel on Climate Change Fifth Assessment (2014), [115]	The potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values. Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk results from the interaction of vulnerability, exposure and hazard.
Aven (2013), [13]; Aven and Renn (2009), [23]	Risk is uncertainty about the occurrence and severity of an event and its consequences $$(C, U)$$

There is major confusion about the concept of risk [15]. These misconceptions exist within the professional risk analysis bodies and have propagated into misunderstandings of risk by other disciplines. This hinders the awareness of risk science knowledge and techniques by other disciplines (Chapter 7) and fosters the ill-advised divergence of fields such as “resilience analysis” that, in many cases, means the existing risk literature is ignored [20].

The conceptual definition of risk we recommend is [23]:

> Risk is uncertainty about and severity of the consequences (or outcomes) of an activity with respect to something that humans value.

This is expressed as (C, U), where C is the consequence of the activity, and U indicates that there is uncertainty. The risk can be *described* using (A', C', Q, K) where A' is the event identified, C' are the consequences, Q is the measure of uncertainty, and K is the background knowledge that informed C' and Q.

However, this definition is not widely adopted and table 1.1 presents selected definitions of risk, the first six being common in the urban planning literature. A source of confusion about risk is a failure to distinguish between the concept of risk and its measure. This is an essential distinction. This distinction is similar for the case of distance; while there are multiple measures for distance (e.g. Euclidean, Manhattan, Network etc.) the concept of distance is without controversy [15].

The confusion between the concept and its measure partially explains these definitions. The problem arises when a simple measure is used and then incorrectly described as the definition. For example, [85] defines risk as the probability of a hazard occurring. Another definition is that risk is the threat [174]. A third example is the definition that risk is expected consequence: "Risk = magnitude x probability" [96]. These contrasting definitions are in fact simple measures of risk. The problem with treating measures like these as definitions, as this literature does, is that it limits how and when risk and therefore risk science can be used.

Another major misconception of risk is based on Knight's [181] idea that risk is only relevant in situations with 'measurable' uncertainty [181, 206]. This has led to probability-based definitions of risk, such as those used by the IPCC [115]. Using a single probability or distribution to describe uncertainty can mask information about the portion of underlying knowledge that is epistemic (arising from a lack of knowledge) versus aleatory (arising from natural variations) [102, 253, 296] as well as the strength of the knowledge which supports the assigning of those probabilities [296].

It is therefore unsurprising that urban planners are experiencing challenges when they limit the concept of risk to these definitions. These definitions are clearly unsuitable for situations with uncertainty or complexity [19] and urban planners are working in situations with both.

Instead, the recommended definition, (C, U), incorporates a broader understanding of uncertainty into the concept of risk. It enables measures of risk to be include a qualitative description of uncertainty and the strength of knowledge upon which the uncertainty and consequence are based. Quantitatively or qualitatively capturing the uncertainty and strength of the knowledge supporting estimates of consequences and likelihoods of events is essential in the era of climate change given that baseline conditions are shifting and historical data is decreasingly reliable [296].

Ultimately, the recommended definition provides a general risk concept which captures both consequence and uncertainty within risk. This makes risk relevant for planners. Addressing misconceptions of risk is remains a major discussion. For example, we argue that comprehensive risk analysis captures the entire consequences, from event to post-recovery, of a hazard. This perspective means that resilience analysis [197] is included within risk analysis [20]. Urban planning should be part of the discussion as we continue to discuss and research how we measure, represent, and communicate risk.

1.2.2 Uncertainty

Uncertainty occurs when there is incomplete knowledge [253]. As we have discussed, uncertainty is an inherent part of the risk concept. If risk was only suitable for situations when an 'objective' probability distribution could be assigned, it would be useless for most situations of interest [15], including urban planning [1]. In fact, the goal of risk is to support management in situations when phenomena are not fully understood [253], that is, cases of uncertainty. The task now is to explore how to measure, represent, and communicate the uncertainty.

Uncertainty is commonly expressed using three dimensions: 1) the magnitude of uncertainty, 2) the nature of the uncertainty, and 3) the source of the uncertainty. The magnitude of uncertainty describes the severity of uncertainty from complete knowledge through to complete ignorance [1, 80, 117, 337]. The magnitude of uncertainty has been represented as a spectrum [337] and as more discrete levels [80](see Table 1.2). The nature of the uncertainty describes whether the uncertainty is epistemic or aleatory (caused by lack of knowledge or inherent variability, respectively). The source of the uncertainty refers to which aspect or quality of the system that is uncertain.

Every aspect of a system has some magnitude of uncertainty [1, 337]. Identifying the source as a dimension of uncertainty formalizes thorough consideration of each of the system's components. For example, in a model, the sources (or locations) of potential uncertainty include the input data and parameters, the structure of the model, the system's representation, and the model's output [337]. These sources and the potential magnitude of uncertainty is described in Table 1.2, which explicitly outlines levels in the uncertainty spectrum.

Table 1.2: Cox's taxonomy of uncertainties [80]

		Level 1	Level 2	Level 3	Level 4	
				Deep Uncertainty		
	Context	A clear enough future	Alternate futures (with probabilities)	A multiplicity of plausible futures	Unknown future	
	System model	A single system model	A single system model with a probabilistic parameterization	Several system models, with different structures	Unknown system model: know we don't know	
Determinism	**System outcomes**	A point estimate and confidence interval for each outcome	Several sets of point estimates and confidence intervals for the outcomes, with a probability attached to each set	A known range of outcomes	Unknown outcomes: know we don't know	**Total ignorance**
	Weights on outcomes	A single estimate of weights	Several sets of weights, with a probability attached to each set	A known range of weights	Unknown weights: know we don't know	

In urban planning, uncertainty includes environmental and planning process uncertainty [1]. Environmental uncertainty includes politics and natural events, while planning process uncertainty includes the uncertainty in decision-maker values, priorities on objectives, and levels of risk. The planner must address uncertainties at the intersection of these sources, such as resulting uncertainty on climate impacts to which a community is exposed [1, 219, 255]. This uncertainty includes both aleatory and epistemic uncertainty. However, to further complicate the uncertainty in urban planning, there are factors, such as climate change, in which the relevance of past data is questionable, and experts disagree so there is no way to establish probabilistic representations of the uncertainty that are both informative and that we can be confident in [24]. This is known as deep uncertainty [44, 80, 192].

Accounting for uncertainty, and deep uncertainty in particular, requires a change to traditional approaches to decision making. Traditionally, decisions are made based on probabilistic predictions of the future and the subsequently deduced 'optimal' course of action. In these cases, probability distributions are the most common way to represent uncertainty. Probabilistic methods offer the advantages of a strong theoretical background and long history of development of practical methods. However, in cases of deep uncertainty or when the information on which the probabilities are defined is lacking, these probabilistic methods cannot be used because the probabilistic representations either do not exist or are not credible. Instead there are two approaches from risk literature that are emerging to address the problem of probability assessment under uncertainty. The first approach is by changing the assessment from one of precise probabilities and probability distributions to either probability bounds or non-probabilistic representations of uncertainty such as fuzzy sets [117]. The second is to change the focus of the decision support framework to finding robust or adaptive [80], rather than optimal, solutions. That is, rather than conducting an uncertainty assessment followed by optimization, which can fail due to sensitivity in parameter variations [44], the aim is to find alternatives that perform well over a wide range of the possible outcome scenarios. The main examples of this approach are Robust Optimization [44, 91], Robust Decision Making (RDM) [146, 192, 295] and Info-Gap [41]. A further example of this second approach exists within the urban planning literature: scenario planning. Scenario planning is a consultative process that consists of conceiving, crafting, and evaluating possible futures [35]. Thinking about these alternative futures enables decisions to be explored [67] and so it can be used as an exploratory tool to analyze options and explore robustness [64].

Advances still need to be made. Questions remain about the appropriate use and theory of each approach in terms of search for robust or adaptive solutions for situations of deep uncertainty [146, 276, 296]. Each approach has different limitations in how risk is considered, how uncertainty is captured, how results are presented, and how stakeholders are engaged in the process. How society deals with sea level rise is but one example where adaptive or robust solutions will be useful. More generally, reflecting uncertainty in risk analysis requires thinking beyond probabilities, [117] and advances in foundational risk issues will assist planners. Further questions include how to apply the precautionary principle[3] and how to plan for unforeseen events and black swans [15] as well as how to communicate geographic uncertainty [120].

[3]The precautionary principle states that where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation [280]

1.2.3 Communication and perception

Communication and perception of risk is vital to urban planning. Risk communication has undergone significant development and there are lessons to be learned so we can avoid previous mistakes [116]. However, communicating uncertainty remains an active challenge, and geographical risk (let alone uncertainty) is substantially understudied [120]. Major research questions include how to represent uncertainty and interpret probabilities. These questions are complicated by the addition of both spatial and temporal dimensions. Who risk is communicated to is equally an important factor. Many studies provide guidance on communicating with the public, but few provide guidance for working with decision makers [120]. This is important in urban planning because local authorities and elected officials do not always have expertise in risk [96]. Another instance where uncertainty communication is not only important, but time-pressured, is crisis management. For example, action needs to be taken immediately following any hazardous event, but information is usually limited. Where supplies or response teams are to be sent (for example as described in Chapter 5) is dependent on damage extent as well as the number of people who sheltered in-place. Similarly, evacuation decisions and their timing can directly put people at risk if decisions are based on poorly suited models or without understanding the uncertainty in the assessment. Again, the compounding uncertainty needs to be presented to decision makers with varying levels of experience, training, and knowledge [96, 120].

One promising approach to improving how spatiotemporal uncertainty is communicated is using multiple scenarios [120]. By engaging a range of stakeholders to explore scenarios in a scenario-planning manner, we can communicate the spatiotemporal uncertainty. This is a viable option also for improving how deep uncertainty is both addressed and communicated. Scenario planning is already an approach common to urban planners. Thus, using it as an exercise for other stakeholders is an example of the two-way knowledge sharing possible between these disciplines.

Risk perception is also a significant factor as building the trust of the public is critical. The community needs help to understand risks due to the psychological difficulties people have in perceiving hazards. Perception has been categorized into two types of thinking: intuitive (gut) reaction and informed evaluation [223]. Ad hoc risk communication could lead to misperception of the risk faced due to how the information is framed or interpreted. The result is that people may ignore or discount the potential for disaster by assuming that defensive structures have eliminated exposure or become fatalistic [56]. Another challenge is if people inaccurately believe action is improving a situation. Disaster-driven decision making, due to high salience, can motivate action that not only does not help, but diverts attention from truly adaptive actions [9]. Such thinking is pertinent to risk perception studies and understanding what factors motivate people to judge risk as acceptable [300]. Given major decisions about avoiding future threats through adaptation, mitigation, or retreat are necessary, the study of risk communication and perception will assist urban planners.

Salience driven decision making can be maladaptive [9] and this emphasizes the need to help local authorities and elected officials, most of whom will have not expertise in risk [96] or understand the risks and uncertainties facing their communities.

1.2.4 Understanding Complex Systems

Most current risk applications involve systems or complex systems of systems [144]. Characteristic of these systems is often multiple interacting components, dynamic feedbacks, competing objectives, and varying levels of uncertainty. The interdependent systems also have the potential for cascading failures whereby a failure in one causes failures in others. An analogy for this would be a failure in the electricity network causing a failure in the transportation network. To manage and understand the risks of such systems we need advances in risk analysis [24]. We need the ability to assess a range of threats and approximate their consequences [24]. Quantifying potential consequences and their likelihoods in complex systems requires inferential, predictive, and causal models. Constructing and validating these models is complicated by limited data and so will require treatment of uncertainty and the ability to extrapolate beyond observed conditions [296]. This need for extrapolation means that we need to advance regression tools. Existing tree-based regression models have proven highly useful for predictive and inferential situations, but they have limited power to extrapolate because they can only predict values within the range of the observed values. In addition to existing regression tools, we need advances in how the models interact. Potentially, we will require interacting models such as coupled or multi-scale, so we can capture the interdependencies. These advances will need to further address the spatial and temporal aspect, establish suitable ways for validating spatially dependent models (see Chapter 3 for an example), and adequately treat uncertainty.

Naturally, urban planning is about managing complex systems [119]. These systems include cyber-physical infrastructure, natural systems, social systems, land-use systems, and the interdependencies between them all. In managing these systems, we likely will need to address multiple objectives [62, 295] and the various synergies and trade-offs that arise. Examples of questions critical to planners also include what the effects of an incoming hurricane will be, what urban characteristics exacerbate heat waves, and how urban form influences public health outcomes. Modeling of systems is not new to planners; Models have been used since the 1960s [202]. Models can provide the ability to further understand a system, perform what-if style analysis, achieve greater efficiencies, and guide smart urban development [37, 66, 148]. The types of models in use include system dynamic models, statistical models, cellular models, and agent-based models. Advances to risk science can both utilize and develop the models used in planning. Such models can further risk science advances in how we capture human behavior and how behavior acts as an adaptive response to interventions that may produce unintended consequences (e.g. [200]). Similar to terrorism risk analysis, risk treatment must account for the adaptive actions by agents [22]. In turn, risk science can contribute to improving how the complex systems models are validated and how uncertainty is treated. A fundamental challenge of modelling urban development is that the underlying processes are unobservable [106] and the uncertainties in the subprocesses can compound [90].

Issues for complex systems models include both equi- and multifinality, which means that models can fit data equally well but for the wrong reasons [232, 351]. Similar challenges arise for statistical models. Climate change is changing the baseline conditions and forcing us to extrapolate beyond observed data. How can we be confident that inferences and predictions stand when the baseline conditions have shifted? How can we extrapolate consequences beyond what has been previously observed in a reasonable way? These questions are well within the purview of risk science and motivate the engagement of risk professionals in addressing them.

1.2.5 Societal decision making and co-production

The essence of the interface between urban planning and risk science is in providing support for risk-informed decision making. Risk assessment itself is intended to support management and policy decisions without necessarily having a comprehensive understanding of the system and phenomena [253]. Understanding societal risk decision making is a foundation of risk science [24]. It requires integrating considerations of science, economics, society, and value judgements [24]. Societal decision making dictates that people are affected by decisions, and therefore people should be put at the center of risk considerations (e.g. [100, 213, 227], Chapter 5).

When planning our cities we need to move beyond predict and plan models and embrace adaptive or robust management approaches [147, 267, 310]. Ranking risk reduction alternatives will require assessing the risk of maladaptation, making ethical judgements, and evaluating multiple criteria. Advances in using modeling for policy currently underway include improvements to participatory decision making [329]. Furthermore, issues regarding model credibility are being addressed [192]. Ultimately, due to environmental, population, and demographic shifts, designing our cities to adapt to and mitigate climate change and hazards is underlined by a growing sense of urgency. To further support potential action, research priority must shift from "what are the relationships" to "what can we do, given the current information."

This urgency also motivates the undertaking of these challenges in a manner that is inclusive and collaborative. Collaboration provides opportunities for risk professionals to test and improve methods for communicating risk, understanding perceptions, and identifying threats. Working in interdisciplinary teams, in addition to enabling high impact problems to be addressed, forces us as risk scientists to sharpen our language and understanding of the terminology. Challenges for such collaboration include the lack of a shared knowledge base, different success measures or objectives, and unfamiliar or conflicting terminology. Tools that assist with interdisciplinary research are being proposed such as agent-based models [273]. But education and training should be the first step. Whether within courses, degree structure, or through ongoing professional development, risk professionals need to learn how to collaborate beyond their familiar discipline. Additionally, we can work with urban planners to engage stakeholders and foster co-production of knowledge within communities. Co-production of knowledge occurs when research questions are jointly identified and then addressed with end-users [265]. These initiatives provide opportunities for foundational risk advances by providing case studies, data, and focus groups which allow us to build approaches that are relevant for a range of hazards from natural to behavioral and how we treat uncertainty and communicate risk can be iterated upon. These cases will also offer situations of varying limitations in which levels of uncertainty treatment, risk measures, or communication techniques are appropriate. Co-production is also highly beneficial for improving our understanding of the system as we integrate perspectives and insights from people with knowledge of the systems we seek to assess and these insights can strengthen threat and uncertainty evaluation. However, while there is the potential to use these cases to test and evaluate techniques, we must be highly aware of potential ethical challenges.

1.2.6 Ethics

In the context of urban planning, where people's quality of life, livelihoods, and lives are impacted by the decisions made the handling of risk issues carries substantial ethical weight. However, it is surprising that ethical consideration has not been identified as a foundation of risk science to date given that risk science is comprised of both theory and practice [21]. It is also surprising that 'ethical aspects' is only briefly mentioned as a sub-sub-topic in the Society of Risk Analysis' "Core Subjects of Risk Analysis" guidelines [305]. In today's atmosphere of mistrust in science and the quandary of environmental degradation and growing societal inequality, ethical aspects should be a pillar of risk science.

Key dimensions needing ethical consideration at the interface of urban planning and risk science include how we advocate new technology, how we address the potential of maladaptation, what we choose to measure, and how we reduce (or at least do not exacerbate) inequity.

Integrating risk and resilience analysis into urban planning practices will involve working with practitioners of varying levels of training in statistics and these sciences. Therefore, how the accuracy of models and the situations for appropriate use need to be communicated clearly. This cannot be a case of "what the customer thinks they have and what the product actually is." Communicating the uncertainty and the limitations of the technologies is important, as practitioners need to know when to rely rely on existing practice rather than the models. The onus is on us to demonstrate that our models improve decision making compared to existing practice. For example, misrepresented claims of accuracy could lead emergency responders to take different actions and result in worse outcomes. Consider a manager responding to a flood model that erroneously declares or delays a declaration to evacuate. The evacuation of Hurricane Rita, for example, killed 107 people as they evacuated the Houston area, only for the hurricane to veer far east of the city [159]. Misrepresenting accuracy is not necessarily intentional. It could result from the model being used beyond what it was designed for, such as under different environmental conditions, in different locations, or for different events. The range of potential consequences from new methods cannot easily be predicted in this case as it is an example of the Collingridge Dilemma, which states that impacts cannot be easily assessed until a technology is widely used, but by that point the technology is not easily regulated [75]. However, it is the responsibility of the risk professional to determine the potential pitfalls of methods they advocate.

Maladaptation is another risk that we must be aware of when working in the planning space. Maladaptation results when an intervention intended to reduce vulnerability actually increased it [32, 208]. For example, a seawall intended to protect one community may cause major issues to neighboring communities [28]. Additionally, that seawall may have raise the exposure of the future residents of the very community it was built to protect (Chapter 2, [56, 200]) and divert attention from measures that would be more effective [9]. This could be the result of missing factors in the model that, given the characteristics of complex adaptive systems, could reverse the effect of an intervention. It stresses the importance of collaboration with professional in other disciplines who may be aware of such potential.

There is also the potential for approaches to exacerbate social injustices. The risks relate to both how we measure and model phenomena and how we communicate and act on the results. What we choose to measure and how we choose to measure it matters [193]. For example, consider recent resilience indicators such as the disaster resilience of place (DROP) model [87]; if a firm were to select a location based on the perceived resilience of a town and the indicator used included a negative attribution for low-income people or people of color, that would divert that firm's investment away from this town that could benefit from such an investment. Similarly, if an important dimension is not included, positive investment and attention may be diverted away from people in need [193].

How we use and communicate understanding of risk to land can also have a major effect on social justice. Informing residents of the risks could lead to house prices in at-risk areas decreasing so that low-income and vulnerable people move in. Another example is in New Zealand where insurance companies recently adopted spatially heterogeneous risk-based pricing [68]. This suddenly changed the amount customers had to pay while the insurance companies saw little-to-no loss. As before, the result could be that low-income families move into these areas for the cheaper capital cost but cannot afford insurance, further exacerbating their vulnerability. Risk professionals need to be aware of and actively look for the potential pathways that exacerbate social injustice. Their awareness means that they can work with city officials to adopt standards and initiatives that increase equity and support vulnerable people [133].

To ensure we do not fail the communities we are trying to assist, risk professionals need to be educated in ethics. Education must be more than existing training that often simply repeats tenants such as 'do not cheat.' Instead, ethics education must involve complex discussion and explore how ethical decisions are influenced by perspectives and values. Risk professionals must be trained to identify ethical challenges in complex situations, empowered to raise the issues they identify in their research or with communities or companies they work with, and guided in how to engage in the resulting discussions. I urge that ethics be considered a foundation of risk science and a core component of a risk professional's education.

1.3 Dissertation outline

This dissertation is structured as follows. Chapters 1-5 are structured as independent academic papers. This first chapter intends to introduce the opportunities to advancing foundational risk science through collaboration with urban planning.

Chapter 2 [200] explores risk analysis over time and with feed backs from human behavior. The chapter was motivated by the Japanese tsunami in 2011 and the subsequent questions as to whether sea walls, a type of hard-adaptive measure, increased or reduced the community's vulnerability. Addressing this question required building a complex systems model that incorporated the growth of a town, the repeatable hazard, and the community's response to alternative sea walls. This links the community's risk perception with the spatiotemporal changes in the community due to a repeatable hazard. By demonstrating that the community's vulnerability to unexpected hazards in fact increases with large seawalls, this study provides quantitative evidence of the safe development paradox, [56], as well as emphasizes the importance of considering dynamic feed backs in risk analysis.

Chapter 3 demonstrates the potential of machine learning in understanding how urban form affects risk. In this case, I explore how land surface temperature is associated with different urban characteristics. In doing so, I present how cross-validation should be undertaken in a spatial setting, then, represent both the data and model uncertainty present in the diagrams representing the urban characteristics' influences.

I then present two closely related paper on community resilience: Chapters 4 and 5. The objective here is to propose an operational approach to building community resilience. In our framework, we consider people's access to essential services as opposed to existing approaches, which focus on indicators of community capicity or infrastructure network measurements to measure robustness and vulnerability. For a community to function, people need access to services such as food, health care, education, and culture. For a community to build cohesion and social sustainability, this access needs to be equitable. Chapter 4 therefore proposes a modern approach to measuring access to services that leverages open data and computational power. The benefits of this approach are that it is fine resolution and therefore can identify vulnerable populations that existing measurement approaches may overlook. This measurement approach is then used in Chapter 5. Here we show how the access to different services changes over the duration of a hazard. In this chapter, we use real data from Hurricanes Florence and Michael. The output of this approach is a map to assist with identifying residents without access to each of the services and statistical representations showing the percentage of the population with inadequate access. Outputs such as these could be used by emergency responders or resilience planners before, during, and after hazards to prepare, respond, and transform communities.

I end with a proposed framework of how to resilience can be managed within using a risk framework 7. The many definitions of resilience have complicated management to reduce the consequences from a hazard, so I demonstrate how these aspects fit within the risk concept. In this chapter, I also expand on how the confusion surrounding the terminology of risk has infiltrated other disciplines, resulting in the unfortunate divergence of resilience analysis.

1.4 Conclusion

Risk science offers significant promise for tackling societal challenges, including those related to urban planning and climate adaptation. To realize these opportunities, we require a fundamental shift in thinking about risk and how we, as risk professionals, communicate it. Putting the concept of risk into practice to address these challenges motivates foundational advances in nearly every sub-discipline of risk science and calls for increased collaboration between these sub-disciplines as well as with fields beyond our own.

I hope that my thesis further steps towards that shift in thinking and will inspire further theoretical and practical advances. The challenges at the intersection of risk and urban planning require your urgent attention.

Chapter 2

Hard-Adaptive Measures and Maladaptation [4]

Whether hard-adaptive measures (e.g. seawalls) actually reduce vulnerability to natural hazards is the subject of considerable debate. Existing quantitative risk assessments often ignore behavioral feed backs that some claim lead to increased development in hazardous zones. Here, we couple a tsunami model with a land-use change model and find that hard-adaptive measures can induce a false sense of security and inadvertently lead to increased vulnerability (i.e. are maladaptive). We also observe that heightened hazard awareness (a type of soft-adaptation) can reduce vulnerability. Our results have two major implications:

1. they challenge existing hazard adaptation practice by quantitatively demonstrating the potential for hard-adaptive measures to be maladaptive; and

2. they highlight that ignoring the behavioral feed backs in hazard assessment can alter the conclusions to the extent that they fail to identify maladaptive actions.

In addition to the demonstrated case of tsunamis, the result may be relevant to other, repeatable natural hazards where urban growth influences exposure (e.g. storm surge). Ultimately, neglecting future urban development and the temporal evolution of risk can result in incorrect conclusions regarding adaptation strategies; including these processes is therefore an essential consideration for the natural hazard and climate change impact communities.

[4] Logan, T. M., Guikema, S. D., & Bricker, J. D. (2018). Hard-adaptive measures can increase vulnerability to storm surge and tsunami hazards over time. *Nature Sustainability*, 1(9), 526–530.

2.1 Background

There remains considerable debate about the efficacy of hard-adaptive measures, such as seawalls, at reducing the vulnerability of coastal communities to natural events [114, 225, 245, 319]. A limitation of existing analyses [4, 225, 230, 353] is the omission of the interdependent evolution of urban growth in response to hazards and the adaptive measures implemented [3, 250, 353]. Adaptive measures influence behavior by changing risk perception, which can affect how land-use changes over time [235]. Adaptive measures are classed as either hard infrastructure, such as seawalls, and soft* measures, such as community education [308]. While some claim that hard-adaptive measures are effective [225], others argue that they provide a false sense of security and encourage vulnerable development [56, 77, 97, 208, 245]. This phenomenon can lead to maladaptation [32, 208], whereby protective structures prevent small events and so encourage development that is then exposed to large events [222] (e.g. simply rebuilding the levees in New Orleans [77]). This is known as the safe development paradox [56], or the levee effect [97, 344]. Maladaptation occurs when actions unintentionally increase the vulnerability of a community. Adaptive measures may mitigate low impact hazards that are relatively frequent, causing hazardous areas to be perceived safe. This can result in development that is vulnerable to larger events in future [56, 97]. Nevertheless, hard-defensive structures are being built and re-built (e.g. following the 2011 Japan tsunami [319] and Hurricane Katrina [77]). We combine the physical effects of adaptive measures with consequent community behavior to quantitatively explore how, over time, the vulnerability of a simulated community is affected by hard vs soft adaptive measures. Because hazards are inherently location-specific we analyze simulated tsunami impacts in Taro, Japan, which has experienced four tsunamis in the past 120 years.

While quantitative studies exist, many avoid the question of interaction among hazards, behavior, and learning over time [225, 334]. When the interaction between adaptive measures and community behavior is excluded, co-evolution is ignored [250, 299], making projections of risk potentially unrealistic [97]. For example, the behavior of the community may change with the installation of a protective measure because of their altered perception of the risk. Other previous studies have also excluded spatial heterogeneity in development over time (that changes may occur unevenly across a space [97]), and so overlook potentially significant differences within communities due to the topography. Existing statistical studies have conflicting conclusions, demonstrating their sensitivity to data from previous events [6, 230]. Continued planning based on historical events, without understanding of the processes, may lead to ad hoc adaptation, like the repeated levee upgrades which have occurred in New Orleans, USA and Palmerston North, New Zealand [235].

2.2 Coupling hazard and land-use change models

To better understand maladaptation from adaptive measures, we ask:

1. How do hard-adaptive measures affect the vulnerability of a community over time when subject to repeated hazards?
2. Do hard-adaptive measures increase vulnerability to future events (e.g. the levee effect)?
3. What is the effect of information-based soft-adaptive measures on vulnerability and do we observe community adaptation that decreases vulnerability?

To address these questions, we develop a cellular automaton (CA) simulation to model land-use change and couple this with a hydrodynamic model for tsunamis. CAs are frequently used to model land-use change [36, 334, 346]. The CA represents the region as a grid of cells and the state of each cell changes with time based on transition rules or destruction by a tsunami.

We quantify vulnerability using a measure from the Society of Risk Analysis [306]: A probability distribution for the loss given the occurrence of a specific event. This measure captures two of the key dimensions of vulnerability [48, 323], exposure and hazard, although does not include the socio-economic dimension such as the resident's age, income, or other characteristics. The hazard in this study is a tsunami. Over the course of the simulations, different tsunamis with varying magnitudes may impact the community. Exposure is a measure of assets that are within a hazard's geographic extent [48]. In this case, we approximate vulnerability as the sum of the likelihood of development multiplied by the probability of damage for each cell. The damage probability is computed from a fragility curve [312] based on the inundation depth at the land cell for a given tsunami (Section §4). Therefore, we are representing vulnerability as the number, or percentage, of damaged land cells.

Our model is developed for Taro, Japan. Taro has been impacted by four tsunamis since 1896 [224]. We simulate 300 years of urban growth, initialized with the 1900 land-use map [316]. Development is influenced by regional population change and the transition potential of a cell [346]. Among other factors, a cell's transition potential is influenced by hazard awareness, dependent on the time since the last tsunami inundation. This awareness decays with time [110]. Tsunami occurrence and intensity are drawn from independent distributions. The damage caused by a tsunami is approximated using a fragility curve for wooden buildings developed for this region following the 2011 tsunami [312]. Model and parameter details, sensitivity analysis results, and model validation results are included in the supplemental material.

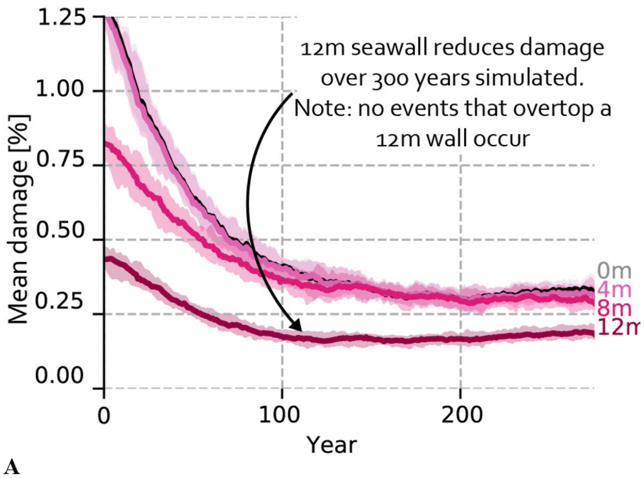
2.3 Expected events: Hard-adaptive measures reduce vulnerability

To address our first question (how hard-adaptive measures affect vulnerability over time given repeated hazards), we simulate the community with a range of seawall heights that are fixed for each simulation's duration. For each time step (year) across the simulations the mean damage from tsunami is calculated to represent vulnerability. Damage in each time step is normalized by the total number of developed cells, to allow for comparison over time. A 25-year moving-average of the mean damage is calculated due to the infrequency of damaging events. Previous statistical analysis found that larger seawalls reduced damage in northeast Japan [230]. This is supported by the simulation model (Figure 2.1A), provided the tsunami height does not exceed the seawall height. Damage is initially high and decreases as the community adapts. While there is little difference in vulnerability with no seawall, a 4m, and an 8m seawall, the 12m seawall reduces vulnerability.

This result indicates that large hard-adaptive measures reduce damage, and reinforce similar conclusions, provided the tsunami height does not exceed the capacity of the protective measure. However, the development trends resulting from the high seawall indicate dense development behind the seawall, an area historically within tsunami inundation zones (Figure 2.1B). This potentially increases the vulnerability to larger events in future (i.e. the levee effect). The primary difference between the 12 m seawall and the smaller heights simulated is that none of the tsunami scenarios substantially over top the 12 m seawall. Any claim that the 12 m seawall (or any hard-adaptive measure) protects the community is therefore sensitive to the hazard magnitudes experienced.

2.4 Unexpected events: Need for capturing the feed backs

The levee effect is caused by hard-adaptive measures mitigating the impact of frequent events, thus encouraging development potentially vulnerable to future events [97]. Understanding vulnerability to unanticipated, extreme events [56, 97, 114], aka "black swans" [13], is essential



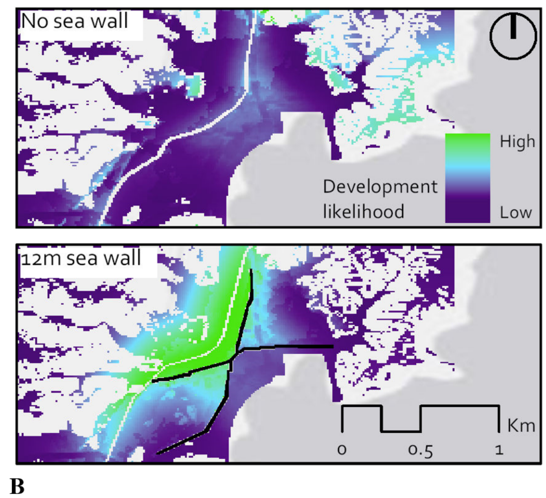


Figure 2.1: The result of seawalls on mean (average) damage and development patterns. Damage approximates vulnerability. It is calculated as the sum of the likelihood of development multiplied by the probability of damage for each cell. The damage probability is computed from a fragility curve based on the inundation depth at the land cell for a given tsunami. In (A) the 25-year moving average of damage is reduced when a 12 m seawall is present. Here, damage is the number of developed cells destroyed by a tsunami, normalized by the number of developed cells. The lines, with 5th and 90th percentiles, represent the four different fixed seawall heights. The 0 m seawall line, shown in black, is almost indistinguishable from the 4 m line. (B) shows the likelihood of a cell being developed and demonstrates how development patterns are influenced by seawalls.

due to the incomplete historical record of natural events, and given how global environmental change, such as sea level rise, may change the severity of these events. Tsunamis, while not climate-induced [149], may have their impact exacerbated by sea level rise. To investigate vulnerability to unanticipated extreme events, we examine the effect on the community if it experienced a tsunami larger than any in the historical record; such an event is considered a type III black swan [16] given it is known to be possible but judged to be extremely unlikely to occur. Vulnerability, as described, is measured as the sum of the likelihood of development multiplied by the damage probability for each cell. Figure 2.2A shows the future vulnerability of the community with different size seawalls to tsunamis of different heights. The 13.2 m and 15.0 m tsunamis exceed those in the simulated "historical" record experienced by the communities. This allows us to assess the vulnerability to potential unanticipated events. Figure 2.2A demonstrates that maladaptation is occurring; while the 12 m seawall protected the community initially, it increased vulnerability to larger events. The distributions for expected losses in Figure 2.2A are substantially higher for the 12 m seawall than for the other seawall heights for the larger tsunamis. The communities with lower, or no, seawalls adapted their development pattern over time to avoid areas subsequently inundated by the larger events. This shows hard-adaptive structures preventing the community from learning from tsunami experience, reducing their ability to adapt. This is a quantitative demonstration of the levee effect.

2.5 Community awareness

In contrast to the levee effect, the adaptation effect is the theory that vulnerability decreases when the frequency of natural hazards increases [97]. We evaluate this theory by varying the frequency of tsunamis for a community with no seawall (Figure 2.2B). The frequency is varied between an average of zero to six tsunamis during a 100-year period. Our results indicate the adaptation effect is occurring, suggesting that the frequent events provide more opportunities for the community to learn and adapt.

We explore using heightened hazard awareness (a soft-adaptive measure such as community education or signs showing previous inundation levels) to leverage the adaptation effect to reduce vulnerability. The adaptation effect is a result of risk perception, and this awareness can cause aversion to hazard-prone development [235]. However, awareness of a hazard fades over time as the generation with direct experience age or move away, followed by the subsequent generation with secondhand experience [110]. Investment in education and evacuation training

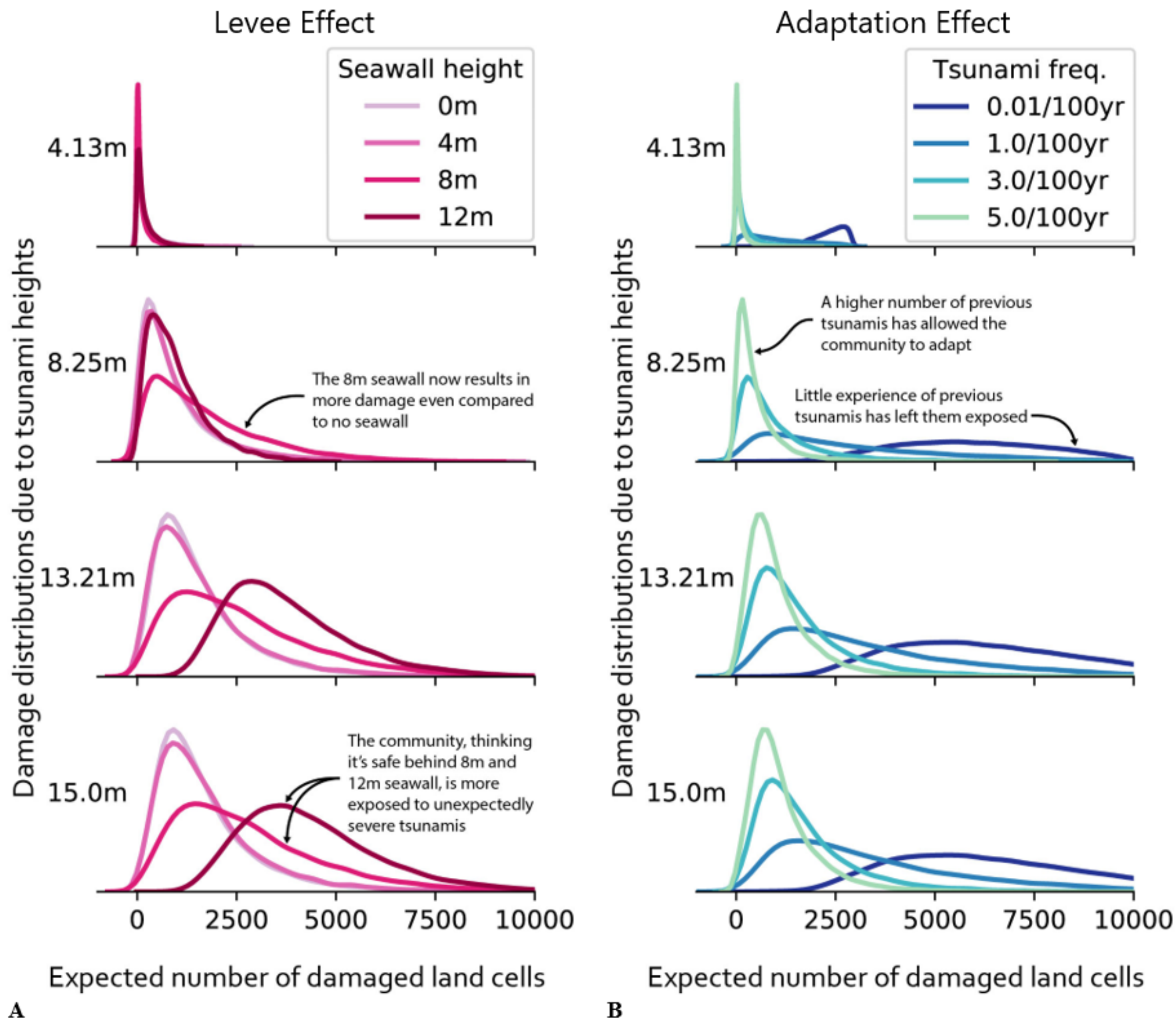


Figure 2.2: The density functions (distributions) for number of damaged land cells given a tsunami to during the final 100 years of the simulation. In contrast to Figure 2.1A, where 10.66 m was the largest possible tsunami, here two larger tsunamis are tested. (A) demonstrates the levee effect: high seawalls result in greater damage to events which the community has no experience of. (B) demonstrates the adaptation effect: more frequent hazards reduce the vulnerability of the community (note this is when no seawall is present).

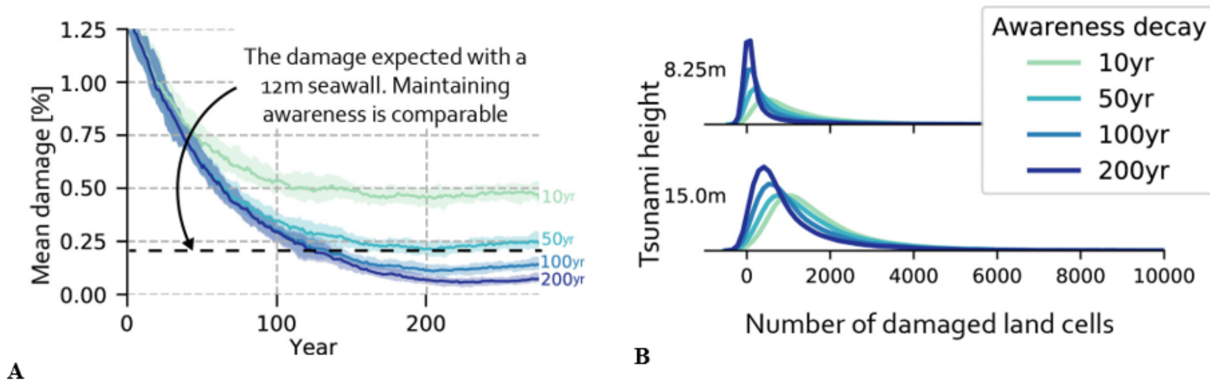


Figure 2.3: Increasing the time that the community remains aware of the hazard (A) reduces the damage comparable to a 12 m seawall and (B) does not result in increased vulnerability to large events. Note the seawall height is 0m in these simulations. See section S11 for the results with a 12 m seawall, where the larger tsunami does significantly more damage.

is one way to maintain awareness [110]. We simulate how vulnerability changes over time when the awareness decay rate, given by the generation length, is varied (Figure 3). The results show that long-term awareness of the hazard can achieve vulnerability reductions comparable to the largest hard-adaptive measure. Note, however, that the effect of hazard events on awareness is complex and can be site and hazard specific [122]. Furthermore, experience alone may not be sufficient to elicit adaptive responses [122], so further analysis is required.

The levee and adaptation effects are both the result of hazard awareness. The levee effect occurs where hard-adaptive measures confuse perceptions of risk. The adaptation effect is where risk perception is heightened due to frequent exposure. This means that hard and soft adaptive measures may not be synergistic. Although coupling heightened hazard awareness with large hard-adaptive measures results in reduced vulnerability over time, hard-adaptive measures still increase vulnerability to previously unexperienced events (supplemental section §10). This is because the seawall prevents smaller events, meaning that awareness and aversion to the hazard zone does not occur.

2.6 Conclusions

By modeling the dynamics between urban growth, repeated hazards, and adaptive measures, we have shown that hard-adaptive measures may inadvertently increase vulnerability to extreme coastal events. While short-term vulnerability to hazards, such as tsunamis, can be reduced using hard-adaptive measures, these hard-measures can cause a false sense of security (known as the levee effect) and encourage development that is vulnerable in the long-term. We also find that raising community awareness can reduce vulnerability without risk of maladaptation. This study limits its assessment to efficacy of adaptation measures and does not consider benefit-cost efficiency, which are often used to justify protective schemes [255, 301]. Through simulation, our results show the need for capturing the behavioral and spatiotemporal dynamics when assessing natural hazard and climate adaptation strategies. Furthermore, these results demonstrate, in the case of tsunamis, that not doing so can be maladaptive.

Chapter 3

Data mining and urban land surface temperature [5]

Abstract

Heat waves are among the deadliest natural hazards and are expected to increase in frequency and severity under climate change. Their impacts in cities can be exacerbated by the urban heat island (UHI), but the mechanisms that underlie severity and timing of the UHI and its interactions with heat waves are poorly understood. Understanding these mechanisms is necessary to design strategies that reduce land surface temperature and mitigate the effect of heat waves. Making use of recently available high-resolution day and night thermal satellite imagery and employing advanced nonlinear statistical models, we seek to answer the question *"What is the influence and relative importance of urban characteristics on land surface temperature, during both the day and night?"* To answer this question, we analyze urban land surface temperature in four cities across the United States. In our analysis, we include variables related to vegetation, water, the built-environment, and topography. We model the effects of these variables using nonlinear statistical methods which allow for their independent effects to be assessed. The effects from the daytime and nighttime analysis are compared to determine if previously reported relationships hold between cities and during both the day and night. Our results suggest that vegetation and impervious surfaces are the most important urban characteristics associated with land surface temperature. Increasing and decreasing these, respectively, is necessary for reducing high urban temperatures during both night and day. Our results also demonstrate the potential for

[5] Submitted to *Remote Sensing of Environment* as Logan, T, Zaitchik, B, Guikema, S, & Nisbet, A. Night and day: What is the influence and relative importance of urban characteristics on land surface temperature?

using nonlinear statistical analysis to investigate land surface temperature and its relationships with urban characteristics. For example, we can evaluate the compounding influence of two urban characteristics on the temperature. Improved understanding of these relationships influencing both night and day land surface temperature will assist planners undertaking climate change adaptation and heat wave mitigation.

3.1 Introduction

In a warming world, understanding the factors contributing to high land surface temperature (LST) and the urban heat island (UHI) will aid in adapting cities in mitigating urban heat for the health and wellbeing of their communities. And mitigate they must; the 1995 Chicago heat wave, which killed more than 700 people,[6] is expected to become an annual occurrence by 2080 [180]. Heat waves' effect on people is exacerbated by the urban heat island (UHI) [104, 347]. The UHI is understood to be a product of multiple factors including: enhanced absorption of solar radiation, geometric effects that limit radiative cooling and ventilation, anthropogenic heat from vehicles and buildings, air pollution that traps outgoing radiation, high ratios between sensible and latent heat flux due to low vegetation cover and high impervious land cover, and the radiative characteristics of building materials. The result is increased diurnal and nocturnal temperatures that reduce people's ability to cool off, especially during the night, which drives an increase in mortality [104, 226].

Studies of urban heat include analyses of air temperature, which is a conventional meteorological variable that is often associated with health outcomes(e.g. [288]), and studies that use satellite-derived land surface temperature (LST) [167, 260, 261, 333, 363]. LST correlates with air temperature at large scales, but there are differences at intra-urban scales [134]. While LST is not a conventional meteorological variable, it is directly related to the urban heat budget and has the advantage of being available with extensive spatial coverage in gridded satellite products [164]. We analyze LST in this study.

Most existing LST studies focus on the daytime [70, 260, 339, 362]. However, the mechanisms and urban characteristics driving LST allegedly differ between night and day [69, 104, 164, 236, 261, 304, 347, 361, 363]. Given that UHI is primarily a nocturnal phenomena, the lack of study on nighttime LST leaves a critical gap in our understanding. This can now be addressed as high resolution nighttime satellite images have become available.

[6] The 2003 European heatwave killed 70,000 [277] and the 2015 European heat wave increased mortality up to 30% [331]

Most existing studies that have analyzed LST, particularly nighttime LST, have used low-resolution imagery, making it challenging to deduce a clear understanding of the influence and relative importance of the associated urban characteristics [69, 104, 347, 363]. Additionally, these studies can be enhanced by: 1) studying multiple regions, 2) considering 2D and 3D urban characteristics, 3) diversifying their statistical models and relaxing their linear assumption, 4) rigorously testing and validating their models. The data availability has limited previous nocturnal studies, meaning that many rely on MODIS images with a 1km resolution [104, 261, 338, 363]. 1km resolution makes it difficult to attribute LST to urban characteristics. However, 100m resolution LandSat8 (L8) night scenes have recently become available. Due to the wide spatial availability of L8 imagery, comparative studies between cities that are necessary to understand the generalizability of findings [164, 261], can now be conducted for day and night.

Existing studies have also been criticized for the explanatory variables they've used [69, 260]. There is ongoing disagreement regarding the importance of 3D (e.g. building height) vs 2D (such as albedo) variables. Competing studies suggest that 3D factors are not important [42], while others find that ignoring 3D incorrectly conflates the effect of different 2D variables [69]. Beyond the 2D or 3D debate, important variables include green space, water bodies, albedo, and socio-economic factors [260]. However, many studies do not capture these categories and many analyze only the single effect of each variable [220, 325, 361] (see [69, 260] for further discussion). Considering a variable in isolation, without accounting for potential conflating by other variables, limits the understanding of the interdependent effects that exist.

The third potential enhancement is in the statistical models. Almost all studies use linear techniques (e.g. [69, 70, 104, 195, 260, 261, 338, 339, 347, 363]. Using linear models incurs a number of major challenges that limit these studies' ability to explain the interdependencies between variables. The first is that many of the urban characteristics exhibit high multicollinearity [363]. The second is that linear models are limited in their ability to quantify the independent effects of characteristics and their relative influence on LST [260, 363].

Finally, most existing studies do not rigorously validate their models. The approach they use to assess their accuracy is in-sample validation. In-sample validation means that model accuracy is assessed with the same data used in the training, rather than unseen data. This risks overestimating the accuracy of their models.

The question we address is: *"What is the influence and relative importance of urban characteristics on land surface temperature, during both the day and night?"* To achieve this we conduct a comparative study of four cities in the United States using nonlinear statistical techniques which capture the interdependencies and relative importance between the urban characteristics. In addressing our question, we will address the, at times fundamental, limitations of existing studies. We look at nighttime temperature as well as daytime, we appropriately validate our statistical models, and we use tools that allow us to explore the interdependent, nonlinear, effects of urban characteristics on urban heat. While we do not claim causality, understanding the associations between urban characteristics on temperatures can complement and further inform our understanding of the processes that lead to high urban land surface temperature. The results therefore have implications for mitigating the severity of future heat waves.

3.2 Data and Methods

3.2.1 Cities studied

We study four cities in the contiguous United States (Figure 3.1): Baltimore, MD; Detroit, MI; Phoenix, AZ; and Portland, OR. These four cities were selected as they include East and West coast cities, a mid-western city, and an arid central city. Phoenix, additionally, has been the subject of numerous other studies on land surface temperature. The cities were also selected due to lidar availability which is required for calculating the 3D variables. The constraint on selecting more cities was the time and computational requirements primarily for the LST and sky view factor calculations.

Figure 3.1 shows the 500m gridded nighttime LST data for each of the cities and Figure 3.2 shows the distribution of each city's 100m resolution day and night land surface temperature.

3.2.2 Land surface temperature

We calculate land surface temperature using Landsat 8 (Land Processes Distributed Active Archive Center product) imagery, land cover data, and an air temperature observation (data sources provided in B.1). Our code is available on our Github[7] repository, and is as follows: We convert Band-10 digital-number data to top-of-atmosphere radiance [171]. We correct for emissivity using land cover data [8], and then calculate the at-satellite brightness temperature [171]. Finally, an atmospheric correction is made as per the mono-window algorithm [266] using the maximum observed temperature of the day from a nearby weather station. This follows the process is described in [288].

[7] URL redacted for review

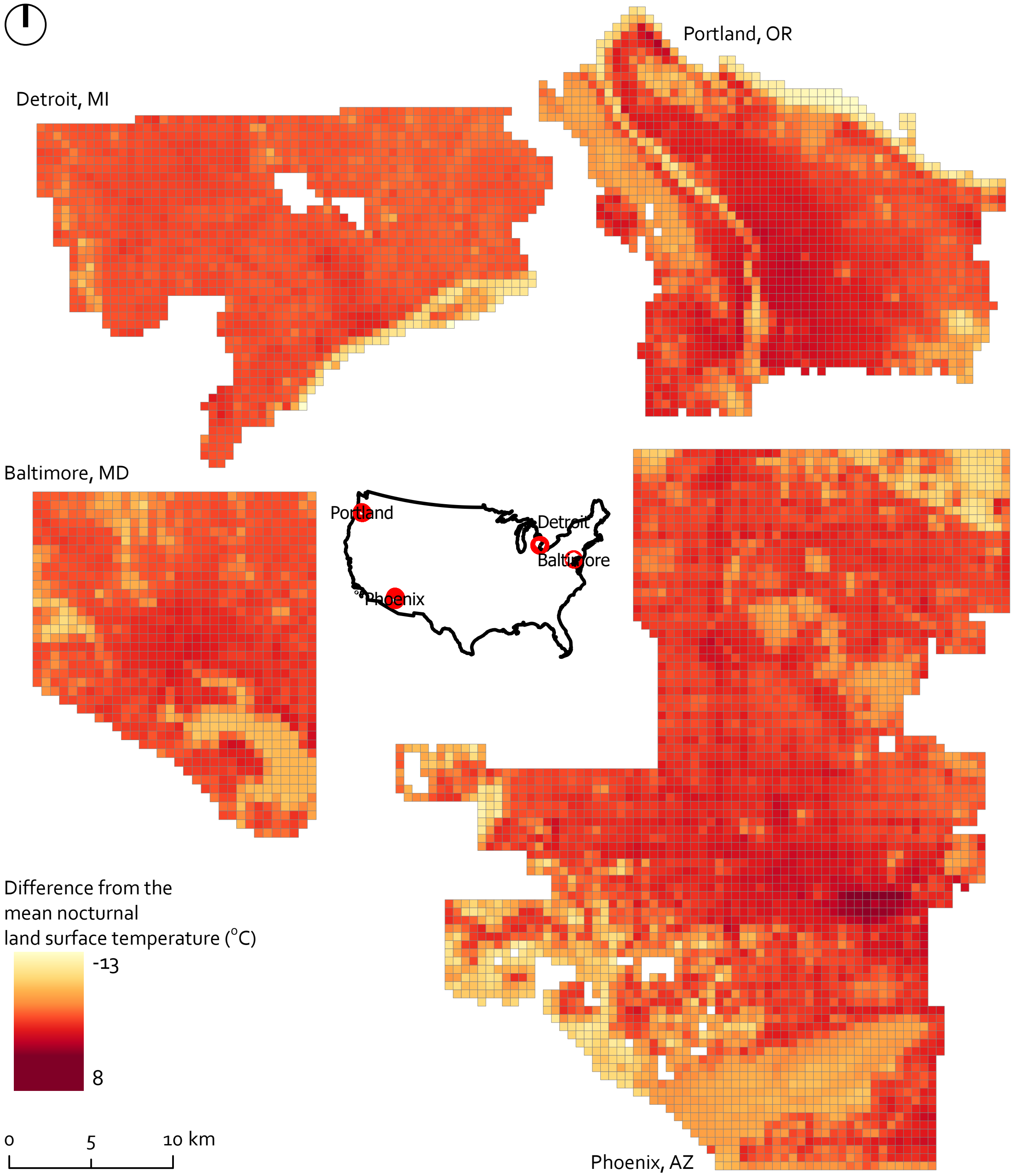


Figure 3.1: The nighttime land surface temperature in ^{o}C, gridded into 500-meter cells, for the cities studied. This is change from the mean (average) for each city.

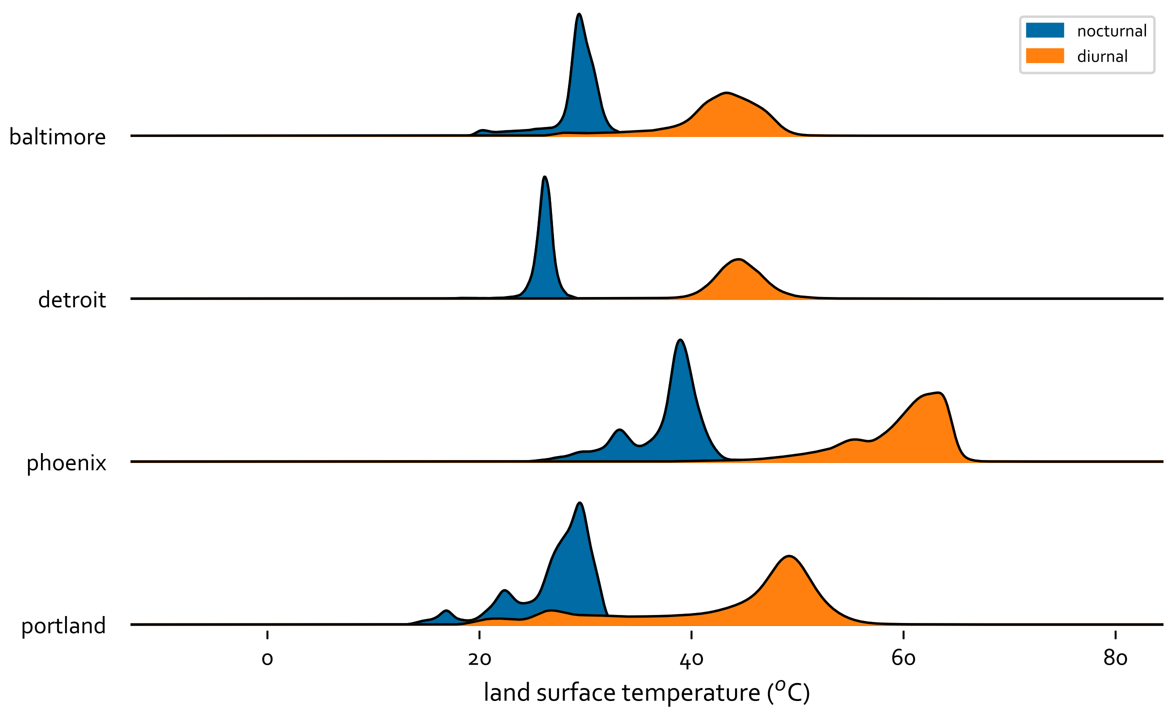


Figure 3.2: The distribution of nocturnal and diurnal land surface temperature of the cities studied. 100m resolution.

To ameliorate the effect of ephemeral changes [362] we use at least three minimal-cloud images for each city and night/day period and calculate the mean of LST.

So we can conduct the comparative study between the cities, the land surface temperature for each city is calculated as the difference from the city's mean.

3.2.3 Independent variables

Albedo. Albedo is a measure of the reflectivity or brightness of a surface. It is normalized between 0-100 where the darker surfaces are lower values. Albedo is calculated using the LandSat8 images using the algorithm described in [196, 303].

Building floor area. The building floor area within the cell. This uses data released in 2018 by Microsoft where building footprints are estimated using areal images.

Elevation. 1/3 arc-second (10m) bare-earth elevation (topography) data is available courtesy the U.S. Geological Survey.

Surface elevation. The surface elevation is determined from the lidar data. Surface elevation captures the natural and built features.

Impervious surface percentage. This is provided in the National Land Cover Database from the Multi-Resolution Land Charasteristic Consortium [357]. To generate the impervious surface area (ISA), the consortium uses LandSat data, NLCD land cover, and nighttime light imagery. The stable nighttime light intensity is only used to estimate the boundary of urban areas. The Landsat images were converted to top-of-atmosphere reflectance. The data is provided at a 30m resolution.

Land cover. Classification of land cover is described in [158]. However, as it is used in the calculation of emissivity when calculating the LST it cannot be used as an independent variable. The only landcover that we use is category 11, water.

NDBI. Normalized difference built-up index indicates the intensity of imperviousness [45]. It is calculated from satellite images as

$$NDBI = \frac{B_{SWIR} - B_{NIR}}{B_{SWIR} + B_{NIR}}$$

where B_{NIR} and B_{SWIR} are the reflectances in the near-infrared and short-wave infrared bands respectively [7]. Using LandSat8 imagery, this is

$$NDBI = \frac{B6 - B5}{B6 + B5}$$

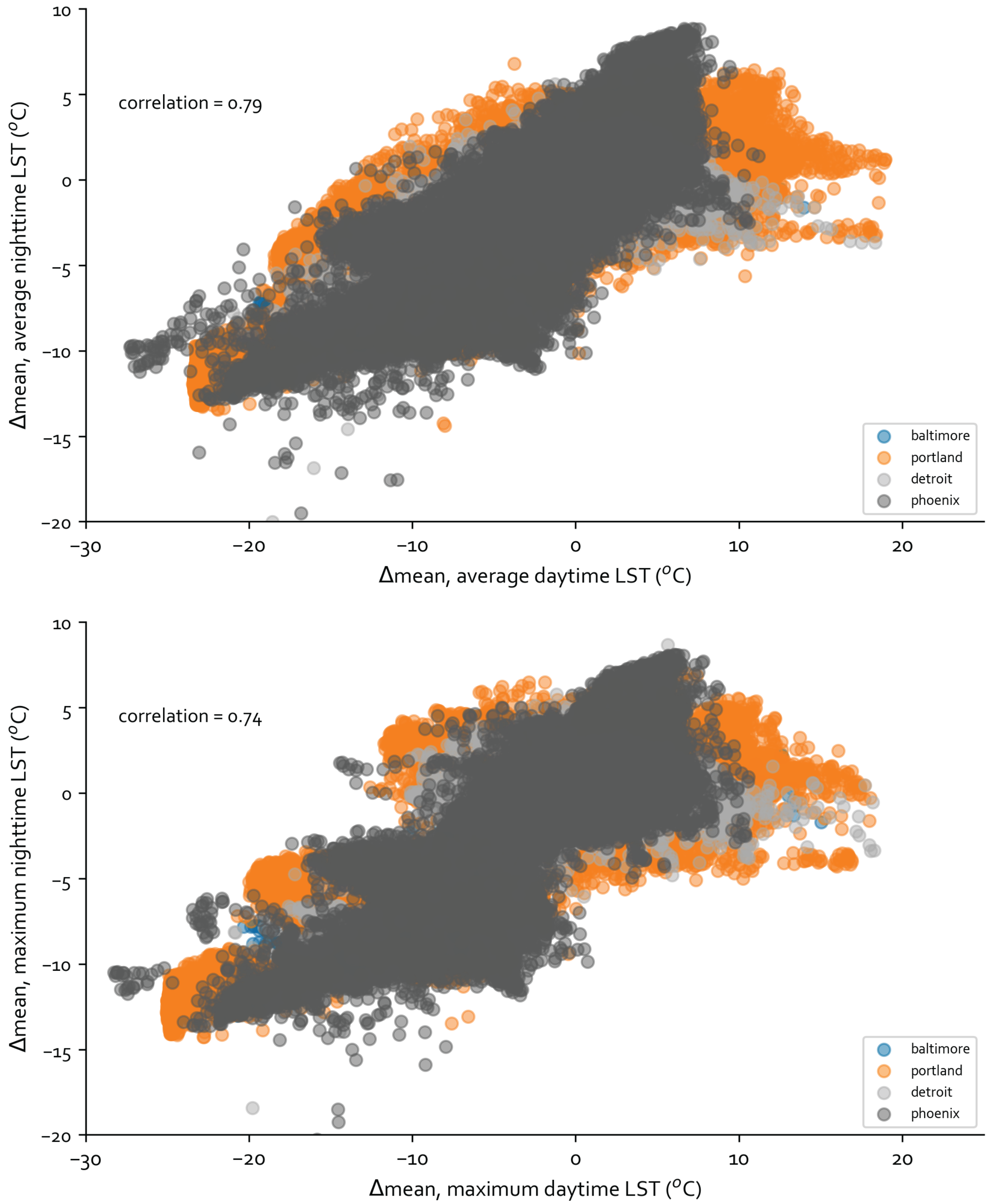


Figure 3.3: The land surface temperature in ^oC of the cities studied at a 100m square resolution.

[34].

NDVI. The normalized difference vegetation index (NDVI) measures green vegetation. It is calculated from satellite images as

$$NDVI = \frac{B_{NIR} - B_{red}}{B_{NIR} + B_{red}}$$

where B_{NIR} and B_{red} are the reflectances in the near-infrared and red bands respectively [7]. Using LandSat8 imagery, this is

$$NDVI = \frac{B5 - B4}{B5 + B4}$$

[34].

Population density. Some studies have found that population density has a positive influence on LST [195, 260], although this may be the result of confounding with other factors. We calculate population density using the U.S. census at the block level. The most recent census was 2010, so we use that data as an estimator of where people reside in the evening. This data is also at a lower resolution that the grid cells used, so the grid cell assumes the density of the block that its centroid is contained within.

Sky view factor. Urban canyons have been found to have an effect on UHI because they prevent air circulation and hinder nighttime radiative cooling [69, 186] and are used to indicate radiation flux within complex environments [214]. We calculate SVF using the R packages *horizon* [330] that is based off the algorithm presented in [101]. We use the same parameters used by [69]: the number of search directions, $\phi = 10^o$; and the radius of the reference circle, $R = 300m$. We use a spatial resolution of 6 meters.

Tree canopy cover. The 2011 edition of percent tree canopy cover is calculated using National Agriculture Imagery Program (NAIP) aerial imagery, Landsat 5 imagery, elevation, and existing NLCD data [78, 158]. The data provided is at a 30m resolution. The six reflective bands from Landsat 5 are used to calculate top-of-atmosphere reflectance [78] so the data does not contain information used in the LST calculation (which requires radiance).

3.2.4 Data preparation and robustness

The objective of our study is to determine the most influential urban characteristics and understand how they relate to land surface temperature. To do this, we use partial dependence plots to understand how the urban characteristics are associated with land surface temperature. For a selected characteristic, partial dependence is calculated by fixing the value of that characteristic in all observations in the dataset and predicting the land surface temperature. This is repeated over a range for the feature of interest. To evaluate how multiple urban characteristics interact, partial dependence can also be conducted in multiple dimensions. The swing [294] measures the relative importance of variables by calculating the magnitude of change in temperature associated with each variable. To calculate partial dependence, we need a data set and a statistical model.

To analyze the data, it needs to be transformed into a suitable format that is consistent between the variables. The raw data is a variety of spatial data types from "area level" (the population density data), to "geostatistical raster" (e.g. the land surface temperature). We choose to resample the data into a grid of square cells. We conduct the resampling twice to produce a grid of 100 and 500-meter square cells.

Having two resolutions allowed us to evaluate whether our conclusions are robust. For each of the cells the mean, maximum, and minimum of all variables were calculated. To further account for spatial effects of each variable, the mean of the surrounding cells (including diagonal) was calculated and the resulting spatial lag variable was included as an additional independent variable. To address multicollinearity between the variables that would confound our analysis of influence, we remove variables iteratively that have a Variance Inflation Factor greater than 5. The result is a data set with which we can train statistical models.

Various statistical models (§3.2.5) were trained and then validated on unseen data using a technique known as holdout cross-validation. This approach partitions 80% of the data into a training set and the remaining 20% into the testing set. The model resulting from the training is then tested on this unseen test set (known as out-of-bag) to get an estimate of the model accuracy. This is repeated 100 times and the distribution of the accuracy metric (here we use the mean absolute error (MAE) and variance explained (R^2)). Holdout cross-validation of this type is crucial for statistical analysis to ensure that models are not overfit to data [128]. Over fitting occurs when a model fits to the randomness in a dataset, causing it to be unsuitable for generalizations. When models' accuracy metrics are reported based on in-sample data (the same data it was trained on), the accuracy metrics are high. Avoiding overfitting is therefore essential when working with statistical models and is overlooked by the majority of existing studies. Cross-validation helps to avoid this by evaluating the model on unseen data.

A further way to avoid overfitting is to carefully consider how the test data is selected. This is especially important with spatial data. Therefore, when selecting the test and training data the grid cells were grouped into a larger 8x8 grid. This avoids overfitting of the model by training the model on a cell adjacent to a cell that is included in the test set.

Finally, we attempt to capture uncertainty in the data and the models. To represent the data uncertainty, we draw a random sample from our data, with replacement, to simulate a new dataset. The models are trained on this new dataset and this is repeated. This approach, known as bootstrapping, means that the conclusions' sensitivity to the data can be assessed. If the results are vastly different for each bootstrap sample, we assume that the result is dependent on the data and is unlikely to be generalizable to other cities. Additionally, we capture model uncertainty by using different models and assessing how each model shows the urban characteristics influencing the land surface temperature. If all bootstrapped models are generally in agreement, it suggests that the conclusions are robust.

3.2.5 Statistical models

The relationship between urban characteristics and land surface temperature is complex. This complexity may not be captured by a linear regression model. We fit a series of regression and data-mining models to the data and their predictive accuracy and variable association are compared.

It is important to note that we are assessing the association between the urban characteristics and the land surface temperature. These models are not explicitly evaluating causality. Instead, we use these models to control for urban characteristics and evaluate how land surface temperature changes with changes in each of the other urban characteristic in turn.

Null model: average. The first model, to compare other models against, is the null model. This is a benchmark model to ensure the models we fit are not doing worse than no model. The mean of the observations in the training set is calculated and is used as the prediction for the test observations.

Linear model. Linear models are suitable when the relationship between the explanatory variables (urban characteristics) and the response variable (LST) is linear. That is, linear models take the form

$$y = \beta_0 + \sum_i \beta_i x_i + \varepsilon$$

where y is the response (LST), x_i is each for the variables (urban characteristics), β_0 is the intersection, β_i is how the LST changes linearly with each urban characteristic, and ε is the normally distributed error.

Multivariate Adaptive Regression Spline (MARS). MARS models are a type of non-parametric regression approach that are useful for high dimensional problems [152]. They extend the linear model by using piecewise functions to fit the data [121]:

$$y = \sum_i c_i B_i(x)$$

$B_i(x)$ is the basis function that includes multiple linear functions and indicator variables that set these functions to zero for certain ranges of x. That is, multiple linear approximations are summed across the variable range and provide a nonlinear estimate of the LST [121].

Generalized Additive Model (GAM). The GAM is also an extension of the linear model but relaxes the assumption that the relationship is linear [151]. Instead, the response variable is estimated as the sum of smoothing functions, splines, that are applied to each covariate or set of covariates:

$$y = \sum_i s_i(x_i)$$

where $s_i(x_i)$ is the smoothing function applied to each covariate [294].

Random Forest. A random forest is an ensemble model of *Regression Trees.* A regression tree partitions the data based on thresholds for the covariates [52]. The tree continues to 'grow' by recursively partitioning the data with the objective of maximizing the node impurity, so that the partitions are as similar as possible. The result is a tree-like structure that uses thresholds on the covariates to estimate the response.

We use a total of 500 regression trees. Each regression tree is trained on a randomly selected subset of 1/3 of the covariates. The resulting prediction from the random forest is the unweighted mean of the prediction from all of the trees [51]. A subset of the covariates is used to reduce the correlation between the predictions of each tree. Tree-based models do not assume linearity and so are generally very flexible and powerful models [51, 128].

Gradient Boosted Regression Trees. GBRT's are also a collective of regression trees. In contrast to random forest models, each tree is trained sequentially on the residuals of the previous tree. That is, each regression tree has the objective of reducing the error of the previous tree. The prediction from the GBRT is the unweighted mean of all of the regression trees [128]. In this case, we again use 500 trees.

Convolutional Neural Network. CNN's are a new technique in deep learning and have most commonly been used to analyze visual images. Their use in image processing makes them potentially suitable for geographic studies. As with other forms of neural networks, CNN's contain layers of mathematical functions (neurons) that operate on the independent variables

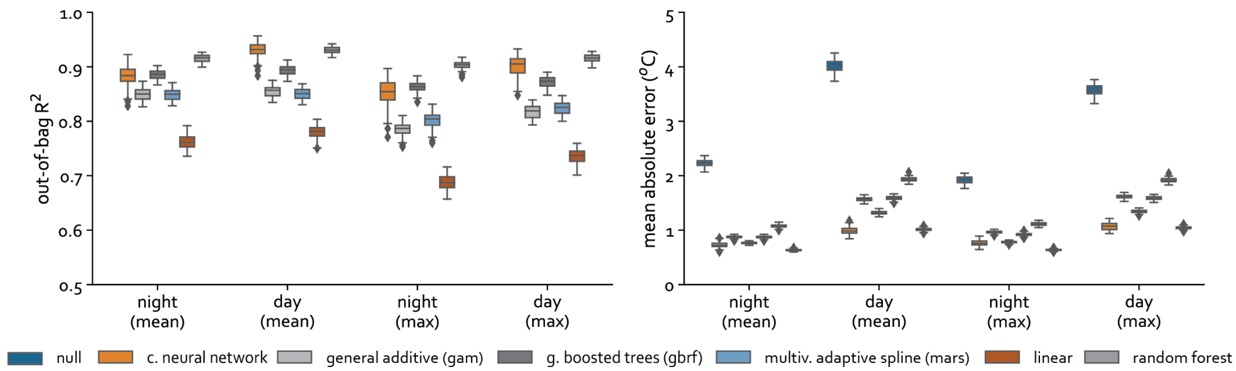


Figure 3.4: Holdout cross-validation results at 100-meter resolution. The out-of-bag (OOB) R^2 and mean absolute error (MAE) of the models from a 100-fold holdout cross-validation. The models were trained on 80% of the data and tested on the unseen 20%. When selecting data for the training and testing sets, spatial subsets were used to account for spatial similarities. OOB R^2 can vary between $(-\infty, 1)$, where better models have a value near 1. Good models have MAE near 0.

[128]. There can be multiple layers of these neurons that pass the results as an input to subsequent layers. In this manner, neural networks can capture nonlinearities. The advantage of convolutional neural networks above other types of neural networks is their ability to capture the spatial dependencies. Because CNN's have seldom been used for geospatial data, we provide a more detailed explanation in (B.3).

3.3 Results and Discussion

In this study we seek to determine the influence and relative importance of urban characteristics on land surface temperature during both the day and night. To achieve this, we first select variables to remove based on collinearity. The remaining variables for both 100 and 500-meter resolution analysis are shown in B.2. The next phase is to assess the accuracy of the statistical models. The results in Figure 3.4 show that the best models can predict both day and night land surface temperature to within 1^oC using urban characteristics. The R^2 results, also based on unseen data, suggest that more than 90% of the data variance is captured by the best models. We find that the most accurate model is the random forest, closely followed by the gradient boosted regression trees and convolutional neural network. The weakest model, consistently with R^2 less than 80%, is the linear regression - incidentally the model that is used in the majority of existing studies into land surface temperature. These results allow us to assess the influence and relative importance that these characteristics.

Relative variable importance for all the urban characteristics, calculated with *swing*, is shown in Figure 3.5. The characteristics, shown on the y axis, are ordered by the mean swing across all of the models, and the models are ordered left-to-right by their cross-validated accuracy. The most important characteristics during the night are tree canopy cover, greenness (NDVI), the sky view factor, and the elevation (digital surface model). The albedo is found to be important when assessing the 100-meter data, while the % area covered in water is important with the 500-meter data. This is likely due to 98% of the cells at 100m resolution having 0% water, so the effect on the dataset is negligible. The important urban characteristics are consistent for both the mean and maximum temperature during the night. The characteristics are also relatively consistent between night and day and between the models. Although albedo is among the top factors, its relative importance is low compared to tree canopy and greenness, especially during the night. This low association with nighttime temperatures is surprising given that darker surfaces store heat during the day that is released during the night [333, 363]. This, and the other influences can be examined using partial dependence.

Vegetation and impervious surfaces. During the day, increasing impervious surfaces and decreasing vegetation causes increased sensible heat flux and lowered latent heat flux [261, 333, 363]. This is thought to be less important during the night because latent and sensible heat are dominant during the day, but ground heat flux dominates at night [333, 363]. Indeed, because transpiration does not occur at night, vegetation's effect on night temperatures is debated. In our study, percentage tree canopy and impervious surface cover must be discussed together because they are 100% correlated in the data (Figure B.10). To distinguish between vegetated surfaces and other pervious surfaces, we include NDVI, a measure of a surface's greenness. At night, we find that % tree canopy (and % impervious surface) is the most influential characteristic on land surface temperature, followed by NDVI (Figure 3.5). The partial dependence results (Figure 3.6) indicate a decrease in up to 10^oC as the percentage area of trees or other pervious surface increases. This reduction in temperature could be due to a reduction in the impervious surfaces that store heat. We also observe that as the NDVI increases, the land surface temperature decreases.

To further evaluate whether the influence with temperature is due to vegetation or pervious surfaces, consider the the two-dimension partial dependence (Figure 3.7d) that evaluates how LST varies with % tree canopy/impervious surface and the NDVI. The greener (higher NDVI) and more pervious (higher % tree canopy cover) a surface is, the cooler it is during the night. The total change here is also approximately 7.5^oC, which is a considerable amount given these

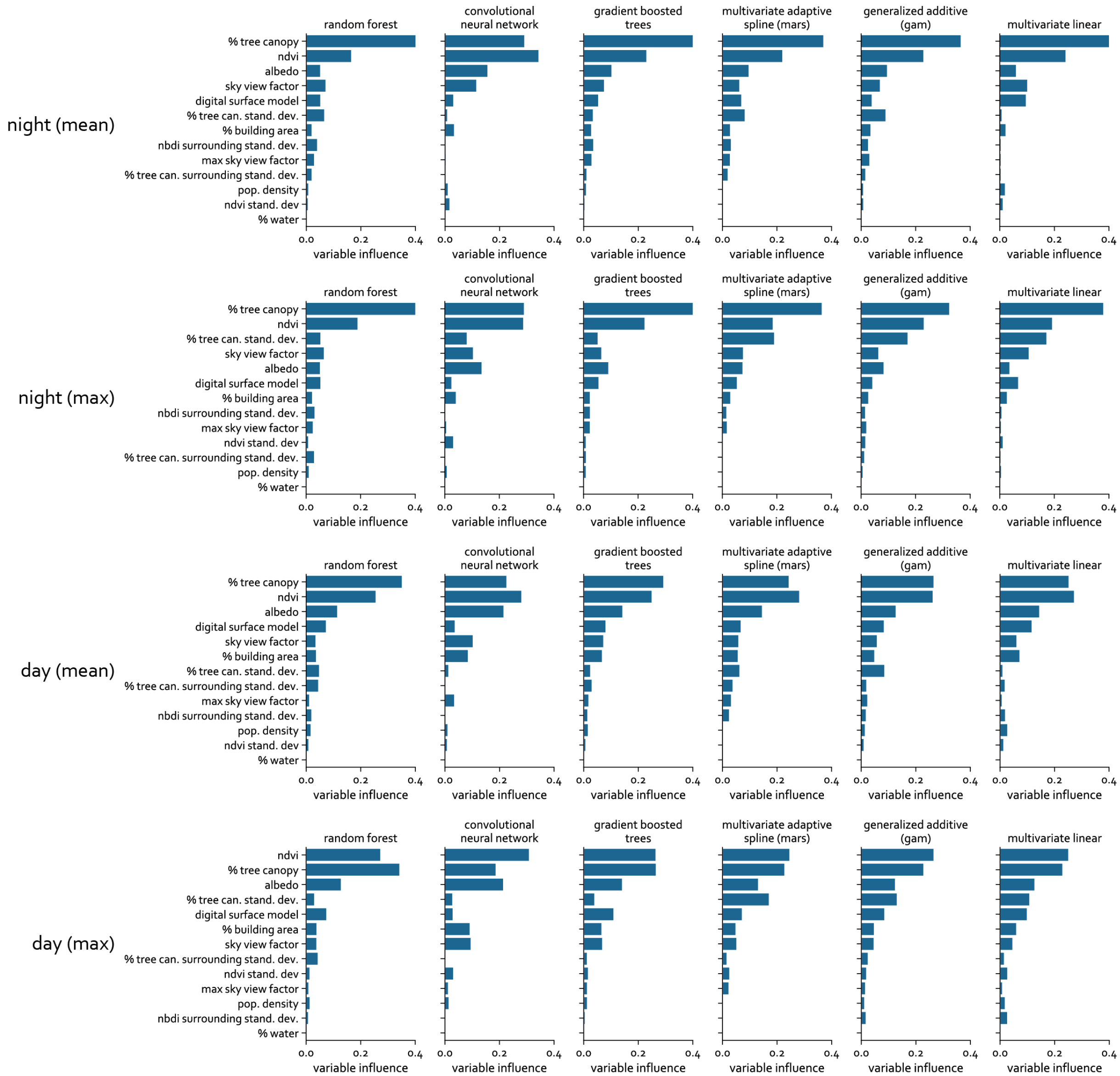


Figure 3.5: Variable influence on LST at 100-meter resolution. The variable influence, measured by swing, shows the relative importance of each urban characteristic on land surface temperature.

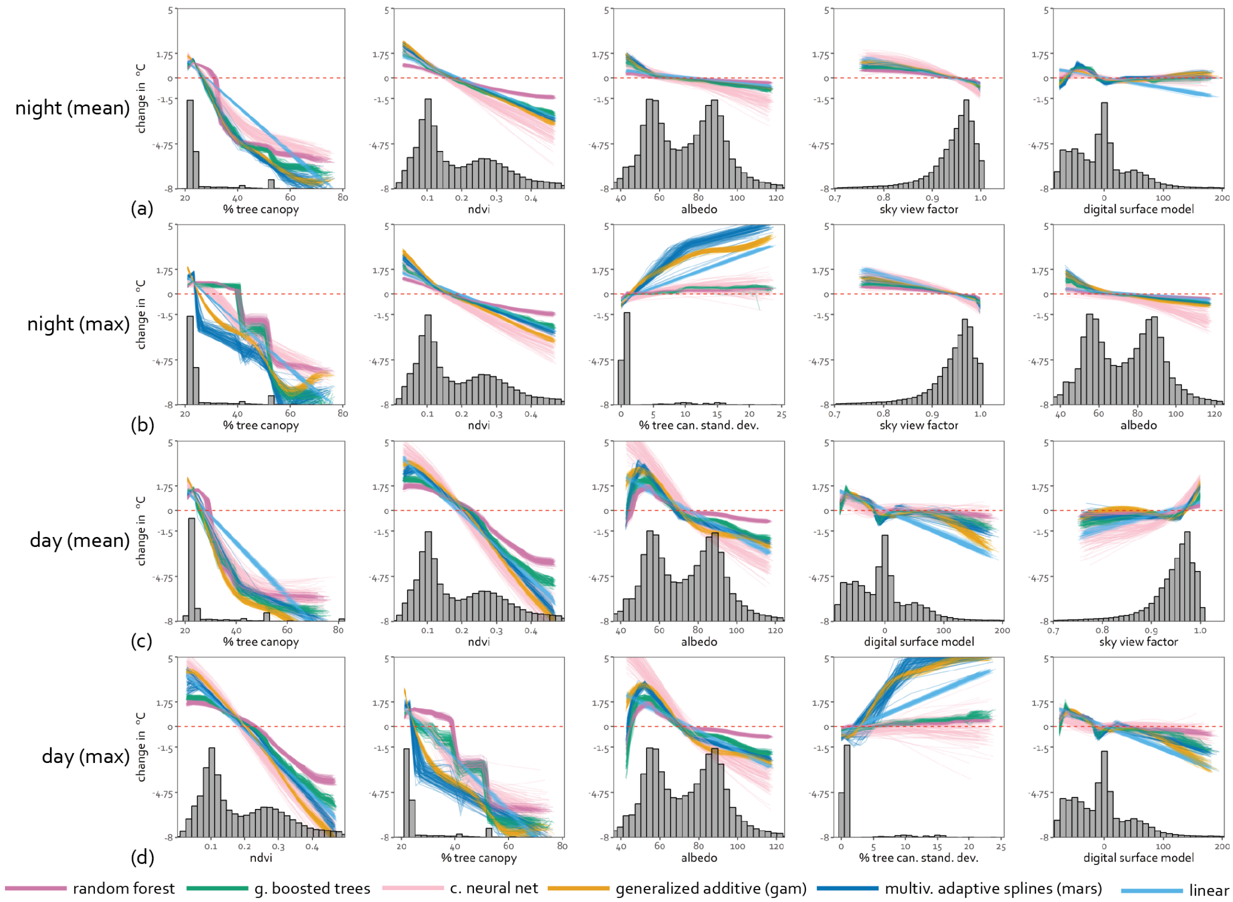


Figure 3.6: Partial dependence plots for LST at 100-meter resolution. Partial dependence plots show how the land surface temperature (^oC, y axis) changes with each urban characteristic as the other variables are held at their average (mean) value. The left hand side shows the effect each variable has on the (a) mean land surface temperature (LST) during the night, (b) maximum LST during the night, (c) mean LST during the day, (d) maximum LST during the day. Each of the models are shown and this indicates the model uncertainty in the relationships. There are multiple lines for each model based on bootstrap samples of the data, which indicates the data uncertainty. The histograms on the x-axis shown the distribution of the observed data. This is for the 500-meter resolution.

two-dimensional partial dependence are calculated using the random forest model, which is the less sensitive of the five models (as seen in Figure 3.6). These results contradict standing conclusions that vegetation has no effect on nighttime LST [261, 363]; although much of the reduction in temperature could be due to the perviousness of the surface, lowered temperatures appear to be associated with the greenness (NDVI) of a surface during the night.

During the day, we again see that vegetation and impervious surfaces are associated with the greatest reduction in land surface temperature, with approximately 15^oC change (Figure 3.8: ndvi vs. % tree canopy). This daytime result is consistent with expectation [69, 70, 260, 338, 363]. Because not all pervious surface types have the same cooling potential, and because of trade-offs with irrigation of vegetated surfaces [130], understanding the ideal vegetated surface type for day and night temperatures is a future step.

Water. Water is widely expected to decrease the LST during the day [339, 347, 362], but some claim it increases LST during the night [69]. The rationale is that water releases heat during the night, resulting in elevated nighttime temperature [69]. Our findings, however, show that water reduces the LST during both the day and night (Figure B.7). Although these results are not supported at the 100-meter resolution because 98% of the data at the 100-meter level has zero percentage water. At the 500-meter resolution, we see that the presence of water can decrease LST between 1.5 and 8^oC during the night and by substantially more during the day (Figure B.7).

Urbanization. Urbanization can lead to heat storage in roads and buildings [333, 363]. We discussed the role of impervious surfaces, alongside the effect of vegetation, but we also considered the influence of albedo (the whiteness of a surface), the percentage area of building, the NDBI (built-up index), and the sky view factor (a measure of the urban canyon effect). The results for albedo are surprisingly low. During both the night and day, albedo has a negative effect on temperature. During the day, this is most pronounced, and whiter surfaces appear to be more than 5°C cooler than darker ones (Figure 3.6). The partial dependence plot (Figure 3.6) also indicates that albedo's influence on temperature is potentially confounded as both vegetation and impervious surfaces can be dark surfaces (with low albedo). This stresses the importance of statistical techniques for evaluating the effect of multiple variables. We can investigate this further using the 2D partial dependence; the highest temperature occurs when there are dark impervious surfaces, but dark vegetated surfaces are cool (Figure 3.7). Additionally, we see that albedo has little affect at night, although the highest temperature does occur when there is high acreage of building footprint with low albedo (Figure 3.7a). During the day, albedo has a greater influence: increasing the whiteness decreases the temperature (Figure 3.6). The highest temperatures are observed when there is significant building area and low albedo (Figure 3.8a), as well as high impervious area and low albedo (Figure 3.8b). This supports existing findings that albedo decreases LST during the day, however, that we find no strong effect during the night contrasts existing reports [261, 363].

The built-up index (NDBI), % building area, and digital surface elevation model also had relatively minor associations with LST. The elevation (non-built-up) variable was excluded because it was found to be collinear with other variables; the digital surface elevation model was included and represents the elevation including buildings and vegetation. However, this elevation only appears to have minor associations with land surface temperature (Figure 3.6 & B.7). The building area had no effect during the night and minorly increased temperature during the day (Figure 3.5). Maximum NDBI appears to have a slight positive associated with maximum daytime LST (Figure B.7), but this effect is not observed at the 100m resolution. This minor-to-negligible relationship is surprising given that NDBI has been reported as among the most important urban characteristics during the day [260]. However, the discrepancy may be due to % impervious surface area being incorporated already with the % tree canopy data.

The canyon effect is also often attributed with causing warmer temperatures [69, 242]. While there was high uncertainty in the models, it appears that during the night, the temperatures decrease as the sky view factor increased (Figure 3.6a,b). This is potentially due to heat being stored within the canyons (areas with low sky view factors). This is supported in the two-dimensional partial dependence plot (Figure 3.7) where the higher temperatures are observed when there is high % building area and low sky view factor. It follows that heat is being captured in the canyons. However, compared to the other urban characteristics this has a lesser affect, changing the temperature by approximately 1.5^{o}C. The effect of the sky view factor during the day is low-to-indiscernible (Figures 3.5 and 3.8), but suggests that there are higher temperatures when the sky view factor is high.

Population density. We found that population density had no discernible effect during night or day (Figure 3.5).

Result sensitivity. To assess the robustness of the results, we conduct the analysis again at the 500-meter resolution (B.5). The results are consistent. Additionally, to ensure that the effects are consistent between cities, we construct the partial dependence plots for each city (B.4). The partial dependence is similar to Figure 3.6. Therefore, the consistency between 100 and 500-meter lends confidence to these conclusions.

Urban strategies.

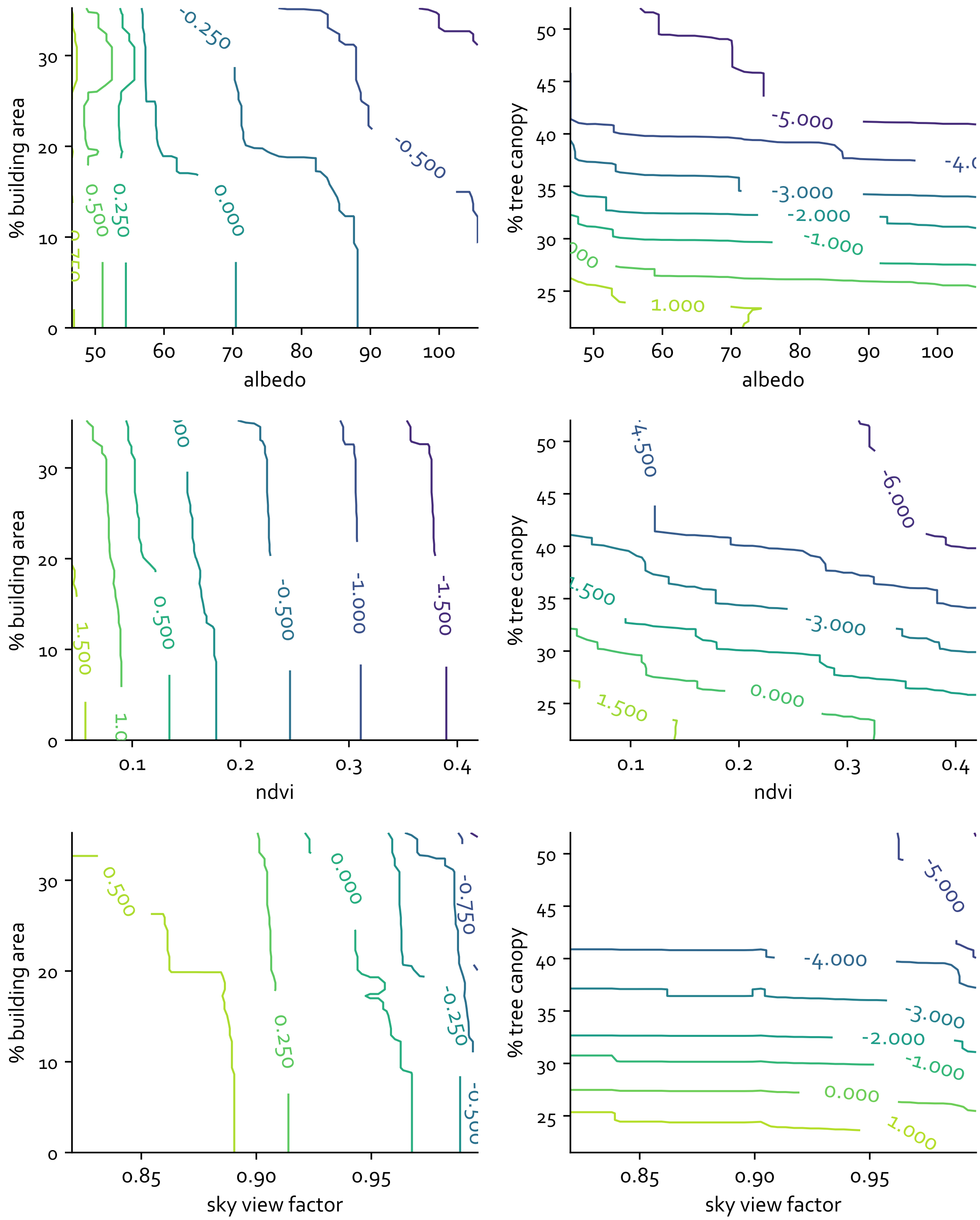


Figure 3.7: Nighttime, mean: A two-dimension partial dependence plot showing how the land surface temperature (^oC, contours) changes the variables on the x and y axes, while the remaining variables are unchanged.

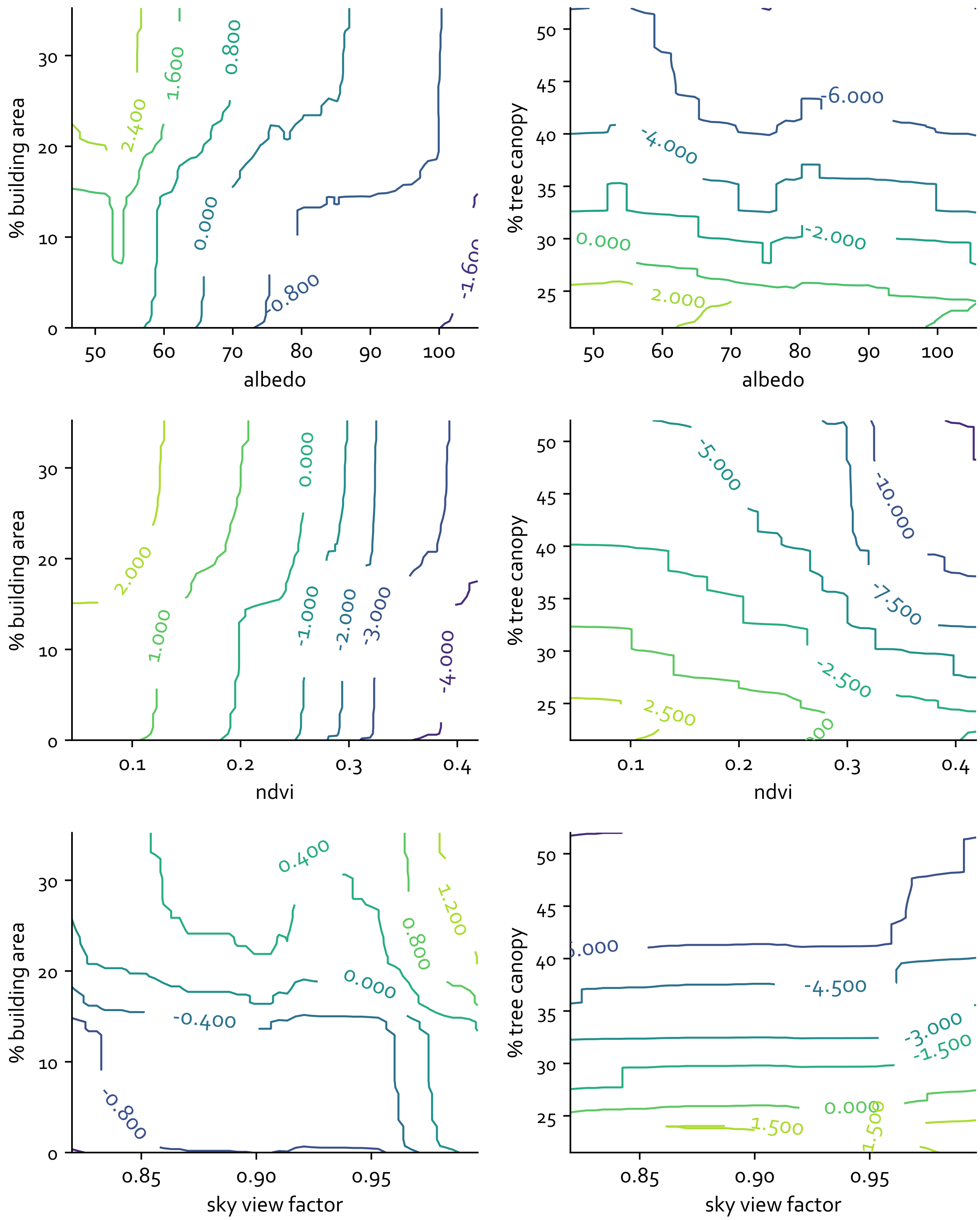


Figure 3.8: Daytime, mean: A two-dimension partial dependence plot showing how the land surface temperature (^oC, contours) changes the variables on the x and y axes, while the remaining variables are unchanged.

3.4 Conclusion

To assist planners tackling climate change, heat waves, and general high urban temperatures, we seek to determine how different urban characteristics are associated with land surface temperatures. The results strongly support initiatives for increasing green infrastructure in cities [189, 217]. We found that increasing vegetation and reducing impervious surface area had the greatest effect on temperature during both night and day, with the potential to reduce the temperature up to 10^{o}C. We also see strong evidence for blue space and increasing the area of water, although there are various limitations with doing so in cities such as Phoenix. We do note that this analysis is for land surface temperature, and not air temperature. The correlation between LST and air temperature is not perfect at intra-urban scales, and the magnitude of LST variability tends to be larger than that of air temperature. Nevertheless, LST is a highly relevant variable for analyses of the urban energy balance, and thus for studies of the UHI process.

Our findings demonstrate that accurate prediction of land surface temperature using urban characteristics is possible. This result opens opportunities for further detailed analysis into potential interventions. Such interventions for mitigating high temperatures are naturally place-specific, and while these results have proven general to four different US cities, work is needed to understand questions such as which types of greenery are better than others [130]. This study also demonstrates the opportunities of modern statistical techniques and the ability to assess potentially nonlinear interactions and the interactions between multiple variables.

Rigorous statistical analysis can continue to answer on-going questions central to land surface temperature. For example, our results support the suggestion that 3D variables (e.g. sky view factor) do not outperform 2D ones (e.g. % tree canopy cover) [42]. However, iteratively removing these variables from the analysis can ameliorate the potential for conflating the importance of different characteristics [69]. Our analysis is not causal inference; such an analysis would require controlled variables and urban spaces. We instead aim to complement and inform existing understanding of the relationships by demonstrating how land surface temperature and the urban characteristics are associated. This can be used to inform potential strategies for urban heat reduction, that is, if an association exists between two variables then we can evaluate the potential for causality based on understanding the physical mechanisms.

However, if no association exists or is in the opposite direction of proposed strategies for heat reduction, then such strategies need to be re-evaluated. For example, our results assessing the relative effect of sky view factor (a measure of building density), population, built-up index, and % building area do not support claims advocating to constrain floor area ratios [69]. Such policy could lead to increased urban sprawl (low-density or single-use urban development characterized by poor accessibility and a lack of functional open-space [111]). Instead, our results show that reducing impervious area and increasing vegetation and greenness have a stronger association with lowered temperatures. Such action could be achieved without constraining floor area ratios. If a constraint is explored, an additional necessary study is to compare sprawling and dense cities, prior to taking steps to dissuade density. Now that 100-meter resolution nighttime data is available, as well as the increasing availability of lidar data, studies advocating creative interventions such as increasing the vertical and horizontal randomness of buildings, increasing the prevalence of green roofs [123, 175], or other urban planning strategies can quantitatively be explored.

This study into daytime and nighttime land surface temperature in four US cities has highlighted the importance of vegetation in our cities' mitigation options. It has also demonstrated the utility of leveraging advanced statistical analysis to study land surface temperature. The results are robust to both data and model uncertainty and are general across the cities studied. They suggest that vegetation and impervious surfaces are the most important urban characteristics associated with land surface temperature. Increasing and decreasing these, respectively, is necessary for reducing high urban temperatures during both night and day.

Chapter 4

Evaluating Urban Accessibility [8]

We revisit the standard methodology for evaluating proximity to urban services and recommend enhancements to address existing limitations. Existing approaches often simplify their measure of proximity by using large areal units and by imposing arbitrary distance thresholds. By doing so, these approaches risk overlooking vulnerable, access-poor populations – the very populations that such studies are often trying to identify. These limitations are primarily motivated by computational constraints. However, recent advances in computational power, open data, and open-source analytics permit high-resolution proximity analyses on large scales. Given the impetus for equitable accessibility in our communities, this is of fundamental importance for researchers and practitioners. In this paper, we present an approach that leverages these open source advances to a) measure proximity using network distance at the building level, b) estimate population at that level, and c) present the resulting distributions so vulnerable populations can be identified. Using three cities and modes of transport, we demonstrate how the approach enhances existing measures and identifies service-poor populations where the previous methods fall short. The proximity results could be used alone, or as inputs to access metrics in other studies. Our collating of these components into an open source code provides opportunities for researchers and practitioners to explore fine-resolution, city-wide accessibility across multiple cities and the host of questions that follow.

[8]Published as Logan, T, Williams, T, Nisbet, A, Liberman, K, Zuo, C, & Guikema, S (2017). Evaluating urban accessibility: Leveraging open-source data and analytics to overcome existing limitations. *Environment and Planning B: Urban Analytics and City Science.* https://doi.org/10.1177/2399808317736528

4.1 Introduction

Accessibility is important for the sustainability and resilience of cities [50] and can lead to significant reductions in greenhouse emissions [95]. Access to destinations such as schools, parks, health care, and supermarkets is important as these services generally satisfy the daily needs of urban residents [314]. Geographic access, or proximity, is a key component of access and is the focus of this study.

Existing studies have often used simplified measures of proximity as part of their evaluation of accessibility. These simplifications risk ignoring the access-poor residents within a city, conflicting with the very aims of these studies. Such simplifications include:

- Large areal units. By using large, aggregated areal units (e.g. census blocks), the results are highly sensitive to the location of the units' centroids. Results also ignore the distribution of access within the area and, hence, do not identify the locations of amenity-poor residents.

- Distance thresholds. By using a subjectively-defined distance threshold (e.g. 400 m) to determine whether a resident has access or not, the results become sensitive to these subjective thresholds. This undermines the robustness of any conclusions. Thresholds also ignore the distribution of accessibility. For instance, although 50% of residents may have "access", the state of the remaining residents is unreported. It is possible that previous studies employing single thresholds have drawn conclusions that are unrepresentative of the entire city's distribution.

- Simplified distance measures. Reporting the Euclidean distance rather than the network distance strictly underestimates distance. The greatest discrepancies will exist in the estimates of distance for communities segregated by geographical obstacles (e.g. motorways).

Prohibitive computational requirements have previously forced studies to make these simplifications. However, the increase in computational capacity, open data sharing, and open source tool availability alleviate the need for these simplifications. Future studies that evaluate proximity now have the opportunity to:

1. Leverage open-source platforms. The growth of the open-source community has provided valuable resources, including data, network routing algorithms, and programming languages that enable analysis and display of spatial data. These free resources continue

to improve with time, and researchers and practitioners should position themselves to utilise these opportunities.

2. Measure from the finest scale possible. It is now computationally feasible to measure the network distance and time from every parcel or building to the nearest destination point. Doing so captures the true distribution of proximity, includes impediments from geographic barriers, and does not simplify the transportation network. Parcel-based assessment avoids ignoring proximity-poor residents who may otherwise be overlooked. Where necessary, parcel-based results can be aggregated up to larger areal units, weighted by population. This method still captures the underlying distribution and is less sensitive to the location or boundaries of the areal unit.

3. Represent the entire distribution of results. Using empirical cumulative distribution functions and city-wide maps of proximity make the results and analysis robust and independent of arbitrary thresholds. Binary "access-or-not", or other subjective measures that have previously been used, lend themselves to statistical biases and false interpretation of the data.

The overall aims of this paper are to a) briefly review past approaches to measuring proximity, b) recommend enhancements that build on this work, and c) demonstrate the benefits and opportunities presented by this approach. Our recommendations address the above limitations and improve our ability to identify previously overlooked, access-poor communities. We demonstrate our approach by evaluating the proximity of supermarkets, health care providers, green space, and high schools by walking, cycling, and driving for the residents of three US cities: Baltimore, Chicago, and Detroit. We provide code[9] so others can conduct this analysis.

Simply put, we want our cities and communities to be accessible. Therefore, planners need to promote accessible urban forms [314]. To help them do that, we need the ability to accurately measure proximity. Our study discusses and demonstrates how recently available tools have lowered the barriers to achieving this.

4.2 Review of measuring proximity

The notion of the accessible city is almost synonymous with that of the sustainable and socially cohesive city. For example, urban green spaces provide multiple benefits to urban residents;

[9]Github repository located at `https://github.com/tommlogan/city_access`

they present opportunities for physical activity, foster community networks and social capital, and improve the mental and physical health of communities [11, 49, 74, 205, 274, 315, 355]. Health care facilities, schools, and grocery stores are other examples of core urban amenities. Accessibility and urban form primarily affect vulnerable populations without access to vehicles [212, 314]. Especially in the case of health care, these people are often those who need it most. It is therefore critical that we have the ability to measure accessibility and provide decision support to those promoting accessible urban form.

Accessibility is multi-dimensional and its measure is dependent on the service or amenity of interest. The traditional dimensions of accessibility are proximity, availability, acceptability, affordability, adequacy, and awareness [259, 283]. When evaluating access in a city, all of these components need to be considered. Nevertheless, we contend that proximity is a necessary, even if it is not a sufficient, condition to having accessibility. It is also the component of urban access that urban planning and amenity location can influence [328] and is almost always included in the evaluation of accessibility. Hence, the measurement of proximity is the focus of this paper.

Table 4.1 summarises how previous studies evaluating accessibility have measured proximity. The summary shows that the question of proximity has challenged researchers and practitioners for a long time. Over this time, the tools available have increased. In 1989, Pacione was ruling a line along the "crow's-flight" path on his maps. Scholars in the 1990s were touting the new capabilities of the Euclidean buffer tool [26], and, by the early 2000s the network analyst tool was being utilised [270].

Once measured, there are countless ways in which proximity has been integrated into sophisticated evaluations of accessibility. For a recent review of access evaluations, including proximity, gravity, topology, and index-based, we refer the reader to Vale, Saraiva, and Pereira [328]. However, in some cases, the sophistication is somewhat lessened due to simplifications applied to the proximity measurement. Table 4.1 identifies some of these limitations, where the shaded columns indicate best practice. The existing approaches in the literature could be enhanced by addressing these limitations:

- Simplified distance measures;
- Arbitrary thresholds;
- Low spatial resolution; and
- Single region of application.

Distance between points has been measured in a variety of ways: Euclidean distance, Manhattan distance, network distance, and network time [328]. The Euclidean and Manhattan distance, or buffer approaches, are the simplest tools. They were common in the literature in the 1990s [26, 161], and their use continues to persist (see Table 4.1). The network distance is often calculated using Dijkstra's algorithm (1959) and became common in the early 2000s. The network approach is the more accurate measure of proximity, as it captures the spatial structure of the transportation infrastructure, which Euclidean or Manhattan measures ignore.

Many studies discretise proximity by specifying a distance threshold or extent and use the resulting, blunter "accessibility metric" [49, 188, 244, 328]. Their conclusions are therefore dependent on the predetermined threshold, which is often the planners' "rule of thumb" of 400 m or 800 m as a walking distance limit [215]. However, people are prepared to travel further [59] and other thresholds have been used [11, 291]. Seldom are these thresholds subject to a sensitivity analysis [328] and they are too blunt to capture the nuances of city-wide accessibility. Another substitute for calculating the proximity is the Walk Score tool (`www.walkscore.com`). Walk Score considers the proximity and a host of other factors to provide a subjective measure of the walkability of a neighbourhood. However, their assessment has been subject to criticism as the metric does not capture the quality of the walking environment [183, 257]. Our proposed approach is advantageous because it is open source and the raw proximity values could be used to provide deeper insight than aggregated indices.

Spatial scale significantly influences indicators of accessibility and can lead to amenity-poor residents being overlooked. For example, consider a census tract where some residents are geographically isolated from an amenity; measuring the distance to the amenity from the census tract's centroid, the segregated residents are unnoticed. This issue has already been identified and discussed [81, 187, 315], yet later studies fail to address the limitation (Table 4.1). A way to address this is to measure accessibility from individual building units, which can be coupled with methods to assign population to the buildings [46, 176, 360]. An often cited reason for not conducting measurement at this resolution is that demographic data is provided at a poorer resolution, and therefore errors arise when down-scaling the data [314]. There are two important fallacies that need to be considered with aggregated data: the ecological inference problem [177] and the modifiable areal unit problem (MAUP) [246]. The ecological fallacy implies that attributing regional characteristics to an individual is not always valid. MAUP addresses how conclusions are not robust to the areal units' sizes and shapes. Regardless of the issues with these two fallacies, proximity at parcel level can be aggregated *up* if necessary, improving the measure even when represented at the poorer resolution [154].

Until recently the aforementioned simplifications were essential due to computational and data constraints [205, 314]. Other studies acknowledge that they have adopted simplistic approaches due to "considerable and cumbersome" analytical requirements [49, 81]. These computational limitations are now only self-imposed, and future studies, when the data is available, can be utilising the options available to them.

The literature shows great diversity in application area for this type of research. It also shows how the research has evolved over the past 30 years following the advent of computational geographic information systems (GIS). Now, as we demonstrate, the open-source community has provided the next advance in tools and data available to scholars and practitioners. In the remainder of this article, we demonstrate a procedure for leveraging these recent advances and discuss opportunities that are now available to researchers, policy makers, and practitioners.

Table 4.1: A variety of different methods for evaluating proximity have been employed in previous studies. Some key characteristics of these methods are summarised here. A shaded column indicates best practice.

		Distance measure		Threshold			Spatial unit		Scale	
	Keywords	Euclidean	Network	Single	Multiple	Continuous	> Parcel	Parcel	Single city/region	Multiple cities
Pacione [249]	Schools	*				*	*		*	
Azar, Ferreira, and Wiggins [26]	Transit	*		*				*	*	
Hsiao et al. [161]	Transit	*		*				*	*	
O'Sullivan, Morrison, and Shearer [248]	Transit		*			*		*†	*	
Randall and Baetz [270]	School, GIS		*	*				*	*	
Wolch, Wilson, and Fehrenbach [356]	Green space	*		*			*		*	
Austin et al. [12]	Food, Schools	*			*				*	
Schuurman et al. [287]	Health care		*	*				*	*	
Langford and Higgs [187]	Health care		*			*	*		*	
Hillsdon et al. [155]	Green space		*		*		*		*	
Kipke et al. [178]	Food, Schools	*			*				*	
Apparicio, Cloutier, and Shearmur [10]	Food outlets		*			*	*		*	
Oliver, Schuurman, and Hall [244]	Land-use	*	*	*				*	*	
Kimpel, Dueker, and El-Geneidy [176]	Transit		*			*		*	*	
Barbosa et al. [29]	Green space		*			*		*	*	
Cohen et al. [74]	Green space	*			*			*	*	
Larsen and Gilliland [188]	Food		*	*			*		*	
Boone et al. [49]	Green space	*		*			*		*	
Biba, Curtin, and Manca [46]	Transit		*	*				*	*	
Lei and Church [191]	Transit		*			*		*	*	
Currie [81]	Transit	*			*		*		*	
Mavoa et al. [215]	Transit		*		*			*	*	
Hawthorne and Kwan [153]	Health care		*			*		*	*	
Mao and Nekorchuk [212]	Health care		*	*			*			*
Sang Lijie, Zhu, and Su [281]	Green space	*	*			*	*		*	
Williams and Wang [350]	Schools	*		*			*		*	
Astell-Burt et al. [11]	Green space	*		*			*			*
Reklaitiene et al. [274]	Green space	*			*			*	*	
Nobles, Serban, and Swann [237]	Health care		*			*	*			*
Koschinsky et al. [183]	Various amenities		*	*			*		*	
SEMCOG [289]	Core services		*	*			*		*	
Lee and Lubienski [190]	Schools		*	*			*		*	
Macedo and Haddad [205]	Green spaces	*		*			*		*	

† used a single parcel location and measured access to various points in the city.

4.3 Procedure for measuring proximity

4.3.1 Overview

In this section we outline our approach for evaluating proximity that overcomes the aforementioned limitations. The approach measures network distance and time from every single building to the nearest destination point (Figure SMC.9). This fine resolution analysis is now tractable at large scales and over multiple cities or regions. Our code is available online[9].

4.3.2 Step 1: Data inputs and processing

To calculate proximity, coordinate points for the origins and destinations are required. The extent of pre-processing to generate these points depends on the type of analysis. For example, when analysing the access to supermarkets the destination can be converted to a point. Similarly, points can be used for parcel or building data. However, it is not always appropriate to represent a destination as a point. For example, when analysing access to green space, representing a park as a single point is inappropriate for two main reasons:

- There may be multiple entry points or open borders; and
- The park may be very large, causing the centroid point to be unreasonably far away from any actual access points.

To address these issues, every park is converted to a series of equally-spaced points around its perimeter (refer to Figure SMC.9). Then, because routing algorithms snap points to the travel network (see Figures SMC.1 and SMC.2), the points are moved 5 m inwards. This encourages snapping to an interior pathway, which results in the route passing through the park's entrance. This is important in the case where physical barriers (e.g. fences) prevent access from every side.

In our analysis, the origins were building shapefiles downloaded from city open data portals, and the destinations were primarily downloaded from OpenStreetMap (OSM). A discussion of important data challenges (e.g. an incomplete or unconnected network) and opportunities (volunteered geographic information) is included in the Supplemental Material (page 160), as are further details of our data sources (page 167).

Once both the origins and destinations are points, the input to the routing algorithm is created.

4.3.3 Step 2: Routing

The routing consists of two main stages. Firstly, the k nearest (by Euclidean) destination points to each origin are found, resulting in k candidate destination points for every origin.

Network distances and times between these origin-destination pairs are then calculated by the chosen routing system. The closest destination (by distance or duration) is then assigned to each origin.

There are multiple different routing algorithms that could be used for this analysis. We used Open-Source Routing Machine [204] (`http://project-osrm.org/`) running via Docker [221] on a local server. The advantage of this is that it allows for an unlimited number of free origin-destination route calculations (see supplemental information and Github for instructions and code). However, if factors such as congestion are important it may be more beneficial to use a routing algorithm with this ability (e.g. Google Maps). Refer to the Supplemental Material (page 161) for a more complete discussion on the choice of routing algorithm.

4.3.4 Step 3: Demographic apportioning

Demographic apportioning (also known as dasymetric mapping) is the process of assigning demographic information to finer resolution units (in our case, buildings) [187, 286]. In our approach, the land-use (where available) is used to exclude buildings that are not zoned as residential. The population of the census block (or areal unit where population data is available) is then evenly divided among the remaining buildings. This provides a population estimate for each building, and, by extension, an approximation of the distance to the nearest service for that fraction of the population. Note that a census block is the smallest geographic unit used in the US census survey and generally corresponds to a city block. While uniformly distributing the residents to the buildings introduces some errors, the small size of the unit limits these, and, to our knowledge, validating a method for finer distribution would be extremely challenging and require potentially sensitive data.

4.3.5 Step 4: Quantification and visualisation

The final step is to present the results of the analysis. Almost all previous work has presented results in the form of tables. The advantage of a table is that it is easily interpretable. However, to use tables the results must be discretised, often via an arbitrary threshold (discussed earlier). An empirical cumulative distribution function (ECDF) is an alternative to the traditional table representation, and gives a complete representation of city-wide accessibility that is independent of any subjective thresholds. The ECDF is a line graph that represents the percentage of residents who have a travel distance or duration less than any value, x. For example, Figure 4.1 shows the walking distance to green space; Detroit has a value of 60% at 1050 m, indicating that 60% of residents in Detroit live within 1.05 km of green space. The ability to overlay multiple ECDFs means that presenting comparisons between cities and/or demographics is simple.

A third option for representing accessibility is a map-based representation (Figures 4.2 and SMC.10). This representation has a different objective to the table and ECDF options and is complementary to both. By graphically representing access, we can quickly identify regions within the city that have poor access to the given service type.

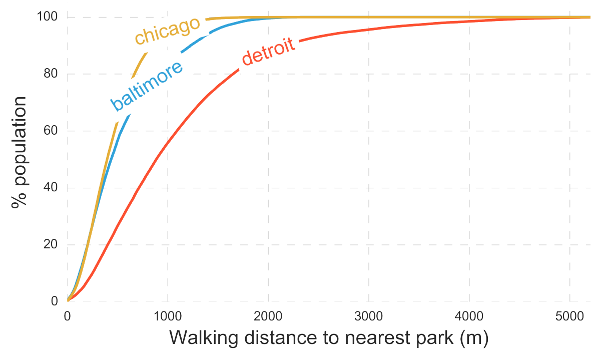


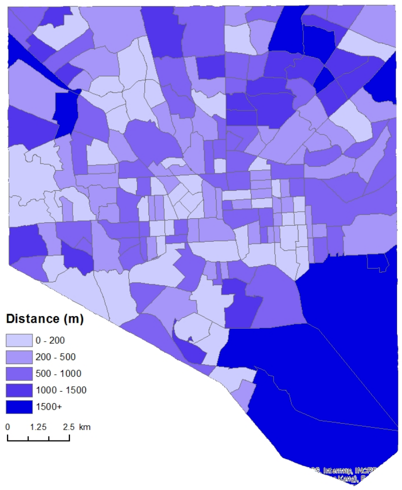
Figure 4.1: ECDF showing distance via walking to the nearest park. Note that had a distance threshold of 400 m been chosen, Chicago and Baltimore would be found to have similar park proximity. However, this figure shows that this would be an incomplete comparison between Baltimore and Chicago.

4.4 Case studies

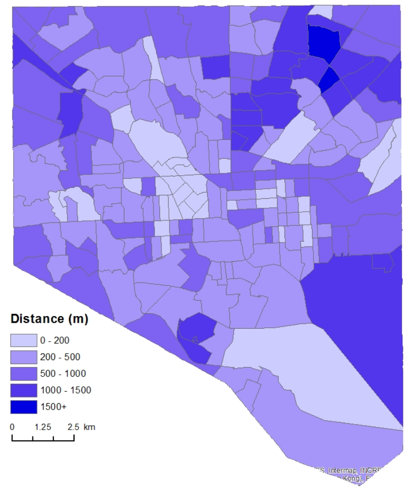
4.4.1 Overview

We now provide examples to demonstrate the wide applicability of this approach. The methodology described above was applied in three US cities (Chicago, Baltimore, and Detroit) to measure proximity for:

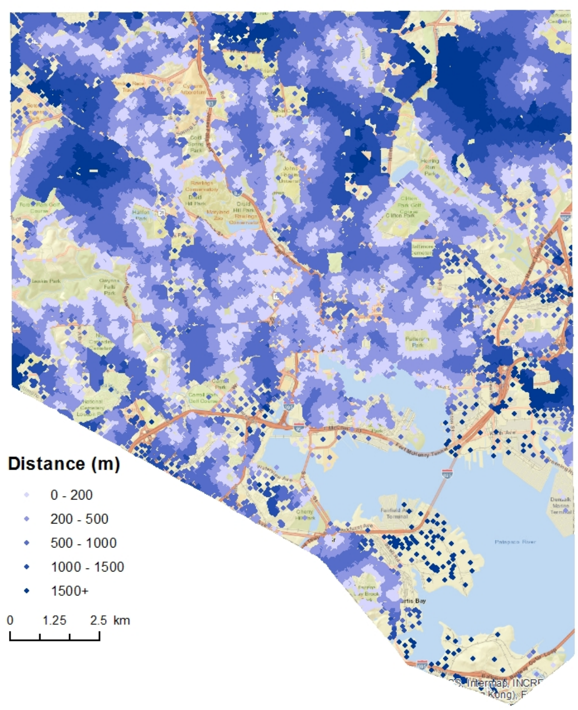
- Walking to green spaces;
- Cycling to public high schools;



(a) Distances are calculated from the centroid of each census tract.



(b) Distances are calculated from every building and then aggregated up to the census tract, which display the mean of all contained buildings.



(c) Distances are calculated from every building, and the point results converted to a raster. See `https://reckoningrisk.com/research/2017/urban-access/` for an interactive map.

Figure 4.2: The distribution of park access in Baltimore when measured at various spatial scales. When census tract centroids are used (in (a)), the results are highly sensitive to centroid locations, and the overall accessibility distribution is erratic. Using building-based estimates (as in (b) and (c)) gives a more accurate representation of accessibility.

- Driving to health care; and
- Walking, cycling, and driving to supermarkets.

These destinations were selected to demonstrate the variety of application domains for our tool and represent amenities that are of vital importance in people's daily life [289, 314]. The corresponding travel modes were deemed suitable for each destination. However, it would be easy to include different modes or different destination types.

The following results demonstrate the enhanced insights that are now possible.

4.4.2 Multi-city comparisons

The results for each application can be represented in three ways: ECDFs, tables, and spatial maps. Walking distance to parks is shown using these alternatives in Figure 4.1, Table 4.2, and Figure 4.2c. Selected results can be interactively explored at `http://adaptingcities.org/city_access.html`. The corresponding results for cycling to high schools, driving to hospitals, and access to supermarkets via all modes are presented in the supplementary material (page 168).

The ECDFs enable simple qualitative and quantitative comparison between cities. For example, we can see that Chicago has the highest access to all destinations via all travel modes, whereas Detroit consistently has the poorest access.

Comparisons between cities can be used to identify exemplar cities and best practices. They can also benchmark a city's accessibility against that of another, add statistical rigour to hypotheses by testing across cities, and enhance conclusions made in existing studies. Due to data and computational limitations, very little previous work has made comparisons between different cities or regions like this (refer to Table 4.1).

4.4.3 Removing the thresholds

An additional benefit of using ECDFs is that they represent the entire distribution of a city's access, unlike the conventional tabular display. Consequently, we can draw conclusions independently of any subjective distance or time thresholds.

Closer inspection of Figure 4.1 and Table 4.2 highlights the insight that can be gained through an ECDF; if a distance of 400 m is chosen as the threshold for walking access to green space (a common value in the literature), we conclude that 50% of Chicago's, 46% of Baltimore's,

Table 4.2: Percentage of population with access to green spaces, high schools and health care at selected distances (rounded to the closest percentage point).

	Distance (km)								
	Walk to parks			Cycle to schools			Drive to health care		
	0.4	0.5	1	0.5	1	2	2	4	6
Chicago	50%	63%	95%	11%	41%	87%	39%	83%	97%
Baltimore	46%	56%	84%	6%	24%	70%	35%	83%	99%
Detroit	20%	27%	56%	5%	20%	59%	12%	47%	77%

and 20% of Detroit's residents live within 400 m walk of a park. In other words, Chicago and Baltimore have similar access, while Detroit is considerably lower. While this is indeed true, it is incomplete. If we instead choose a threshold distance of 1 km, we conclude that 96% of Chicago's residents have access to green space, in comparison to Baltimore's 84%. That is, there are more than three times as many people in Baltimore than Chicago without park access (as a fraction of total city population). These considerably different conclusions demonstrate the sensitivity to the thresholds. The difference is immediately observable in the ECDF shown in Figure 4.1, but may have gone unnoticed had tables been used for the analysis.

It is possible that previous studies employing single thresholds have drawn conclusions that are unrepresentative of the entire city's distribution. Such conclusions ignore the tail of the distribution, where the access poor residents lie. It is these very groups that the majority of similar studies are trying to address, and we argue that considering only a single threshold distance conflicts with these very goals.

4.4.4 Benefits of fine resolution

Poor resolution can lead to errors that should no longer be acceptable given the tools available to us. Imposing a discrete spatial structure over a continuous population surface results in the modifiable areal unit problem (MAUP) [246]. An areal unit's size and location is arbitrary, and the results are sensitive to these parameters. The problem, therefore, is that the results are not robust.

Figure 4.2 shows the spatial distribution of proximity to parks in Baltimore based on analysis at different spatial resolutions. In Figure 4.2a, the distance to nearest park is calculated from the centroid of each census tract. We observe erratic heterogeneity in the results, which demonstrates the sensitivity of the results to the centroid locations. Figure 4.2b displays the

Figure 4.3: The distribution of proximity to nearest park within a census tract in Baltimore. The distance of the tract's centroid to nearest park, a commonly used approach, is not representative of the proximity distribution of residents calculated at the building-level.

building-level results from our analysis aggregated up to the census tract. As each census tract's assigned value is calculated from a large number of results, we see a smoother pattern than in Figure 4.2b because the entire distribution within each tract is acknowledged, removing this sensitivity to arbitrary centroid location.

As well as being sensitive to centroid location, the traditional tract-level approach assumes that the distance from the centroid is representative of the actual distribution of building-level access. Figure 4.3 illustrates how this can be a poor assumption, by showing that the value calculated using the tract centroid (vertical solid line) does not reflect the actual distribution of proximity within the tract. Moreover, collapsing this entire distribution to a single number (whether the centroid value or weighted mean) does not differentiate the access-poor residents from those with better access.

Figure 4.3 also shows that there is a bimodal distribution within the given census tract. This is because there is a railway running through the census tract, which impedes access for a portion of the population. The needs of these segregated residents would be overlooked if only the tract centroid was used to represent proximity.

The availability of fine resolution data and advances in modern computing allow for building-level assessment. This easily identifies access-poor areas, for example the park-poor residents in Figure 4.2c, or food deserts in Figure SMC.10. The bias that is introduced by areal units, regardless of the size, should no longer be acceptable, especially when identifying vulnerable residents is the goal. If areal units are necessary, integrating up from a finer resolution as in Figure 4.2 is the most robust approach.

4.4.5 Network distance

The use of Euclidean distance as a proximity measure appears to be declining, but for a few cases. The supplemental material (page 166) provides discussion and evidence (Figure SMC.6) showing how Euclidean distance underestimates the distance to services.

4.5 Limitations and further opportunities

4.5.1 Further opportunities

Leveraging the data as we suggest opens the field of research to enumerable lines of querying. For example, our approach could be extended to:

- Compare access between different subgroups within a city (e.g. low-income, race, age, etc.). There has been a substantial amount of previous research that has investigated these relationships, and the results generated via this method may help researchers to draw further insights into issues of inequity of access (Chapter 5 demonstrates this in terms of access to supermarkets and gas stations over the course of a natural hazard).

- Quantify the effects of adding or removing a destination (e.g. opening or closing a school) on the overall city-wide access. This could also be combined with the previous example to determine marginal effects on different demographics.

- Assess the validity of previous thresholds. As has been shown above, it is possible that previous studies with predetermined distance (or time) thresholds have misrepresented both regional and local accessibility. For example, consider a city that has excellent access for 50% of its residents and terrible access for the other 50%. If a threshold distance of

400 m finds that 50% of residents have access, this city will be considered to have high accessibility. This means that access can be over-rated, and the needs of those access-poor residents are ignored.

- Combine results of access to various core services to create an all-encompassing accessibility measure. This would require (subjectively) weighting different services based on their perceived importance but would allow the definition of a single distribution to characterise an entire city. This could then be used to either compare between cities or between demographics.
- Analyse the accessibility of proposed residential developments.

4.5.2 Limitations

Open source data and analytics have a number of benefits, but there are limitations. Users should be aware of these and of some approaches for working with them. Addressing these limitations are important future challenges for the research, philanthropic, and governmental communities. Some limitations include:

- Volunteered geographical information (VGI) is not always complete and thorough checks are necessary if it is going to be used. In many cases, ESRI and Google maps have accurate data available. Data from any source available to the user can be input into the code we provide.
- OSM can lag in updating infrastructure such as street networks. Some cities, for example, provide up-to-date street networks to ESRI, but to our knowledge such agreements do not exist with OSM. However, as shown in Figures SMC.1 and SMC.2, both OSM and Google Maps can have incomplete walking trail networks.
- There are many routing algorithms available to use, and the choice should depend on the application. OSRM, for example, is free to use, but currently does not incorporate traffic congestion or public transit. OpenTripPlanner and Google also are alternatives for examining transit travel. However, in the case of OpenTripPlanner, data on transit schedules (usually sourced from the cities) is required. A comparison between OSRM and Google Maps is provided in the supplemental material (page 161).

- The routing algorithms make different assumptions in their calculations, for example the travel speed on certain road surfaces or penalties for turns. In OSRM these can be modified (see supplemental material, page 158).

- This approach measures the proximity to the nearest service. It does not incorporate the amenity or safety of the walking environment.

- Evenly dividing the population of a census block between buildings introduces some error. This error is relatively minor given a US census block generally corresponds to a city block. Approaches to improve dasymetric mapping would be a valuable future contribution.

4.6 Conclusion

The aims of this study were to a) propose a methodology for measuring proximity that builds on previous work, and b) demonstrate the benefits and opportunities associated with using this approach.

There are several limiting simplifications inherent in existing methods for measuring proximity. With reference to Table 4.1, these limitations are:

- Single region of application. Focussing on single cities prevents hypotheses from being rigorously tested and comparisons between cities being made.

- Large areal units. This ignores the distribution of access within the areal units, and means that results are sensitive to the unit centroid locations.

- Arbitrary thresholds. The majority of studies rely on subjectively-defined thresholds, which vary considerably between applications and can misrepresent a city's access.

- Simplified proximity measures. Despite network measures being the most accurate, Euclidean measures continue to be used.

These were once reasonable simplifications based on restrictions to computation and data availability. This is no longer the case. In our approach, network distance and time are measured from every single building to the nearest destination point. From this, figures can be plotted that display the city-wide proximity to a given destination that are independent of any subjectively-defined distance or time thresholds. By leveraging open-source data and analytics, this fine resolution analysis is now tractable at large scales and over multiple cities or regions. Additionally, it no longer overlooks the amenity-poor residents whom many of the existing proximity studies aim to identify.

Comparisons between cities can be used to identify exemplar cities and best practices. They can also benchmark a city's accessibility against that of another, add statistical rigour to hypotheses by testing across cities, and enhance conclusions made in existing studies. We analyse the proximity of supermarkets, health care providers, green space, and high schools by walking, cycling, and driving for the residents of US cities Baltimore, Chicago, and Detroit. We show that Detroit has the poorest access to amenities of the three cities and that Chicago generally has the best. Due to data and computational limitations, very little previous work has made comparisons between different cities or regions like this (refer to Table 4.1).

Results generated using large areal units are sensitive to the units' centroid locations. Also, by using only a single point estimate to represent the entire unit, the distribution of the residents' access is ignored. This means that access-poor communities can be ignored. Using Baltimore as a case study, we demonstrate the discrepancies between analyses at different spatial scales. We present maps showing that park-poor residents can be quickly and easily identified using fine resolution analysis. Where areal units are necessary, integrating building level data up is the best approach. We provide an example of a census tract with poor access that would be considered exemplary under many of the previous approaches, thus highlighting the need for using the method we outline.

The majority of studies rely on subjectively-defined thresholds, which vary considerably between applications. This means that distributions of access are simplified to a single value. When the distribution of proximity, is ignored amenity-poor residents can be overlooked. For example, although $x\%$ of residents may have "access", the state of the remaining residents is unreported. Reducing proximity to a binary variable (access or not) also means conclusions are sensitive to the chosen parameters and therefore are not robust. We provide an example where the use of two different thresholds yields strikingly different conclusions. These thresholds provide incomplete information regarding access to amenities and can be avoided by using empirical cumulative distribution functions (ECDFs), which display the entire distribution of access throughout a city. We therefore recommend them as useful tools to include in future proximity analyses.

Accessibility is a key factor for the resilience and sustainability of a city. In 1994, Azar, Ferreira, and Wiggins discussed how the advance of computer and GIS technologies would transform city planning and accessibility analysis. Since then, computer speeds have significantly increased. Going forward, we must leverage this increase as well as the open-source data and tools now available to us. Simplifications in existing approaches risk overlooking amenity-poor communities, which in fact contradicts the goals of many of the studies. These simplifications are no longer necessary and are addressed using the methodology we propose. Leveraging the tools now available to us, evaluating accessibility within cities is possible at scales previously considered intractable. The opportunities that this presents us as researchers, policy makers, and practitioners are vast.

4.7 Summary for policy makers and practitioners

There appears to be a growing interest from policy makers in evaluating access in our cities [289, 314]. With the availability of open-source (and hence free) tools and the reliability of data increasing daily, our cities, policy makers, practitioners, and NGOs should position themselves to leverage this. Increasingly, city planning can be informed by data. For example, evaluating proposals for new facility location or residential development could include analysis of proximity and, by extension, accessibility. Additionally, we encourage cities to make their own data available open source. Our paper identifies the limitations of existing approaches and provides evidence for why these can and should be overcome. But, most essentially for policy makers and practitioners, we provide instruction, code, and examples of how to conduct the approach we recommend.

Chapter 5

Building community resilience through equitable access to essential services [10]

We urgently need to understand how to put concepts of resilience into practice if we are to prepare our communities for climate change and exacerbated natural hazards. Yet, despite the extensive discussion surrounding resilience, operationalizing the concept remains challenging. The dominant approaches for assessing resilience focus on either evaluating community characteristics or infrastructure functionality. While both remain useful, they have several limitations to their ability to provide actionable insight. More importantly, the current conceptualizations do not consider essential services or how access is impaired by hazards. We argue that people need access to services such as food, education, healthcare, and cultural amenities to get back some semblance of normal life. Providing equitable access to these types of services and quickly restoring that access following a disruption is the heart of community resilience. We propose a new conceptualization of resilience that is based on access to essential services, together with a way of measuring the resilience of a community based on this conceptualization. Using two illustrative examples from the impacts of Hurricanes Florence and Michael, we demonstrate how decision makers and planners can use this framework to visualize the effect of a hazard and quantify resilience-enhancing interventions. This equitable access to essentials approach is a resilience framework that integrates with spatial planning, and will enable communities not only to ”bounce back” from a disruption, but to “bound forward” and improve the resilience and quality of life for all residents.

[10] Submitted to *Journal of Risk Analysis* as Logan, T & Guikema, S. The Heart of Community Resilience: A Framework and Approach to Ensure People Have Equitable Access to Essential Services.

5.1 Introduction

Access to services is not something we should take for granted, not before nor after a disaster. Following Hurricane Katrina, residents of New Orleans' Lower 9^{th} Ward were forced to take three buses to reach their nearest grocer [234]. The 2017 South Asian floods raised fears that thousands of children permanently dropped out of school [342]. Even without these disasters, many people worldwide live within food deserts, health care deserts, and without access to other essential services. Access to services, such as food, education, healthcare, and culture, is integral for communities to function well [94, 201, 326, 354]. This means that equitable access to essential services is fundamental to community resilience.

How to operationalize resilience is among today's most impactful research questions [60]. This is perhaps because resilience is conceptually malleable and multidimensional [60, 218]. To capture this complexity, it is widely accepted that no single metric will be sufficient [54, 84, 86, 143, 193, 290]. We, as a research community, need to develop approaches that complement one another.

One existing approach for operationalizing resilience focuses on community capacity. Motivating this approach is an understanding that resilience relies on qualities that enable a community to prepare for, respond to, recover from, and improve after hazards [86, 359]. Indicators are used to quantify these qualities. These indicators capture aspects including the social, economic, institutional, and infrastructure characteristics [84, 86, 89, 292], and the vulnerability and adaptability of communities [184]. This approach is not event-specific [182]. Rather, the objective is to determine qualities of a community that can be strengthened to enhance the community's ability to respond and recover [86, 89, 292].

Infrastructure functionality is the other approach. It focuses on critical infrastructure networks, such as electricity, transportation, communications, potable water, and sewers, with the goal of limiting damage, mitigating the consequences, and hastening the recovery [30, 54, 82, 139, 143, 160]. Central to this approach is the resilience function or recovery curve, where the network's state (e.g., percent operational) is the focus. Much of the research in this area has improved how that recovery function is quantified [25, 54, 65, 71, 290, 335]. Other work has advanced how infrastructure networks can be optimized to reduce their vulnerability or speed their recovery [160, 358]. Ongoing advances address the interdependence of the infrastructure to understand how failures may cascade through a system [124, 139]. More recent extensions [72, 124, 140] have begun applying the capabilities-approach, which focuses on understanding how hazards affect the opportunities of individuals including being educated and being healthy

[227]. This existing work, however, remains focused on the effects from damage to centralized infrastructure.

Although these traditional approaches are invaluable for understanding resilience, both have limitations in their ability to provide actionable insight for building resilience. The indicators of community characteristics remain heavily focused on socio-economic aspects of communities [182] and approaches for improvement, such as increasing the community's education, operate on decadal time-scales. They are not spatially explicit and some lack validation [27]. Primarily, they are not intended to provide information regarding how a community responds to a specific hazard or instruction for decision-makers in those cases. On the other hand, the infrastructure functionality approach is useful for hazard response. However, it assumes the services are provided by centralized infrastructure and often lack spatial specificity. Additionally, the approach has ignored, until very recently, the actual people it aims to serve and has remained independent of their needs and vulnerabilities [87, 89, 100].

Most importantly, neither approach captures how a community can ensure people have access to essential services. The accessibility of services such as education, healthcare, food, and cultural amenities (that critical infrastructure exists to support) is crucial for a community's vitality, livability, and cohesion [94, 314, 326, 354] (Figure 5.1). These are what people need so they may recover and return to some semblance of normal life. Without such services, people will leave a community. Currently the approaches to resilience cannot address questions specific to vital community function: Following a disaster how long must people go without acceptable access to food?

We need to rethink our approach to community resilience to address this unsolved challenge. This will require integrating our understanding of the social system and the physical infrastructure and truly focusing on the needs of and opportunities for the residents [84, 182]. Although infrastructure is necessary for many opportunities, it is not sufficient on its own [100]. Equally, possessing the characteristics of a strong and healthy community is vital, but alone is insufficient.

We offer a fresh perspective on community resilience. We propose the equitable access to essentials (EAE) resilience framework that integrates and complements the existing approaches to provide actionable insight for communities trying to build their resilience.

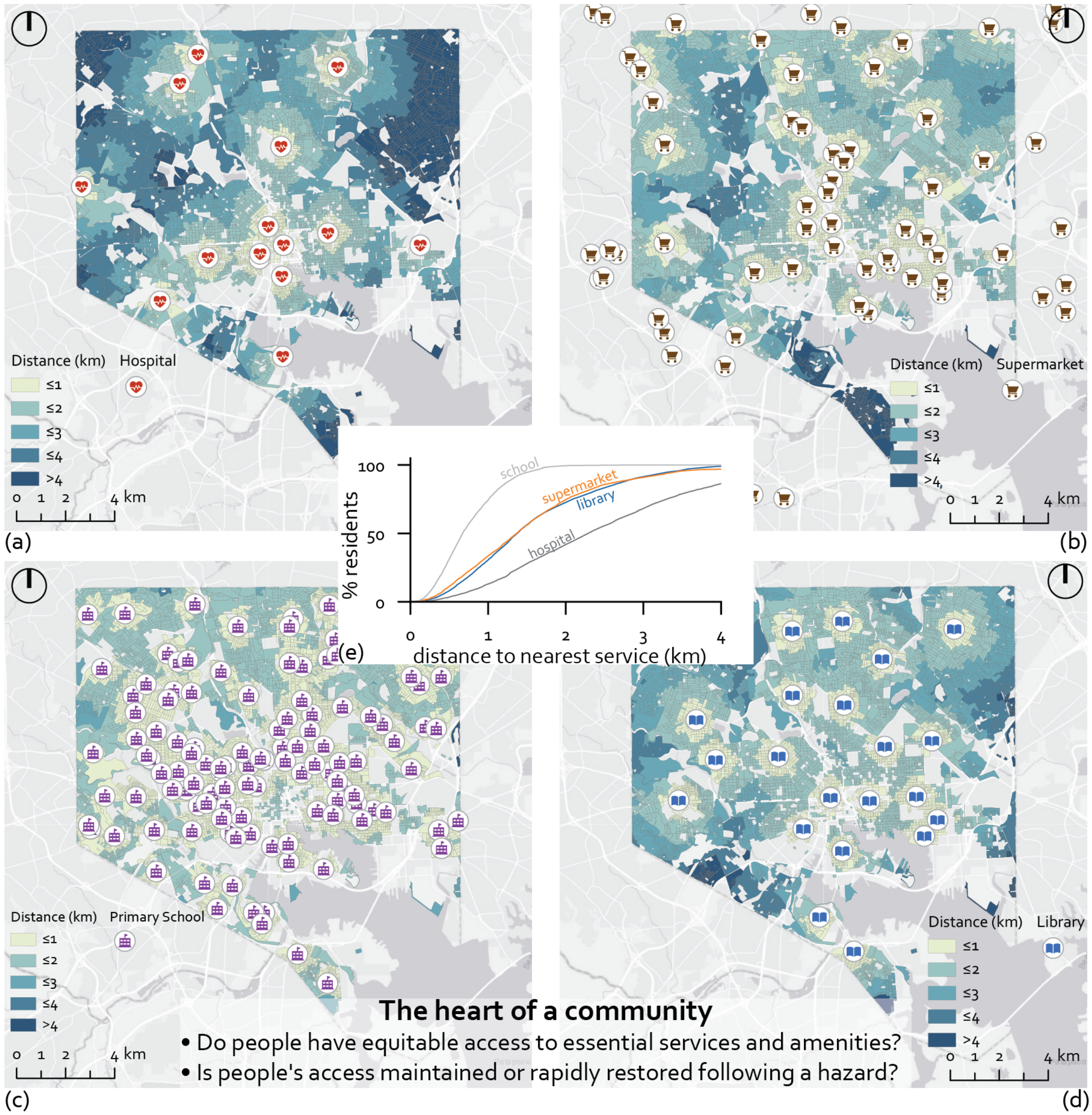


Figure 5.1: Equitable and acceptable access to services is essential for a communities viability and cohesion. These maps of Baltimore, MD, show the distance to the nearest (a) hospital, (b) supermarket, (c) public primary school, (d) library (an example of a cultural amenity). Figure (e) shows the percentage of residents who live within x kilometers of their nearest service.

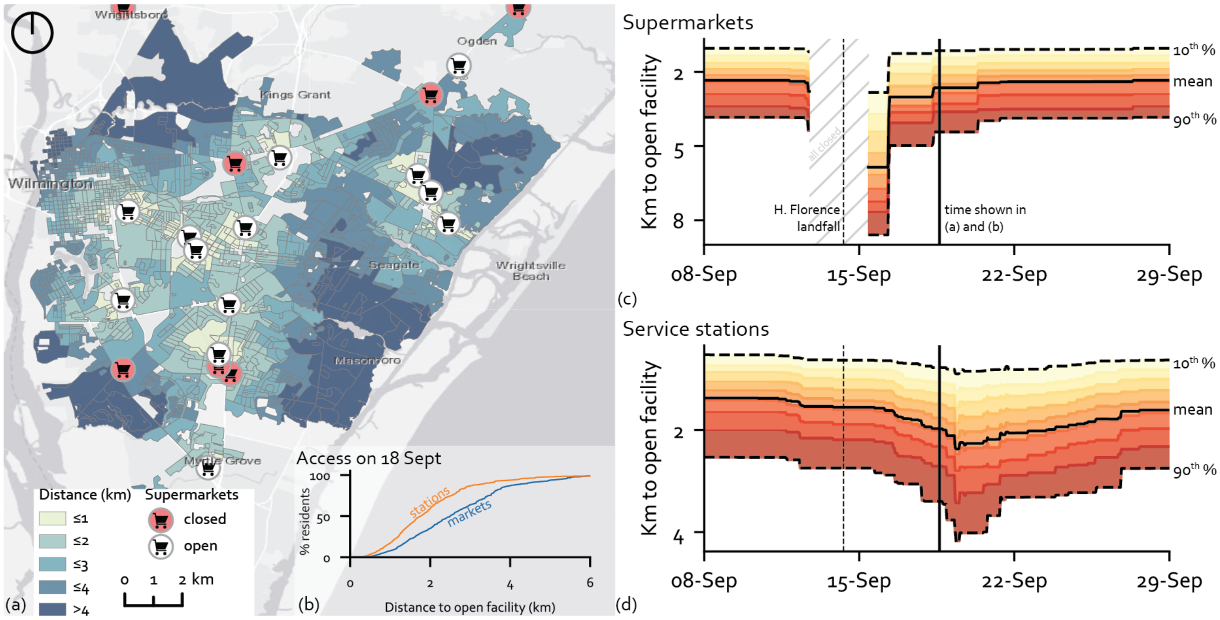


Figure 5.2: Wilmington, NC on the 18th of September, 2018. (a) The map of distance to nearest operational supermarket for census blocks with non-zero populations, (b) the cumulative distribution function showing the percentage of residents who are closer than x to their nearest operational supermarket and service station, and (c, d) the resilience curves showing how the distribution in access changes over time.

5.2 Equitable access to essentials (EAE) resilience framework

EAE measures the distance of residents within a community to their nearest operational essential services. As facilities shutter and reopen due to a hazard, we can evaluate what percentage of people are affected, how long it takes to recover, and how the experiences differ across different groups of the population. This spatially and temporally explicit approach both 1) identifies where and who requires attention from emergency responders, and 2) encourages interventions to reduce service deserts (e.g., food), both before and after a hazard, to reduce inequity and strengthen the community.

We intentionally do not specify which services are essential to a community. This is community and culture specific and requires community engagement. While, we focus on services requiring people to go to a centralized location, the technique could be also used to locate services such as "Meals on Wheels" that send people out from a central location, if proximity is important. The approach's flexibility means that (re)construction focuses on places and services of significance to people [326].

We also intend EAE to be applicable for a wide range of hazards. For example, before any hazardous event, EAE can be used to address inequality and to identify critical service locations. Following a hazard that damages services or their supporting infrastructure, such as an earthquake or weather induced event (hurricane, flooding, heat wave), EAE can guide decision making on restoration. Following any hazard, regardless of the scale of destruction, EAE provides support to decision makers on where supplies need to be provided. In the event of a complete destruction, such as the result of a major wildfire or even sea level rise, EAE can guide new development to ensure it meets the needs of people.

For a specified region, the equitable access to essentials resilience framework involves:

1. Engaging the community
    a) Work with a range of community partners to establish which services are essential and how access needs differ throughout the community
2. Measuring accessibility
    a) For each of the essential services, identify the locations of service provision facilities within the region
    b) From each block within the region, determine the network distance to all facilities
    c) For each block, determine the distance to the nearest operational facility
    d) Map the distances to nearest service (Figure 5.2a)
    e) Plot the distribution of nearest distances (Figure 5.2b)
3. Monitoring the impacts from a hazard
    a) Update the distance to nearest operational services as facilities open and close
    b) Construct the resilience curve showing how residents' access changes over time (Figures 5.2c, 5.4)
4. Evaluating equality and equity (Figure 5.5)
    a) Differentiate residents based on demographics or vulnerability scores
    b) Compare how the access for these various groups changes over time
    c) Identify vulnerable areas to which to provide additional services and improve equity.

5. Intervening to build resilience (Figure 5.8)

This is a new way of conceptualizing and quantifying community resilience that can support building resilience, independent of the hazard. EAE can be simulated using both the critical infrastructure and community capacity information. Critical infrastructure simulation provides ways of estimating which services will not be operational following a hazard. The community characteristics can be used to evaluate need and assess equity following these simulated disruptions. In turn, community indicators can be assessed and updated based on these simulations. Thus, EAE is a resilience framework that integrates the existing approaches with a clear focus on the well-being of the community's residents.

5.2.1 Acceptable access

It is possible to specify a minimum acceptable standard for accessibility for each of the services and determine the portion of the community with acceptable access (Figure 5.3). The percentage of the residents with that acceptable access is determined from the cumulative distribution functions (the process is shown in Figure 5.4). The threshold must be place-based and service-specific and determined through community engagement [251, 326].

We recognize that while we argue for considering access to essential services as a measure of resilience, we currently present proximity to services. Access, in fact, is comprised of proximity, availability, acceptability, affordability, adequacy, and awareness [258, 284]. Drawing on, and advancing, the relevant literature will lead to the additional dimensions being included for each service. These additional dimensions can be included through the use of a metric that defines acceptable access. This would specify a minimum level suitable for human well-being [100]. It may even require that proximity, cost, capacity, and other dimensions of accessibility vary based on the characteristics and vulnerabilities of the community to consider social justice (for example, proximity may vary based on car-ownership). This standard would be normatively indexed, i.e., the standard of acceptability is arbitrary and evolving (analogous to the poverty line, which is geographically specific) [76].

Nevertheless, proximity is a necessary component for access to services and provides insight into the resilience of a community. A major benefit derived from using proximity, or any continuous measure of access, is the ability to assess the distribution of access across the population. There is a very real risk when using thresholds that the residents with extremely poor access, who are often among the most vulnerable, are overlooked because they are aggregated by a binary metric [201]. This is especially important given that poverty lies at the root of disaster

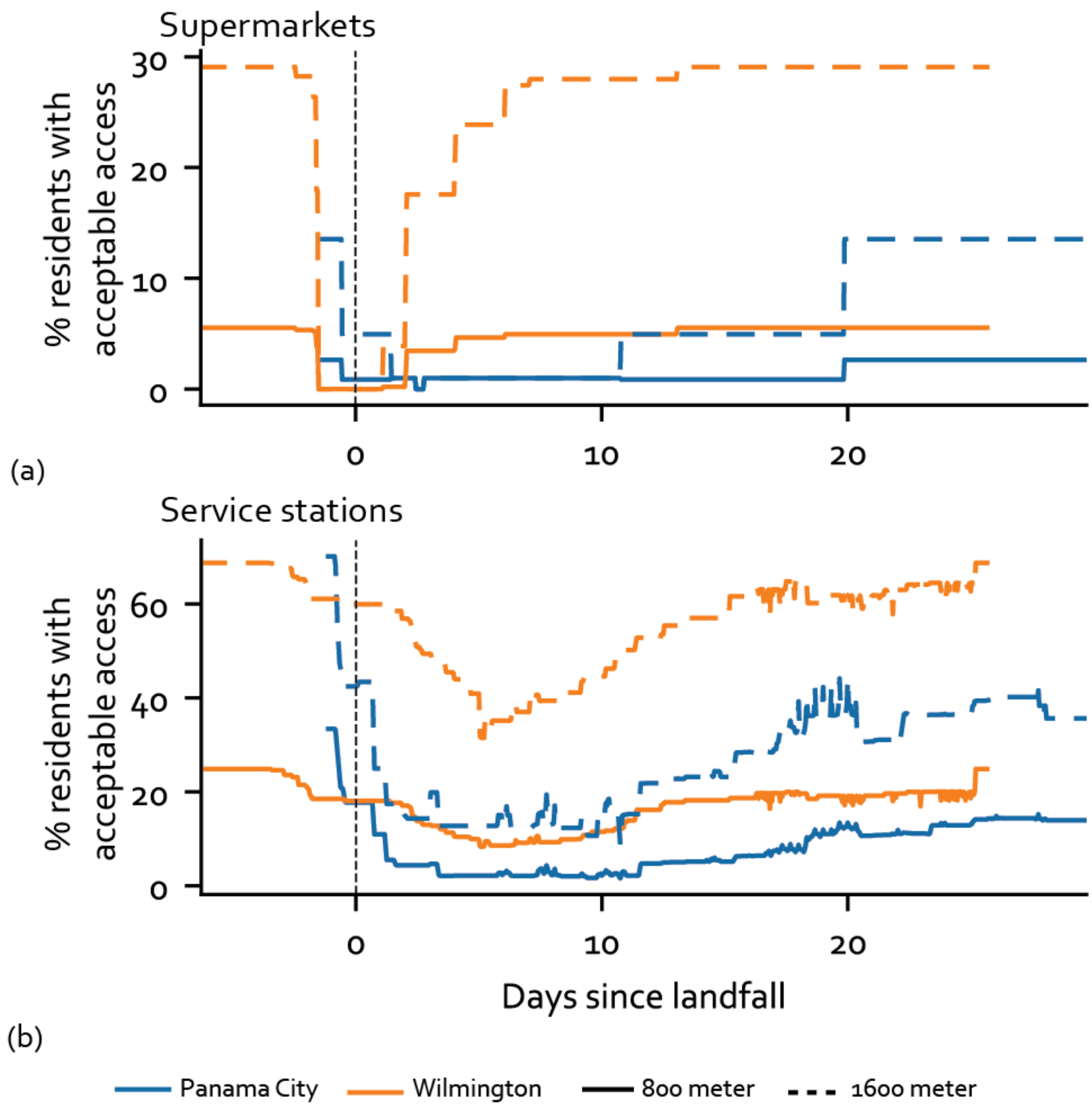


Figure 5.3: The recovery curves, for Panama City following Michael and Wilmington following Florence, showing the percentage of residents in each city with acceptable access to both (a) supermarkets and (b) service stations. Acceptable access is defined by two distance thresholds.

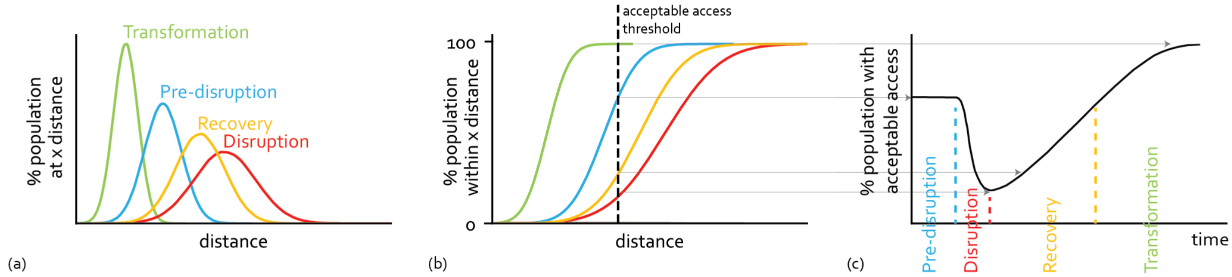


Figure 5.4: How the distribution of access maps onto the resilience function (aka recovery curve). (a) these are the density functions (idealized histograms) of the distance of residents to their nearest service. Each distribution curve represents a different phase of the hazard cycle. (b) these cumulative distribution functions are variants of (a) and show the percentage of the population that live less than the distance on the x axis. The threshold of acceptable access is shown here. Where this line intersects with the CDFs we can identify what percentage of the population has acceptable access. (c) mapping these values onto their associated time results in this figure that shows acceptable access changing with time, and is a recovery curve.

vulnerability so true resilience approaches must help correct this [251].

5.2.2 Equality and equity

Inequalities may be present before the occurrence of a hazard and are often exacerbated after an event [124]. EAE can parse different socio-economic characteristics and evaluate the accessibility of services across demographic groups (Figure 5.5) [352]. This allows for needs-based assessments and the integration with indicators of social vulnerability and community capacity. Potential interventions can be assessed based on how they affect these different groups within the community.

5.2.3 Promoting transformation

The many resilience approaches that prioritize "bouncing back", and quantify resilience using a "change-in functionality", risk further institutionalizing inequity [166, 207, 239]. Claims such as "residents have grown used to" these abysmal conditions, fail to value the importance of equity and community sustainability for resilience to future events [94, 251]. They fail because they do not promote transformation and mitigation that encourages communities to "bound forward."

EAE is deliberately constructed to promote transformation of communities to enhance eq-

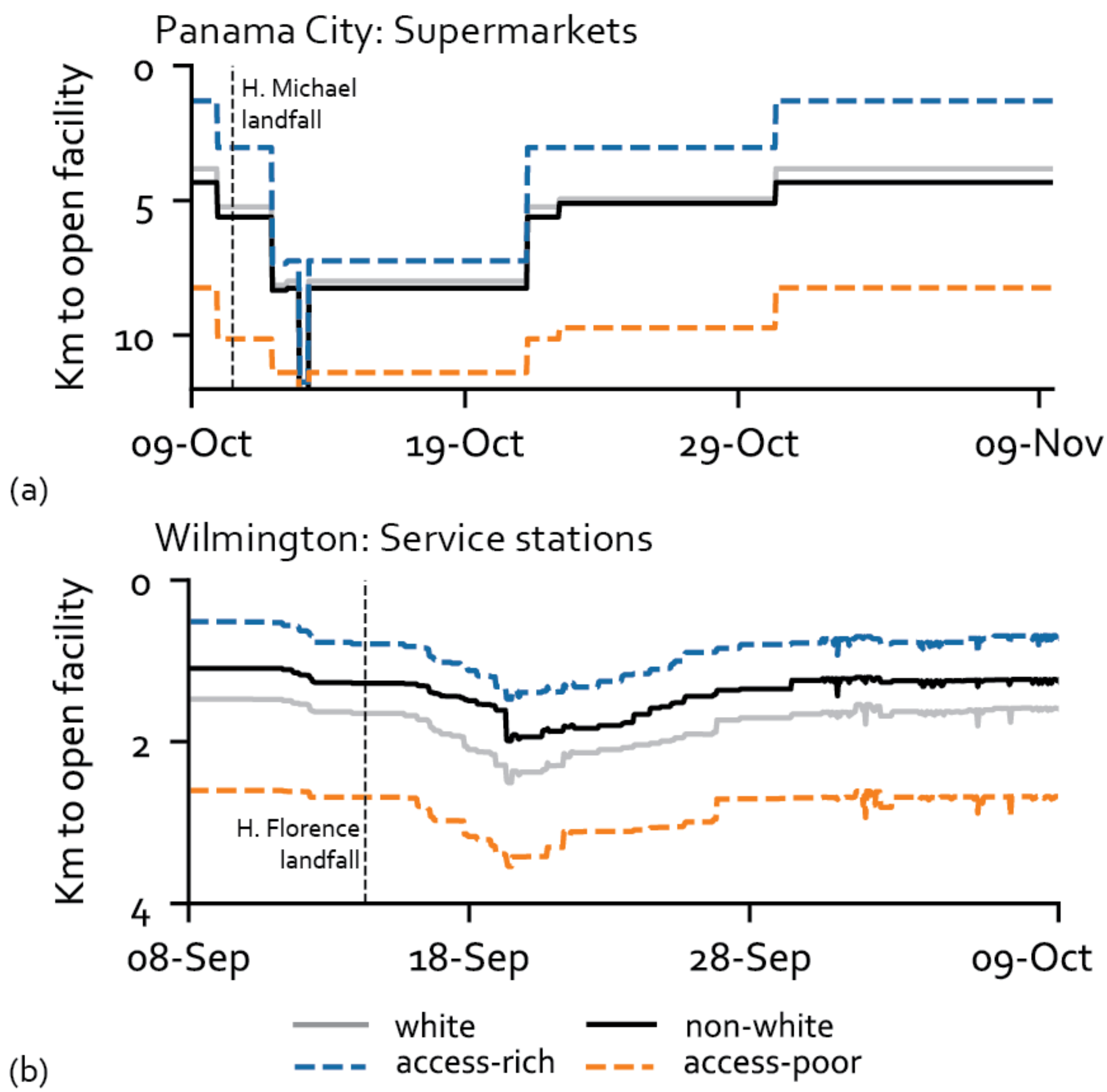


Figure 5.5: Comparing how access to essentials varies between demographic groups and initially access-rich/poor residents (the top and bottom 20% of residents). This could also be done based on indicators of social vulnerability or community capacity.

uity, both before and after a disruption. This is achieved primarily in two ways. First, unlike the critical infrastructure approach, which predominately focuses on the state of infrastructure damage [89], EAE assesses the value residents derive from the system. This distinction is important because restoring functionality is not analogous to returning to the previous state e.g., the services can be rebuilt in more desirable spatial configurations. Second, by assessing actual distance, rather than the difference at any point in time with the initial state ("change-in"), EAE identifies the service-poor residents. For example, in Figure 5.5, the largest change in access is experienced by the service-rich residents. If decisions were made on the basis of this differential, then interventions would be targeted to improve the resilience of service-rich residents, and further exacerbate inequalities. Instead, decision makers should be aware of pre- and post-hazard service deserts. This should mean that both mitigation and reconstruction target and improve the standard of living for all residents [251]. This is essential for building sustainable communities, that are enabled to enhance their adaptive capacity and future resilience [282].

5.2.4 Spatially explicit

The access map is one of the most important decision support tools from EAE. This spatial focus contrasts with the existing approaches to resilience that are primarily spatially independent. Existing approaches do not explicitly require information about a community's layout nor do they support urban planners. Examining the EAE maps allow decision makers to understand the distribution of damage, vulnerable people, and services and act accordingly.

More generally, integrating land-use planning with resilience quantification is essential because spatial planning is among the most effective tools for reducing exposure and sensitivity to extreme events [55, 61, 165] (see [9] for climate related examples). Surprisingly, there has been little attempt to integrate climate protection and spatial planning in practice [31]. EAE brings spatial planning to the forefront of resilience quantification by clearly linking it with urban changes and social sustainability. Incorporating EAE into planning can identify service-deserts and key facilities that many people depend on. This can guide urban planners to strengthen existing facilities or incentive the development of additional ones. Additionally it can be used to guide both green and brown field development to ensure that people's access to essential services is provided equitably. In this way, EAE links policy discussion regarding accessibility and equity with resilience and hazard planning. This supports rethinking how our cities are designed, planned, managed, and lived in, in the pursuit of community and urban resilience [60].

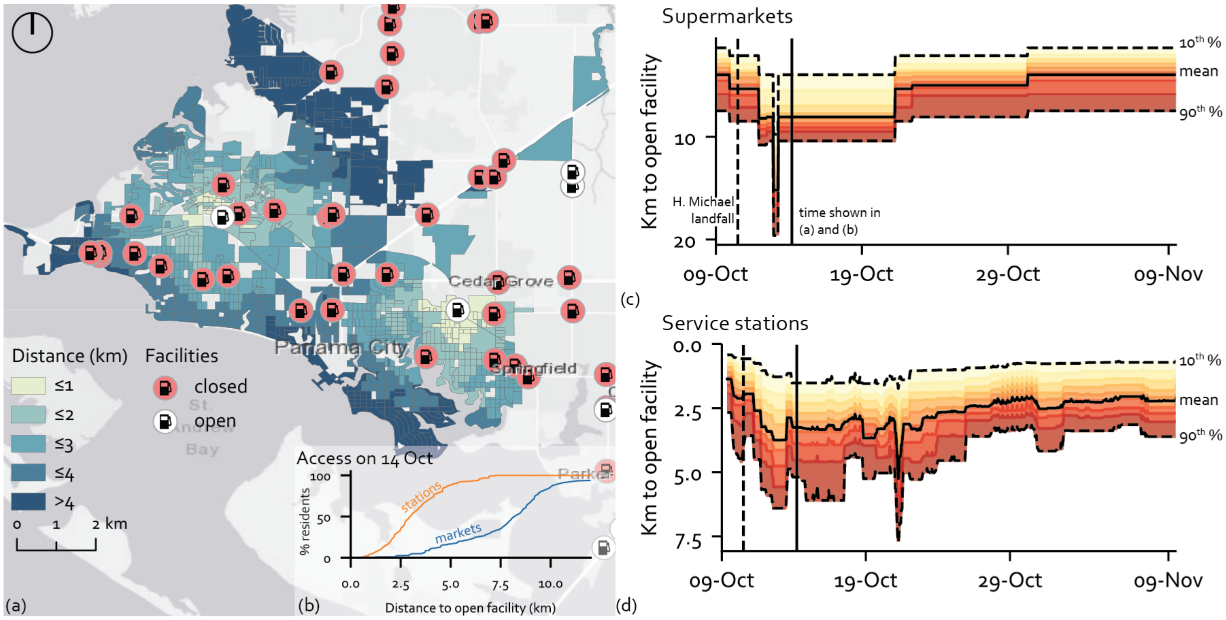


Figure 5.6: Access in Panama City, FL on the 14th of October, 2018. (a) The map of distance to nearest operational service station, (b) the cumulative distribution function showing how many residents are closer than x to their nearest operational service station and supermarket, and (c, d) the resilience curves showing how the distribution in access changes over time.

5.3 Illustrative examples

5.3.1 Overview and scope

We now present two illustrative examples focused on Wilmington, North Carolina, and Panama City, Florida. In late 2018 they were struck by Hurricanes Florence and Michael respectively. The examples demonstrate how the access to two services (grocery stores and service stations) change due to the hurricanes. Specifically, we seek to 1) understand the spatial extent of service disruption so service-poor residents can be identified, 2) assess the resilience of the community to these hazards. Note that our use of grocery stores and service stations is for demonstration purposes; in practice, determining which services are essential and what distance is acceptable requires community engagement.

Wilmington, NC is located on the southeastern North Carolina coast. It has a population of approximately 120,000 people. Hurricane Florence made landfall slightly east of Wilmington in the early hours of September 14, 2018, as a Category 1 hurricane. Due to the hurricane's

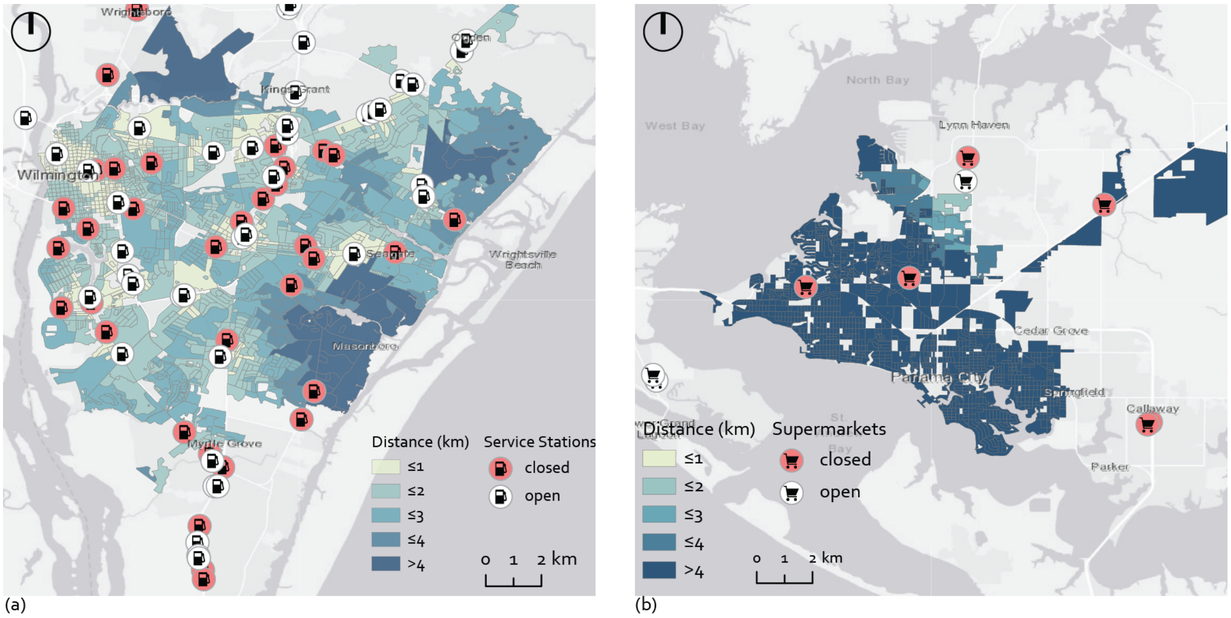


Figure 5.7: The map of distance to nearest operational service: (a) Access to service stations in Wilmington, NC on the 18th of September, 2018. (b) Access to supermarkets in Panama City, FL on the 14th of October, 2018.

slow movement, it resulted in heavy rainfall beginning September 13, and coupled with strong storm surge, this resulted in heavy flooding.

By contrast, Panama City, FL, has approximately 37,000 residents and is located along the Emerald Coast of the Florida Panhandle. Hurricane Michael made landfall 40km Southeast of Panama City as a Category 4 hurricane on October 10. While Florence was notable for its rainfall, Michael caused catastrophic damage due to extreme winds (the strongest in the USA since 1992 with 208 km/h winds) and storm surge.

5.3.2 Inputs

For this illustrative example we present the access to grocery stores and service stations before and following the hurricanes. Service locations were determined using GasBuddy[11] and supermarkets were identified manually using Google Maps. Access to these services was calculated at the US census block (neighborhood block) level and shapefiles and demographic data was sourced from IPUMS [209]. The Open Street Map street network was downloaded

[11]https://tracker.gasbuddy.com

from Geofabrik[12]. The distance from each block to all services was calculated using the Open Source Routing Machine using the approach described in [201] (Chapter 4). Facility closure was recorded from GasBuddy, Twitter, and the supermarket websites.

5.3.3 Results

Figures 5.2, 5.6, S2 & S3 show access in Wilmington and Panama City following the hurricanes. The maps can be used to identify service-deserts and the recovery functions show how quickly the cities restore access and how acceptable that access is.

As an example, there appears to be a food-desert in western Wilmington 5.2a, so these residents may require emergency food supplies even after the other stores reopen. Note that due to data availability, the supermarket results do not include all food outlets as we only obtained information for stores that were reporting their opening times. Although these results do not comprehensively present food-deserts, they provide a demonstration of using this approach. These maps could be varied to highlight sectors of the community with high social vulnerability, or, for example, a higher proportion of aged residents, so that emergency response can target need.

Recovery times and access quality are shown in Figures 5.2c,d, 5.6c,d, and 5.3. Supermarkets appear to reopen faster than service stations, likely due to resources provided by their parent companies. In Wilmington, this was a matter of days. Access to service stations in Wilmington was still deteriorating by the time supermarket access was almost restored (Figures 5.2 & 5.3). This is likely due to failures in the supply chains. However, inventory information was unavailable to us for supermarkets.

In Panama City, the recovery took significantly longer for both supermarkets and service stations (Figure 5.3). However, this comparison does not reflect differences between the cities' resilience, because the hurricanes were different. Nevertheless, it is clear that Panama City suffered more and for longer.

In both cities, the access to supermarkets is less than desirable (Figure 5.3). Even before the hurricanes, only 30% of residents in Wilmington live within 1 mile (1600 meters), which is further than the majority of distance thresholds considered acceptable (e.g., [314]). This is worse in Panama City, but the results are skewed due to our omission of some food stores that would be included in practice. Regardless, this shows that there are likely service-deserts existing within the cities that could be mitigated prior to a hazard.

[12] http://download.geofabrik.de/

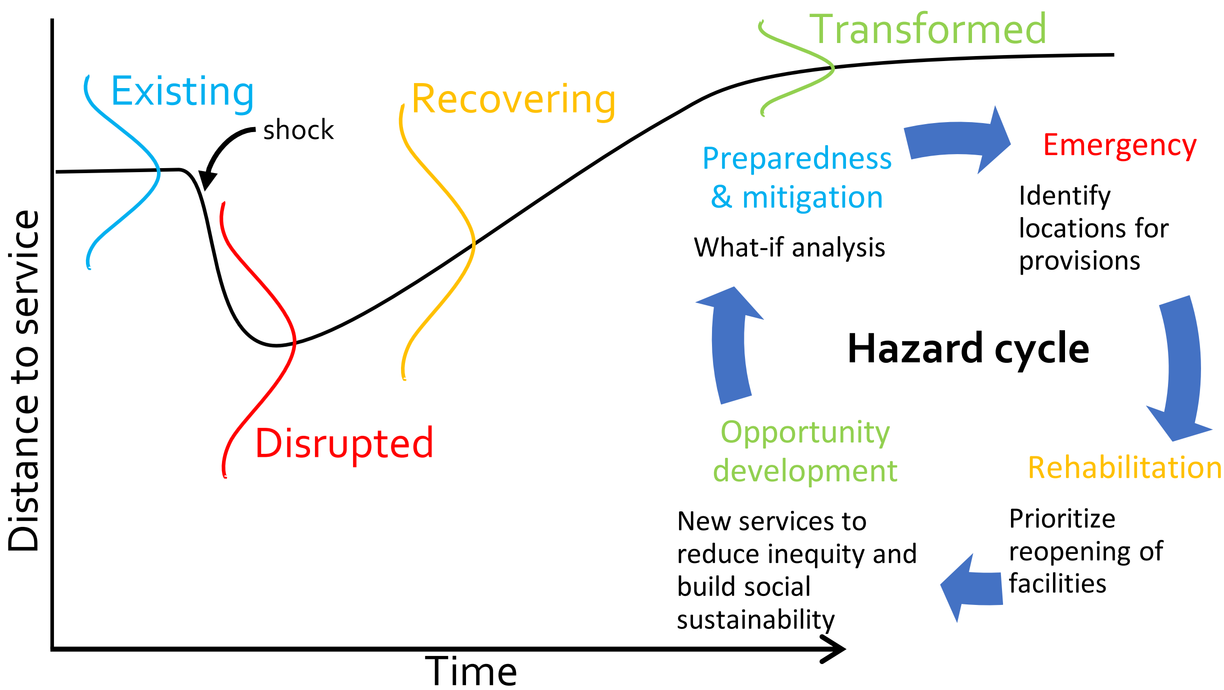


Figure 5.8: This resilience function (aka recovery curve) shows how the access, and its distribution, may change before, during, and after a hazard. The hazard cycle shows how the EAE resilience framework can be utilized by decision-makers from mitigation to recovery.

5.4 Application throughout the hazard cycle

EAE can enhance decision making throughout the hazard management cycle. The cycle (Figure 5.8) involves preparing for and mitigating potential hazards; emergency response; and recovery, including the immediate rehabilitation and longer term (re)construction: opportunity development [275].

Implementing this framework in the field will require real-time information about the functioning of services. For example, local networks or reporting systems could be implemented. This, coupled with improvements in proximity analysis [201, 238], mean that essential service access can be evaluated before, during, and after a hazard strikes. This can be used to guide emergency response as well as short-term and long-term recovery and development.

5.4.1 Mitigation and preparedness

Before any hazard occurs, existing inequities to service-deserts should be addressed. This will enhance community cohesion and social capital [94] and enable residents to utilize all opportunities [89]. Additionally, ”what-if” simulation can determine which facilities are critical in servicing the community. This type of analysis can be used to build redundancy or robustness into the system [340].

5.4.2 Emergency response

During and immediately following a disruption, EAE enables responders to identify impacted areas and allocate resources appropriately. To leverage this tool, appropriate data collection systems are needed. This could be simply scraping websites such as Twitter or GasBuddy, or, ideally, could be a crowdsourced setup where facilities or the public report damage or closures, similar to the "call 311" system used by a number of USA cities to report non-emergency problems. Such data would allow the service accessibility map to be updated in real-time and would support targeting supplies like food and health care to places in need. Based on population characteristics, vulnerabilities and needs could be considered so that situations such as the ignoring of vulnerable residents in the Rockaways, NY, following Hurricane Sandy [311], do not reoccur.

5.4.3 Rehabilitation

During this phase, short term and basic essential services are restored [275]. Facility reopening can be coordinated and optimized to maximize accessibility.

5.4.4 Opportunity development

This latter phase of recovery is referred to as "opportunity development" rather than reconstruction (returning to the previous state) [251, 275]. We should build back better [275] by not only enhancing protection against future hazards [263], but by improving equity and residents' quality of life [251]. In this phase, urban planning must be leveraged to encourage desired amenities such as grocery stores to establish in certain locations. For example, comprehensive plans can be used to set minimum numbers for food retailers, zoning mechanisms can simplify the regulatory process, and subsidies or other incentives can recruit retailers to in-need areas

[268, 269].

5.5 Summary

The urgent need for communities to build their resilience means that understanding how is among today's most impactful research questions and practical challenges [60]. While there has been significant work on resilience, the existing approaches are limited in the actionable insight they provide. The existing thinking on resilience does not focus on the provision of everyday amenities such as food, health care, and education, which are vital for residents to participate in life. The equitable access to essentials (EAE) resilience framework that we propose integrates key aspects of the traditional approaches to resilience and complements their use with the goal of maintaining, restoring, and improving equitable access to essential services.

EAE provides a spatially explicit and hazard-general approach to quantifying resilience of access to services with a direct focus on people's well-being. It involves measuring the access of residents to the services and monitoring how that access changes before, during, and after a hazard event. Critical to our framework is the ability to discern how access changes between different demographics and vulnerable groups within a community. Equally important is that we have devised the framework in a way that promotes continuous improvement of access to all residents and transforming the system, rather than bouncing back to pre-event conditions. EAE has utility during all phases of the hazard cycle by providing actionable information to decision makers from preparation to post-event improvement. By being spatially explicit, EAE integrates resilience quantification with urban planning, which is crucial for our society's response to evolving threats exacerbated by climate change.

To end-users, we reiterate that while this approach is adaptable and scalable, resilience is place-based and therefore community specific, so the application of this framework must succeed community engagement and understanding.

Rethinking resilience as access to essential services promotes bounding forward, rather than bouncing back. It complements and integrates aspects of both dominant existing approaches to community resilience. We encourage transformation by shifting the focus from the state of infrastructure to the value it provides to people. This naturally enhances adaptive capacity of the community and existing capacity indicators can be used to prioritize vulnerable residents. The equitable access to essentials framework formalizes resilience in a way that enables and encourages communities to build their resilience equitably.

Chapter 6

Risk: Revising the concept and description to include time [13]

Abstract

"Over what time frame?" is an essential consideration for risk assessment. However, currently dimensions of time are typically not explicitly included in the conceptual definition and description of risk and the associated notation. We suggest updating the notation of risk such that time is included: for some S, α_τ we define $\text{risk}_T = (C_T, U)$. Where C_T are the consequences evaluated over time T and U represents that those consequences are uncertain. This expression requires the pertinent system S, activity α, and period of time τ for which the risk is considered be specified. Additionally, we suggest that the notation of the risk description also reflects these changes and we present changes to achieve this. Making time explicit in how we express risk carries implications such as intergenerational equity and raises challenges of interest to many risk analysis applications. Ultimately, including the temporal dimensions improves the suitability of risk analysis for tackling the major challenges of our time.

6.1 Introduction

We all know that fundamental to, albeit implicit in most conceptual definitions of, risk is time. Consider the example from Aven [18] (page 14): we are concerned about the health risk for a

[13] I intend to submit a modified version of this chapter as a perspective paper to the *Journal of Risk Analysis* as Logan, T, Flage, R, Guikema, S & Aven, T. Revising the expressions of the concept and description of risk to include time

person for a specific period of time or the rest of their life. If we choose to consider the health risk for the rest of (e.g.) John's life, the risk is clear and well defined. The time over which we consider events and consequences is bounded. However, what if we consider John's health risk over a ten year period; what happens if he contracts a disease that has consequences beyond that ten year period? In situations such as these, common throughout problems tackled by risk analysts, we must be explicit in how we address time.

The risk assessment process, outlined in Kaplan and Garrick [173] proposed the following questions: "What can go wrong", "what is the likelihood", and "what are the consequences?" A fourth consideration was proposed: "over what time frame?" [142]. This is absolutely necessary. However Haimes [142] is only referring to one of two necessary temporal considerations:

1. the time frame over which the activity occurs.

The second consideration is:

2. the time over which the consequences are assessed.

Both time dimensions remain omitted in how the risk concept and description is notationally defined.

This does not mean that risk analysts are ignoring time. Some are not. Consider the Yucca Mountain Nuclear Waste Site risk-assessment [156]. In this situation the time horizon used for evaluating the consequence (the occurrence of a volcanic eruption) was 10,000 years. Clearly, time was an important factor for the risk analysis. In fact, risk analysts tackling these applications are making decisions about how they address the temporal dimensions, but formalizing our notation of the conceptual definition and description of risk to include time ensures that those decisions are made explicit. This formalization also can help to avoid confusion regarding the applicability of risk analysis.

One such potential confusion has arisen in calls for diverging resilience analysis from risk analysis. This is divergence is sometimes motivated by the argument that risk is simply referring to the "total reduction in critical functionality" [197, 198]. By arguing that risk is not related to the ongoing consequences or influenced by the recovery, the time dimension of risk is implicitly omitted.

A goal of risk analysis is to support decision-making. However, if that analysis ignores how the consequences of actions or decisions evolve over time, it becomes a short-sighted decision-making tool. Challenges like resource depletion, urban planning, nuclear waste management, and climate change all have deeply inherent temporal considerations [5]. If risk analysis is to address these challenges, it must be explicit how we address time. In this paper, we propose that the formal definition of the concept and description of risk be revised to make the consideration of time explicit. In doing so, we also recommend minor changes that seek to clarify the concept and description of risk.

6.2 The risk definition

The Society of Risk Analysis' (SRA's) glossary [306] introduces risk in the context of a future activity, for example the operation of a system or the existence of an ecosystem. Risk is then defined in relation to the consequences of this activity with respect to something that humans value. A general conceptual definition of risk, listed in the SRA glossary, is

> *Risk is uncertainty about and severity of the consequences of an activity with respect to something that humans value*

[23]. This has been schematically written as risk $= (C, U)$. This notation indicates that risk is a two-dimensional combination that includes (i) that the activity considered leads to consequences, C, and (ii) that these consequences are not known, U [18] (page 13). The consequences arise from the occurrence of events A, but the schematic expression of risk is deemed equivalent $(C, U) \equiv (A, C, U)$, without loss of generality.

As an example, consider a community's risk. The consequences (C) relate to the occurrence or not of specific hazards (known or unknown types), their time of occurrence, and their effect on the community (e.g., no negative effects, complete collapse, etc.). The uncertainty (U) says that today we do not know if or when the community will experience a hazard, nor do we know what the consequences will be.

In this example, we are concerned about the risk to the community "for a specific period of time" [18] (page 14). However, there are two temporal dimensions we need to consider and it would be useful if both were expressed in the notation. For instance, does this "specific period of time" refer to the occurrence of events or the time over which consequences are evaluated, or both? That is, if a community is struck by a hurricane at the end of the specified time period, do we ignore the consequences to the economy, environment, and people's well-being that may last for years if not decades into the future? It is critical that our approach to and decisions relating to this consideration of time be clarified.

Therefore, we propose that the conceptual definition of risk include the temporal dimension explicitly. In the risk concept there are two aspects pertaining to time:

1. the period over which the activity and associated events occurs (τ)
2. the time for which we consider the consequences (T)

Schematically, we propose that risk be written as

$$\text{risk}_T = (C_T, U)$$

where the subscript T expresses that the consequences include everything that occurs up until time T. For clarity, C_T simply represents that we estimate consequences of an event over the time frame T. This is no different to how C is defined in (e.g.,) Aven [18], except that the time over which consequences are assessed is stated. Therefore, if we were to be representign the Yucca Mountain consequences, we would write $C_10,000$ because they were assessed over a 10,000 year period. In a risk analysis into hurrican risk, if we only evaluated losses up to one year following an event, we would write C_1. Where the consequence is binary, the time dimension may be set to zero, as it would be in Huang and van Gelder's [163]'s study of whether or not a collision occurs. These decisions are frequently made by risk analysts during their risk assessments.

In addition to this schematic representation, we also need to be explicit in the time frame over which the activity is considered, τ. This is important for identifying potential events. To provide the most clarity (and still without loss of generality), the concept of risk should include the specification of the system S over which it operates and α_τ,the activity occurring over the time frame. To limit confusion with "A" for activity, we define $\mathcal{E}$ as the event or events that occur. That is, we express risk as: for some S and α_τ

$$\text{risk}_T = (\mathcal{E}, C_T, U)$$

This is consistent with Haimes [142] that identified risk as a function of the initiating event, the system/environment, and the time frame. As is tradition, without loss of generality the events can be omitted, this can be written as: for some S and α_τ

$$\text{risk}_T = (C_T, U)$$

6.2.1 Alternative conceptual definitions of risk

Given our argument is framed for the most general risk concept, it holds for the other conceptual definitions of risk [306]. The definitions enumerated in the *Society of Risk Analysis'* glossary [306] are as follows:

1. Risk is the possibility of an unfortunate occurrence
2. Risk is the potential for realization of unwanted, negative consequences of an event
3. Risk is exposure to a proposition (e.g., the occurrence of a loss) of which one is uncertain
4. Risk is the consequences of the activity and associated uncertainties
5. Risk is uncertainty about and severity of the consequences of an activity with respect to something that humans value
6. Risk is the occurrences of some specified consequences of the activity and associated uncertainties
7. Risk is the deviation from a reference value and associated uncertainties.

In all of these definitions, one must specify the time frame τ over which the risk is being expressed. For example, if risk is the possibility of an unfortunate occurrence, it is essential to state over what time this in reference to. In any definition referring to the consequence of an event (positive or negative), the time T over which the consequences are considered also needs to be explicit. To provide additional clarity, we recommend that the system S and activity α_τ are specified.

6.3 The risk description

To assess and manage risk, we need a way of describing it. Aven [18] describes risk using (C', Q, K). This expresses that risk is described by the set of **specified** consequences C', **the measure of uncertainty** Q, and the background knowledge on which the assessments of C', Q are based. To illustrate, we continue with the example of a community at risk from hazards. For simplicity in this example, we consider only the economic consequences. In the risk assessment, N possible event-consequence pairs are identified. One of these consequences could be, for example, a hurricane that results in $1 million in damages ($c_i'$, where c_i' is one of the potential consequences (C') and i indicates the index which is in $1, 2.., N$). q_i is the probability these consequences occurring (although there are alternative measures of uncertainty e.g., [117]). k_i is the knowledge on which we base the assessments for c_i' and q_i (data, information, justified beliefs, assumptions). Using the set notation from Kaplan and Garrick [173], the risk description can be represented as $\{< c', q, k >_i\}$ for $i \in 1..N$. That is, risk is described using a set of triplets that describes each consequence, its uncertainty, and the knowledge behind the assessment.

However, this description is implicit in its inclusion of time. In our example we stated that c' was $1 million in damages. This can and should be specified in terms of time, for example we estimate that there may be $1 million in damages over the first five years; that is, $c_{5,i}' = 1$ where T is expressed in years and consequence is expressed in millions of dollars. Therefore, we propose that risk be explicitly described with reference to the time over which consequences are considered: risk description$_T = \{< c_T', q, k >_i, ...\}, i = 1, 2, ..., N$ where c_T' represents the specific consequences until a specified time T and N is the number of consequences included in the risk description. For example, $c_{\text{1year},i}'$ represents that the potential consequences are evaluated over one year following the considered event. Finally, as the concept of risk pertains to a specific activity over a period of time α_τ and a system S we recommend that these be explicitly stated. $\mathcal{E}'$ represents the set of events identified that will be included in the risk description, and ϵ_i' is one such event. Therefore: for some S, α_τ

$$\text{risk description}_T = \{< \epsilon', c_T', q, k >_i\}, i \in N$$

As before, this can be represented without loss of generality as

$$\text{risk description}_T = \{< c_T', q, k >_i\}, i \in N$$

Our proposed update to the representation of the risk description makes explicit the system, the activity, and the dimension of time.

6.4 Examples

6.4.1 John's illness

A reoccurring example in Aven [18] is our concern with John's health condition. While the level of detail seems belaboured in this example, it avoids potential confusion and is more helpful in the latter examples. We define the following:

Risk

S: John

α_τ: The act of John living over a specific period which we evaluate John and the occurrence or not of specific diseases

$\mathcal{E}$: John contracts a specific disease

C_T: The consequences for John from the event's occurrence assessed until time T (he may die, suffer etc.).

U: Today we do not know if John will contract one or more of these illness, and we do not know what their consequences will be.

Risk description

S, α_τ are as above.

$\mathcal{E}'$: The set of diseases considered

A complete risk description is a set of the following that include different consequences (for example, John recovers during the course of 1 month, 1 month - 1 year, John doesn't recover by time t, John dies within time t as a result of his illness etc.). The following is for one such description in the set:

ϵ_i': John contracts a certain illness next year

T: Five years

$c_{T,i}'$: John dies within time T as a result of his illness

q_i: We choose to express the uncertainty using a probability. We express the probability that John contracts the illness (10%) and the probability that he experiences the specific consequence $c_{T,i}'$ given he has the illness (5%). Therefore $q_i = P(c_T'|k)_i = 0.005$

k_i: The knowledge on which the assessment of $< c_T', q >_i$ are based. k_i does not have to be unique.

6.4.2 A community threatened by hazards

The level of specificity is more useful in a complex example, such as when considering a community at risk from hazards.

Risk

S: The boundary of the community considered and what components are being included: e.g., an urban system, access to healthcare, demographic of customers and their electrical infrastructure, etc.. In this case, consider the economic productivity within the city limits of a specific coastal community

α_τ: The operation of the community over a period of time (e.g., 10 years, the typical length of a municipal plan)

$\mathcal{E}$: Specific natural hazards

C_T: The occurrence or not of specific natural hazards, their time of occurrence, and their consequences for the community's economy (e.g., dollars lost).

U: Today we do not know if a hazard will strike the community, nor do we know what the consequences will be.

Risk description

S, α_τ are as above.

$\mathcal{E}'$: The set of hazards considered: hurricane, flooding, tsunami

The following is one element in the risk description set:

ϵ_i': A 1/100 year flooding event occurs in the 2nd year

T: Twenty years (*the implications of this choice are section 6.5)

$c_{T,i}'$: \$1 billion in lost economic output

q_i: We could express the uncertainty using a probability. The flooding event allegedly occurs with a probability of 1%, and based on our knowledge of the system we estimate the **conditional probability, given the event**, of $c_{T,i}'$ as 20%. Therefore $q_i = P(c_T'|k)_i = 0.002$

k_i: The knowledge on which the assessment of $< c_T', q >_i$ are based.

6.4.3 Exposure/dose-response

Consider the example in [79]. We are interested in how exposure to crystalline silica (CS) increases the risk of lung cancer in humans. Including time into the measure of risk provides clarity. The system S is the person and the activity α_τ is exposure to the carcinogen over time τ, The consequence C_T is the binary outcome of whether lung cancer develops within T years. U is the uncertainty regarding the exposure pathway and patient response. The risk description then follows from this specification. Because C_T is binary, risk is measured using the probability of cancer developing within T years of τ years exposed. This can be represented on the exposure/dose-response figures (e.g., Figure 2 in [79]) such that τ is on the existing x-axis (cumulative exposure time), and T is an additional dimension that results in the curve becoming a response surface: P(cancer)$_T = f(\text{exposure}(\tau), T)$.

6.4.4 Nuclear waste

As one last example of defining both τ and T, consider the risk assessment into the Yucca Mountain nuclear waste site [156].

In this case, they define the system S as the waste site and a volcano within a bounded region (Figure 3 in [156]), and the activity α_τ as the burying of nuclear waste at Yucca Mountain. In this case, τ is the period of time for the burying. It is the time T that is the focus of this particular risk assessment, as the recommended isolation period for radioactive waste decay is defined as 10,000 years [156]. They consider the consequence as the occurrence or not of a volcanic hazard within that time period: $C_1 0,000$.

6.5 Discussion

There are major implications invoked by making time explicit in the conceptual definition and description of risk, specifically regarding the choice of T in some circumstances. Explicitly framing time in the concept and measure of risk means that issues regarding inter-generational justice must be considered for long-term issues such as nuclear waste management and climate change. Inter-generational equity is a major factor in the discussions around climate change, other environmental crises, resource use, nuclear waste, nuclear weapons, and population growth [5]. Decisions in this realm have far-reaching consequences and for every situation there are different appropriate planning-horizon lengths [309, 313]. One ethically controversial discussion surrounding long-term decision making is the discounting of consequences [39, 243, 285, 297, 313]. Some [39] argue that discounting is an unavoidable, while others [297] point out that discounting consequence can result in policy choices that simply transfer risk rather than address it. Is discounting simply a way by which people avoid the "as low as reasonably practical" (ALARP) principle for risk management?

The time dimension therefore raises foundational questions for risk science. How do we communicate uncertainty and small probabilities in a long-term risk context [313]? What frameworks exist for intergenerational decision-making situations [24]? What guidance is available for determining whether, how, and under what circumstances, discounting should be used? Should, and if so how should, the time horizon be chosen over which to estimate consequences? Thompson et al. [320] addressed the question of discounting in a way that avoids an arbitrary time horizon in the case of species extinctions. Additionally, acknowledging the temporal dimension also raises the question: Should disaster-response assistance be focused on those who have been directly affected by the event, or should the emphasis be on reducing the risk for future generations? [129]. Explicitly including time in the notation of the concept and description of risk encourages such discussion and consideration in future risk analysis work.

This paper is about how to include time in our concept and description of risk. Doing so allows our field to be more definitive in our research and practice. This may help to prevent the confusion that may be associated with sub-fields suggesting they diverge from ours (e.g. "resilience analysis"). However, the common failure to distinguish between the definition and measure is another factor contributing to the confusion and is one we now briefly address. It would be highly beneficial to limit this confusion if risk researchers distinguish between their adopted concept and a measure of risk [14]. For example, and with great deference to the authors, a recent publication in this journal [163] defined risk as "risk is the probability of an unwanted event." What they have done is specify the *measure* of risk that they use, rather than a *definition*. Additionally, this measure fits within the conceptual definitions provided in the SRA glossary (e.g., numbers 1, 2, 3, and 5). This type of confusion can lead people to think that risk analysis is unsuitable for some types of analysis. To prevent this, we encourage authors to clearly distinguish between their measure and definition of risk. Perhaps guiding authors to clearly make this distinction (between the measure they use and a conceptual definition) in the journal's "instruction to authors" would be a simple intervention to the Society's and science's benefit.

6.6 Conclusion

We have presented an update to the risk concept and description, and their expressions which allows for the explicit representation of the temporal dimension of risk. In doing so, and without loss of generality, we argue that risk analysts should specifically define the system and activity over which the risk is considered. The result is that risk can be expressed as: for some system S and activity over time α_τ

$$\text{risk}_T = (C_T, U)$$

This is consistent with the general definition in Aven [14, 18, 23] and, as such, incorporates uncertainty in its broadest sense into the risk concept. Additionally, we suggest that the system S and activity over a time frame α_τ be specified, as per the recommendation of Haimes [142]. Importantly, we are explicit when referring to the time over which consequences are considered and express consequences as C_T. This means that the decisions, already been made when estimating consequences for a risk assessment, are now clear in the risk notation. It also confirms that time is an essential consideration and encourages discussions regarding the potential trade-offs and ethical decisions between the present and future generations affected by our risk analysis [129]. This is especially necessary so that risk can be used to address complex questions with intergenerational implications, including resilience analysis.

Chapter 7

Risk: A holistic framework for the analysis and management of resilience [14]

Abstract

We argue that the concept of risk can provide an integrated framework for resilience analysis and management. The persistent confusion surrounding the management of resilience, even including calls to independently manage inherently related aspects, are detrimental to our communities. Siloing the thinking and management will jeopardize communities threatened by hazards and lead to inefficient resource use. In this paper, we present a review of resilience definitions with the objective of identifying key components of resilience. We then demonstrate how these components fit within a risk framework to enable their integrated management. Grounding resilience analysis in the existing risk analysis literature enables existing techniques and approaches, that may otherwise be overlooked, to be used. It also enables us to analyze and manage various hazards and surprises in a holistic and collaborative manner; this is essential if we are to tackle the challenges on the horizon.

[14] We intend to submit a modified version of this chapter as a perspective paper.

7.1 Introduction

In this paper, we argue that risk analysis (the assessment, characterization, communication, and management of risk, along with related policy [306]) can be used for the analysis and, therefore, management of resilience. Our communities face unprecedented threats from the climate crisis and understanding how to put the concept of resilience into practice is essential for guiding how we manage these hazards. While there has been rapid and extensive growth of the resilience literature, including proposed definitions and approaches for conceptualizing resilience, resilience analysis and management remain in its infancy [60, 179].

To move from discussion to action, we need the ability to analyze and then enhance resilience. At times, however, dimensions of resilience can conflict, for example, creating a system that is both resistant and flexible to change [203]. Due to these trade-offs, there have been calls to manage dimensions of resilience independently (e.g., independently managing the ability to withstand a shock and the capacity to quickly recover [197, 198]). However, independent management means that rather than avoiding trade-offs we institutionalize them and sacrifice opportunities for synergies [40]. Independent management is potentially short-sighted and may jeopardize our communities. Additionally, the independent perspective contrasts with the discussion that tackling climate change requires holistic thinking (e.g., [265]). Consider a hypothetical seaside community. This community is "resilient" under the definition that it can quickly return to its existing state when impacted by a hazard [71, 157, 197, 323]. However, it is simple to see a perpetual cycle of damage and rebuilding as the hazard repeats that wastes resources and threatens lives. This is not a long-term solution [282]. Similarly, investing solely in the robustness, understood as the ability to absorb or withstand impacts, for example by building a seawall, may be devastating if the community is unable to recover in the event of a failure. However, even balancing robustness and recovery is insufficient, given shifting environmental conditions. Instead, the seaside community needs the capacity to persist, adapt and, transform so it can maintain stability when appropriate and change when necessary [40].

Another issue with the definitions of "resilience" is in the variety of uses of terms. That is, different terms are often used to describe similar aspects, or the same terms to describe different aspects. For example, the initial consequence of a disruption has been referred to as both risk and robustness, while the process of recovering has been referred to as recovery, resilience, and rapidity [54, 197, 264]. The detriment is when established concepts, such as risk, that have expansive literature including tools and techniques, are ignored because erroneous use (such as in [197]) leads to misconceptions. The confusion can also lead to reinventing the wheel that impedes scientific progress and delays action.

Potentially the cause of the emergence of the “resilience” field is due to a misunderstanding of the concept of risk. “Resilience analysis”, additionally, appears to have arisen due to limitations with traditional risk analysis approaches; however, advances in risk science mean that resilience analysis is well within the purview of risk analysis [20]. This is not purely semantics - it is detrimental to both science and the long-term sustainability of our communities. Rather than the continued divergence between the fields of risk and resilience, we need to maintain their integration for the benefit of management, policy development, balancing concerns, and optimizing resource use [20]. To do this, we require a framework that enables integrated management of the dimensions of resilience. In this paper, we propose such a framework. This framework offers an approach for conceptualizing and managing what has commonly been referred to as “resilience” grounded within the existing literature and practice of risk analysis.

7.2 Risk

A general conceptual definition of risk, listed in the Society of Risk Analysis’ glossary, is

> *Risk is uncertainty about and severity of the consequences*

[23, 306]. When considering risk, we consider a system S and an activity α_τ taking place within that system over a specified period of time τ. This activity can result in events $\mathcal{E}$ that have consequences C_T. Note that when consequences are assessed, there is a practical limit to the length of time they are evaluated until; we represent that time horizon with T, so that C_T represents the consequences up until time T 6. These consequences are not known - there is uncertainty U [18]. This is schematically written as: for some S and α_τ

$$\text{risk}_T = (C_T, U)$$

To illustrate the risk concept, consider a community as our system S. The act of operating exposes the community to consequences (C_T) arising from the occurrence or not of specific hazards (known or unknown types), their time of occurrence, and their effect on the community (e.g., no negative effects, complete collapse, etc.). The subscript T represents that C_T include all consequences up until time T following the occurrence of the event. The uncertainty (U) says that today we do not know if or when the community will experience a hazard, nor do we know what the consequences will be. Additional examples of the risk concept are provided in 6.

We describe risk using the set of triplets $\{< c'_T, q, k >_i\}$ 6. Each triplet includes a potential consequence (c'_T), the measure of uncertainty associated (q), and the knowledge (k) on which the assessment of $< c'_T, q >$ is based. If there are N triplets identified during the risk assessment, i is the integer representing the index and can be $1, 2, .., N$. Additionally, we specify the system S and an activity that occurs over some time frame α_τ. To illustrate, we continue with the example from before. For the sake of the argument, we consider only the economic consequences. We limit our assessment of the consequence to a five year period (i.e., $T = 5$) and one possible event-consequence combination is a hurricane that results in $1 million in damages. This is just one of the event-consequence combinations we estimate, and we write $c'_{5\text{year},i} = 1\text{million}$. q_i is the probability of the such an event occurring with those consequence (although there are alternative measures of uncertainty). k_i is the knowledge on which we base the assessments of $c'_{5,i}$ and q_i (i.e., a list of the data, information, justified beliefs, assumptions) [18].

7.2.1 Misconceptions of risk and its description

A critical issue with misconceptions of the risk concept arises when people inaccurately believe the risk literature and tools are not applicable. That is, they self-impose limitations on their analysis or they remain unaware of tools that would be useful for tackling their problems, and instead try to reinvent the wheel.

Uncertainty

One instance arises where out-dated definitions of risk contrast risk with uncertainty and claim that the risk concept is only suitable for situations where probabilities can be reasonably estimated [181, 206]. While this may have been the case in the 1920s, risk science has since evolved.

In fact, the purpose of risk analysis is to inform decision-making in situations of incomplete knowledge [253]. Incomplete knowledge is uncertainty [253]. This uncertainty can exist in both the occurrence and severity of the consequences. Addressing uncertainty is a major subject of ongoing risk advances [24]. This includes how to deal with surprising events (e.g., black swans [13, 252]) and deep uncertainty or ambiguity (where reasonable probability estimates are unavailable or the relevance of past data is in doubt [80, 296]). These development in risk science are ongoing and will continue to provide insight for addressing uncertainty in complex problems, such as climate change.

Consequence

Recent publications have contended that risk is only concerned with the initial consequences from an event (i.e., c'_0) e.g., [197]. Consider an event such as Hurricane Maria which devastated Puerto Rico in 2017; the consequences of the hurricane continue to this day. Therefore, restricting the consideration of the consequences to the immediate aftermath of an event vastly underestimates an event's consequence. Done properly, risk analysis includes an evaluation of consequences over time 6. Therefore, the post-event recovery is a necessary consideration for risk analysis.

The risk concept

Additionally, there are major confusions regarding the conceptual definition of risk [17]. These limitations have developed into limitations on how risk is being used. Table 7.1 presents definitions of risk from papers relevant to planning and hazard management. The categories of risk definitions used in Table 7.1, paraphrased from [17], are as follows:

(1) Risk is an event or consequence:
If we use this definition, how can risk be compared or be described as being 'high' or 'low'? [19]

(2) Risk is the probability of an event:
The concept of risk should not be restricted to using probability to represent uncertainty [17]. This definition becomes problematic for risk analysis when unique or poorly understood phenomena such as climate change are the subject of interest.

(3) Risk is the expected loss:
In this definition, risk = probability x consequence. However, an additional issue is that expected value can be similar for two very different probability distributions. These scenarios should be managed differently, but this would not be reflected when using this definition [17].

(4) Risk is the pair of probability and consequence:
This definition is beginning to converge with the recommended definition. The difference is that uncertainty, in this definition, is described strictly as the probability. As we have discussed, we require a broader description of uncertainty for the concept of risk [19].

These definitions have since been replaced by more general conceptual definitions of risk as the field has evolved to tackle more complex problems. An explanation of why these definitions are unsuitable for the conceptual definition of risk is provided in Aven [17, 19].

Table 7.1: Definitions of risk from the planning, hazards, and climate change literature

Author (year)	Definition	Category
Kasperson et al. (1985) [174]	Threats to human beings and what they value	1
Cutter et al. (1996), [85]	Risk is the likelihood of occurrence (or probability) of a hazard. Risk has two domains: 1) potential sources of risk (industrial, flooding) and contextual nature of the risk (high consequence, low consequence) 2) simple probabilistic estimate based on frequency of occurrence	2
Deyle et al. (1998), [96]	Risk = magnitude x probability	3
Intergovernmental Panel on Climate Change (2014), [115]	The potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values. Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk results from the interaction of vulnerability, exposure and hazard.	3
Burby et al. (2000), [58]	Magnitude or possible losses and the probabilities of losses across the full spectrum of possible natural hazard events	4
UN International Strategy for Disaster Reduction (2004), [169]	Probability of harmful consequences or expected losses	1, 3
Paton et al. (2000), [254]	Risk describes the assessment of the frequency of occurrence and magnitude of consequences associated with hazard (stressor) activity	4
Jones (2001), [172]	Risk is the probability that a substance or situation will produce harm under specified conditions. Risk is a combination of two factors: 1) the probability that an adverse event will occur 2) the consequence of the adverse event	4
Turner (2003), [323]	Risk is the probability and magnitude of consequences after a hazard	4
Rose (2007), [279]	Risk= f(threat, vulnerability, consequence)	4
Birkmann (2013), [48]	Risk is defined as the probability of harmful consequences or losses resulting from interactions between hazard and vulnerable conditions	1, 3
Linkov et al. (2018), [198]	Risk is the capacity to withstand and respond	N/A

7.3 Resilience

To analyze resilience we need to understand its fundamental components. To identify these components, we review a number of resilience definitions (Appendix Table E.1). Common to these definitions is that resilience is the ability to deal with impacts of adverse changes and shocks [40], that is resilience is about reducing the consequences from a shock. Resilience appears to be comprised of three main components [40]: i) persistence, continuing in the current state by buffering and absorbing impacts, ii) adaptation, adjustments, in response to actual or expected hazards, to moderate consequences without qualitatively changing the system's state; and iii) transformation, adjustments, in response to actual or expected hazards, to moderate

Table 7.2: Identifying aspects of resilience from the definitions

Author (year)	**Journal**	**Capacity to prepare**	**Capacity to absorb**	**Capacity to adapt**	**Capacity to transform**	**Capacity to anticipate**
Holling (1973), [157]	A. R. Ecological Systems		*			
Pimm (1984), [262]	Nature		*			
Mileti (1999), [222]	*Disasters by Design*	*	*			
Adger (2000), [2]	P. Human Geography		*			
Bruneau et al. (2003), [54]	Earthquake Spectra	*	*	*		
Turner et al. (2003), [323]	PNAS		*			
Walker et al. (2004), [336]	Ecology & Society		*	*		
Manyena (2006), [211]	Disasters		*	*		
Berkes (2007), [43]	Natural Hazards		*			
Cutter et al. (2008), [87]	Global Environmental Change		*	*		
Lamond & Proverbs (2009), [185]	Proc. Inst. Civil Engineers		*			
Cimellaro et al. (2010), [71]	Engineering Structures		*			
Turner et al. (2010), [322]	Global Environmental Change		*			
Béné et al. (2012), [40]	I. Development Studies		*	*	*	
National Research Council (2012), [231]	*Disaster Resilience*	*	*	*		*
Barrett & Constas (2014), [33]	PNAS		*			
Saunders & Becker (2015), [282]	I. J. Disaster Risk Reduction			*		
Tendall et al. (2015), [318]	Global Food Security		*			
Meerow et al. (2016), [218]	Landscape & Urban Planning		*	*	*	
Platt et al. (2016), [264]	I. J. Disaster Risk Reduction		*	*	*	
Nan & Sansavini (2017), [229]	Reliability Engineering & System Safety		*			
Linkov et al. (2018), [198]	Nature		*	*		

consequences that do qualitatively change the system's state (see Table 7.3 for definitions). By this framework, resilience emerges as a result of the combination of these components. Note that, in contrast to some other definitions that mischaracterize robustness and recovery as incompatible (e.g. [197, 198]), both are part of persistence. This is motivated by the understanding that a system that can prevent a disaster by resisting a stressor is critical to resilience [240].

Persistence, adaptation, and transformation in a system are enabled and supported by properties of the system. Béné et al. [40] identifies the capacities to *absorb*, *adapt*, and *transform* as being the primary components. Following our review of the definitions (Table 7.2) we include the capacities to *prepare* and *anticipate*. These five capacities collectively capture all of the important dimensions identified in the definitions we review. These capacities are often measured by indicators such as those presented in the following papers: [87, 88, 89, 118, 199, 256].

Table 7.3: The terminology we adopt in this paper.

Term	**Definition**
Adaptation	Adjustments, in response to actual or expected hazards, to moderate consequences without qualitatively changing the system's state (modified from [168])
Persistence	Continuing in the current state by buffering and absorbing impacts (modified from [40, 87])
Recovery	The return to an acceptable level of functionality
Reliability	The ability to maintain an acceptable functionality
Risk	Uncertainty about and severity of the consequences [23]
Robustness	The ability to absorb or withstand impacts
Transformation	Adjustments, in response to actual or expected hazards, to moderate consequences that qualitatively change the system's state (modified from [168]).

To illustrate the three dimensions of resilience, consider the coastal community. The community persists if it rebuilds, as-was, following a coastal flood; a community adapts if it rebuilds and increases the robustness of its structures, provides sandbags to residents, and educates them on flood hazards; and a community transforms if it retreats from the threatened zone and rebuilds in a safer area. To truly build resilience, the community must strengthen each component and recognize the inter-dependencies between them. We need a framework for resilience analysis that embraces this inter-dependence and, with which we can both address trade-offs and leverage synergies.

7.4 Risk as a holistic framework for resilience

If the consequences from any event are fundamental to a system's resilience, risk analysis can be used to analyze and manage resilience. Consider a community that is threatened by a hazard. We represent the risk picture, using a bowtie diagram, in Figure 7.1. The system (S) is a community, the activity is it's existence over a specified time frame (α_τ), and the event ($\mathcal{E}$) is that the community experiences a specific hazard. The bowtie diagram shows the causal picture that leads, over time, to the consequences (shown on the right) of the event. The barriers (center-left) are the actions and measures that the community has taken that increase the community's robustness or preparedness. These actions may prevent the hazard from causing damage (for example, a sea wall in a flooding situation) or mitigate the amount of damage (e.g., building strengthening in a hurricane event) as well as evacuation measures. The barriers to the right of the event are consequence reducing actions and measures that occur post-event. In terms of the hazard cycle, these occur during the immediate response, the rehabilitation, and the post-event development. These measures include those that support the recovery as well as those that enable adaptation and transformation. The performance of all of the actions and measures are influenced by the risk-influencing factors (features of the system) which are shown on the far-left of the bowtie. Given the reoccurring nature of hazards in communities, the post-event actions, measures, and consequences will influence the system's features and preparedness for future events.

Clearly this risk-picture describes the resilience of a system. Both the pre-event and post-event actions effect the consequences from an event, and so should be managed inter-dependently. This relationship can be formalized using the risk concept:

$$\text{risk}_T = (C_T, U)$$

This states that the risk is a combination of the consequences (C_T) and that these consequences are unknown (U) [18]. The subscript T indicates for how far into the future the consequences have been evaluated 6. Recall, that risk is pertinent to a system (S) undergoing an activity for a specified period of time (α_τ).

Using the bowtie diagram, we can identify what factors contribute to the consequences. The consequences depends on the pre- and post-event actions and measures and, using Béné et al.'s

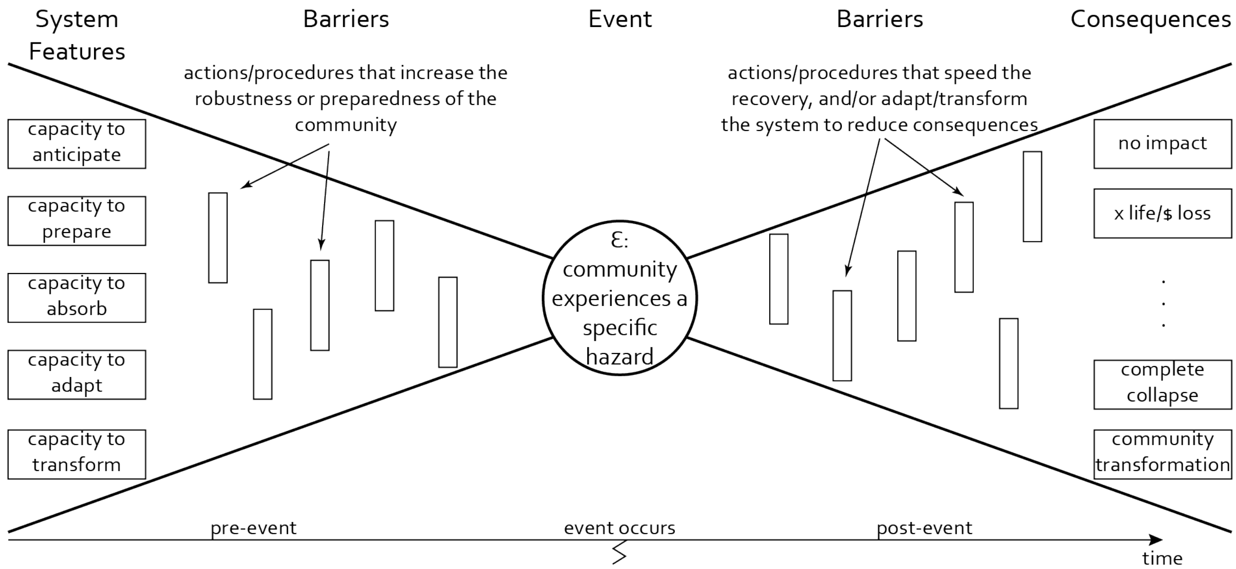


Figure 7.1: The risk-picture for a community. This bowtie diagram shows the system's features (left), pre- and post-event barriers that reduce the consequences (shown on the right).

[40] framework, is a function of persistence, adaptation, and transformation:

$$\text{Consequences} = f(\text{persistence, adaptation, transformation})$$

These components are aided by various abilities and aspects of the system (i.e., system features: $F_1, F_2, \ldots$, for example the capacity to adapt) that can help to reduce the consequences from some event. For example, the persistence (which includes robustness) is improved by enhancing the system's capacity to prepare for a hazard and the capacity to absorb the impacts of a hazard:

$$\text{Robustness} = f(\text{preparatory capacity, absorptive capacity})$$

Similarly, adaptation and transformation each depend on their associated capacities. Supporting all three components is the system's capacity to anticipate. We formalize these dependencies as a schematic in Figure 7.2. Figure 7.2 shows how these system properties manifest to reduce consequences.

Risk analysis provides a way of identifying risk-reducing measures, these measures could be either probability reducing or consequence reducing [18]. The schematic (Figure 7.2) demonstrates how properties associated with resilience can be targeted to reduce the risk faced by our systems and communities. That is, we can reduce the consequence, address the uncertainty, and strengthen our knowledge. We can reduce the consequence of an event by increasing the system's ability to resist and recover, whether through system hardening, or by investing in the capacities of the system. Additionally, as the consequences are due to events, we can prevent events or reduce their likelihood of occurring. For example, we may be able to prevent events or reduce their likelihood of occurring by mitigating climate change. Alternatively, we could move the system away from the threatened area. Finally, reducing the uncertainty and increasing the strength of knowledge (the anticipatory capacity) could improve risk-informed decision making, inform adaptation or transformation initiatives, and enhance the other capacities of the system.

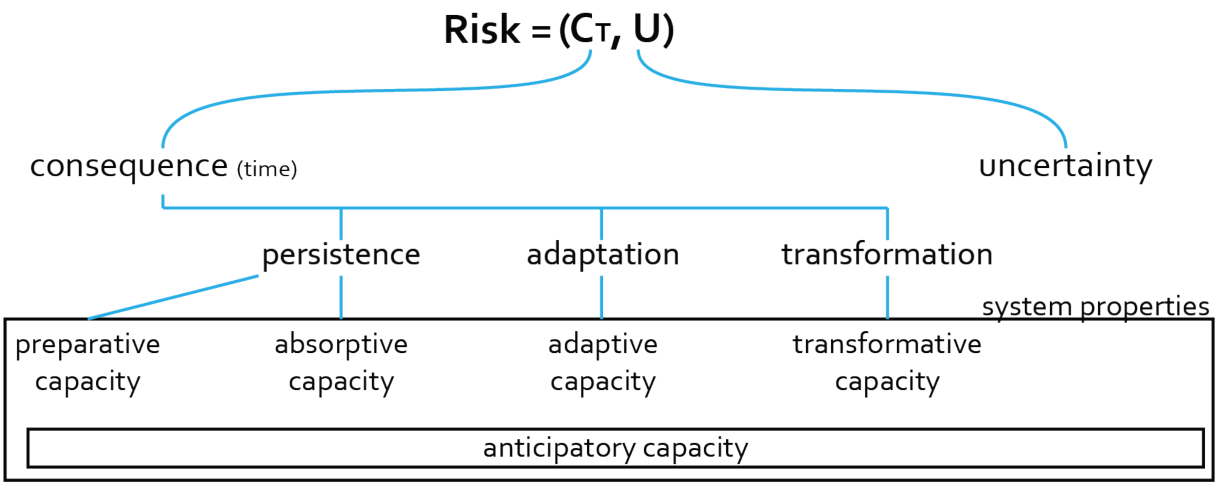


Figure 7.2: Community properties that characterize resilience can be managed and balanced within the concept of risk. This shows how the intrinsic properties of communities and systems influence the the consequence of an event.

Therefore, with this thinking we can interdependently or jointly manage all aspects of resilience within a risk framework. This integrated management can promote efficient use of resources and holistic decision-making, whereas divergence may hamper efforts to enhance resilience [40]. This framework allows for the consideration of tradeoffs, contradictions, and synergies. Again, consider the seaside community. Under this framework, the community can reduce its risk by reducing the consequences. One option is that they build a seawall, but they may also choose to invest in insurance or strategies that build community cohesion to enhance the recovery. Additionally, they may use hazard zoning and take a more transformative approach that moves residential areas away from threatened areas. Or they may do both. This type of thinking fits within a risk management approach.

Management under a risk framework also enables the various practices referred to under the umbrella of resilience to be implemented by improving existing risk strategies. Risk management plans are common in local authorities. For example, in the USA, hazard mitigation plans are required by the Federal Emergency Management Agency (FEMA) [310]. With the recent increasing emphasis on "resilience", organizations may be tempted to create separate "resilience plans" or employ separate "resilience officers". Instead, we argue that resilience can be built by broadening and strengthening the purview of existing risk management. This means that rather than creating 'resilience' plans, bureaucracy can be avoided. This holistic way of thinking also prevents siloing research and encourages progress towards "resilient communities." Holism and interdisciplinary cooperation is the way forward and this comprehensive framework provides exactly that.

7.5 Conceptual example of an opportunity

Interventions that reduce the risk from one hazard can increase the risk from others [62]. For example, consider the burying of overhead electricity wires. This reduces the threat from high wind events, but may increase the consequence and recovery time from an earthquake if it damages subterranean lines. The existing resilience field has to-date managed this quandary by defining 'specific' and 'general' resilience. Specific resilience refers to an identified hazard [83], while general resilience refers to the intrinsic properties of the system. The risk framework, and techniques from the literature may provide a promising alternative.

Frequency-number (F-N) diagrams, a risk analysis technique, offer a potential solution for integrated management and decision informing for comparing alternative interventions that have tradeoffs for different hazards. F-N diagrams are a common tool in risk analysis for presenting frequency-consequence data [63]. Events are assessed for their occurrence probability and their consequence. The consequence may be number of lives lost or the economic loss, for example. The frequency of experiencing a consequence of x or worse is plotted on the y-axis. That is, we can use this to say that the probability of a community having more than (e.g.) c_1 dollars of loss within a given year is p_1.

Figure 7.3 provides a conceptual example for a community that we shall step through. We consider a community that is at risk from floods, wildfires, and hurricanes. 1) The first step is to estimate the consequences (e.g., the economic damage over ten years) of one of these hazards with a particular return time (e.g., a 1/100 year flood) (see [54] for an earthquake example).

This can be repeated for each hazard for a series of occurrence probabilities. Figure 7.3a shows the consequences (shaded for event 1) as the area in the resilience curve for the three types of flooding shown.

2) We then can aggregate the consequence-probability pairs and plot them as an F-N curve (Figure 7.3b). The curve shows the probability (on the y-axis) that (e.g.) a flood will cause more than x consequences. In Figure 7.3b, each type of hazard considered in the example is plotted so there are three lines shown. Now consider an intervention such as prohibiting development near a river. This would potentially shift the flooding curve to the right (there is a lower probability of damage) but may increase the risk from wildfires, thus shifting the wildfire curve to the right.

3) Finally, the hazard specific curves can be aggregated into a single F-N curve (Figure 7.3c). We can also present uncertainty in both the frequency and consequence estimates, which adds uncertainty bounds to the curve, as shown. When considering an intervention, the change to this one curve will indicate how an intervention changes the risk (with respect to the selected consequence) to the community from all considered hazards. This thinking can draw attention to the tradeoffs and synergies for integrated hazard management and forms a basis for trying to operationalize these considerations.

Risk, or F-N, curves relate to resilience as defined by Bruneau et al. [54]. They describe resilience as the annual probability that the system maintains an acceptable level of functionality, when faced by earthquake risk. Although this is more accurately referred to as the reliability of a system, this is a way of capturing what researchers refer to as 'general resilience:' essentially, hazard-independent specific resilience. In terms of the risk, all-hazard risk-curves provide a graphical way of visualizing describing the risk, $\{< c'_T, q >_i\}$. If we were to specify an acceptable consequence, the likelihood of not meeting that acceptable level in a given year can represent the reliability of a system or community. By including multiple hazards, this technique provides a means of evaluating alternative interventions and their tradeoffs. Such a technique is highly valuable for integrated risk management.

7.6 Conclusion

In this article, we argue that the analysis and management of resilience can be achieved using risk analysis. This is not to say that the concept of resilience should be abandoned, but rather than its analysis should leverage and enhance an existing body of literature and the techniques.

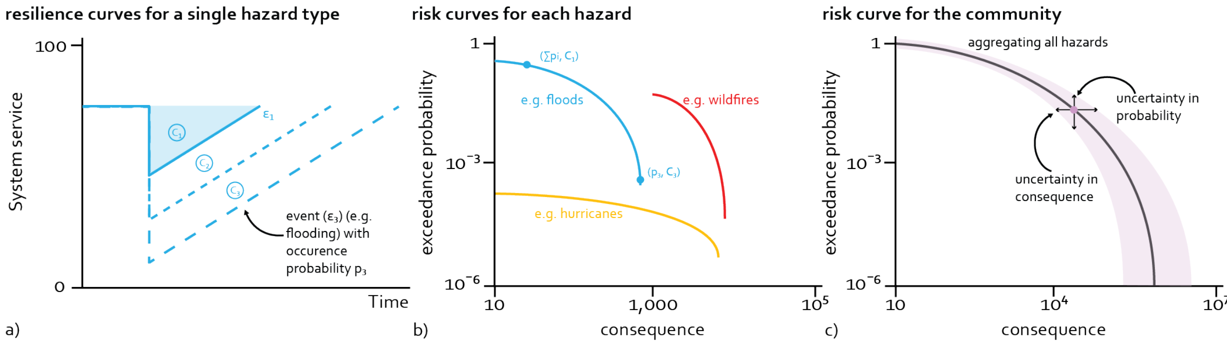


Figure 7.3: Creating a frequency-number curve for representing risk and visualizing interdependencies. (a) shows the resilience curve for different severities of a type of hazard. (b and c) show the F-N curve for each type of event (b) and the aggregate of events (c). Figures such as (b) and (c) can help when alternative interventions may reduce the risk to some hazards, but increase it for others. Incorporating the full consequences from a risk source means that a risk curve can be used to assess a community's risk from different hazards and focus efforts that build resilience. Additionally, it can provide a quantification of a system's or community's general (not hazard specific) risk reduction.

This can help to operationalize resilience, an increasingly urgent matter for our communities threatened by hazards.

We demonstrate how the components of resilience fit within the concept of risk (C_T, U). Risk analysis can provide a way of identifying risk-reducing measures, therefore, a risk-framework can be used to identify approaches that build resilience. For example, the consequences threatening a system or community can be reduced by improving the system's robustness or speed of recovery. Contributing to reducing the consequences are the system's properties that include the capacity to anticipate, prepare, persist, adapt, and transform. This risk framework can guide action, evaluate tradeoffs and synergies, and promote transformative change in a holistic manner.

Situating the resilience paradigm within a risk framework presents a series of opportunities for our communities and the interested research disciplines. The framework we present enables managing the components of resilience in a inter-dependent and holistic manner. This means that tradeoffs and synergies between adaptive interventions can be evaluated and leveraged. It means that we enable communities to avoid the trap of the continual hazard-recover cycle. It clarifies the terminology and provides opportunities for leveraging approaches and techniques in the existing risk and reliability literature. These techniques and further advances may otherwise have been ignored by continuing to operate in silos. Finally, by using a risk framework, we can conduct the necessary changes within existing political planning frameworks that have required risk management for decades. This framework considers all of the components of resilience, it ensures that decisions are made holistically, that tradeoffs are for the best, and that communities are well-informed to prepare for future threats, all within an established field: risk.

Chapter 8

Conclusion

8.1 Summary and Contributions

Over the five years that I have been studying towards my PhD, climate change has gone from a known, but not particularly concerning (to the average person), issue to an outright global emergency [38, 68, 228] that needs to be addressed within 10 years [168]. This has been the backdrop while constructing this thesis. My dissertation is fundamentally motivated by the question of how we can improve our approaches to protecting communities in the face of hazards. Over time, I narrowed the scope into exploring the potential of data-driven urban planning and understanding how we can leverage risk and data science to build the resilience of our communities.

In Chapter 1, I argued that urban planning challenges can motivate advances in foundational risk science. The challenges, including managing natural hazards, chronic diseases, urban sprawl, and air pollution, open numerous collaboration opportunities, data sets, focus groups, and case studies. Risk analysts can use these to advance generic risk analysis practices and research, furthering how we understand, assess, communicate, and manage risk [21]. In the paper I stepped through foundational issues of risk science and identify the synergies that would arise if risk analysts collaborated with urban planners.

I explored how risk analysis and complex system simulation can be used to identify potential maladaptive behavior in Chapter 2. The initial motivation for the chapter was to understand whether seawalls protected communities from tsunami, following the disaster in Japan in 2011. To answer the question we had to capture the temporal evolution of risk and the actions of humans in response to the seawall. I constructed a cellular automaton model for land-use change that was coupled with the hazard model and the dynamic behavioral feedbacks from human's awareness of the hazard. By constructing this model, we unintentionally quantitatively demonstrated the safe development paradox, also known as the levee effect, whereby structural interventions can increase vulnerability by inducing development in areas threatened by hazards. The effect arose from interactions between the community's risk perception, the spatiotemporal changes, and the repeating hazard. This chapter demonstrates the importance of understanding how interventions may affect communities and why interdisciplinary collaboration is important for addressing natural hazards and avoiding maladaptive actions.

In Chapter 3, I used machine learning techniques to explore spatial factors that contribute to the threat from a natural hazard to a community. The objective of this chapter is to understand how different urban characteristics are associated with land surface temperatures and identify their relative importance. To achieve this I processed the spatial data at different scales and performed a rigorous cross-validation to ensure the spatial aspect was not causing the model to be overfit. I present the results, showing both data and model uncertainty in the figures showing the association between urban characteristics and land surface temperature. Our findings demonstrate that accurate prediction of land surface temperature using urban characteristics is possible. The machine learning models were accurate within 1^{o}C of the observed land surface temperature. Our results strongly support initiatives for increasing green infrastructure in cities and open opportunities for further detailed analysis into potential interventions. Rigorous statistical analysis can continue to answer on-going questions central to land surface temperature.

I then presented a pair of chapters that center around people's access to essential services: Chapters 4 and 5. In Chapter 4, we presented an approach for measuring people's proximity to any urban service. This approach utilizes open-data and leverages the increasing computational capacity available to researchers and practitioners. We calculate at the parcel level the distance from each person's home to their nearest services. The service can be selected by the analyst, but we demonstrated the approach using schools, green space, hospitals, and grocery stores. We then explore ways of presenting the overall proximity of the community and compare it with other communities. We also explored how sensitive the results were to the spatial resolution of the data to be sure we avoided the modifiable unit areal problem (MAUP) that can arise when spatial phenomena are aggregated. Improving the ability to measure proximity to services enables access and access equity to be evaluated in a rigorous manner.

In Chapter 5, I utilize the approach to measuring proximity to services and assess how people's access to services changes over the course of a natural hazard. Services such as health care, food, and education are essential for a community's vitality and viability. Without them the residents will be destitute or will migrate. Also important for a community's social sustainability and cohesion is that this access is equitable. In recognizing the importance of access to services to a community, we proposed that this be a measure of resilience. That is, does a community maintain or quickly restore access to essential services following a disruption, and does it mitigate, adapt, or transform its provision of services both before and after a disruption to ensure equal access? We measure this by assessing how the proximity of residents' to their nearest service changes over time. Additionally, by including demographic factors, we can assess how equitable the provision, maintenance, and recovery of these services is. Unlike other schools of thought on resilience, this specifically describes resilience in terms of both a hazard and the community's need. Ultimately, this framework and approach can be put into practice to reduce the risk of communities losing their access to essential services in the event of a hazard. The approach is spatially explicit, so can be used by decision makers to identify areas within the community needing attention, both before, during, and after a disruption. This is a promising tool for transforming communities to be sustainable, equitable, and livable.

I concluded the dissertation by presenting a framework that both integrates the dimensions of resilience into the concept of risk and enables holistic management of these concepts (Chapter 7). The literature remains unclear about how to define 'resilience,' much less achieve it in our communities. This lack of understanding may put communities in jeopardy by not providing them adequate tools and management practices to prepare for disasters, or by inefficiently using resources by managing connected aspects independently. We require a framework that can guide action, evaluate tradeoffs and synergies, and promote transformative change in a holistic manner. Fundamental to the definitions of resilience is the notion that we need to reduce the consequences that a hazard inflicts on a system or community. This suggests that the risk concept, a function of the uncertainty about and severity of the consequences of a hazard, (C, U), could provide a suitable framework for holistically thinking about and managing communities and the hazards they face. We showed that the risk concept is a logical way of thinking about the dimensions of resilience. In short, the aspects that constitute the definitions of resilience can be addressed within the concept of risk. This understanding means that resilience, and resilience analysis, is well within the purview of modern risk analysis.

8.2 Final remarks and future research

My ongoing research will be guided by the same underlying motivation of understanding and improving our approaches to protect communities in the face of hazards. Throughout my graduate studies and during my internship at a startup working in this space, I have come to understand that adapting to climate change and mitigating natural hazards must be 1) conducted in an interdisciplinary and collaborative manner and, where possible, conducted alongside community partners; 2) actively cognizant of potential pitfalls that could result in maladaptation or increased inequity. I intend to build my expertise in these aspects further to then integrate them into my future work.

8.2.1 Ethics

The emergence of tools and data, along with increased computational ability provides the power of insight to an array of people. The potential downside is that as we use this technology to understand counter-intuitive systems. It is increasingly difficult to assess the plausibility of our results against our own intuition or understanding. As these models become more complex, they become more difficult for the practitioner, decision maker, or other end-user to critically evaluate the resulting recommendations. This results in a series of ethical challenges that we need to be actively aware of. As I progress through with my research I am constantly introduced to additional ways that we could inadvertently exacerbate issues for communities and people. For example, if community managers rely exclusively on black-box models without complementing the results with local knowledge and experience, suffering may increase. This is especially true for conditions beyond what the model was trained. Climate, technological, and societal change is shifting the conditions under which we operate, and this poses a challenge to modellers relying on historic data to train and validate their models. It is essential that we communicate the limitations and uncertainties to community partners so they can augment data science with their knowledge of the community. Although guidelines and literature on ethics exist, they are often specific to risk [99], hazard planning (e.g., [132]), and big data [364]. I believe that there are unique challenges at the intersection of these and other fields related to urban planning, climate adaptation, and hazard mitigation. Additionally, the speed of growth in technology means that our ethical guidelines need to be constantly reviewed to ensure they have the capacity to provide support when new and unforeseen challenges arise. To explore this space, I have begun a collaboration with a group of researchers across the academic spectrum (from engineering, public health, behavioral science, policy, etc.) and professionals in the hazard field. The aim of this collaboration is to develop guidelines that can advise academics and practitioners on how to identify, discuss, and avoid potential pitfalls that may arise. These guidelines will, at the very least, guide my future research agenda.

8.2.2 Social justice and "bouncing forward"

Ongoing risk analysis needs to ensure that inequities are not further exacerbated. I intend to build on the work in Chapters 4 & 5, as well as the work of [124, 227, 352] and others in evaluating the effects of risk mitigation and interventions on people and equity.

I also intend to further explore the notion that while 'disasters don't discriminate, resilience and recovery efforts often do' [107]. The concept of resilience has been criticized for perpetuating and further institutionalizing inequity [141, 166, 207, 218, 239]. Potentially this "bouncing back" is due to how the concept has been measured. That is, resilience measurement often is calculated as the decrease from the pre-existing or 'baseline' function. I plan to explore how the choice and construction of the resilience metric can impact post-disaster recovery efforts and priorities.

8.2.3 Urban form and hazards

Urban form, the way that our cities are designed, affects how people live in them, how vulnerable they are to hazards, and how susceptible they are to chronic disease. The design of cities is also pertinent to sustainability, and climate adaptation and mitigation. I intend to further explore how urban form and urban characteristics can be used to improve our cities. Building on techniques in Chapter 3, I want to identify and evaluate potential interventions. This will require using spatial statistics, methods of capturing geographic uncertainties [120], and comparative studies, in which mixed-effects modeling will likely arise. More specifically, I plan to explore how urban density affects public health in cities and whether consistent trends emerge.

8.2.4 Aotearoa New Zealand

Above all, I intend to pivot my research focus towards New Zealand, my home country. New Zealand is an island nation that is threatened by an array of natural hazards and is highly vulnerable to sea level rise. It is an ideal case study for assessing potential strategies for natural hazard mitigation and climate adaptation because of the natural system boundaries. Additionally, there is relatively well recorded spatial data about the infrastructure and property that can be used in the models. The results of findings in a New Zealand context would be well suited for generalizing to other industrialized regions.

Among the first projects I intend to work on is a comparative evaluation of New Zealand climate adaptation planning. My assessment to date suggests that most regions in New Zealand are well behind the proactive states and communities in the US. However, this may be changing with the current government which has made climate change a priority.

A further benefit to working in New Zealand is the potential for co-production of knowledge. Communities in New Zealand are willing to engage with academics and the local governments often are open to science-informed decision making. In my new role as faculty at the University of Canterbury in Christchurch, New Zealand I plan to build expertise in community-engaged research and partner with faculty who are already succeeding to do so. I want my future research to challenge the borders of traditional disciplinary research which is essential for tackling the global challenges we face. To tackle these challenges I will seek the opportunity to partner with interdisciplinary academics and the wider community to ensure that research can be both foundational and useful.

I have grave concerns for our society based on the emerging threats that are unlike those our society has faced [175]. However, I am cautiously optimistic that we can leverage science to guide our response and actions so that we can manage the unavoidable and avoid the unmanageable [47]. To do so, we urgently need to mobilize research to support decision-making. My future research will continue to focus will be on integrating risk science and urban planning so that we can do our best to mitigate hazards and protect our communities.

Appendix A

Supplements to Hard-adaptive measures and maladaptation

A.1 Model framework

We model land-use change of a small-town subject to repeated tsunamis using a cellular automaton (CA) model. CA models have extensively been used for land-use change modeling [36, 73, 194, 307, 334, 345, 346]. Their ease of integration with geographic information and simple grid structure makes CA a natural candidate for simulating change and dynamics of an urban form. Based on transition rules dependent on the environment and interactions with neighbors, the CA can model spatiotemporal changes of a heterogeneous population of cells [148, 162, 302, 307, 334, 346]. We use these models to examine how the general behavior of the land-use trajectory changes under different scenarios.

The initial development pattern of the town is based on the 1901 land-use map [316]. Elevation data at a five-meter resolution is used [127]. The simulation area is a (2.4 km)^2 square around the city of Taro, divided into a (10 m)^2 grid. A single replication of the model occurs over 300 time steps, where a time step is a year.

For each time step of a model replication

1. A tsunami may strike the region (Section S3.2)

2. The town will grow or shrink depending on growth rate (Section S5) and transition potential (Section S6).

A.2 Case study location

Taro, Japan (Figure A.1), is used as a case study site to provide data and a validation option. It has experienced multiple tsunamis over the past century (Table A.1) [224, 298]. The 1896 Meiji Sanriku Earthquake and the 1933 Showa Sanriku Earthquake caused tsunamis that resulted in severe damage and casualties. In 1960, Taro's newly completed seawall prevented damage from the tsunami generated by the Great Chilean Earthquake. Most recently, in 2011, the Great East Japan Earthquake caused a tsunami which over topped the seawall and once again devastated the community.

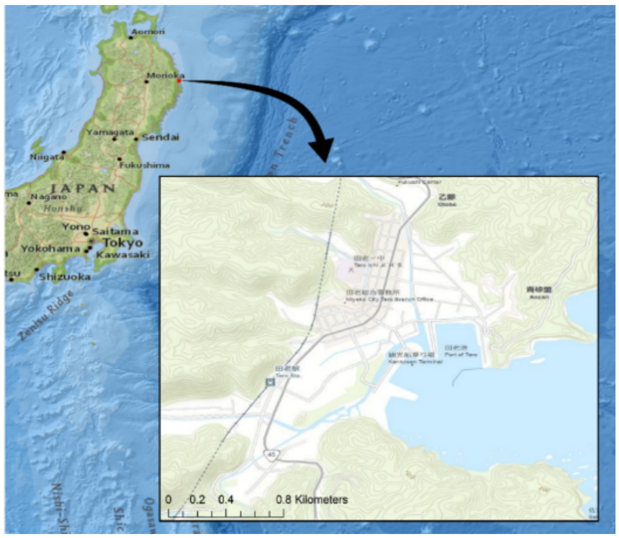


Figure A.1: The case study location: Taro, Japan.

Table A.1: Details of the four most recent tsunamis which have occurred in Taro, Japan [230]

Year	Tsunami runup (m TP)	Seawall elevation (m TP)	Inundated area (sq. km)	Number and percentage of people killed		Number and percentage of dwellings destroyed	
1896	12.85	0.0	0.22	1869	51%	345	56%
1933	11.80	0.0	0.19	911	19%	505	60%
1960	4.30	10.0	0	0	0%	0	0%
2011	28.76	10.0	1.20	181	4%	729	50%

A.3 Tsunami model

A.3.1 Synthetic tsunami library

To approximate the effect of a tsunami on the town's developed land using depth-damage relations formulated for this region [312], we need the maximum water depth at every point. Rather than simulating the tsunamis real-time within the model, we reduce computational demand by generating a synthetic library of maximum inundation depths for a range of tsunamis (Table A.2). Delft3D Flow is the 3D hydrodynamic modeling tool used to determine the maximum inundation height for each cell of the land-use model for each tsunami scenario [92]. The initial wave height, produced by Delft Dashboard [93] implementation of the Okada model [241] from the fault line parameters, is the model input. To minimize computational time, inundation heights for tsunamis were run prior to the land-use model. This approach assumes that land-use changes and roughness are unchanged.

The inundation model and input parameters were validated by comparing against three historical tsunamis (1896, 1933, 2011) and their observed inundation depths (Section A.7).

Table A.2: Water inundation relative to TP (Tokyo Peil, the Japanese vertical datum) of different tsunamis with no seawall along coastline. For each historical rupture location, three magnitudes are generated. The first is the historically observed, the latter two are a magnitude smaller and greater.

Year	Magnitude (Mw)	Mean water inundation along coastline (m Tokyo Peil)
1896	8.5	7.13
	8.3	6.27
	8.7	8.15
1933	8.1	4.13
	7.9	2.33
	8.3	5.26
2011	9.0	8.25
	8.8	6.67
	9.2	10.66

For each fault event and magnitude, the initial wave height is required for the inundation model. We use Delft Dashboard to approximate the initial wave height [93]. This requires the fault location and magnitude of rupture. The three historical rupture locations were used and assumed to be straight lines. However, modeling complex fault ruptures as straight lines is an insufficient simplification. The result is an initial wave height that does not cause tsunami inundations comparable to those observed. To allow for the fault simplification, the slip parameter is modified by a multiplicative factor so that the inundation in Taro is similar to observed levels and provides a range of inundation heights along the coast (Table A.3). This is justified in Ulutas [324]. Once the fault and magnitude are input, Dashboard uses the Hanks and Kanamori formulas [343] to calculate the relationships between parameters. Table A.3 lists the parameters used to generate the initial wave heights in Delft Dashboard.

Table A.3: Tsunami earthquake source parameters. For each historical rupture location, three magnitudes are generated. The first is the historically observed, the latter two are a magnitude smaller and greater.

Year	Magnitude (Mw)	Slip (m)	Slip factor	Depth (km)	Dip (°)	Slip/rake (°)	Reference
1896	8.5	12.5	2.2	1	20	58	50
	8.3	9.8					
	8.7	15.6					
1933	8.1	3.8	1	0	45	270	51
	7.9	2.8					
	8.3	4.5					
2011	9.0	20	2	24	10	92	48
	8.8	16					
	9.2	25					

The Delft 3D model was simulated for each of these fault parameter sets. The model was decomposed into smaller domains for computational stability. The parameters for each decomposition are show in Table A.4.

Table A.4: The computational parameters of the simulation used in the nested Delft model, beginning with the largest domain. The spatial extent and number of grid points define the resolution. The NE and SW coordinates define the boundaries of the bounding box. The Manning roughness is defined in both horizontal directions.

Number of grid points	Extent (NE) (lat, lon)	Extent (SW) (lat, lon)	Roughness (uniform)	Time step (min)
(442, 296)	40.802500, 145.238775	37.862808, 140.841218	Manning (0.02, 0.02)	0.005
(257, 97)	39.852693, 142.338815	39.662948, 141.836668	Manning (0.02, 0.02)	0.005
(532, 322)	39.756696, 142.024836	39.692418, 141.918988	Manning (0.02, 0.02)	0.005
(854, 401)	39.748804, 142.001908	39.722121, 141.945025	Manning (0.02, 0.02)	0.005

A.3.2 Tsunami occurrence

We assume that tsunami inter-event arrival times are independent and draw them from a Poisson process. Poisson processes have traditionally been used to model tsunami arrival times [126] and while there is recent debate as to their suitability [125], the Poisson process provides an approximate and generalizable distribution for many natural hazards. The critique of the Poisson model for tsunamis is due to large earthquake events resulting in aftershocks within the 7-10 year period following [125]. However, the model is simplified to ignore these short-term subsequent events. Also, due to the large geographical region where tsunamis which have previously struck Japan have originated from (e.g. Chile), we assume the events are independent. Given four tsunamis struck Taro, Japan between 1896 and 2011, we use a Poisson distribution with a mean number of occurrences of three events per hundred years. The mean frequency is varied to see the result of frequency on vulnerability (Figure 2.2).

A.3.3 Tsunami magnitude

We assume that inter-event magnitudes are independent [126]. Our intention is to generate pseudo-realistic tsunamis, with which to threaten the town. Therefore, we need tsunamis with a range of heights and associated probabilities. With each of our validated historic tsunamis (1869, 1933, 2011) we model them again with a magnitude change of ±0.2. This gives us a range of wave heights. The height of simulated tsunamis is randomly chosen using a triangular distribution (Equation A.1). The likelihood of each tsunami height is shown in Figure A.2. The distribution is selected so that smaller waves are more likely to occur. By keeping the distribution of tsunamis simple, we can gain insights into Taro, as well as generalize them to other communities. The slope of the triangular distribution is subject to sensitivity analysis (see Section A.9.1).

$$F(x) = 1 - \frac{(b-x)^2}{b^2} \tag{A.1}$$

where:

$F(x)$ = cumulative probability of tsunami height given a tsunami occurs
x = wave height (m)
b = earthquake intensity parameter, which dictates the slope

We acknowledge the limitations and simplifications in generating initial wave height and determining occurrence probabilities. However, we stress that the intention is to generate re-

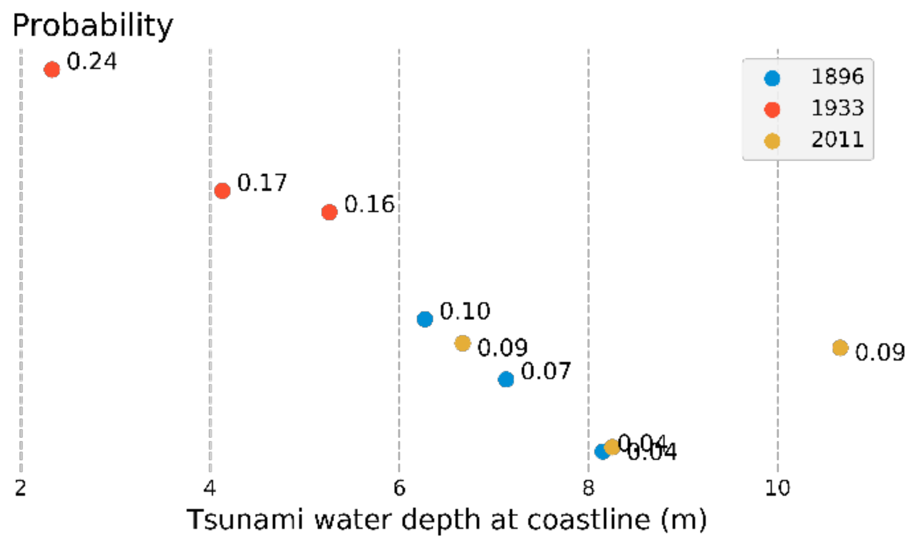


Figure A.2: The probability of a tsunami height given that a tsunami is occurring. The height is drawn from a triangular distribution (Equation A.1).

alistic tsunamis to observe their impact on the urbanization of the affected town and not to exactly match the past or predict the future tsunami environment.

A.3.4 Effect of Seawalls

Seawalls reduce the area inundated and inundation height resulting from a tsunami. A seawall is included in the hydraulic inundation model by raising the land elevation in the model. The seawall implemented in each simulation uses the footprint of the seawall in Taro before the 2011 tsunami, but the height is variable. In the land change model, the seawall height is fixed from the beginning, and throughout the duration, of the simulation. When different heights are being compared, the height is changed. For the adaptation effect assessment, the seawall height is 0m. For the sensitivity analysis, the parameters are tested with a seawall of 0m and 12m.

A.4 Land Damage

A survey of the region following the 2011 tsunami developed fragility curves for the buildings [312]. Most of the structures are wooden, so the depth-damage curve for wooden structures has been used in this model as a generalization (Equation A.2). We consider major damage or worse to result in a destroyed cell. For each land cell, the probability of major damage is calculated and a random value from a standard uniform distribution drawn. If this value is less than the probability of major damage, the land-use is reverted to undeveloped. This occurs stochastically, but in many simulations will occur at a frequency equivalent to the probability of major damage (i.e. if the probability of major damage is 80%, then 80% of uniform random numbers will be less than 0.8).

$$P(x) = \phi[\frac{x - \mu}{\sigma}] \tag{A.2}$$

where:

$P(x)$ = Probability of damage to structure when inundated by x water
ϕ = standardized normal distribution function
μ = 3.8458
σ = 0.8516
x = inundation depth (m)

(see [312] for wooden house, major damage).

A.5 Land Demand

A.5.1 Demand

We assume that land demand is driven by the town's population growth rate (Section A.5.2). Each year, cells are developed or undeveloped based on the direction of the growth rate and the transition potential of the cell (Section A.6). In the event of a tsunami, the development on some of the land is destroyed (Section A.4). The occupants of the land (proxying one per cell) may choose to stay or leave. Those that leave, exit the model. Those that stay add to the land demand over the course of several years until they have been distributed. We model only two types of non-fixed land-use: developed or undeveloped (section A.6). Developed land is urban land where improvements have been made.

A.5.2 Growth Rate

The growth rate changes with each time step of the model. In lieu of an exogenous forcing model for the growth rate, a random walk is used. A normal distribution is fit to the change in percentage growth rate for Iwate prefecture, Japan between 1950 and 2000 [170]. That is, the growth rate is determined for each year, and the difference between each years' growth rate is calculated. Data between 1950 and 2000 are used due to the variation in the growth rate before 1950 due to wars and the 1933 tsunami. The random walk is seeded with a growth rate of 1%. Each year, a change in growth rate is drawn from the fitted distribution and added. Figure A.3 shows a realization of growth rate for the duration of a simulation and compares it with the historic growth rate in the region. It shows that the fluctuations are similar to the post-1950 historic growth rate.

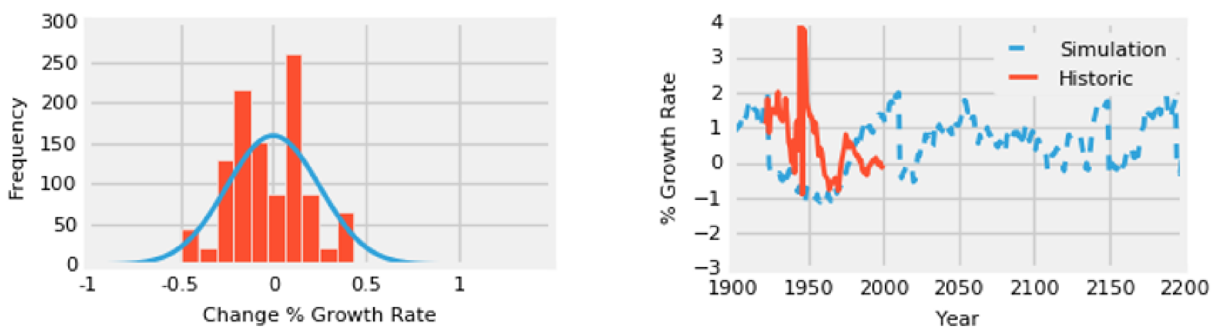


Figure A.3: The population growth rate for the simulation. (A) shows the histogram of population grow in Iwate prefecture, Japan, between 1950 and 2000, as well as the fitted normal probability distribution. (B) shows the historic population and one realization of the randomly simulated population change. .

A.6 Transition potential

The transition potential dictates which cells change from undeveloped to developed land. Figure A.4 shows the transition potential changing over time following a tsunami. All land-use types are classified into one of three categories: fixed, passive, or active [346]. Road, sea, and seawall are all fixed. This means that once a cell has this land-use it does not change. A passive cell, e.g. developed cells, change only when there is an external intervention (such as tsunami inundation resulting in damage). Active cells have associated transition potentials. Undeveloped cells are active cells. The "undeveloped" cells with the highest transition potential are changed to "developed" cells at each time step. The transition potential (modified for a single land-use type from White et al. [346]) for each cell is a function of the neighborhood effect, suitability, accessibility, and a stochastic perturbation (Equation A.3):

$$V_i = r_i N_i A_i R_i S_i \tag{A.3}$$

where:

V_i = transition potential for cell i
r_i = stochastic perturbation for cell i
N_i = neighborhood effect for cell i
A_i = awareness of the tsunami risk for cell i
R_i = accessibility for cell i
S_i = suitability for cell i.

Without a stochastic perturbation term, the model is deterministic. The perturbation captures some of the inherent variability in human-environmental systems. For each land cell, the stochastic perturbation r_i, is calculated by Equation A.4:

$$r_i = 1 + \left[-ln\ (U) \right]^{\alpha} \tag{A.4}$$

where:

U = standard uniform random variable
α = parameter controlling the size of the skewed distribution [346].

The stochastic perturbation parameter was subjected to a sensitivity analysis (Section A.9.3). Once the transition potential for each active cell is calculated, the cells are ranked in decreasing order. The number of cells required to meet the growth rate (Section A.5) are selected from the undeveloped cells in order of transition potential and developed. If there are no cells developed (and therefore 0%) and there is a positive percentage growth rate, 20 cells are developed as a seed community.

A.6.1 Neighborhood effect

The neighborhood effect of a cell is determined by the number of developed cells in the vicinity. For computational efficiency, the neighborhood is divided into two rings. The first ring is the cells within a 200 m radius of the subject cell, a distance generally assumed to the approximate size of a local neighborhood [346]. The second ring has an outer radius of 400 m. 400 m was selected as it is a standard walking distance threshold. The number of neighboring developed cells is assumed to have a positive, but nonlinear effect on the desirability of a location such the

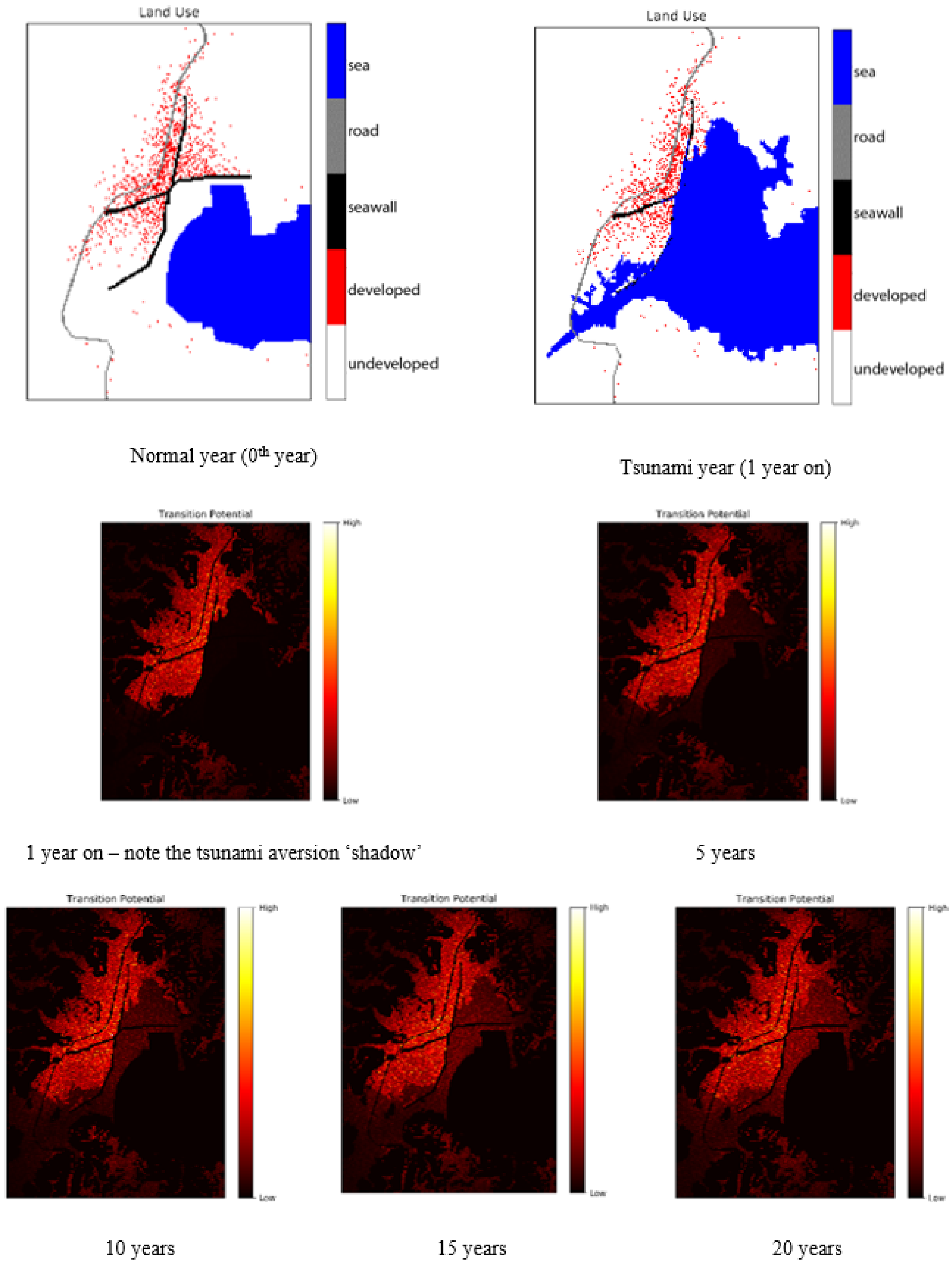


Figure A.4: Transition potential following a tsunami, indicating the likelihood of a cell being developed. The area inundated by the tsunami initially has very low potential for development – note the shadow in the map where the tsunami inundated. The memory of the danger fades with time and the potential development increases back to normal. This is depicted above as the inundation 'shadow' fades with time.

effect of additional neighbors decreases [346]. We approximate this neighborhood effect from the development within each band using Equation A.5, shown in Figure A.5.

$$N_{b_j} = 1 - \frac{1}{1 + \frac{n_{b_j}}{\sqrt{O_{b_j}^2 - o_{b_j}^2}}} \tag{A.5}$$

where:

N_{b_j} = neighborhood effect of band j

n_{b_j} = number of developed cells within band j

$O_{b_j}^2 - o_{b_j}^2$ = the outer radius squared minus the inner radius squared of band j. This normalizes the value wi

The neighborhood effect is calculated with a loss function based on the contribution from each band (Equation A.6):

$$N_i = 1 + \sum_j w_j N_{b_j} \tag{A.6}$$

where:

w_j = 2 and 1 for inner and outer band respectively

1 is added so the function's minimum is 1.

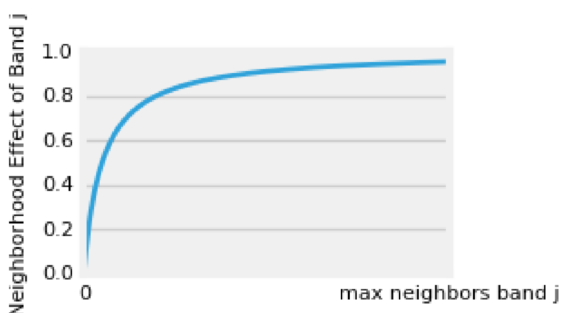


Figure A.5: The effect of developed cells nearby is initially significant, but reduces with more development.

A.6.2 Tsunami awareness

Tsunami awareness decreases following an event, and is considered negligible after three [human] generations [109]. Therefore, following a tsunami, the inundated cells are highly aware of the tsunami risk and that awareness gradually dissipates. We approximate these reports with a curve that approximates the empirical behavior (Equation A.7; Figure A.6). The generation length in similar regions was approximated by measurement at 30 years [109], and we explore the effect of changing this generational memory length in the paper (Figure 2.3).

$$A_i = 1 - \frac{1}{exp(\frac{t_i}{g})} \tag{A.7}$$

where:

t_i = the time elapsed since cell i was last inundated by a tsunami
g = generation length.

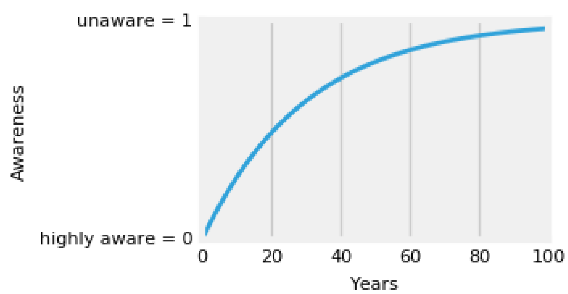


Figure A.6: Awareness of tsunami hazard decreases with time.

A.6.3 Cell accessibility

The accessibility of a cell is determined by its proximity to the ocean and the road. This is important for a fishing town such as those on the Pacific coast of Japan. We approximate the accessibility factor of a cell using an exponential decay function, normalized so that the furthest points from the road or sea have no improvement value due to their proximity (Equation A.8; Figure A.7). The factors normalize the decay curve between [0,1]. The weighting parameter for distance to the ocean is subject to sensitivity analysis (see Section A.9.2).

$$R_{O_i} = \frac{2w_s}{exp(10d_i) + 1} \tag{A.8}$$

where:

w_s $=$ the weighting parameter = 1
d_i $=$ the normalized distance from the ocean ∈(0,1]
R_{O_i} $=$ the accessibility value for distance from the ocean ∈(0,1].

The function for accessibility of road is identical, expect d_i is the normalized distance from the road. The accessibility is then determined by adding 1 to each value and multiplying them together (Equation A.9):

$$R_i = (1 + R_{O_i})(1 + R_{R_i}) \tag{A.9}$$

where:

R_{O_i} $=$ the accessibility value for distance from the ocean ∈(0,1]
R_{R_i} $=$ the accessibility value for distance from the ocean ∈(0,1].

An example screen shot of the model is shown in Figure A.8. Figures A.9 and A.10 show the influence the road and ocean have on the transition potential of the cells.

A.6.4 Cell suitability

The land slope of a cell affects its suitability [346]. Some land is too steep to build on without significant cost. To simplify the complexities in utility and land steepness, land that has a gradient exceeding 0.5 (1:2) is assumed unsuitable for develop. In practice this value is dependent on soil properties and building code among other factors.

A.7 Validation of the urban development model

Assessing the validity of land-use models involves confronting the tension between predictive and process accuracy [53]. Predictive accuracy is where the model correctly simulates land developed historically. However this historical map is only one realization of a complex process [53, 346]. Because land-use models can be path dependent, they can be multi-final and therefore result in different outputs from an accurate model. Process accuracy is based on how well the model captures these driving forces. Approaches to validation include location accuracy, pattern accuracy, uncertainty analysis, and sensitivity analysis [332]. Here we present the results of location and pattern accuracy determined from the invariant-variant method [332] and additional statistics commonly used for evaluating classification algorithms. Section A.9 presents a sensitivity analysis.

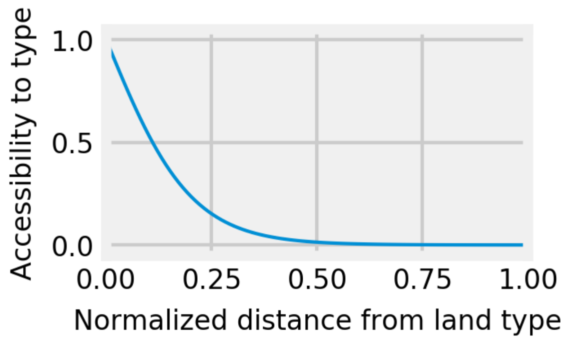


Figure A.7: The desirability of a cell decreases with its distance from the relevant land type.

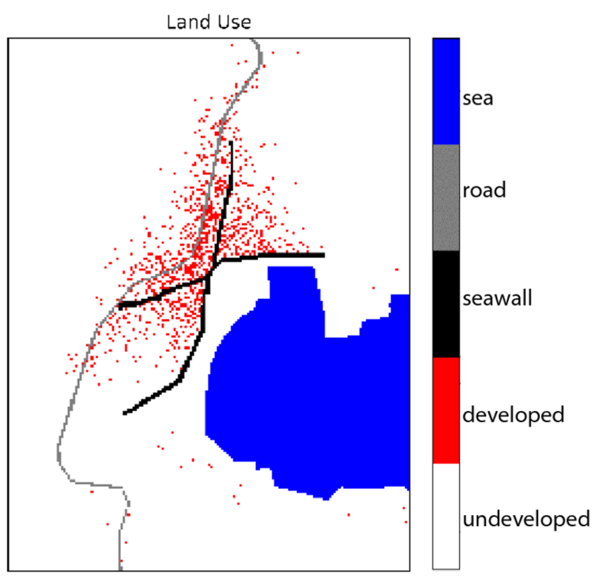


Figure A.8: An example of the model and the land-use.

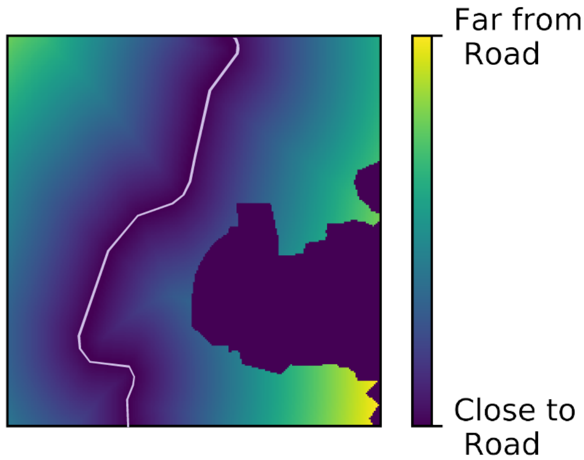


Figure A.9: Distance from the road

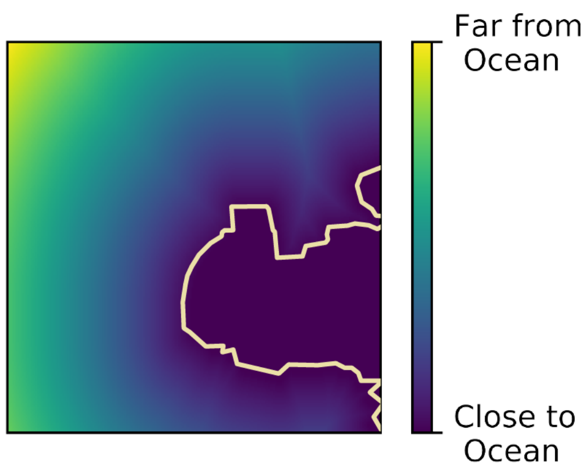


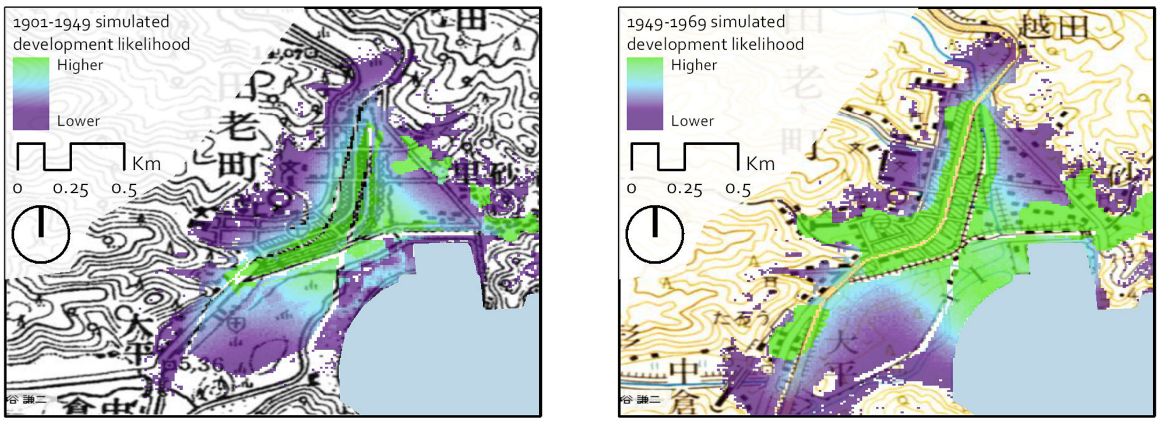
Figure A.10: Distance from the ocean

We conduct the validation using two historical periods. The first was between the years 1901 and 1949. The second was between 1949 and 1969. These two periods were selected due to the availability of the historic land-use maps. Additionally, they provide one validation case that includes, and one that excludes, a destructive tsunami event.

The maps (Figure A.11) present the historic land-use maps overlaid with the likelihood of that land cell being developed in 500 simulations. Due to multi-finality, the likelihood maps should not exactly match the actual occurrence. However, if the model is capturing the underlying process correctly, then the historical development should have a nonzero likelihood. In the figures, the color indicates the likelihood that a certain cell will be developed in the final year of the simulation. In this case, green indicates high likelihood and purple is low. In this qualitative validation, a good result is one where actual development (the black buildings) is included within the colored region. This shows that the development that occurred is likely within the model. A poor result is where actual development is not colored, indicating zero likelihood of development, or where the actual development is the only thing colored and colored with high likelihood of development, indicating the model is over fit [346].

Statistical validation results are presented in Table A.12. The first presented is the AUC, balanced accuracy, and mean percentage developed correctly. These are metrics commonly used to assess the accuracy of classification algorithms [113] and have been used to measure the accuracy of probabilistic classifications compared to observed land-use patterns [112]. The AUC (area under the receiver operating characteristic curve) indicates the probability that a classifier will "rank a randomly chosen positive instance higher than a randomly chosen negative instance" [113]. The closer the AUC is to one, the better the algorithm is classifying. The balanced accuracy is the accuracy of a classifier to predict classes, weighted by the number of instances in each class. A value of 100% would indicate perfect predictive accuracy. In the results shown, the balanced accuracy is computed at the 0.5 probability threshold to define developed or not. The percentage developed correctly is calculated for each realization from the model by comparing it with the historical. The mean is calculated from the 500 model replications.

The variant-invariant method [53] is used to compute the remaining metrics. This approach divides the region into the invariant (path independent) and variant (path dependent) regions. The invariant region is where the simulation predicts the same class more than $\theta\%$ of the time. This region should therefore be constant between all realizations including the historically observed. The accuracy of the invariant developed (ID) and invariant undeveloped (IU) regions is therefore calculated as the percentage agreement with the historical map. That is, ID accuracy is the number of cells developed in the historical map that are within the model's invariant developed region, divided by the number of invariant developed cells. This captures the accuracy of the path independent component of the model in predicting the historical. The variant region remains and can be used to assess the effect of path dependence and, therefore, the process. The statistic VC/VRD (variant correct divided by variant randomly developed) represents the ratio of correctly predicted developed cells against a process which simply develops cells at random. Due to the path dependence, however, the interpretation of this statistic is open. A VC/VRD above 1 indicates that the process is representing the observed development better than random, but a value below 1 could still be the result of a correct process model and suggest the observed development is unlikely [53]. A more complete discussion is presented in Brown et al. [53].



A **B**

Figure A.11: Likelihood of development averaged over 500 model replications and overlaying the historical development maps. (A) is the 1949 development. (B) is the 1969 development.

A.7.1 1901-1949

During this period a tsunami occurred, the seawall built, and the road rerouted. The construction of the 10 m high seawall was actually completed in 1958, however in this model it is added immediately following the 1933 tsunami (i.e. timestep 34).

The model is initialized with the development map from 1901 and predicts the 1949 development patterns (Figure A.11A), which can be compared to the actual 1949 development map, under laid.

Figure A.12: Validation results for the land-use models indicate the models are suitable.

	1901-1949		1949-1969	
	Model used	Inc. river and marsh	Model used	Inc. river and marsh
AUC	0.91	0.88	0.92	0.88
Balanced accuracy	71.05	67.89	77.97	73.25
Mean %Dev Correct	50.18	46.16	62.88	57.26
ID	86.17	87.24	96.55	96.55
IU	99.59	98.98	98.88	95.27
VC/VRD	1.21	0.96	0.80	0.34

Qualitative: The simulation accurately maintains development around the core downtown and begins to extend north and south along the road, as well as east before reaching the hills. It suggests that regions to the south which appear boggy in the historic map are likely to develop, however, the marshland and rivers are unknown to the model. The simulation accurately captures development to the south-west.

Quantitative classification: The validation statistics (Table A.12) indicate successful performance in classifying between developed and undeveloped land. The AUC, indicating probability of ranking a randomly chosen positive instance higher than a negative instance, is 0.91 (out of 1). The balanced accuracy, which weights the accuracy by the number in each class, is 71%. Finally, the mean of percentage of cells developed as historical is 50%. This result indicates the model is not over fitting, which may be the case if it developed the same historic region every simulation.

Quantitative variant-invariant: The model performs accurately in the invariant (path independent) region. We use θ=1. This is where the simulated model should be the same as the historic model. The accuracy for the invariant developed and undeveloped regions is 86 and 99.6% respectively. The invariant (path dependent) region is assessed using the ratio VC/VRD, which is the ratio of historically accurate cells against a process of random selection). The result, 1.2, is greater than 1, suggesting this model captures the underlying process better than random [53].

A.7.2 1949-1969

Between 1949 and 1969 Taro experienced a tsunami that was prevented by its newly built seawall. This is not modeled, so this second validation period includes no exogenous events. It is simply the evolution of the land-use based on the development preferences of being near neighbors, the ocean, and the main road. The model is initialized with the 1949 development map.

The simulation (Fig A.11B) shows the likely development extent includes most of the developed regions. It models development near the coast more than has been observed, but, as before, the river and marshland are unknown to the simulation. However, because it is unaware of the 1933 and 1960 tsunami there is no aversion to living near the ocean. Also, the disruption caused by the seawall construction (which was complete in 1958) is omitted.

Therefore, although the classification and invariant accuracy metrics are similar if not better than the 1901-1949 period, the VC/VRD ratio is less than 1 (Table A.12), indicating a random process better captures the development process in the variant region. This is likely due to the tsunami construction, the 1933 hazard awareness not persisting into this simulation, and the 1960 tsunami being ignored. Because of these factors, the actual development may in fact not represent the usual processes and therefore a value of 0.8 is still a reasonable result.

A.7.3 River and marshland effect

The river and marsh areas were excluded in the primary simulations to both simplify the model and maintain generality with other regions. When validation was conducted with the river and marshland masked as open water the accuracies drop for all metrics (Table A.12). This may be due to the land-use change rule stating a preference for developing near open water, which is how the marsh and river were defined. However, with the river and marshland excluded the validation metrics suggest strong accuracy in representing historic development patterns and capturing development processes.

A.8 Validation of Inundation Model Against Historical Tsunamis

Here we provide a validation of the tsunami inundation model against the three historic tsunamis. The parameters for the simulated tsunamis, as described in Section A.3.1, were selected from the literature to approximate the initial offshore wave height [93, 324]. The Delft3D hydraulic model accepts as inputs a fault line and set of fault parameters, which produce an initial offshore wave height [92] (Section A.3.1). The fault parameters for the historic tsunamis are shown in

Table A.3. The result of this model is then compared with on-shore water inundation heights. Water inundation heights for the tsunamis which struck Taro, Japan in 1896, 1933, and 2011 are available from Tohoku University [321]. We used observations with moderate and high confidence from the database to compare with the simulated heights from the Delft3D model.

Validation results are shown in Figures A.13-A.16. As shown in Figure A.16, the mean absolute error is approximately 2 m. Compared with other results of tsunami inundation models in the literature, a 2 m error is relatively minor. For example, Grilli et al. [138] find that two source models under predict inundation along the Sanriku/Ria coast, due to its complex bathymetry. Their findings for the region slightly south had under prediction on the order of a factor of 2. (Note Taro is at latitude 39.7^o on Fig. A.18 and Fig. A.19 of Grilli et al, 2013. [138]) Goto et al. [137] also presents results with errors exceeding 2 m between observed and modeled inundations. Similar differences are reported in Shimozono et al. [293], Tappin et al. [317], and Goda et al. [131]. Goto et al. [137], describe the reason for these disparities, stating:

"*numerical modeling might not reproduce minor inundation ... without sufficiently high-resolution topographic data because data for the modeling are usually rough, and the highway, small channels, and street gutters, which played an important role in local inundation, are too small a resolution to be recognized in the model. (p1247)*"

Furthermore, the inundation model we used is based on a simplified line source, as opposed to a detailed tsunami source based on inverse solutions of tide and seismic data (e.g. Tappin et al. [317]). This simplified line source is used because it allows computationally efficient evaluation of many hypothetical tsunamis with sources of various magnitudes and epicenter locations. This strategy is necessary for the stochastic evaluation of development behavior with the cellular automaton model. It is distinct from the analyses of Grilli et al. [138], Shimozono et al. [293], Tappin et al. [317], Goda et al. [131], and Goto et al. [137], all of whom aimed to hindcast one particular event as accurately as possible, thereby requiring resolution of a detailed and accurate tsunami source. Nonetheless, the simplified line source model performs similarly to these more sophisticated tsunami source models in this case, in terms of mean error in inundation heights.

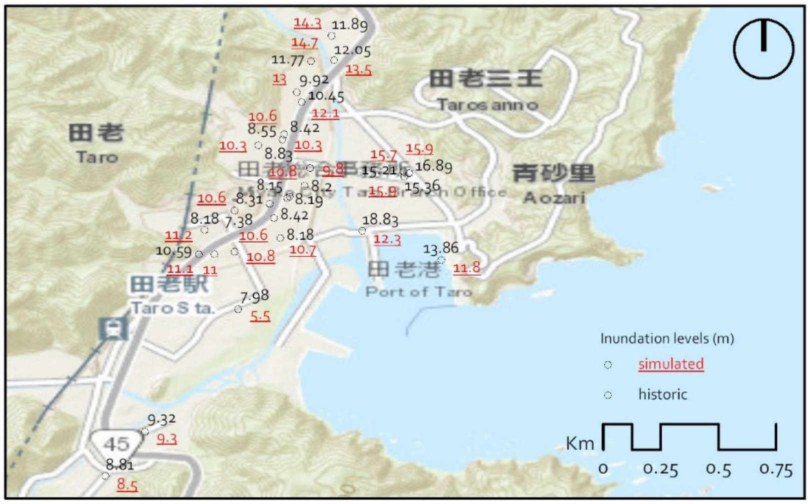


Figure A.13: Comparison of simulated vs observed water inundation as validation for the 2011 tsunami. Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, © OpenStreetMap contributors, and the GIS User Community

Figure A.14: Comparison of simulated vs observed water inundation as validation for the 1933 tsunami.

Figure A.15: Comparison of simulated vs observed water inundation as validation for the 1896 tsunami.

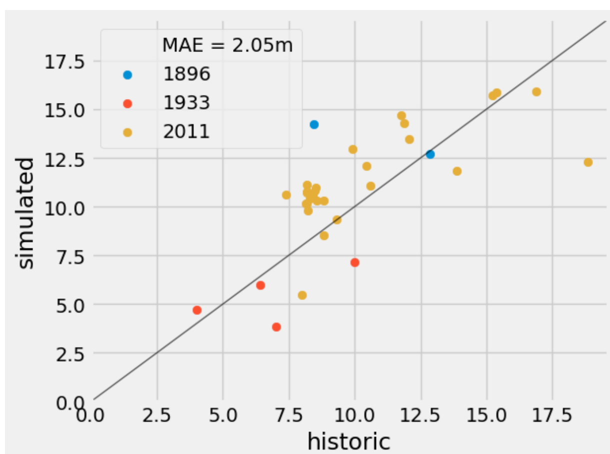


Figure A.16: Scatter plot of the tsunami heights historic vs simulated for the three tsunamis. The mean absolute error (MAE) is the mean difference between the heights.

A.9 Sensitivity Analysis

A.9.1 Tsunami Intensity

The severity of a tsunami is drawn from a triangular distribution (§A.3.3). We vary the slope (the tsunami intensity parameter) of the distribution to determine whether our conclusions are robust to varying the average severity of the tsunami. Note that the tsunami heights remain the same, just the relative frequency between them changes (Figure A.17). A higher modifier results in more major tsunamis.

The results indicate the same trends regarding the levee effect. Reducing the severity of tsunamis significantly reduces the damage over time, while the other modifiers result in minor differences between damage in the different simulations scenarios. The levee effect continues to be observed. In the no-seawall case, the damage from different tsunamis (for the same modifier) is similar. However, when a seawall is present the larger events result in more damage given the seawall has resulted in development within the inundation-hazard zone. This is apparent for the range of tsunami severity.

Note that when the distribution is modified by a factor of 0.5 the result is that the large events may not occur. This means that those large events are unanticipated, extreme events themselves and the levee effect is observed in the figures with these tsunamis as well as the major tsunamis.

A.9.2 Proximity to the ocean

Often, we build our communities near the ocean and one of the factors influencing the transition potential of a cell is its proximity to the ocean. We subject the weighting factor of that distance to a sensitivity analysis to determine whether these results change based on the community's relative desire to develop land near the ocean (Figure A.18).

We observe the levee effect for a range of weighting parameters for desire to live near the ocean (Equation A.8). Although the results appear to suggest that reducing the appeal of seaside living increases the damage from tsunamis, this is because of the topography in Taro, Japan which has land with close 'Euclidean' (straight line) proximity to the sea atop cliffs and hills. When there is no desire to live near the sea, the community clusters near the road and existing community which is primarily in a valley, prone to inundation.

These results (Figure A.18) show that the levee effect is still observed for a range of sea appeal factors and is therefore not sensitive to this factor.

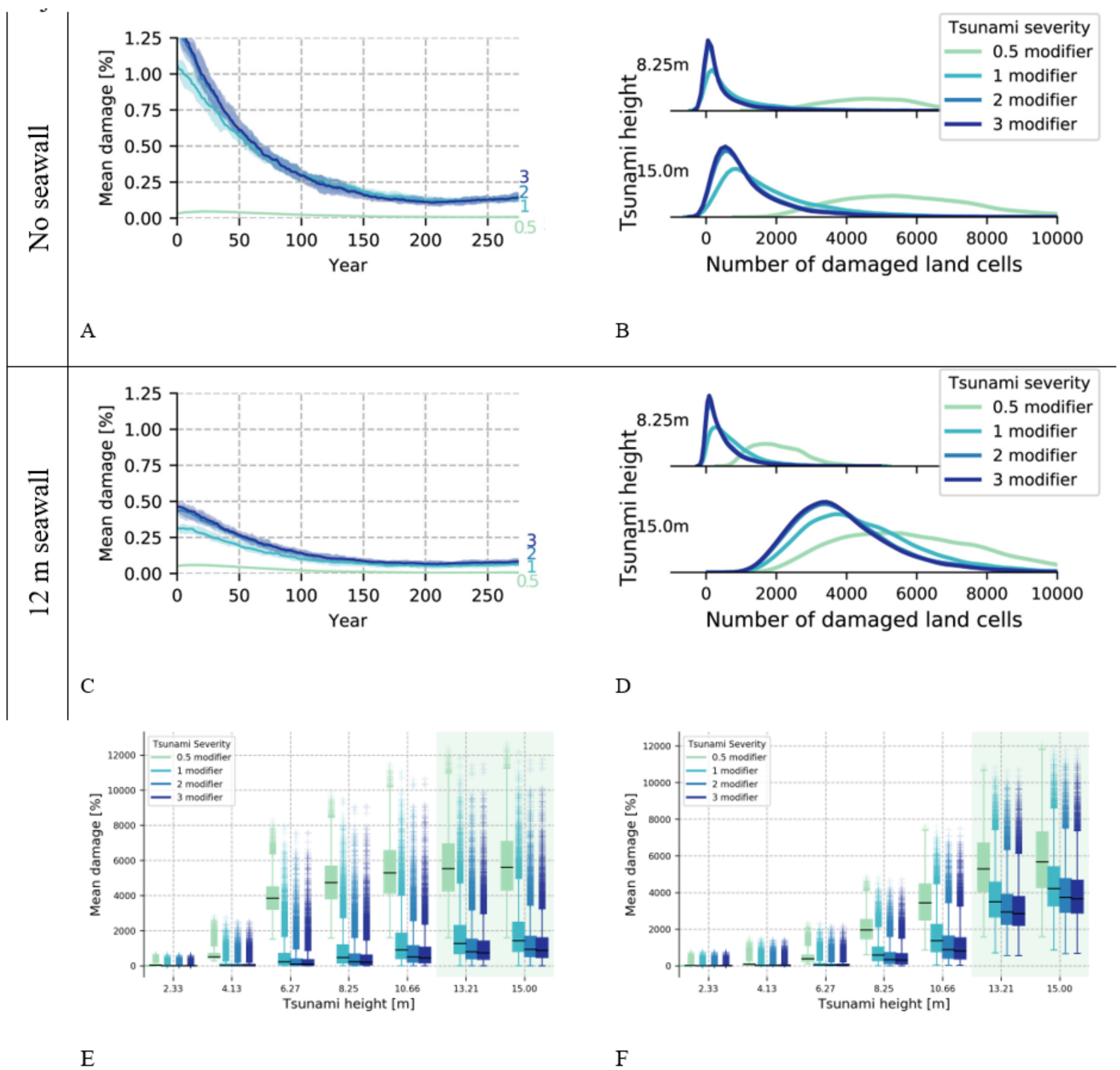


Figure A.17: The damage over time and damage from unexpected events when the tsunami intensity is varied. The conclusions are not sensitive to this parameter.
E & F present the results of B and D respectively, with all of the simulated tsunami events. The boxplot represents the median and 25th and 75th percentiles. The outliers are points outside of the 1.5IQR. The shaded blue indicates tsunami heights exceeding what was possible in the 300 years simulated, that is, it exceeds what the community evolved to expect.

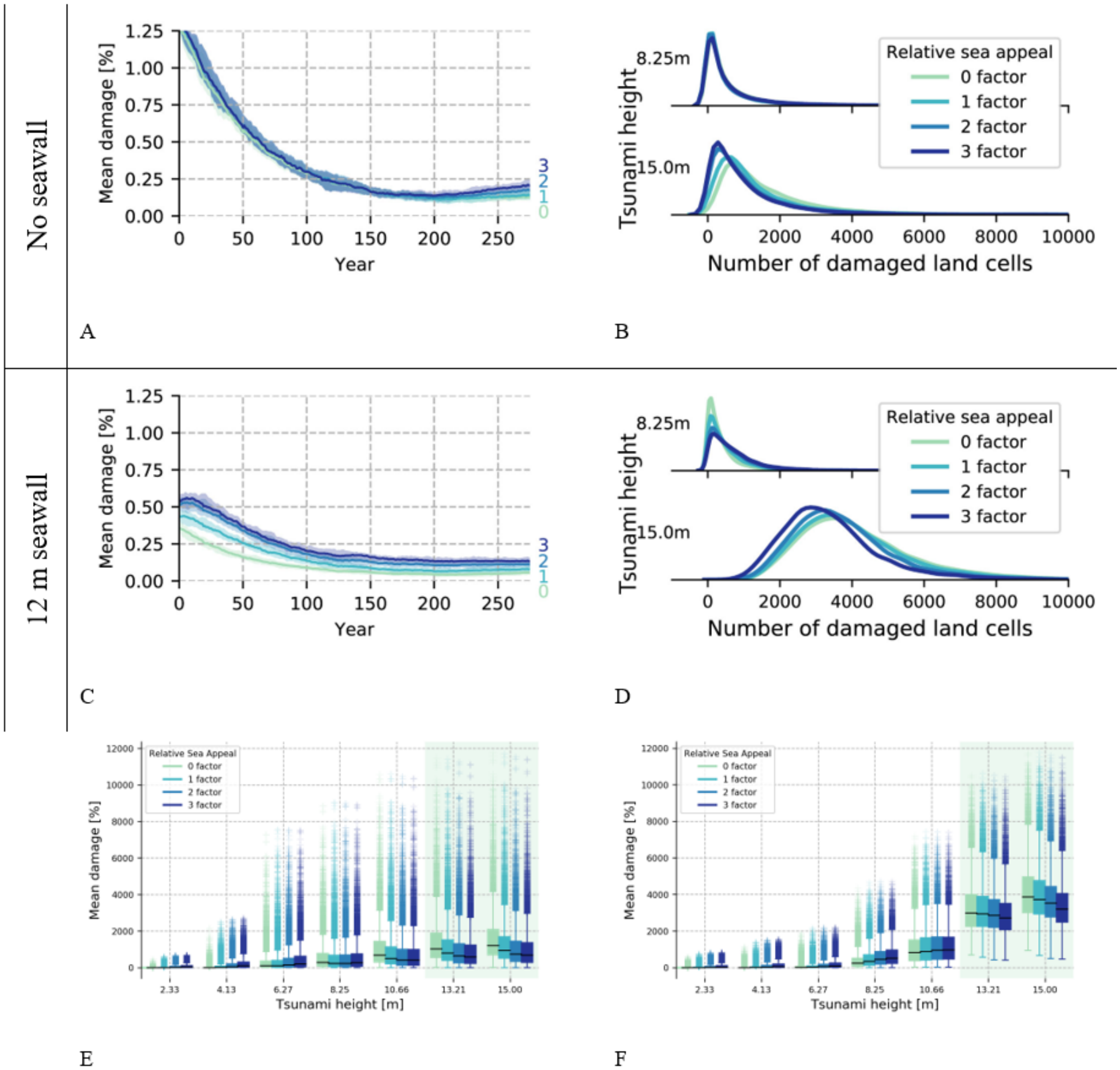


Figure A.18: The damage over time and damage from unexpected events when the importance of “proximity to ocean” on the transition potential is varied (w_s in §A.6.3). The conclusions are not sensitive to this parameter.
E & F present the results of B and D respectively, with all of the simulated tsunami events. The boxplot represents the median and 25th and 75th percentiles. The outliers are points outside of the 1.5IQR. The shaded blue indicates tsunami heights exceeding what was possible in the 300 years simulated, that is, it exceeds what the community evolved to expect.

A.9.3 Stochastic perturbation of land-use change

When modeling the evolution of the land-use over time, there is a random effect as well as the deterministic transition potential (described in §A.6). This stochastic perturbation is intended to capture the heterogeneity due to the human element of city growth. We subject the magnitude of this random effect to a sensitivity analysis to see how cities with different growth patterns behave. That is, we repeat the simulations for a range of magnitudes for this value.

The results, Figure A.19, are unchanged with the stochastic parameter indicating that the conclusions generalize for towns with different growth styles.

A.10 Awareness and the large seawall height

The results shown in the main text regarding awareness (Figure 2.3) were for the 0 m seawall. Although the coupling of maintained risk awareness with large hard-adaptive measures results in reducing damage over time, the large seawall still increases vulnerability to previously unexperienced events. Both cases are shown for comparison in Figure S19.

A.11 Definitions

A.11.1 Hard-adaptive measures

Hard-adaptive measures include seawalls, break waters, levees, and surge barriers.

Note that levees are also known as embankments, stop banks etc.

A.11.2 Soft-adaptive measures

Soft adaptive measures include, but are not limited to, education and awareness focused measures, as well as zoning restrictions, financial incentives, ecological infrastructure etc. Note however, that we do not explore these in this analysis, but we acknowledge that addressing human behavior is more complex than providing the community information regarding the flood risks.

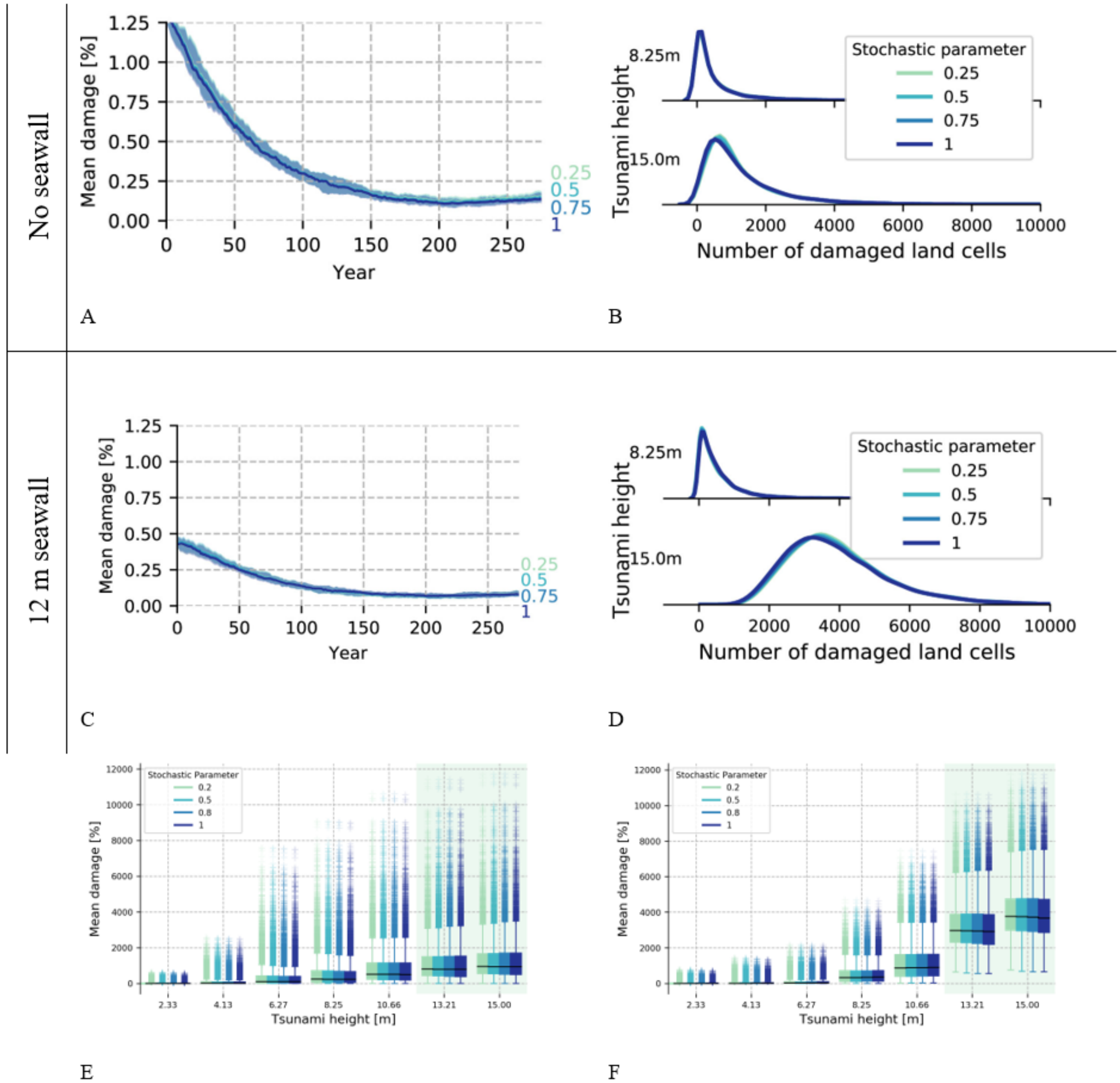


Figure A.19: The damage over time and damage from unexpected events when the land-use stochastic parameter is varied. The conclusions are not sensitive to this parameter. E & F present the results of B and D respectively, with all of the simulated tsunami events. The boxplot represents the median and 25th and 75th percentiles. The outliers are points outside of the 1.5IQR. The shaded blue indicates tsunami heights exceeding what was possible in the 300 years simulated, that is, it exceeds what the community evolved to expect.

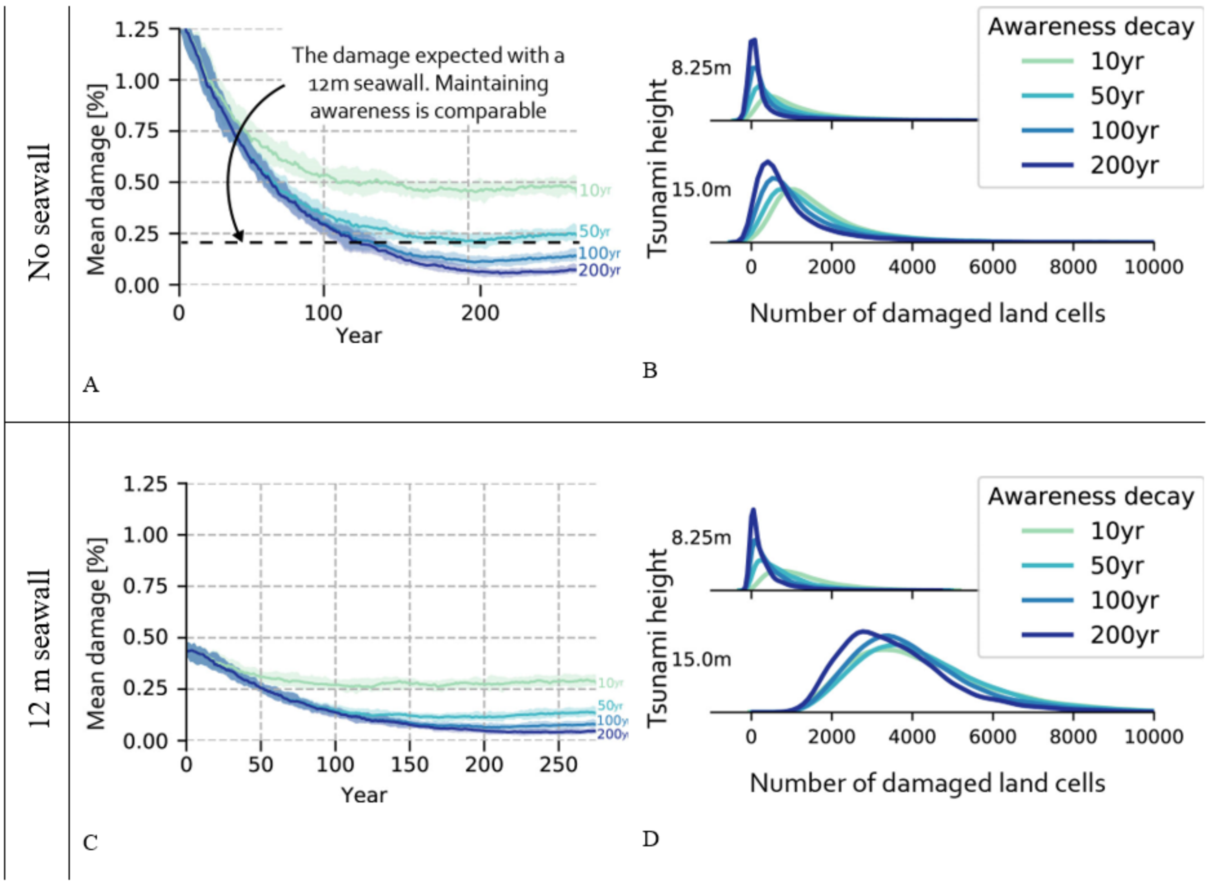


Figure A.20: The effect on damage of increasing the time that the community remains aware of the hazard. (A) and (B) are presented in Fig2.3 and have no seawall. (C) and (D) have a 12m seawall. Comparing distributions (B) and (D) shows that maintaining awareness in the presence of a seawall does not avoid the levee effect because the community believes that it is protected and is unaware of their vulnerability.

Appendix B

Supplements to Data mining and urban land surface temperature

B.1 Data sources

Table B.1: The data sources for the LST analysis.

Data Provider	Data Type	Data Date	Description	Source
U.S. Geological Survey	Raster	2013-2017	Landsat 8 day and night satellite imagery	https://earthexplorer.usgs.gov/
Microsoft	Polygon	2018	Building footprint polygons for the US	https://github.com/Microsoft/USBuildingFootprints
Defense Meteorological Satellite Program	Raster	2013	Stable nighttime light intensity	https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html
Multi-Resolution Land Characteristics Consortium	Raster	2011	Land cover	https://www.mrlc.gov
Multi-Resolution Land Characteristics Consortium	Raster	2011	Percent developed imperviousness	https://viewer.nationalmap.gov
Multi-Resolution Land Characteristics Consortium	Raster	2011	Percent tree canopy cover	https://viewer.nationalmap.gov
U.S. Geological Survey	Raster	2015	1/3 arc-second elevation	https://nationalmap.gov/3DEP/3dep_prodserv.html
U.S. National Oceanic and Atmospheric Administration	Lidar	2014	Point cloud of surface elevation	https://coast.noaa.gov/htdata/lidar2_z/geoid12b/data/6377/
IPUMS NHGIS	Area Level	2010	Block-level population from the US census	[210]

B.2 Covariates included in models

We select variables to include in the model based on the variance inflation factor (VIF). This approach removes variables that exhibit high multicollinearity, that is the variable can be predicted from a combination of other variables. It is important to remove variables with high multicollinearity in inferential studies because otherwise the variables may confound the effect of one another on the variables of interest.

Table B.2: Covariates included after accounting for multicollinearity.

Resolution	Included variable
100-meter	Albedo mean
	NDVI mean
	Sky view factor mean
	% tree canopy stand. dev. spatial lag
	% tree canopy stand. dev.
	NDBI stand. dev. spatial lag
	% building area
	Sky view factor max
	% tree canopy mean
	NDVI stand. dev.
	% water area
	Digital surface model mean
	Population density mean
500-meter	NDVI mean
	Albedo mean
	Sky view factor mean
	Digital surface model stand. dev.
	% building area
	% tree canopy mean
	% water area
	Sky view factor max
	NDBI max
	% tree canopy max
	Population density mean
	Digital surface model mean
	% tree canopy min

B.3 Technical appendix: convolutional neural network

B.3.1 Overview

Our CNN model was adapted from a U-Net architecture [278]. This architecture is commonly used for image segmentation: the input to a U-Net model is a 2D greyscale image, and the output is another 2D image with values representing the classification of each pixel. The novel property of a U-Net CNN is that the internal layers learn at various resampled resolutions of the input data, which makes the model good at learning phenomena that are driven at multiple scales.

Several modifications were made to adapt U-Net to a geospatial use-case, and are outlined below.

B.3.2 Data preparation

The gridded data for each city was treated as an image, with each pixel representing a 100m or 500m cell. Instead of having three channels (red, green, and blue) like a colour image, these images had one channel for each of the independent variables in the dataset. The target was a 2D single channel image of the same shape.

CNNs require all inputs to be the same shape, which isn't the case for our city domains. Each city image was therefore split into images of 32×32 pixels (24×24 for the 500m resolution). Splitting the images up also gives more training samples to work with: each of the small square images is a training sample.

Because the city boundaries aren't square and contain holes, missing data is introduced when placing the data into square images. The missing data needs to be filled because neural networks have no built-in way to handle non-real numbers. A simple approach like replacing with the median for each variable would result in unrealistic abrupt spatial jumps near the city boundaries: these discontinuities would affect the convolution operations in the CNN which can rely on features such as edges and spatial variance. Instead, holes and concave boundaries were filled using linear interpolation, then edges were extended by setting missing-data corner pixels to the median value of each variable and performing linear interpolation. The progression of the missing data filling algorithm is shown in Figure B.1. The result is all-real images with smooth changes at the missing data boundaries.

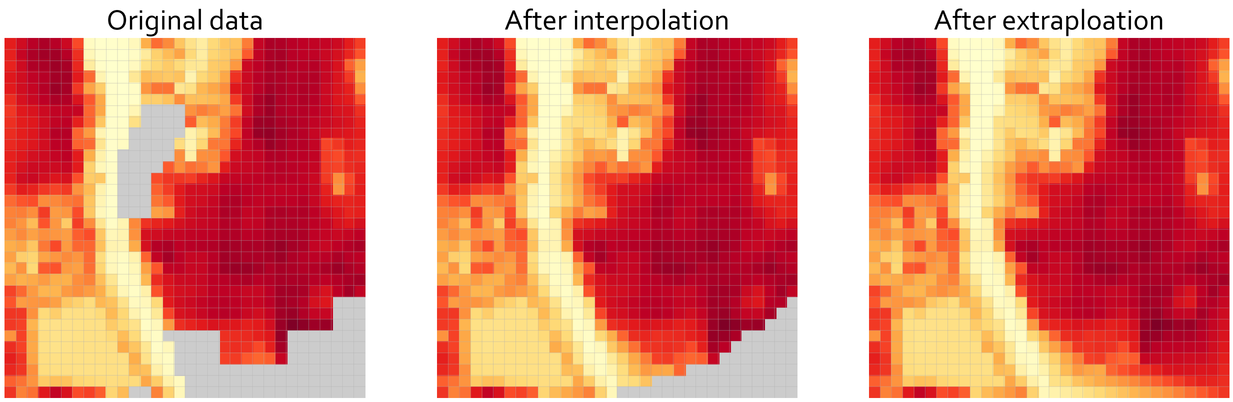


Figure B.1: Handling of missing data for the CNN. The image shown is for a 32×32 cell section of mean day temperature for Portland at the 100m resolution.

B.3.3 Model

The model architecture is shown in Figure B.2. It consists of multiple convolutional layers at both the input resolution and a 50% downsampled resolution. Additionally, a skip connection concatenates the raw input data with one of final layers to reduce the depth between the input and output.

The size of the network is much smaller compared to the original U-Net in order to reduce overfitting due to our small dataset.

The final layer uses a linear activation function to enable regression. All other layers use ReLU activation, and dropout is applied after the contraction.

To prevent the CNN overfitting to the naively-imputed missing data, a masked loss function was used. The mean square error was greatly reduced for cells i with missing data according to a mask M

$$\text{loss}_i = M_i(y_i - \hat{y}_i)^2$$

$$M_i = \begin{cases} 0.01, & \text{if } y_i \text{undefined} \\ 1, & \text{otherwise} \end{cases}$$

This reduces the impact missing data has on the model weights, while leaving a small amount of gradient to avoid numerical issues with lack of convergence. The cells with missing data were excluded from any results presented.

The mask was also added to the input data as an additional channel.

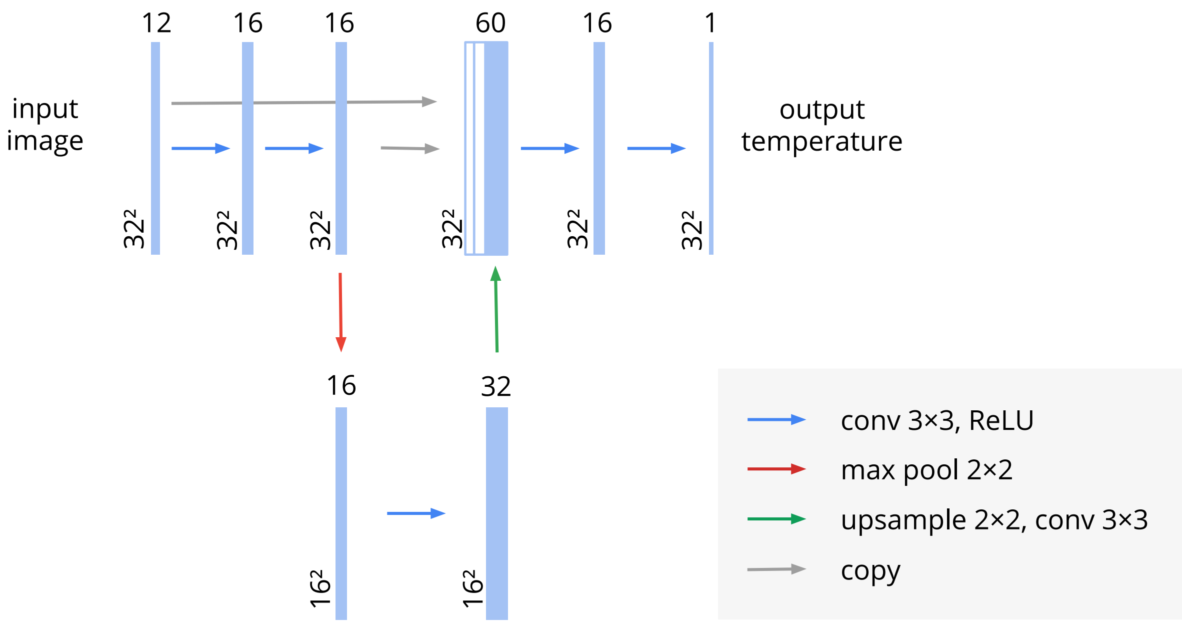


Figure B.2: CNN model architecture. Each layer shows the spatial dimensions (e.g., 32^2) and the number of channels (e.g., 12). In the final $32^2 \times 1$ layer, the ReLU layer is omitted.

B.4 City specific results

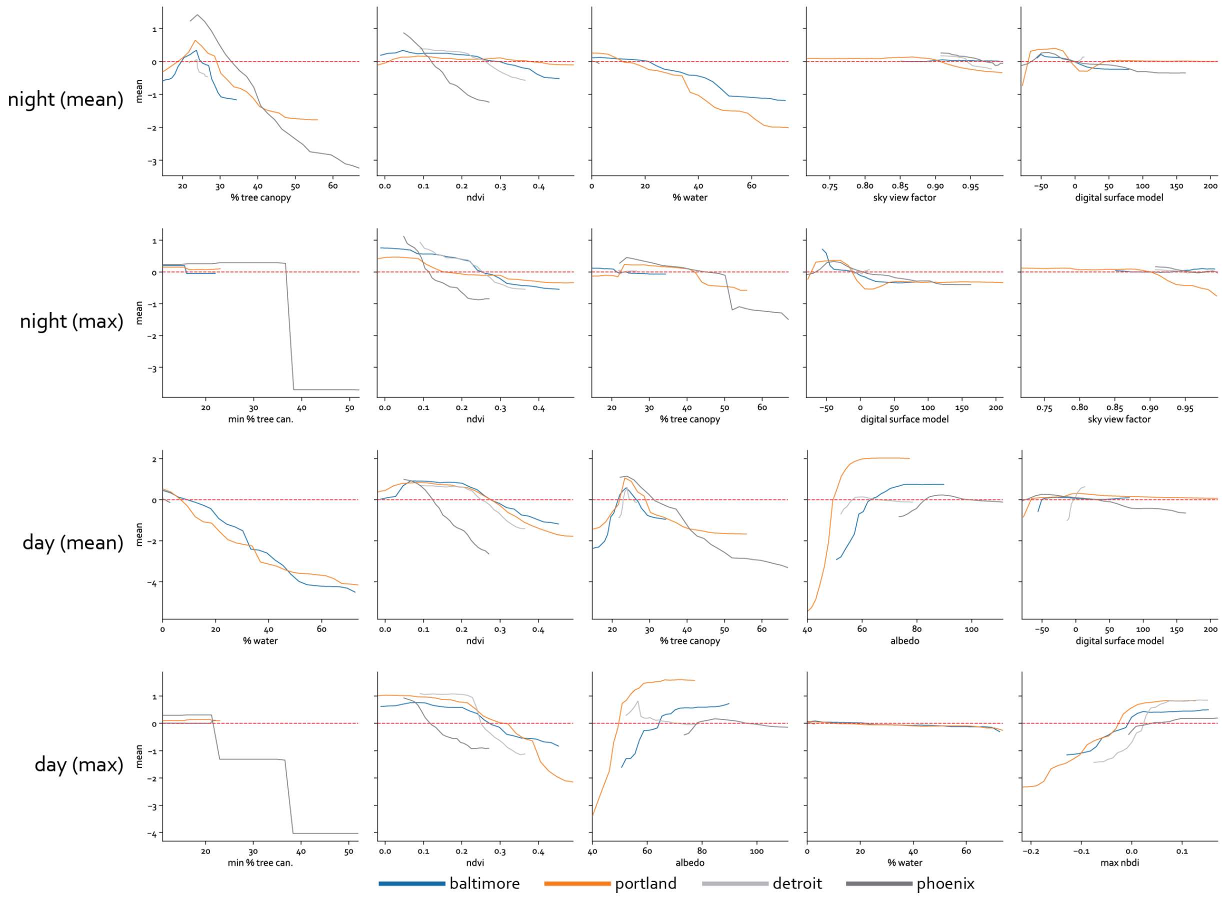


Figure B.3: City specific partial dependence plots at the 500-meter resolution. The partial dependence plots for a random forest model trained on each city. This is to evaluate whether the influence of urban characteristics on LST is consistent between the cities.

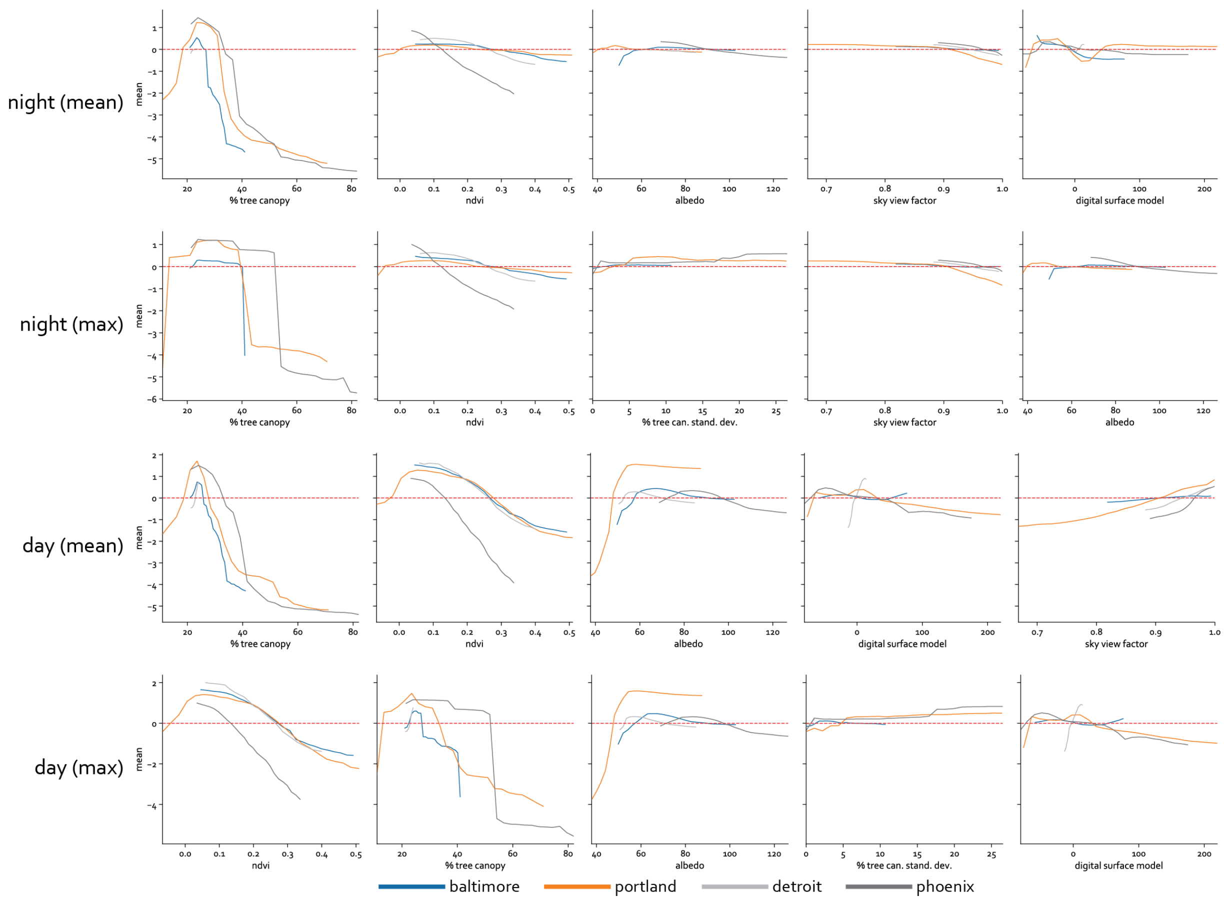


Figure B.4: City specific partial dependence plots at the 100-meter resolution. These are partial dependence plots for a random forest model trained on each city. This is to evaluate whether the influence of urban characteristics on LST is consistent between the cities.

B.5 500-meter resolution results

The figures presented in the main text, are replicated here based on data at a 500-meter resolution.

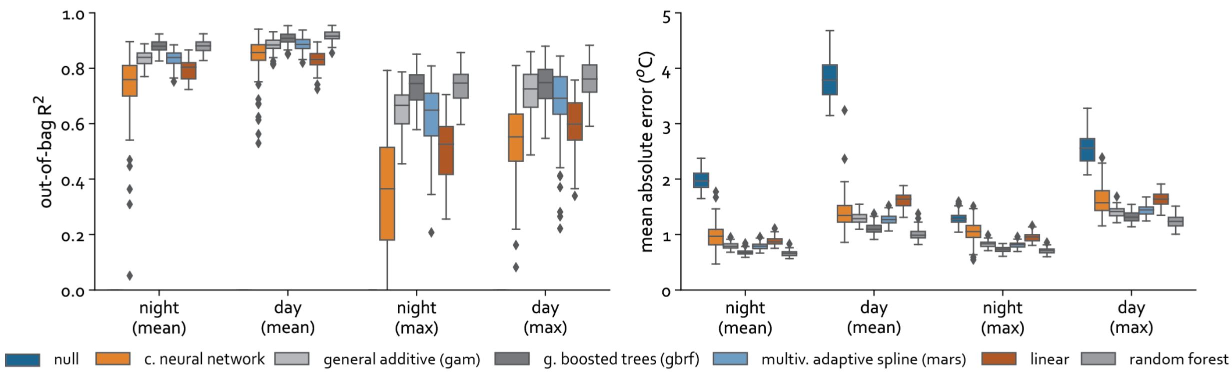


Figure B.5: Holdout cross-validation results at 500-meter resolution. The out-of-bag (OOB) R^2 and mean absolute error (MAE) of the models from a 500-fold holdout cross-validation. The models were trained on 80% of the data and tested on the unseen 20%. When selecting data for the training and testing sets, spatial subsets were used to account for spatial similarities. OOB R^2 can vary between $(-\infty, 1)$, where better models have a value near 1. Good models have MAE near 0.

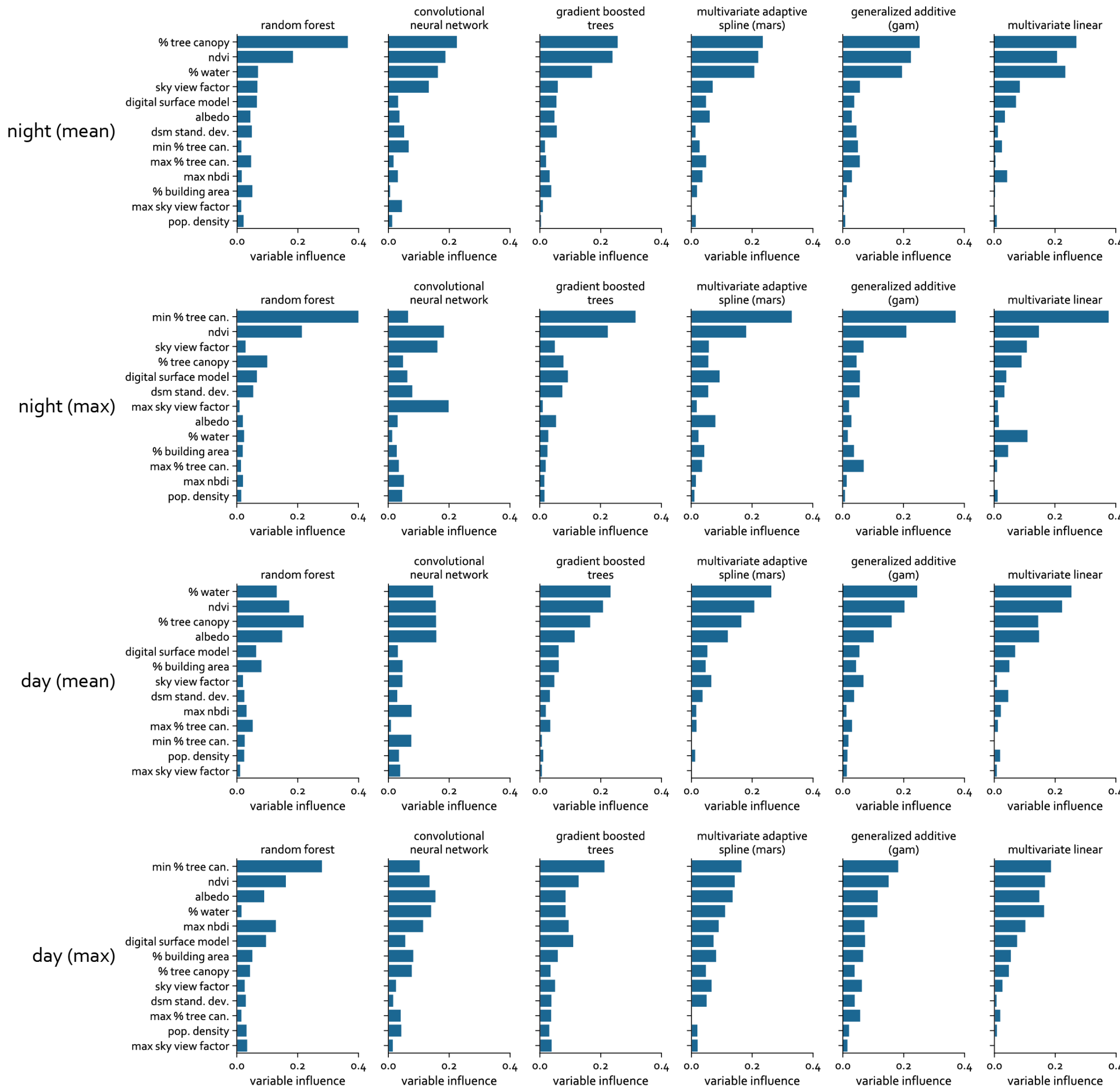


Figure B.6: Variable influence on LST at 500-meter resolution. The variable influence, measured by swing, shows the relative importance of each urban characteristic on land surface temperature.

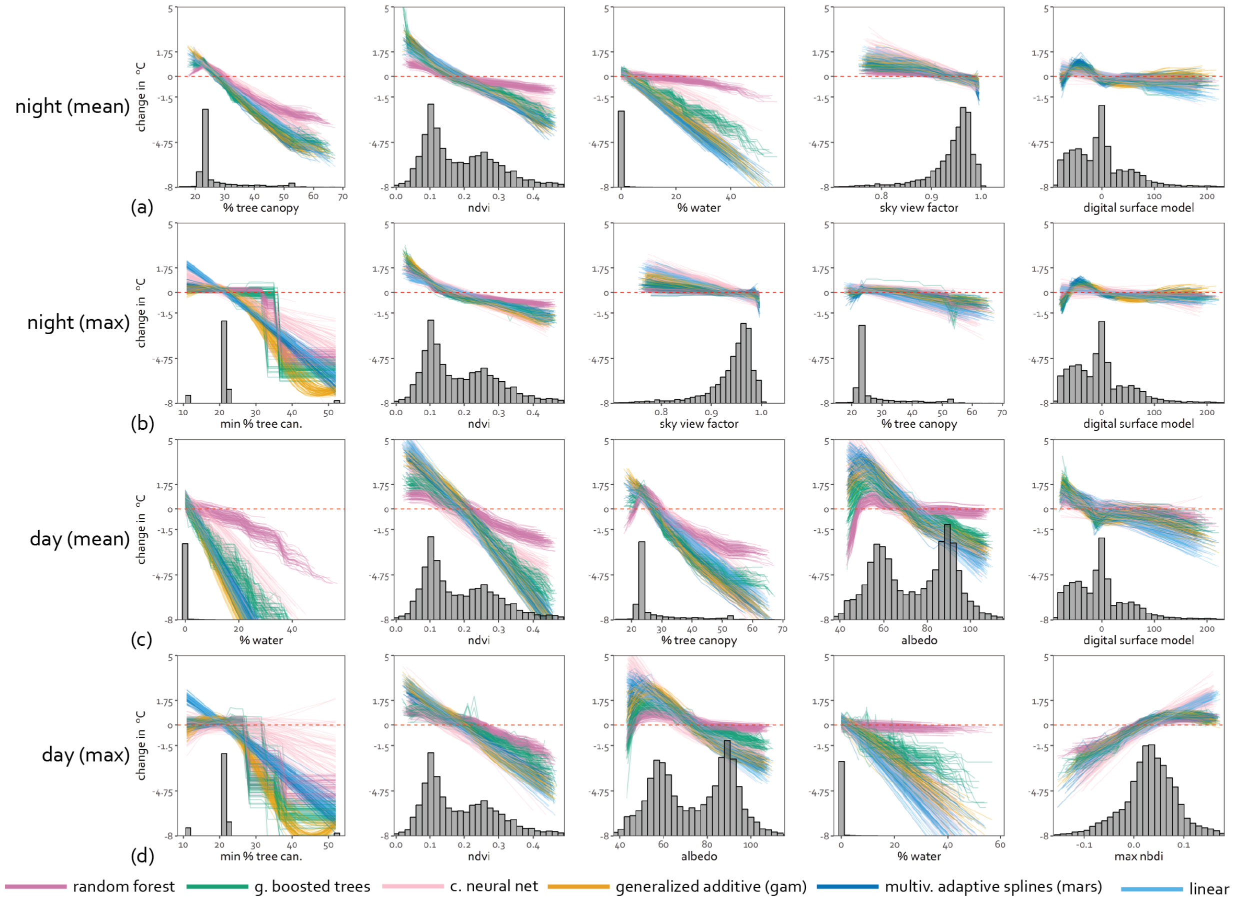


Figure B.7: Partial dependence plots for LST at 500-meter resolution. Partial dependence plots show how the land surface temperature (^oC, y axis) changes with each urban characteristic as the other variables are held at their average (mean) value. The left hand side shows the effect each variable has on the (a) mean land surface temperature (LST) during the night, (b) maximum LST during the night, (c) mean LST during the day, (d) maximum LST during the day. Each of the models are shown and this indicates the model uncertainty in the relationships. There are multiple lines for each model based on bootstrap samples of the data, which indicates the data uncertainty. The histograms on the x-axis shown the distribution of the observed data.

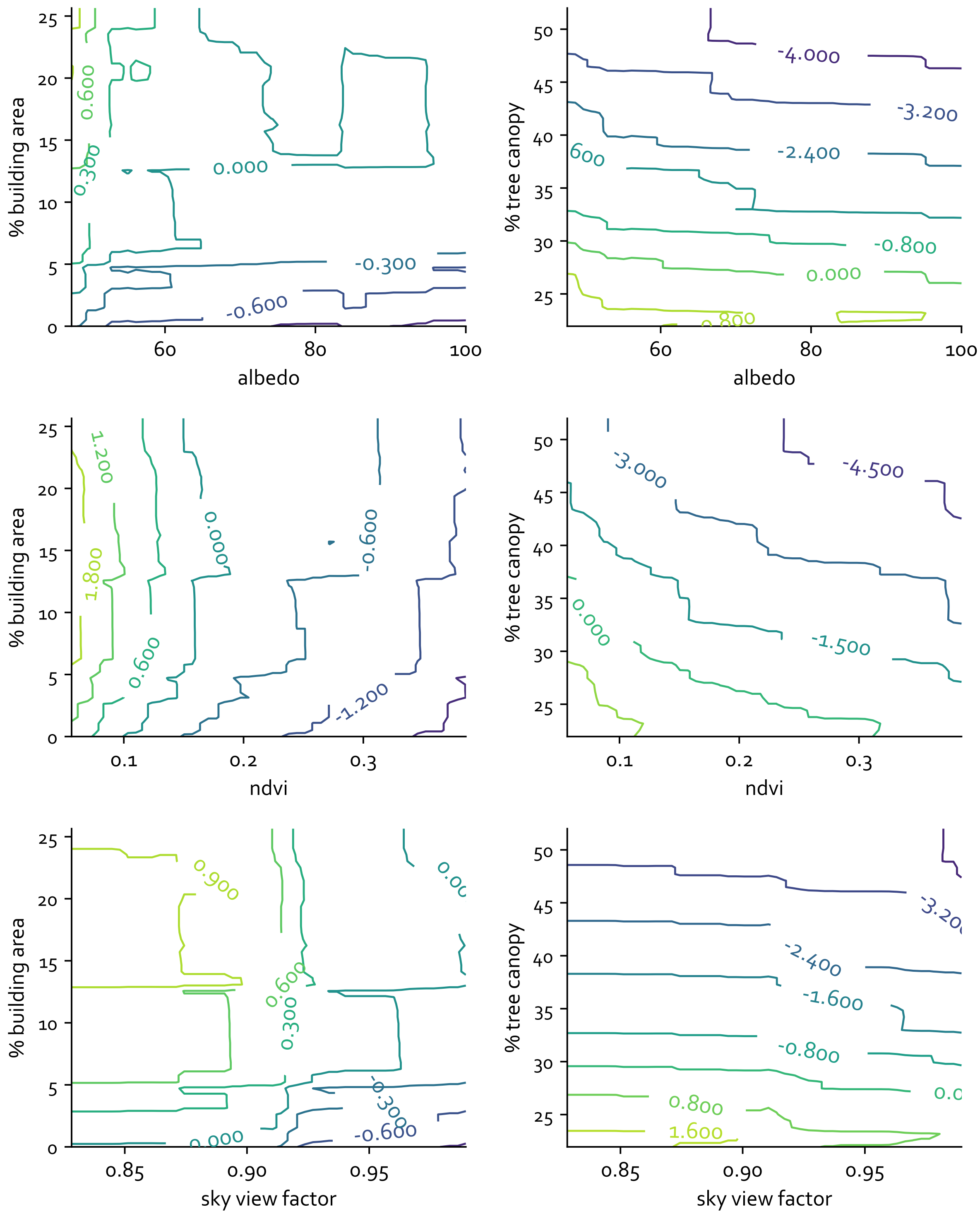


Figure B.8: Partial dependence contour plots for LST at 500-meter resolution during the night. These partial dependence contours show how the land surface temperature (^oC, y axis) changes with each variable as the other variables are held at their average value. The left hand side shows the effect each variable has on LST during the night, while the right hand side shows the effect during the day. This shows that trees coverage in the cell has the greatest influence on the temperature, and the greenness (NDVI) of that coverage matters during the day.

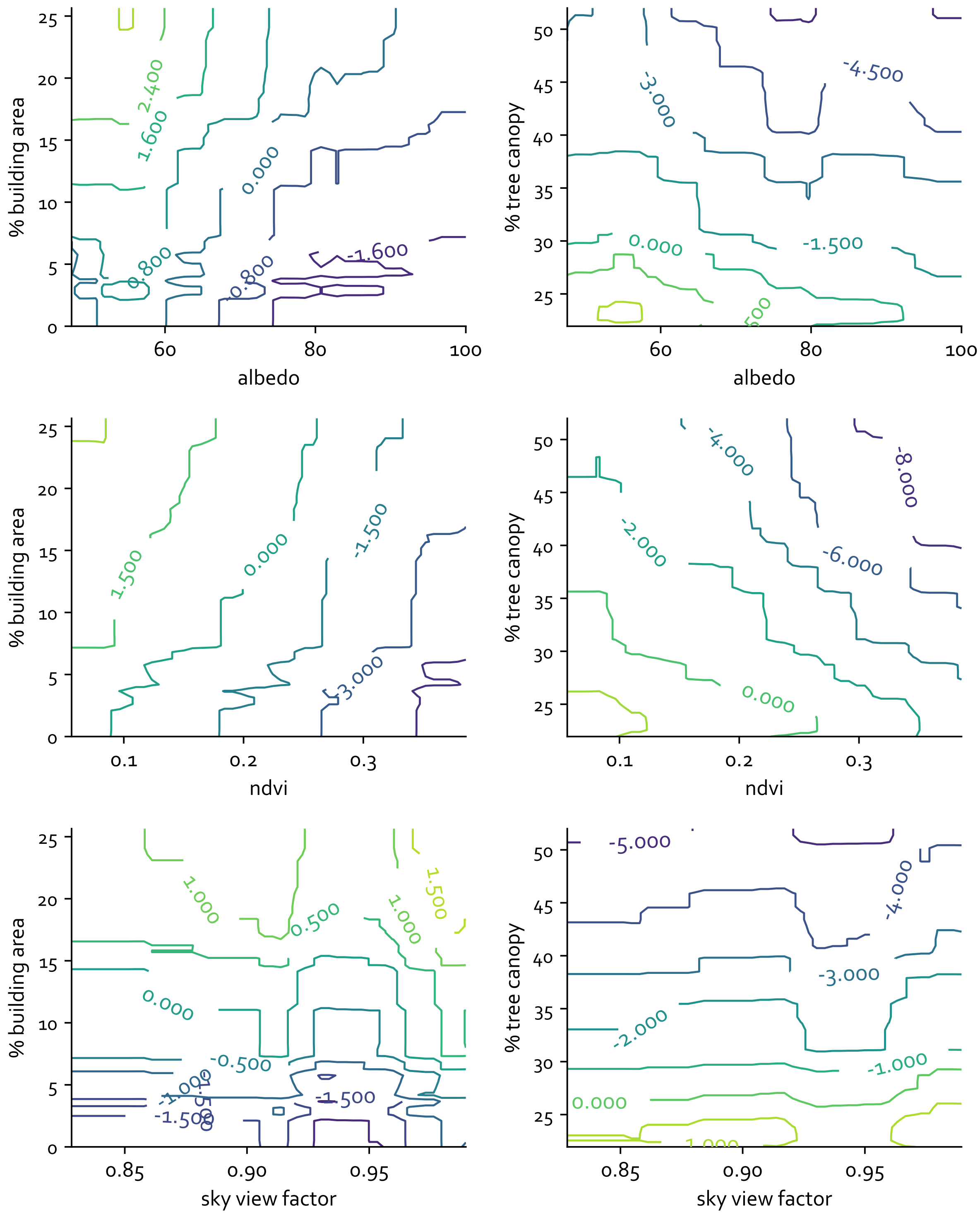


Figure B.9: Partial dependence contour plots for LST at 500-meter resolution during the day. These partial dependence contours show how the land surface temperature (^oC, y axis) changes with each variable as the other variables are held at their average value. The left hand side shows the effect each variable has on LST during the night, while the right hand side shows the effect during the day. This shows that trees coverage in the cell has the greatest influence on the temperature, and the greenness (NDVI) of that coverage matters during the day.

B.6 Additional figures

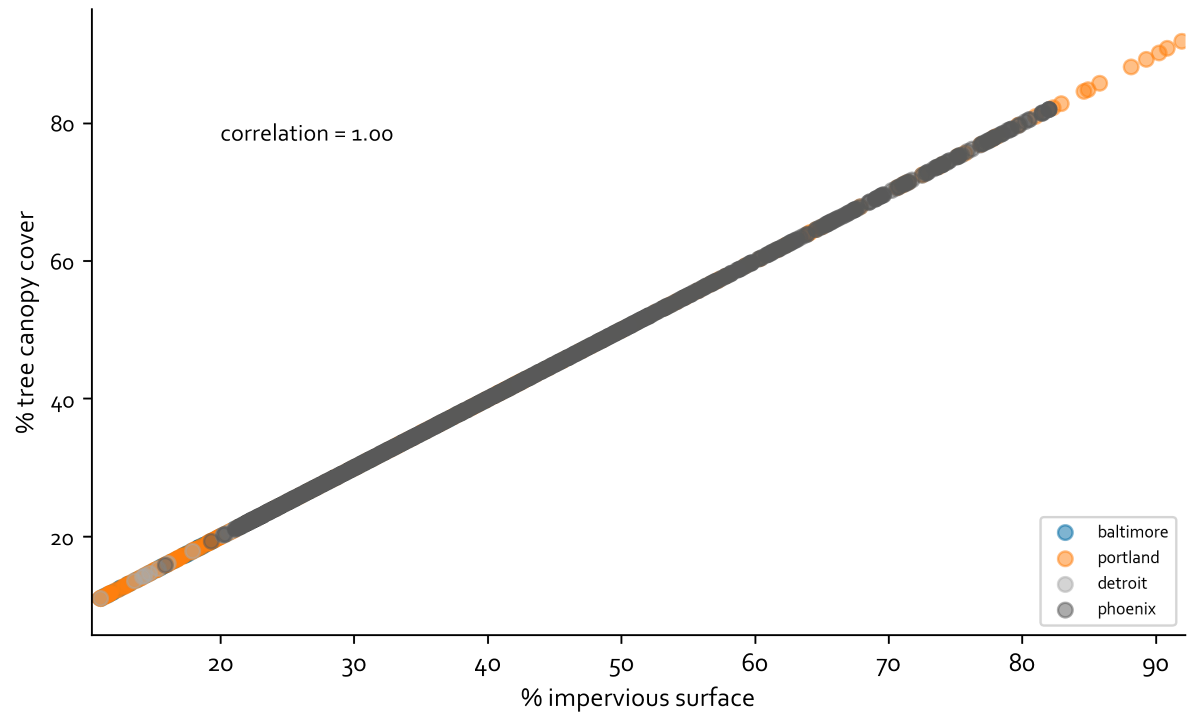


Figure B.10: Percentage tree canopy cover and impervious surface are 100% correlated.

Appendix C

Supplements to Evaluating Urban Accessibility

C.1 Using the Open-Source Routing Machine

The open-source Routing Machine (OSRM) [204] is a tool that calculates optimal routes for a given geographical area and a given transport profile (car, bicycle, pedestrian, etc). The use of OSRM depends on the operating system you are using: Mac and Linux are supported by the OSRM team, while we have provided code for setting up OSRM on Windows. A brief summary is also provided at `https://reckoningrisk.com/coding/2017/OSRM-server/`.

C.1.1 Mac and Linux

Up-to-date instructions for installing OSRM on Mac and Linux are given on the OSRM project page: `https://github.com/Project-OSRM/osrm-backend#quick-start`. Once running, the url of the OSRM server can be passed to the provided R code using the 'osrm.url' variable.

C.1.2 Windows

1. Download an OpenStreetMap '.osm.pbf' file for the region you are interested in. You can get these from sources such as `http://download.geofabrik.de/`. The location of this file should be the 'osm.pbf.path' variable in the R code.

2. Set up a transport '.lua' profile. It's best to start with one of the profiles included in the 'lib/osrm/profiles', and modify it to your needs. You can change things like speeds

for different road surfaces, penalties for turns, and which road classes are allowed to be taken. The location of this file should be the 'osrm.profile.path' variable.

3. Modify the other parameters of the code as required/desired and run. The function 'StartOSRMServer' will set up an OSRM server that is used by the rest of the code, or could be accessed for your own calculations.

C.2 Consideration of data quality

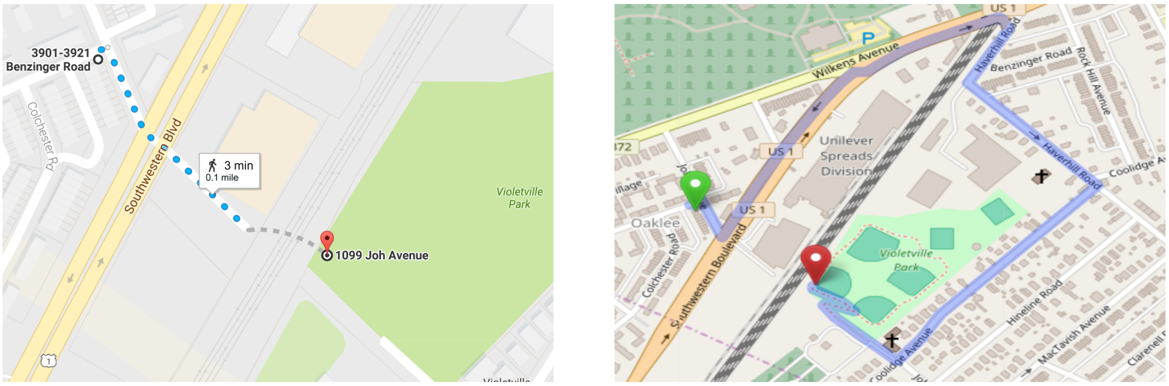
C.2.1 Volunteered Geographical Information (VGI)

Data availability and quality continues to be a challenge for researchers and practitioners. Volunteered geographical information (VGI) is a promising solution [135, 145, 233]. One platform for VGI is OpenStreetMap (OSM). OSM is an online, user-contributed, open-source database containing a wide variety of land-use and coverage information. While the accuracy is not uniform, the OSM database covers large portions of the developed and developing world, offering great potential to extend this analysis to other cities and regions [233]. In developing countries, lack of data is a primary limitation for urban analysis [205]. However, in some cases, VGI is the only source of geographic information [135]. The online suite of open access data has vastly simplified data collection. In our analysis, we used OSM as the source of our transportation network and destination data (parks, supermarkets, and hospitals). In any case, when the goal is to make conclusions about the proximity within a city, destination data should be checked thoroughly.

C.2.2 Coordinate snapping and incomplete network

Network-based distance algorithms rely on snapping coordinate points (both origins and destinations) onto the nearest point (by Euclidean) on the transport grid. When their path network is incomplete, this snapping can result in errors. For example, when the nearest road is on the other side of a physical barrier, such as the railway in Figure C.1, the routing algorithm grossly underestimates the distance. Another example is when the park has an entrance that is ignored, due to the routing snapping to an object outside of the park (Figure C.2). In both cases, the correct distance is calculated when the destination snaps to a pathway inside the park. However, these pathways do not always exist in either Google maps or OSM. When the paths do exist, we encourage the algorithm to snap to them, by using the -5m buffer to bring the park destination points further inside the park.

Both Google and open-source mapping data have incomplete networks. For example, it has been found that in low-income areas, especially rural, the accuracy of OSM data decreases [145]. However, this was almost 10 years ago, and much work has been invested into OSM since then. Also, much of the proximity analysis is in metropolitan areas, which do not exhibit the same degree of sparsity. OSM data is also a focus of improvement in developing countries. Governmental agencies are beginning to recognise the value of the tool and are investing heavily in improving the data quality (e.g. MapGive). While Google's network data is arguably better, the advantage of using open map data is that we, as researchers and practitioners, can correct and update the maps online or as a downloaded copy.



(a) In this case, Google snaps the destination to the road on the other side of the railway

(b) OSRM snaps to a trail within the park and then calculates the longer, more accurate distance

Figure C.1: An example where OSM has more complete data compared to Google, resulting in a Google snapping error.

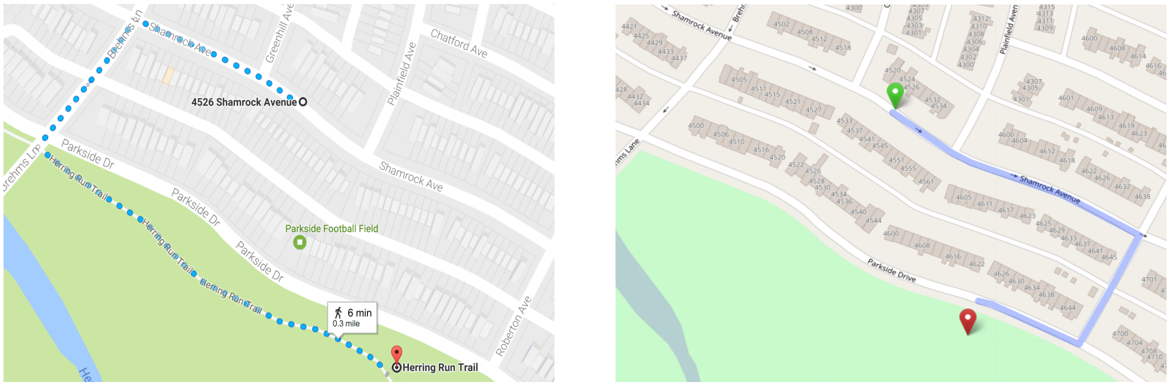
C.2.3 Unconnected ways

Unconnected ways are another issue with map completeness that is present in the open-source mapping data. An unconnected way occurs when paths are not connected as they should be. The result is that the routing algorithm is unable to use the link. This is a well-known issue in the open-source mapping community and one that developers are addressing [247]. There are tools available to identify and correct unconnected ways, so researchers and practitioners can correct the errors present in the mapping data. The open-source mapping data is constantly improving and is kept up-to-date. Many of these issues, especially in major cities, will be addressed in time.

C.3 Considerations for choice of routing algorithm

C.3.1 Motivating issues

Measuring the "shortest path" through a network has an element of subjectivity, and different algorithms are founded upon different assumptions. For example, some algorithms may prefer



(a) In this case, Google snaps to the path inside the park and would identify the shortest distance as being the entry to the park. Our approach captures the entrance as it queries multiple points in the park, so the one closest to the entrance will be selected.

(b) OSRM snaps to the road near the park and then calculates the distance assuming porous boundaries.

Figure C.2: An example where Google has more complete data compared to OSRM, resulting in OSRM snapping.

routes for cyclists with minimal gradient change, while others may place a high value on routes that utilise bike lanes [328]. As a result, different algorithms may generate different paths and hence different distance and time estimates for a given origin-destination pair.

Network time is often preferred by decision-makers as it is more understandable by the public than distance [289]. However, estimating network time adds an additional layer of subjectivity over the network distance, as determining the network time must assume speeds on different road types and surface materials.

Ultimately, a researcher or practitioner can use any routing algorithm they wish to carry out the analysis we propose. OSRM, Google, Graph Hopper, TravelTime, and OpenTripPlanner are just a few examples. To make that selection, they need to be aware of the trade-offs between options. In the remainder of this section we compare and contrast two routing algorithm options and discuss other trade-offs in routing algorithm selection and specification.

C.3.2 Comparing OSRM and Google Maps

Google Maps is considered a reliable routing algorithm that many people use daily. However, Google currently charges 50 USD per 100,000 queries, with a daily cap of 100,000 queries. The approach we present in this paper can require millions of queries. For example, the Baltimore building shapefile has approximately 200,000 buildings. Querying the distance to the closest 50 park boundary points results in 10 million queries, which is both slow and costly through Google. Conversely, the open-source nature of OSRM gives the capability to run the queries on a local computer or server, allowing for an unlimited number of free queries. We find that the results calculated by OSRM are comparable with Google and, in this section, present the results of the comparison in Baltimore.

For the comparison, we needed directly comparable route queries. To avoid the computational time and expense of querying Google for every household, we clustered the buildings into origin points and used these as the basis for our comparison. The Baltimore origin (building) file contained 214,000 points, so we sampled the data set using Hartigan's leader clustering algorithm [150], specifying the approximate cluster radius of 20 m. This clustering resulted in a data set of approximately 56,000 origin points (the cluster centroids) where the mean distance from a building point to its clustroid was 14 m. We then queried Google's Distance Matrix API for each origin and the closest Euclidean ten park points and closest five hospitals and high schools. We queried the same origin-destination pairs on OSRM.

Figure C.3, Table C.1, and the supplemental material display the comparative ECDFs, point difference percentiles, and the point difference spatial distributions. OSRM and Google produced very similar results for walking to parks, while cycling and driving exhibit some differences.

Obstructions between the origin and destination and query limit are one cause of error. Occasionally, the closest park by Euclidean distance is on the other side of an obstruction (e.g. Figure C.1). If the number of queries is small enough that all queries are on points within this park rather than a park that is actually closer by network distance, the routing algorithm fails. Open-source routing algorithms do not have this issue as, unlike Google, they are not limited by the number of queries. Other disparities between the OSRM and Google results may be due to the algorithms' different preferences in their route choices. As previously noted, these can be especially significant for cycling. Similarly, different driving algorithms will have different preferences for shortest distance versus shortest time routes, leading to different results.

It should be noted that the majority of previous studies focussing on network distance measures have used the Network Analyst tool in ESRI (Environmental Systems Research Institute) ArcMap. This is a valid routing algorithm and uses data provided to ESRI from government agencies. However, it is not available to many groups as it is a paid extension to ArcMap. Hence, we have not included a comparison to the Network Analyst tool in this section.

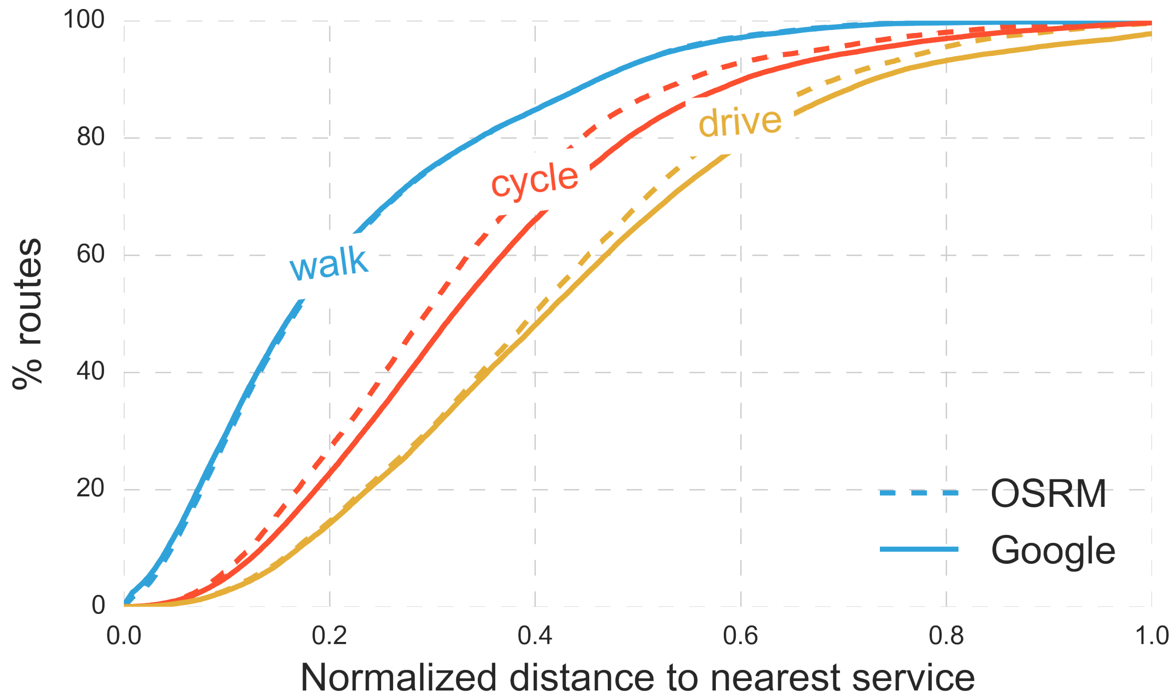


Figure C.3: Comparing Google and OSRM routing algorithms in terms of overall city-wide accessibility.

C.3.3 Travel profiles and congestion

When comparing travel times, one limitation with current open-source routing approaches is the lack of data regarding congestion. This is a complex factor to incorporate into a routing algorithm. OSRM uses a driving profile, which assumes various speeds depending on the road hierarchy and the road material. In our analysis, we have used OSRM's default profiles for walking, cycling, and driving which assume a walking speed of 5 km/h, a cycling speed of 15 km/h, and a driving speed on residential roads of 25 km/h. The assumptions behind these travel profiles are accessible and modifiable. However, regardless of which settings are chosen, the closest destination (by duration) in free-flow conditions may not be the closest destination during rush hour, and OSRM has no in-built ability to account for this.

Leveraging Google is recommended for studies where congestion is important. In our comparison, we queried Google's Distance Matrix API specifying a future departure time of 10am on a Tuesday. Figure C.4 shows this comparison of driving times between OSRM and Google. The effect of congestion is clear.

Table C.1: Percentiles of the difference between OSRM's and Google's calculated distances (in m) to closest amenity. Distances are to green spaces (walking), high schools (cycling), and hospitals (driving).

	10%	25%	50%	75%	90%
Walk	-36	-5	1	19	55
Cycle	-473	-235	-65	15	138
Drive	-631	-163	-15	43	197

The OSRM travel profile can also lead to other differences when compared to Google Maps. The profile assigns some road classes that are not usable for each mode (e.g. you should not walk on a highway). A community separated from its core service via a significant highway may therefore be routed differently between algorithms (e.g. the southern end of Baltimore city, see supplemental material, page 165). As previously stated, the profile can also apply different travel times to gradients and pavements, or define preferences for cycleways. This will all contribute to differences in results from different routing algorithms.

C.4 Spatial distribution of differences between OSRM and Google

Figure C.5 shows the differences between the OSRM and Google routing algorithms. Differences occur due to the aforementioned differences between Google and OSRM. They appear to increase with the distance to services and increase as the number of services decreases. For example, if OSRM and Google select different 'closest' facilities, there can be a significant difference. This may occur from assumptions about speed of travel along roads, road travel permissions (e.g. cycle on highways or one-way streets), or congestion. Google also selects the fastest route, based on estimated travel time due to traffic and travel speed. This can result in differences in distance travelled in the OSRM and Google route. Being aware of these differences and the assumptions when selecting routing algorithms is important.

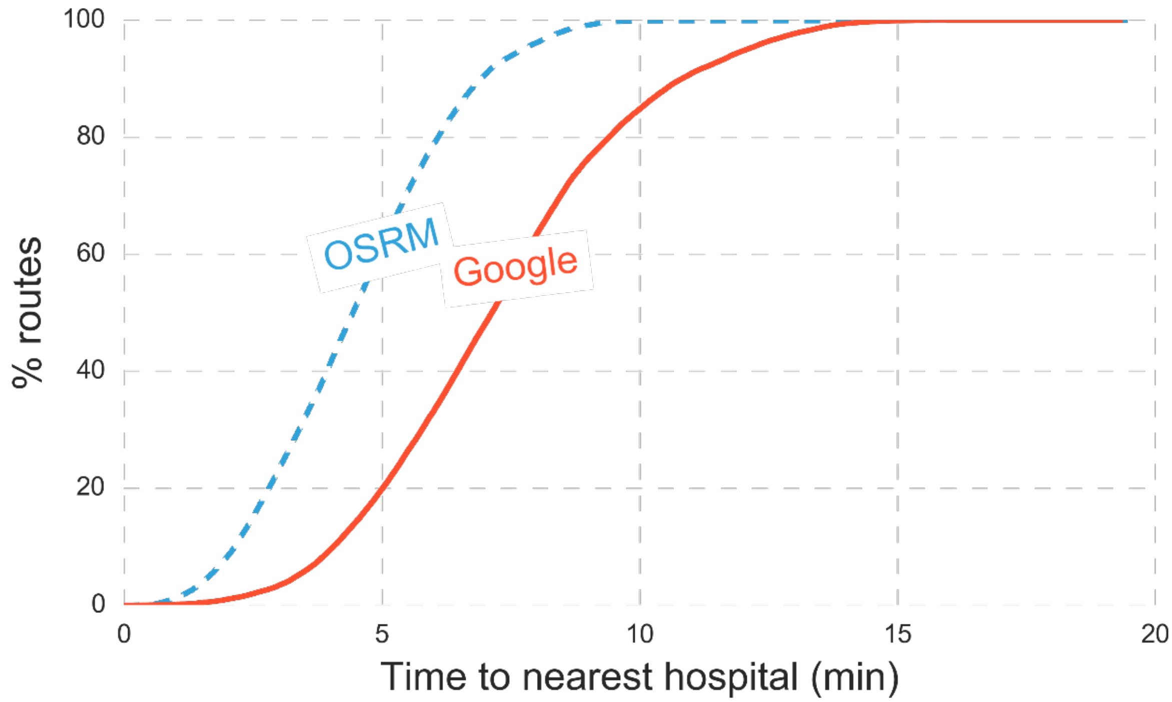


Figure C.4: A comparison of driving times between OSRM and Google at 10am on Tuesday 6 December 2016. OSRM does not capture congestion, so underestimates the travel time.

C.5 Differences between OSRM (Network distance) and Euclidean distance

By definition the Euclidean distance is strictly less than or equal the network distance. That is, the straight line path is always shorter (except in the case of coordinate snapping, discussed previously). Some papers (e.g. Boone et al. [49]) argue that this difference is negligible. Other studies use Euclidean distance due to limited data (e.g. Macedo and Haddad [205]). In some cases use of the Euclidean would introduce only minor error. However, when geographical obstacles are present, this error grows and can constantly overlook service-poor communities. It also over estimates the quality of city-wide access as shown in Figure C.6, which shows the differences between the OSRM network routing algorithm and the Euclidean. The error grows as the distance to the service grows, indicating that the use of the Euclidean as an approximation should be limited to short distances where possible.

C.6 Data sources

Parks, supermarkets, and hospitals were downloaded from `http://overpass-turbo.eu/`. The query keys that were used are shown in Table C.2. The other data sources are presented in Table C.3.

Table C.2: Overview of the `overpass-turbo.eu` query keys used to extract location data from OSM for the case study

Service	Overpass-turbo query
Parks	leisure=park
Hospitals	amenity=hospital
Grocery Stores	shop=supermarket

Table C.3: Data sources

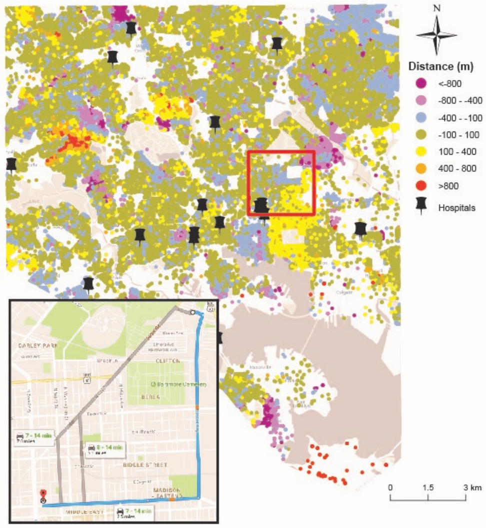
City	Buildings	High schools	Land-use
Baltimore	(Maryland Dept. of Planning, 2013)	`https://data.baltimorecity.gov/Neighborhoods/`	`http://www.baltimorecity.gov/OfficeoftheMayor`
Chicago	`https://data.cityofchicago.org/Buildings/`	`https://data.cityofchicago.org/Education`	None
Detroit	`http://maps.semcog.opendata.arcgis.com/`	`https://geo.btaa.org/catalog`	`http://portal.datadrivendetroit.org`

Table C.4: Percentage of population with access to supermarkets via walking, cycling, and driving (rounded to the closest percentage point).

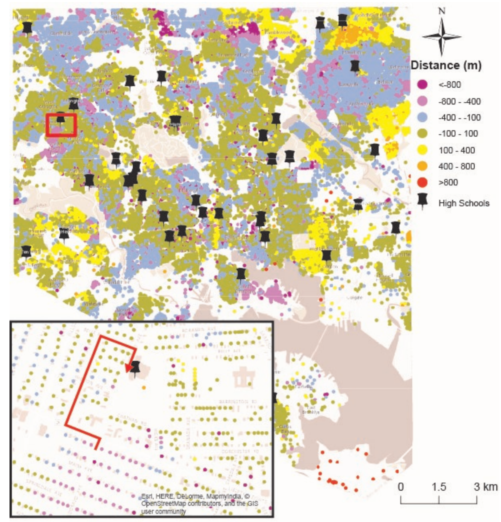
	Time to supermarket (min)								
	Walk			Cycle			Drive		
	5	10	20	5	10	15	3	5	10
Chicago	12%	39%	78%	56%	90%	99%	68%	96%	100%
Baltimore	6%	21%	54%	30%	72%	90%	47%	83%	100%
Detroit	2%	8%	23%	12%	37%	66%	29%	67%	100%

C.7 Additional results

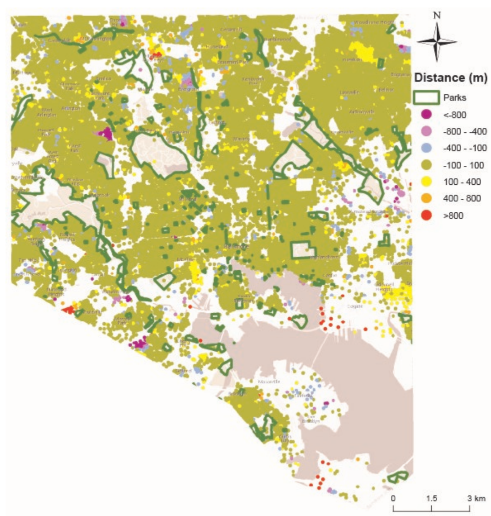
Figure C.7 presents the ECDFs by distance for cycling to high schools and driving to hospitals. Table 4.2 includes the corresponding discretised results. Similarly, Figure C.8 and Table C.4 show the walking, cycling, and driving times to the nearest supermarket.



(a) Driving distance to hospitals. Inset shows Google's alternative routes, which prioritizes shortest travel time, which can result in a longer travel distance compared to OSRM.



(b) Cycling distance to high schools. Inset shows the Google route, as it avoids travel against the one-way street.



(c) Walking distance to green space

Figure C.5: The spatial distribution of differences in the network distance when calculated using Google Distance Matrix API and OSRM. Maps show the OSRM distance minus the Google Distance.

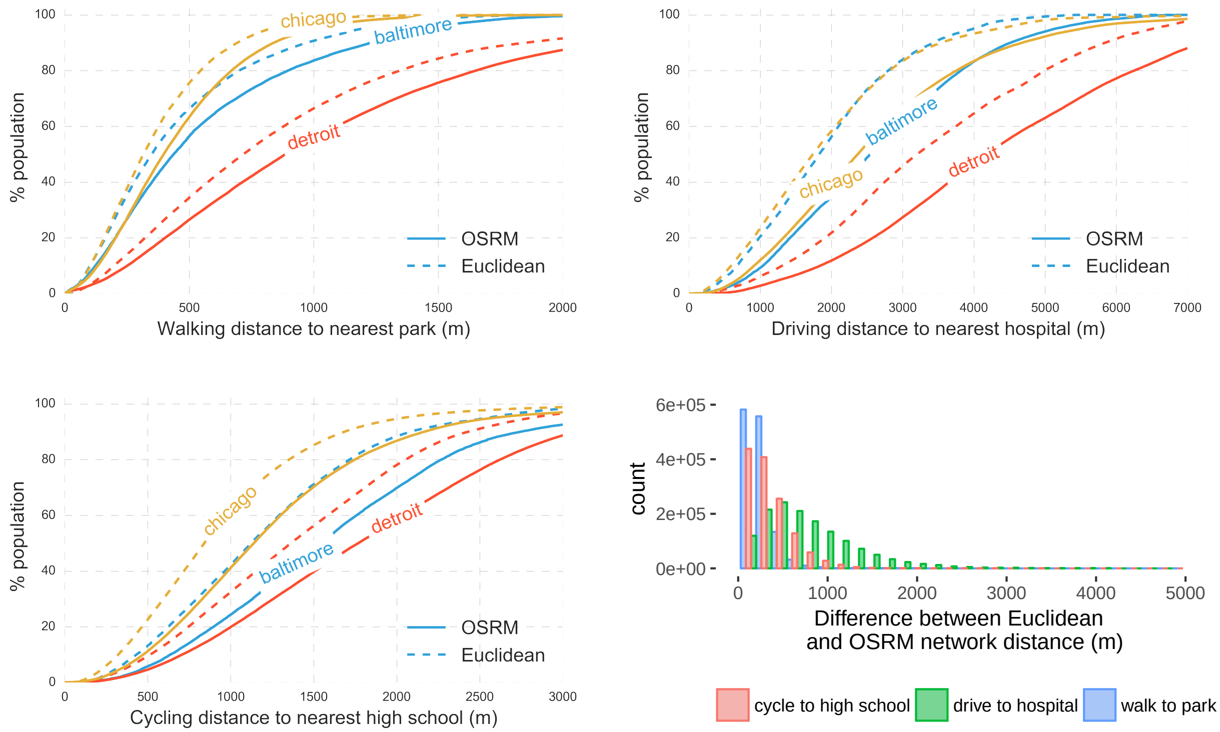


Figure C.6: These ECDFs demonstrate the error resulting from using the Euclidean distance to approximate proximity. They show distance via walking, driving, and cycling to the nearest park, hospital, and high school respectively. The dotted line shows the distribution when the distance is estimated using the Euclidean distance and the solid line is the network distance using the OSRM routing algorithm. The histogram shows the difference between Euclidean and OSRM for all cities in each of the travel modes. The Euclidean distance consistently overestimates the quality of access to services.

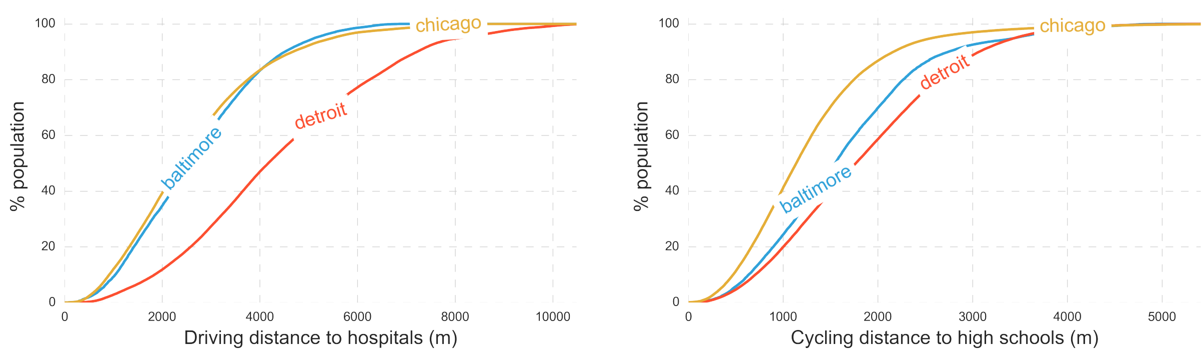


Figure C.7: ECDFs showing distance via driving and cycling to the nearest hospital and high school respectively.

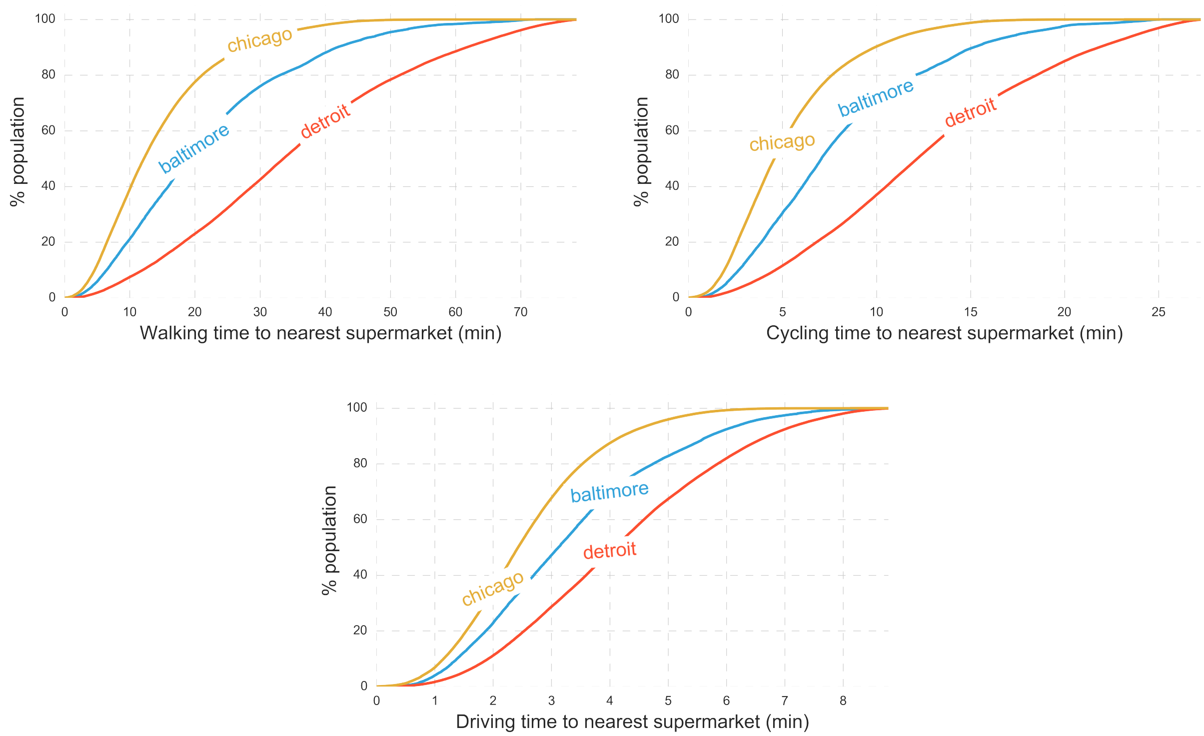


Figure C.8: ECDFs showing time to nearest supermarket via walking, cycling, and driving.

C.8 Supplemental figures

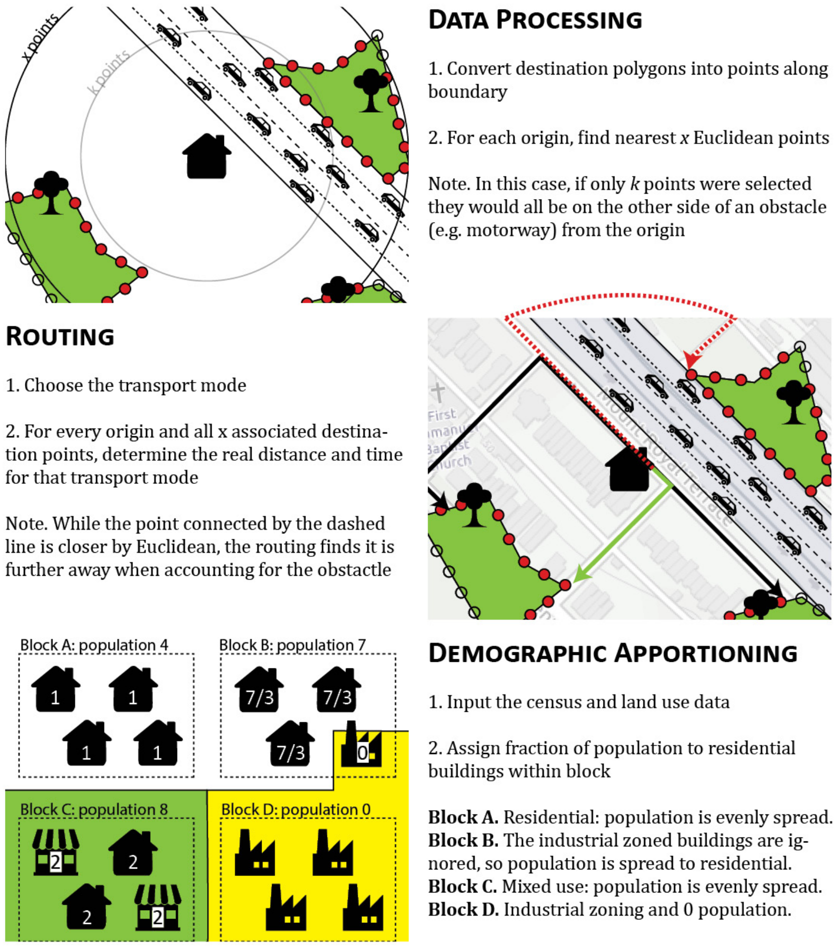


Figure C.9: Procedure for approximating the proximity of a service type for a city's residents.

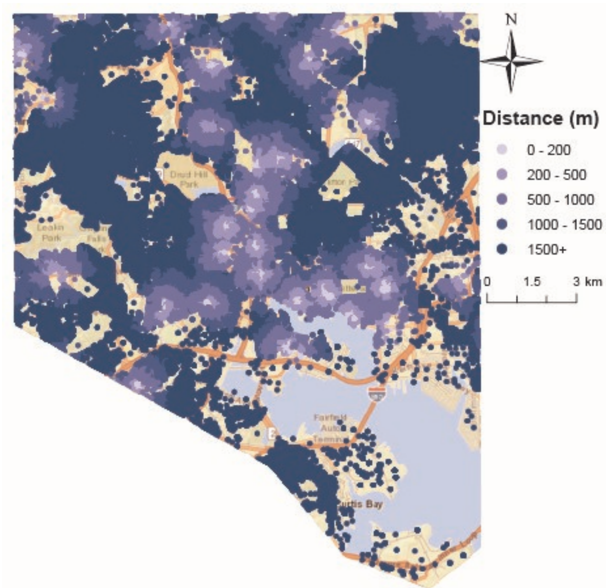


Figure C.10: Walking distance from building to nearest supermarket in Baltimore, MD. The dark areas of this map are food deserts because of their low proximity to supermarkets. See `https://reckoningrisk.com/research/2017/urban-access/` for interactive map.

Appendix D

Supplements to Building community resilience through equitable access to essential services

D.1 Technical guide

Tools to conduct this analysis are becoming increasingly user-friendly (e.g. [238]), but currently coding ability is required. This technical appendix outlines the approach, tools, and steps:

1. Regional data

   One of the first steps is to acquire the geographic data for the region of interest. You need to decide the spatial resolution at which to conduct the analysis. Here, we use the census block level (generally equivalent in size to a city block) however this could also be conducted at the parcel or block group level. The tradeoff is the computational burden and the accuracy. Also, using larger spatial areas risks overlooking vulnerable populations [201]. Shapefiles for the USA can be downloaded from [209]. Demographic data that can be joined to the shapefiles is available from [209] or [327].

2. Service/facility/amenity locations

   The geo-location of all facilities is needed for the analysis. These are often available from open-data portals hosted by the city or OpenStreetMap (OSM). For example, the services used in Figure 5.1 were retrieved from the following locations:

   - *Schools, libraries, and hospitals*: `https://data.baltimorecity.gov/dataset`

- *Supermarkets*: `https://overpass-turbo.eu/` using the "shop=supermarket" key. This data can be downloaded as a .kml file.

3. Routing/Network distance

   We now require the network distance from all origins to destinations. The approach we use is described in [201]. We use OpenStreetMap (OSM) data and the Open Source Routing Machine (OSRM) [204] (`http://project-osrm.org/`) running via Docker [221] on a local server. However, there are other routing algorithm options that are improving the computational speed, such as [238]. Instructions to set-up an OSRM server are available online, for example: `https://reckoningrisk.com/coding/2017/OSRM-server/`. A more user-friendly approach is to install 'Docker' (essentially a virtual environment) on your computer and pull (download) an OSRM server that has already been setup: `https://hub.docker.com/r/osrm/osrm-backend/`.

4. Nearest service through time

   Access is currently specified as being the distance to the *nearest* service (although this can and should be enhanced). Therefore, each city block is assigned the distance to each of the nearest types of service. To understand how access changes through time, the facilities need to be assigned an indicator for whether it is operating. For any point in time then, the distance from each block to the service is the distance to the nearest operating service.

5. Graphical and statistical output

   The paper uses Python and ArcGIS Pro to construct the figures and maps. The code for the plotting in Python is provided in the Github repository. The ECDF's are explained in [201].

Appendix E

Supplements to Risk: A holistic framework for resilience

Table E.1: Definitions of resilience from across the literature. These definitions are classified in Table 7.2

Author (year)	**Definition**
Holling (1973), [157]	A measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables
Pimm (1984), [262]	How fast a variable that has been displaced from equilibrium returns to it. Population resilience is the rate at which populations recover their former densities
Mileti (1999), [222]	Disaster resilient community can “withstand an extreme natural event with a tolerable level of losses” and “take mitigation actions consistent with achieving that level of protection”
Adger (2000), [2]	Social resilience is the ability of groups or communities to cope with external stresses and disturbances as a result of social, political, and environmental change
Bruneau et al. (2003), [54]	The ability of social units to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future earthquakes. Specifically, a resilient system should demonstrate three characteristics: reduced failure probabilities, reduced consequences from failure, and reduced time to recovery
Turner et al. (2003), [323]	The system’s capacities to cope or respond
Walker et al. (2004), [336]	The capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks
Manyena (2006), [211]	Intrinsic capacity of a system, community, or society predisposed to a shock or stress to adapt and survive by changing its non-essential attributes and rebuilding itself
Berkes (2007), [43]	Capacity of a system to absorb recurrent disturbances, such as natural disasters, so as to retain essential structures, processes and feedbacks
Cutter et al. (2008), [87]	Resilience is the ability of a social system to respond and recover from disasters and includes the conditions that allow the system to absorb impacts, cope, and adapt
Lamond & Proverbs (2009), [185]	Urban resilience encompasses the idea that towns and cities should be able to recover quickly from major and minor disasters
Cimellaro et al. (2010), [71]	Resilience is defined as a function indicating the capability to sustain a level of functionality or performance for a given building, bridge, lifeline networks, or community, over a period defined as the control time that is usually decided by owners, or society
Turner et al. (2010), [322]	Resilience is the amount of disturbance a system can absorb and still remain within the same stateor domain of attraction
Béné et al. (2012), [40]	Resilience emerges as the result not of one but all of these three capacities: absorptive, adaptive and transformative capacities, each of them leading to different outcomes: persistence, incremental adjustment, or transformational responses.
National Research Council (2012), [231]	The ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions
Barrett & Constas (2014), [33]	Development resilience is the capacity over time of a person, house- hold or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is resilient.
Saunders & Becker (2015), [282]	Resilience is the ability to adapt to the demands, challenges, and changes encountered during and after a disaster
Tendall et al. (2015), [318]	Capacity over time of a food system and its units at multiple levels, to provide sufficient, appropriate and accessible food to all, in the face of various and even unforeseen disturbances.
Meerow et al. (2016), [218]	Urban resilience refers to the ability of an urban system - ... - to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity
Platt et al. (2016), [264]	Resilience is the speed of recovery
Nan & Sansavini (2017), [229]	The ability of a system to resist the effects of a disruptive force and to reduce performance deviation
Linkov et al. (2018), [198]	The ability to adapt and recover

Bibliography

[1] J. Abbott. "Understanding and managing the unknown: The nature of uncertainty in planning". In: *Journal of Planning Education and Research* 24.3 (2005), pp. 237–251.

[2] W. N. Adger. "Social and ecological resilience: are they related?" In: *Progress in human geography* 24.3 (Sept. 2000), pp. 347–364. ISSN: 0309-1325. DOI: 10 . 1191 / 030913200701540465.

[3] J. C. J. H. Aerts, W. J. Botzen, K. C. Clarke, S. L. Cutter, J. W. Hall, B. Merz, E. Michel-Kerjan, J. Mysiak, S. Surminski, and H. Kunreuther. "Integrating human behaviour dynamics into flood disaster risk assessment". In: *Nature climate change* 8.3 (Mar. 2018), pp. 193–199. ISSN: 1758-678X, 1758-6798. DOI: 10.1038/s41558-018-0085-1.

[4] J. C. J. H. Aerts, W. J. W. Botzen, K. Emanuel, N. Lin, H. de Moel, and E. O. Michel-Kerjan. "Climate adaptation. Evaluating flood resilience strategies for coastal megacities". en. In: *Science* 344.6183 (May 2014), pp. 473–475. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.1248222.

[5] J. F. Ahearne. "Intergenerational issues regarding nuclear power, nuclear waste, and nuclear weapons". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 763–770. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206070.

[6] D. P. Aldrich and Y. Sawada. "The physical and social determinants of mortality in the 3.11 tsunami". In: *Social science & medicine* 124 (2015), pp. 66–75. ISSN: 0037-7856.

[7] R. H. Alhawiti and D. Mitsova. "USING LANDSAT-8 DATA TO EXPLORE THE CORRELATION BETWEEN URBAN HEAT ISLAND AND URBAN LAND USES". In: *International Journal of Research in Engineering and Technology* 5.3 (2016).

[8] T. Alipour, M. R. Sarajian, and A. Esmaeily. "Land surface temperature estimation from thermal band of landsat sensor, case study: Alashtar city". In: *The International Achieves of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 38.4 (2003).

[9] S. E. Anderson, R. R. Bart, M. C. Kennedy, A. J. MacDonald, M. A. Moritz, A. J. Plantinga, C. L. Tague, and M. Wibbenmeyer. "The dangers of disaster-driven responses to climate change". In: *Nature climate change* 8.8 (Aug. 2018), pp. 651–653. ISSN: 1758-678X, 1758-6798. DOI: 10.1038/s41558-018-0208-8.

[10] P. Apparicio, M.-S. Cloutier, and R. Shearmur. “The case of Montreal’s missing food deserts: evaluation of accessibility to food supermarkets”. In: *International Journal of Health Geographics* 6.1 (2007), p. 4.

[11] T. Astell-Burt, X. Feng, S. Mavoa, H. M. Badland, and B. Giles-Corti. “Do low-income neighbourhoods have the least green space? A cross-sectional study of Australia’s most populous cities”. In: *BMC Public Health* 14 (2014), p. 292.

[12] S. B. Austin, S. J. Melly, B. N. Sanchez, A. Patel, S. Buka, and S. L. Gortmaker. “Clustering of fast-food restaurants around schools: a novel application of spatial statistics to the study of food environments”. In: *American Journal of Public Health* 95.9 (2005), pp. 1575–1581.

[13] T. Aven. “On the meaning of a black swan in a risk context”. In: *Safety science* (2013). ISSN: 0925-7535.

[14] T. Aven. “A risk concept applicable for both probabilistic and non-probabilistic perspectives”. In: *Safety science* 49.8 (Oct. 2011), pp. 1080–1086. ISSN: 0925-7535. DOI: 10.1016/j.ssci.2011.04.017.

[15] T. Aven. “Foundational issues in risk assessment and risk management”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 32.10 (Oct. 2012), pp. 1647–1656. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.2012.01798.x.

[16] T. Aven. “Implications of black swans to the foundations and practice of risk assessment and management”. In: *Reliability Engineering & System Safety* 134 (Feb. 2015), pp. 83–91. ISSN: 0951-8320. DOI: 10.1016/j.ress.2014.10.004.

[17] T. Aven. *Misconceptions of Risk*. Chichester, UK: John Wiley & Sons, Ltd, Jan. 2010. ISBN: 9780470686539, 9780470683880. DOI: 10.1002/9780470686539.

[18] T. Aven. *Risk Analysis*. en. John Wiley & Sons, Sept. 2015. ISBN: 9781119057796.

[19] T. Aven. *Risk, Surprises and Black Swans: Fundamental Ideas and Concepts in Risk Assessment and Risk Management*. en. Routledge, Aug. 2014. ISBN: 9781317626329.

[20] T. Aven. “The Call for a Shift from Risk to Resilience: What Does it Mean?” en. In: *Risk analysis: an official publication of the Society for Risk Analysis* (Dec. 2018). ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.13247.

[21] T. Aven. “What Defines Us as Professionals in the Field of Risk Analysis?” en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 37.5 (May 2017), pp. 854–860. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12680.

[22] T. Aven and S. Guikema. “On the Concept and Definition of Terrorism Risk”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 35.12 (Dec. 2015), pp. 2162–2171. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12518.

[23] T. Aven and O. Renn. “On risk defined as an event where the outcome is uncertain”. In: *Journal of risk research* 12.1 (2009), pp. 1–11. ISSN: 1366-9877.

[24] T. Aven and E. Zio. “Foundational issues in risk assessment and risk management”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 34.7 (July 2014), pp. 1164–1172. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12132.

[25] B. M. Ayyub. “Systems resilience for multihazard environments: definition, metrics, and valuation for decision making”. en. In: *Risk analysis* 34.2 (Feb. 2014), pp. 340–355. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12093.

[26] K. T. Azar, J. Ferreira, and L. Wiggins. “Using GIS tools to improve transit ridership on routes serving large employment centers: The Boston South End Medical Area case study”. In: *Computers, environment and urban systems* 18.3 (1994), pp. 205–231.

[27] L. A. Bakkensen, C. Fox-Lent, L. K. Read, and I. Linkov. “Validating Resilience and Vulnerability Indices in the Context of Natural Disasters”. en. In: *Risk analysis* 37.5 (Aug. 2016), pp. 982–1004. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12677.

[28] R. Balaji, S. Sathish Kumar, and A. Misra. “Understanding the effects of seawall construction using a combination of analytical modelling and remote sensing techniques: Case study of Fansa, Gujarat, India”. In: *The International Journal of Ocean and Climate Systems* 8.3 (Dec. 2017), pp. 153–160. ISSN: 1759-3131. DOI: 10.1177/1759313117712180.

[29] O. Barbosa, J. A. Tratalos, P. R. Armsworth, R. G. Davies, R. A. Fuller, P. Johnson, and K. J. Gaston. “Who benefits from access to green space? A case study from Sheffield, UK”. In: *Landsc. Urban Plan.* 83.2–3 (19 11 2007), pp. 187–195.

[30] K. Barker, J. E. Ramirez-Marquez, and C. M. Rocco. “Resilience-based network component importance measures”. In: *Reliability Engineering & System Safety* 117 (Sept. 2013), pp. 89–97. ISSN: 0951-8320. DOI: 10.1016/j.ress.2013.03.012.

[31] A. Barnes and V. Nel. “Putting Spatial Resilience into Practice”. In: *Urban Forum* 28.2 (June 2017), pp. 219–232. ISSN: 1874-6330. DOI: 10.1007/s12132-017-9303-6.

[32] J. Barnett. *Smart growth in a changing world*. Chicago: Planners Press, 2007. ISBN: 9781932364361.

[33] C. B. Barrett and M. A. Constas. “Toward a theory of resilience for international development applications”. en. In: *Proceedings of the National Academy of Sciences of the United States of America* 111.40 (Oct. 2014), pp. 14625–14630. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1320880111.

[34] J. A. Barsi, K. Lee, G. Kvaran, B. L. Markham, and J. A. Pedelty. “The Spectral Response of the Landsat-8 Operational Land Imager”. In: *Remote Sensing* 6.10 (2014), pp. 10232–10251. ISSN: 2072-4292. DOI: 10.3390/rs61010232. URL: http://www.mdpi.com/2072-4292/6/10/10232.

[35] K. Bartholomew and R. Ewing. “Land Use–Transportation Scenarios and Future Vehicle Travel and Land Consumption: A Meta-Analysis”. In: *Journal of the American Planning Association. American Planning Association* 75.1 (Dec. 2008), pp. 13–27. ISSN: 0194-4363. DOI: 10.1080/01944360802508726.

[36] M. Batty. "The size, scale, and shape of cities". en. In: *Science* 319.5864 (Feb. 2008), pp. 769–771. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.1151419.

[37] M. Batty, K. W. Axhausen, F. Giannotti, A. Pozdnoukhov, A. Bazzani, M. Wachowicz, G. Ouzounis, and Y. Portugali. "Smart cities of the future". In: *The European physical journal. Special topics* 214.1 (2012), pp. 481–518. ISSN: 1951-6355.

[38] BBC News. "UK Parliament declares climate emergency". In: *BBC* (May 2019).

[39] R. B. Belzer. "Discounting across generations: necessary, not suspect". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 779–792. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206072.

[40] C. Béné, R. G. Wood, A. Newsham, and M. Davies. "Resilience: New Utopia or New Tyranny? Reflection about the Potentials and Limits of the Concept of Resilience in Relation to Vulnerability Reduction Programmes". In: *IDS Working Papers* 2012.405 (Sept. 2012), pp. 1–61. ISSN: 1353-6141. DOI: 10.1111/j.2040-0209.2012.00405.x.

[41] Y. Ben-Haim. *Info-Gap Decision Theory: Decisions Under Severe Uncertainty*. en. Elsevier, Oct. 2006. ISBN: 9780080465708.

[42] C. Berger, J. Rosentreter, M. Voltersen, C. Baumgart, C. Schmullius, and S. Hese. "Spatiotemporal analysis of the relationship between 2D/3D urban site characteristics and land surface temperature". In: *Remote sensing of environment* 193 (May 2017), pp. 225–243. ISSN: 0034-4257. DOI: 10.1016/j.rse.2017.02.020.

[43] F. Berkes. "Understanding uncertainty and reducing vulnerability: lessons from resilience thinking". In: *Natural Hazards* 41.2 (May 2007), pp. 283–295. ISSN: 0921-030X, 1573-0840. DOI: 10.1007/s11069-006-9036-7.

[44] D. Bertsimas, D. B. Brown, and C. Caramanis. "Theory and Applications of Robust Optimization". In: *SIAM Review* 53.3 (2011), pp. 464–501. DOI: 10.1137/080734510. eprint: http://dx.doi.org/10.1137/080734510.

[45] S. S. Bhatti and N. K. Tripathi. "Built-up area extraction using Landsat 8 OLI imagery". In: *GIScience and Remote Sensing* 51.4 (July 2014), pp. 445–467. ISSN: 1548-1603. DOI: 10.1080/15481603.2014.939539.

[46] S. Biba, K. M. Curtin, and G. Manca. "A new method for determining the population with walking access to transit". In: *Int. J. Geogr. Inf. Sci.* 24.3 (2010), pp. 347–364.

[47] R. M. Bierbaum and P. H. Raven. "A two-pronged climate strategy". en. In: *Science* 316.5821 (Apr. 2007), p. 17. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.1143220.

[48] J. Birkmann, O. D. Cardona, M. L. Carreño, A. H. Barbat, M. Pelling, S. Schneiderbauer, S. Kienberger, M. Keiler, D. Alexander, P. Zeil, and T. Welle. "Framing vulnerability, risk and societal responses: the MOVE framework". In: *Natural Hazards* 67.2 (June 2013), pp. 193–211. ISSN: 0921-030X, 1573-0840. DOI: 10.1007/s11069-013-0558-5.

[49] C. G. Boone, G. L. Buckley, J. M. Grove, and C. Sister. “Parks and people: An environmental justice inquiry in Baltimore, Maryland”. In: *Annals of the Association of American Geographers* 99.4 (2009), pp. 767–787.

[50] G. Bramley, N. Dempsey, S. Power, C. Brown, and D. Watkins. “Social sustainability and urban form: evidence from five British cities”. In: *Environment and Planning A* 41.9 (2009), pp. 2125–2142.

[51] L. Breiman. “Random forests”. In: *Machine learning* 45.1 (2001), pp. 5–32. ISSN: 0885-6125.

[52] L. Breiman, J. Friedman, R. Olshen, and C. Stone. “Classification and regression trees. Wadsworth Int”. In: *Group* 37.15 (1984), pp. 237–251.

[53] D. G. Brown, S. Page, R. Riolo, M. Zellner, and W. Rand. “Path dependence and the validation of agent-based spatial models of land use”. In: *International journal of geographical information science: IJGIS* 19.2 (Feb. 2005), pp. 153–174. ISSN: 1365-8816. DOI: 10.1080/13658810410001713399.

[54] M. Bruneau, S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O’Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. Von Winterfeldt. “A framework to quantitatively assess and enhance the seismic resilience of communities”. In: *Earthquake spectra* 19.4 (2003), pp. 733–752.

[55] G. Brunetta and O. Caldarice. “Putting Resilience into Practice. The Spatial Planning Response to Urban Risks”. In: *Urban Resilience for Risk and Adaptation Governance: Theory and Practice*. Ed. by G. e. a. Brunetta. Cham: Springer International Publishing, 2019, pp. 27–41. ISBN: 9783319769448. DOI: 10.1007/978-3-319-76944-8_3.

[56] R. J. Burby. “Hurricane Katrina and the Paradoxes of Government Disaster Policy: Bringing About Wise Governmental Decisions for Hazardous Areas”. In: *The Annals of the American Academy of Political and Social Science* 604.1 (Mar. 2006), pp. 171–191. ISSN: 0002-7162. DOI: 10.1177/0002716205284676.

[57] R. J. Burby. “Natural hazards and land use: An introduction”. In: *Cooperating with Nature: confronting natural hazards with land use planning for sustainable communities* (1998), pp. 1–26.

[58] R. J. Burby, R. E. Deyle, D. R. Godschalk, and R. B. Olshansky. “Creating Hazard Resilient Communities through Land-Use Planning”. In: *Natural Hazards Review* 1.2 (May 2000), pp. 99–106. ISSN: 1527-6988. DOI: 10.1061/(ASCE)1527-6988(2000)1:2(99).

[59] M. Burke and A. L. Brown. “Distances people walk for transport”. In: *Road Transp. Res. J.* 16.3 (2007), pp. 16–29.

[60] O. Caldarice, G. Brunetta, and N. Tollin. “The Challenge of Urban Resilience: Operationalization”. In: *Urban Resilience for Risk and Adaptation Governance: Theory and Practice*. Ed. by G. e. a. Brunetta. Cham: Springer International Publishing, 2019, pp. 1–6. ISBN: 9783319769448. DOI: 10.1007/978-3-319-76944-8_1.

[61] H. Campbell. “Is the Issue of Climate Change too Big for Spatial Planning?” In: *Planning Theory & Practice* 7.2 (June 2006), pp. 201–230. ISSN: 1464-9357. DOI: 10.1080/14649350600681875.

[62] D. Caparros-Midwood, S. Barr, and R. Dawson. “Spatial Optimization of Future Urban Development with Regards to Climate Risk and Sustainability Objectives”. In: *Risk analysis: an official publication of the Society for Risk Analysis* (Apr. 2017). ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12777.

[63] Center for Chemical Process Safety. “Appendix A: Understanding and Using F-N Diagrams”. In: *Guidelines for Developing Quantitative Safety Risk Criteria*. Hoboken, NJ, USA: John Wiley & Sons, Inc., Sept. 2009, pp. 109–117. ISBN: 9780470552940. DOI: 10.1002/9780470552940.app1.

[64] A. Chakraborty and A. McMillan. “Scenario Planning for Urban Planners: Toward a Practitioner’s Guide”. In: *Journal of the American Planning Association. American Planning Association* 81.1 (Jan. 2015), pp. 18–29. ISSN: 0194-4363. DOI: 10.1080/01944363.2015.1038576.

[65] S. E. Chang and M. Shinozuka. “Measuring improvements in the disaster resilience of communities”. In: *Earthquake spectra* 20.3 (2004), pp. 739–755.

[66] L. Chen. “Agent-based modeling in urban and architectural research: A brief literature review”. In: *Frontiers of Architectural Research* 1.2 (June 2012), pp. 166–177. ISSN: 2095-2635. DOI: 10.1016/j.foar.2012.03.003.

[67] T. J. Chermack. “Improving decision-making with scenario planning”. In: *Futures* 36.3 (Apr. 2004), pp. 295–309. ISSN: 0016-3287. DOI: 10.1016/S0016-3287(03)00156-3.

[68] J. Chiang. *Tower Insurance hikes premiums in quake-prone areas*. https://www.radionz.co.nz/news/national/354009/tower-insurance-hikes-premiums-in-quake-prone-areas. Accessed: 2019-5-8. Apr. 2018.

[69] B. Chun and S. Guhathakurta. “Daytime and nighttime urban heat islands statistical models for Atlanta”. In: *Environment and Planning B: Urban Analytics and City Science* 44.2 (Mar. 2017), pp. 308–327. ISSN: 2399-8083. DOI: 10.1177/0265813515624685.

[70] B. Chun and J.-M. Guldmann. “Impact of greening on the urban heat island: Seasonal variations and mitigation strategies”. In: *Computers, environment and urban systems* 71 (Sept. 2018), pp. 165–176. ISSN: 0198-9715. DOI: 10.1016/j.compenvurbsys.2018.05.006.

[71] G. P. Cimellaro, A. M. Reinhorn, and M. Bruneau. “Framework for analytical quantification of disaster resilience”. In: *Engineering Structures* 32.11 (Nov. 2010), pp. 3639–3649. ISSN: 0141-0296. DOI: 10.1016/j.engstruct.2010.08.008.

[72] S. S. Clark, T. P. Seager, and M. V. Chester. “A capabilities approach to the prioritization of critical infrastructure”. en. In: *Environment Systems and Decisions* 38.3 (Sept. 2018), pp. 339–352. ISSN: 2194-5403, 2194-5411. DOI: 10.1007/s10669-018-9691-8.

[73] K. C. Clarke, S. Hoppen, and L. Gaydos. “A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area”. In: *Environment and planning. B, Planning & design* 24.2 (1997), pp. 247–261. ISSN: 0265-8135.

[74] D. A. Cohen, T. L. McKenzie, A. Sehgal, S. Williamson, D. Golinelli, and N. Lurie. “Contribution of public parks to physical activity”. In: *Am. J. Public Health* 97.3 (2007), pp. 509–514.

[75] D. Collingridge. *The social control of technology.* New York, NY, USA: St Martin’s Press, 1982.

[76] M. Constas, T. Frankenberger, and J. Hoddinott. *Resilience measurement principles: Toward an agenda for measurement design.* Tech. rep. 1. Food Security Information Network, 2014.

[77] R. Costanza, W. J. Mitsch, and J. W. Day. “A new vision for New Orleans and the Mississippi delta: applying ecological economics and ecological engineering”. In: *Frontiers in ecology and the environment* 4.9 (Nov. 2006), pp. 465–472. ISSN: 1540-9295, 1540-9309. DOI: 10.1890/1540-9295(2006)4[465:ANVFNO]2.0.CO;2.

[78] J. W. Coulston, G. G. Moisen, B. T. Wilson, M. V. Finco, W. B. Cohen, C. K. Brewer, et al. “Modeling percent tree canopy cover: a pilot study”. In: *Photogrammetric Engineering and Remote Sensing* 78.7 (2012), pp. 715–727.

[79] L. A. T. Cox Jr. “An exposure-response threshold for lung diseases and lung cancer caused by crystalline silica”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 31.10 (Oct. 2011), pp. 1543–1560. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.2011.01610.x.

[80] L. A. Cox Jr. “Confronting deep uncertainties in risk analysis”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 32.10 (Oct. 2012), pp. 1607–1629. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.2012.01792.x.

[81] G. Currie. “Quantifying spatial gaps in public transport supply based on social needs”. In: *J. Transp. Geogr.* 18.1 (2010), pp. 31–41.

[82] C. Curt and J.-M. Tacnet. “Resilience of Critical Infrastructures: Review and Analysis of Current Approaches”. en. In: *Risk analysis* (Aug. 2018). ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.13166.

[83] S. L. Cutter. “Resilience to what? Resilience for whom?” In: *The Geographical journal* 182.2 (2016), pp. 110–113. ISSN: 0016-7398.

[84] S. L. Cutter. “The landscape of disaster resilience indicators in the USA”. In: *Natural Hazards* 80.2 (Jan. 2016), pp. 741–758. ISSN: 0921-030X, 1573-0840. DOI: 10.1007/s11069-015-1993-2.

[85] S. L. Cutter. “Vulnerability to environmental hazards”. In: *Progress in human geography* 20.4 (Dec. 1996), pp. 529–539. ISSN: 0309-1325. DOI: 10.1177/030913259602000407.

[86] S. L. Cutter, K. D. Ash, and C. T. Emrich. “The geographies of community disaster resilience”. In: *Global environmental change: human and policy dimensions* 29 (Nov. 2014), pp. 65–77. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2014.08.005.

[87] S. L. Cutter, L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, and J. Webb. “A place-based model for understanding community resilience to natural disasters”. In: *Global environmental change: human and policy dimensions* 18.4 (Oct. 2008), pp. 598–606. ISSN: 0959-3780.

[88] S. L. Cutter, B. J. Boruff, and W. L. Shirley. “Social vulnerability to environmental hazards”. In: *Social science quarterly* 84.2 (2003), pp. 242–261. ISSN: 0038-4941.

[89] S. L. Cutter, C. G. Burton, and C. T. Emrich. “Disaster resilience indicators for benchmarking baseline conditions”. In: *Journal of Homeland Security and Emergency Management* 7.1 (2010).

[90] P. d’Aquino, P. August, A. Balmann, T. Berger, F. Bousquet, E. Brondízio, D. G. Brown, H. Couclelis, P. Deadman, M. F. Goodchild, et al. “Agent-based models of land-use and land-cover change”. In: *Proc. of an International Workshop*. zef.de, 2002, pp. 4–7.

[91] K. Deb and H. Gupta. “Introducing robustness in multi-objective optimization”. en. In: *Evolutionary computation* 14.4 (2006), pp. 463–494. ISSN: 1063-6560. DOI: 10.1162/evco.2006.14.4.463.

[92] Deltares. *Delft3D 3D-FLOW user manual*. Tech. rep. The Netherlands: Delft, 2006.

[93] Deltares. *DelftDashboard*. 2016.

[94] N. Dempsey, G. Bramley, S. Power, and C. Brown. “The social dimension of sustainable development: Defining urban social sustainability”. In: *Sustainable Development* 19.5 (Sept. 2011), pp. 289–300. ISSN: 0968-0802. DOI: 10.1002/sd.417.

[95] F. Des Rosiers, M. Thériault, G. Biba, and M.-H. Vandersmissen. “Greenhouse gas emissions and urban form: Linking households’ socio-economic status with housing and transportation choices”. In: *Environment and Planning B: Planning and Design* (2016), p. 0265813516656862.

[96] R. E. Deyle, S. P. French, R. B. Olshansky, and R. G. Paterson. “Hazard assessment: the factual basis for planning and mitigation”. In: *Cooperating with Nature: Confronting Natural Hazards with Land-Use Planning for Sustainable Communities*. Ed. by R. J. Burby. Joseph Henry Press, 1998, pp. 119–166.

[97] G. Di Baldassarre, A. Viglione, G. Carr, L. Kuil, K. Yan, L. Brandimarte, and G. Blöschl. “Debates—Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes”. In: *Water resources research* 51.6 (2015), pp. 4770–4781. ISSN: 0043-1397.

[98] E. W. Dijkstra. “A Note on Two Probles in Connexion with Graphs”. In: *Numer. Math.* 1.1 (1959), pp. 269–271.

[99] N. Doorn. “The blind spot in risk ethics: managing natural hazards”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 35.3 (Mar. 2015), pp. 354–360. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12293.

[100] N. Doorn, P. Gardoni, and C. Murphy. “A multidisciplinary definition and evaluation of resilience: the role of social justice in defining resilience”. In: *Sustainable and Resilient Infrastructure* (Apr. 2018), pp. 1–12. ISSN: 2378-9689. DOI: 10.1080/23789689.2018.1428162.

[101] J. Dozier and J. Frew. “Rapid calculation of terrain parameters for radiation modeling from digital elevation data”. In: *IEEE transactions on geoscience and remote sensing: a publication of the IEEE Geoscience and Remote Sensing Society* 28.5 (Sept. 1990), pp. 963–969. ISSN: 0196-2892. DOI: 10.1109/36.58986.

[102] D. Dubois. “Representation, propagation, and decision issues in risk analysis under incomplete probabilistic information”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 30.3 (Mar. 2010), pp. 361–368. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.2010.01359.x.

[103] G. Duranton and M. A. Turner. “The Fundamental Law of Road Congestion: Evidence from US Cities”. In: *The American economic review* 101.6 (Oct. 2011), pp. 2616–2652. ISSN: 0002-8282. DOI: 10.1257/aer.101.6.2616.

[104] L. Echevarria Icaza, A. van den Dobbelsteen, and F. D. van der Hoeven. “Using satellite imagery analysis to classify and redesign provincial parks for a better cooling effect on cities: The case study of South Holland”. In: *Research in Urbanism Series* 4.1 (2016).

[105] Engineering, and Medicine National Academies of Sciences, Division on Earth and Life Studies, Board on Atmospheric Sciences and Climate, Policy and Global Affairs, Science and Technology for Sustainability Program, and Committee on Transition Toward Sustainability After 15 Years: Where Do We Stand in Advancing the Scientific Foundation. *Transitioning Toward Sustainability: Advancing the Scientific Foundation: Proceedings of a Workshop (Transportation and Sustainability)*. en. Ed. by A. Macalady, R. Anderson, Y. Romitti, and D. Brose. National Academies Press, Aug. 2016. ISBN: 9780309443753.

[106] J. M. Epstein. *Generative Social Science: Studies in Agent-Based Computational Modeling*. en. Princeton University Press, 2006. ISBN: 9780691125473.

[107] E. Erdos. *Hurricane Sandy and the Inequalities of Resilience in New York*. https://prospect.org/article/hurricane-sandy-and-inequalities-resilience-new-york. Accessed: 2019-5-21. Oct. 2018.

[108] N. J. Ericksen. *Creating flood disasters?: New Zealand’s need for a new approach to urban flood hazard*. National Water and Soil Conservation Authority, 1986.

[109] M. Esteban, D. T. Nguyen, H. Takagi, P. Valenzuela, and T. T. Tam. “Storm surge and Tsunami awareness and preparedness in Central Vietnam”. In: *Coastal Disasters and Climate Change in Vietnam: Engineering and Planning Perspectives*. Ed. by D. T. Nguyen, H. Takagi, and M. Esteban. Oxford, UK: Butterworth-Heinemann (Elsevier), 2014.

[110] M. Esteban, V. P. Valenzuela, R. Matsumaru, T. Mikami, T. Shibayama, H. Takagi, N. D. Thao, and M. De Leon. “Storm Surge Awareness in the Philippines Prior to Typhoon Haiyan: A Comparative Analysis with Tsunami Awareness in Recent Times”. In: *Coastal Engineering Journal* 58.1 (2016). ISSN: 0578-5634. DOI: 10.1142/S057856341640009X.

[111] R. Ewing and S. Hamidi. “Compactness versus Sprawl: A Review of Recent Evidence from the United States”. In: *Journal of Planning Literature* 30.4 (Nov. 2015), pp. 413–432. ISSN: 0885-4122. DOI: 10.1177/0885412215595439.

[112] S. Fang, G. Z. Gertner, Z. Sun, and A. A. Anderson. “The impact of interactions in spatial simulation of the dynamics of urban sprawl”. In: *Landscape and urban planning* 73.4 (Dec. 2005), pp. 294–306. ISSN: 0169-2046. DOI: 10.1016/j.landurbplan.2004.08.006.

[113] T. Fawcett. “An introduction to ROC analysis”. In: *Pattern recognition letters* 27.8 (June 2006), pp. 861–874. ISSN: 0167-8655. DOI: 10.1016/j.patrec.2005.10.010.

[114] I. Fazey, J. G. P. Gamarra, J. Fischer, M. S. Reed, L. C. Stringer, and M. Christie. “Adaptation strategies for reducing vulnerability to future environmental change”. In: *Frontiers in ecology and the environment* 8.8 (Oct. 2010), pp. 414–422. ISSN: 1540-9295, 1540-9309. DOI: 10.1890/080215.

[115] C. B. Field, V. R. Barros, M. D. Mastrandrea, et al. *Summary for policymakers. Climate change 2014: impacts, adaptation, and vulnerability. Part a: global and sectoral aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change, 1–32.* 2014.

[116] B. Fischhoff. “Risk Perception and Communication Unplugged: Twenty Years of Process”. In: *Risk analysis: an official publication of the Society for Risk Analysis* 15.2 (Apr. 1995), pp. 137–145. ISSN: 0272-4332. DOI: 10.1111/j.1539-6924.1995.tb00308.x.

[117] R. Flage, T. Aven, E. Zio, and P. Baraldi. “Concerns, challenges, and directions of development for the issue of representing uncertainty in risk assessment”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 34.7 (July 2014), pp. 1196–1207. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12247.

[118] B. E. Flanagan, E. W. Gregory, E. J. Hallisey, J. L. Heitgerd, and B. Lewis. “A social vulnerability index for disaster management”. In: *Journal of Homeland Security and Emergency Management* 8.1 (2011).

[119] J. W. Forrester. “Urban dynamics”. In: *IMR; Industrial Management Review (pre-1986)* 11.3 (1970), p. 67.

[120] S. French, N. Argyris, S. M. Haywood, M. C. Hort, and J. Q. Smith. “Communicating Geographical Risks in Crisis Management: The Need for Research”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 39.1 (Jan. 2019), pp. 9–16. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12904.

[121] J. H. Friedman. "Multivariate Adaptive Regression Splines". en. In: *Annals of statistics* 19.1 (Mar. 1991), pp. 1–67. ISSN: 0090-5364, 2168-8966. DOI: 10.1214/aos/1176347963.

[122] S. Fuchs, K. Karagiorgos, K. Kitikidou, F. Maris, S. Paparrizos, and T. Thaler. "Flood risk perception and adaptation capacity: a contribution to the socio-hydrology debate". en. In: *Hydrology and Earth System Sciences; Katlenburg-Lindau* 21.6 (2017), pp. 3183–3198. DOI: 10.5194/hess-21-3183-2017.

[123] E. J. Gago, J. Roldan, R. Pacheco-Torres, and J. Ordóñez. "The city and urban heat islands: A review of strategies to mitigate adverse effects". In: *Renewable and Sustainable Energy Reviews* 25 (Sept. 2013), pp. 749–758. ISSN: 1364-0321. DOI: 10.1016/j.rser.2013.05.057.

[124] P. Gardoni and C. Murphy. "Society-based design: promoting societal well-being by designing sustainable and resilient infrastructure". In: *Sustainable and Resilient Infrastructure* (May 2018), pp. 1–16. ISSN: 2378-9689. DOI: 10.1080/23789689.2018.1448667.

[125] E. L. Geist and T. Parsons. "Assessing historical rate changes in global tsunami occurrence". In: *Geophysical Journal International* 187.1 (Oct. 2011), pp. 497–509. ISSN: 0956-540X. DOI: 10.1111/j.1365-246X.2011.05160.x.

[126] E. L. Geist and T. Parsons. "Probabilistic Analysis of Tsunami Hazards*". en. In: *Natural Hazards* 37.3 (Mar. 2006), pp. 277–314. ISSN: 0921-030X, 1573-0840. DOI: 10.1007/s11069-005-4646-z.

[127] Geospatial Information Authority of Japan. *5-m mesh survey data.*

[128] A. Géron. *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems.* en. "O'Reilly Media, Inc.", Mar. 2017. ISBN: 9781491962268.

[129] M. Glantz and D. Jamieson. "Societal response to Hurricane Mitch and intra- versus intergenerational equity issues: whose norms should apply?" en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 869–882. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206080.

[130] P. Gober, A. Brazel, R. Quay, S. Myint, S. Grossman-Clarke, A. Miller, and S. Rossi. "Using Watered Landscapes to Manipulate Urban Heat Island Effects: How Much Water Will It Take to Cool Phoenix?" In: *Journal of the American Planning Association. American Planning Association* 76.1 (Dec. 2009), pp. 109–121. ISSN: 0194-4363. DOI: 10.1080/01944360903433113.

[131] K. Goda, P. M. Mai, T. Yasuda, and N. Mori. "Sensitivity of tsunami wave profiles and inundation simulations to earthquake slip and fault geometry for the 2011 Tohoku earthquake". In: *Earth, Planets and Space* 66.1 (Sept. 2014), p. 105. ISSN: 1343-8832, 1880-5981. DOI: 10.1186/1880-5981-66-105.

[132] "Ethical Guidelines for Hazard Mitigation". In: *Natural hazard mitigation: Recasting disaster policy and planning*. Ed. by D. Godschalk, T. Beatley, P. Berke, D. Brower, and E. J. Kaiser. Washington, DC: Island Press, 1999, pp. 479–525.

[133] D. R. Godschalk. "Urban Hazard Mitigation: Creating Resilient Cities". In: *Natural Hazards Review* 4.3 (Aug. 2003), pp. 136–143. ISSN: 1527-6988. DOI: `10.1061/(ASCE)1527-6988(2003)4:3(136)`.

[134] E. J. Good. "An in situ-based analysis of the relationship between land surface "skin" and screen-level air temperatures: Land Skin-Air Temperature Relationship". In: *Journal of Geophysical Research, D: Atmospheres* 121.15 (Aug. 2016), pp. 8801–8819. ISSN: 2169-897X. DOI: `10.1002/2016JD025318`.

[135] M. F. Goodchild. "Citizens as sensors: the world of volunteered geography". en. In: *GeoJournal* 69.4 (Jan. 2007), pp. 211–221.

[136] J. Goodell. *Houston: A Global Warning*. `https://www.rollingstone.com/politics/politics-features/houston-a-global-warning-124675/`. Accessed: 2018-8-23. Aug. 2017.

[137] K. Goto, K. Fujima, D. Sugawara, S. Fujino, K. Imai, R. Tsudaka, T. Abe, and T. Haraguchi. "Field measurements and numerical modeling for the run-up heights and inundation distances of the 2011 Tohoku-oki tsunami at Sendai Plain, Japan". In: *Earth, Planets and Space* 64.12 (Jan. 2013), p. 20. ISSN: 1343-8832, 1880-5981. DOI: `10.5047/eps.2012.02.007`.

[138] S. T. Grilli, J. C. Harris, T. S. Tajalli Bakhsh, T. L. Masterlark, C. Kyriakopoulos, J. T. Kirby, and F. Shi. "Numerical Simulation of the 2011 Tohoku Tsunami Based on a New Transient FEM Co-seismic Source: Comparison to Far- and Near-Field Observations". In: *Pure and Applied Geophysics* 170.6 (June 2013), pp. 1333–1359. ISSN: 0033-4553, 1420-9136. DOI: `10.1007/s00024-012-0528-y`.

[139] R. Guidotti, H. Chmielewski, V. Unnikrishnan, P. Gardoni, T. McAllister, and J. van de Lindt. "Modeling the resilience of critical infrastructure: The role of network dependencies". In: *Sustainable and resilient infrastructure* 1.3-4 (2016), pp. 153–168.

[140] R. Guidotti, P. Gardoni, and N. Rosenheim. "Integration of physical infrastructure and social systems in communities' reliability and resilience analysis". In: *Reliability Engineering & System Safety* (2019). ISSN: 0951-8320.

[141] L. H. Gunderson. *Panarchy: Understanding Transformations in Human and Natural Systems*. en. Island Press, Dec. 2001. ISBN: 9781597269391.

[142] Y. Y. Haimes. "On the complex definition of risk: a systems-based approach". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 29.12 (Dec. 2009), pp. 1647–1654. ISSN: 0272-4332, 1539-6924. DOI: `10.1111/j.1539-6924.2009.01310.x`.

[143] Y. Y. Haimes. "On the definition of resilience in systems". In: *Risk Analysis* 29.4 (2009), pp. 498–501.

[144] Y. Y. Haimes. "Risk Modeling of Interdependent Complex Systems of Systems: Theory and Practice". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* (Apr. 2017). ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12804.

[145] M. Haklay. "How Good is Volunteered Geographical Information? A Comparative Study of OpenStreetMap and Ordnance Survey Datasets". en. In: *Environment and planning B: Planning and design* 37.4 (Jan. 2010), pp. 682–703.

[146] J. W. Hall, R. J. Lempert, K. Keller, A. Hackbarth, C. Mijere, and D. J. McInerney. "Robust climate policies under uncertainty: a comparison of robust decision making and info-gap methods". In: *Risk analysis: an official publication of the Society for Risk Analysis* 32.10 (2012), pp. 1657–1672. ISSN: 0272-4332.

[147] S. Hallegatte. "Strategies to adapt to an uncertain climate change". In: *Glob. Environ. Change* 19.2 (2009), pp. 240–247.

[148] J. Han, Y. Hayashi, X. Cao, and H. Imura. "Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China". In: *Landscape and urban planning* (2009). ISSN: 0169-2046.

[149] C. E. Haque and I. Burton. "Adaptation Options Strategies for Hazards and Vulnerability Mitigation: An International Perspective". In: *Mitigation and Adaptation Strategies for Global Change* 10.3 (July 2005), pp. 335–353. ISSN: 1573-1596. DOI: 10.1007/s11027-005-0050-y.

[150] J. A. Hartigan and M. A. Wong. "Algorithm AS 136: A k-means clustering algorithm". In: *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 28.1 (1979), pp. 100–108.

[151] T. J. Hastie and R. J. Tibshirani. *Generalized additive models*. Vol. 43. CRC Press, 1990. ISBN: 9780412343902.

[152] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning*. Vol. 2. Springer, 2009.

[153] T. L. Hawthorne and M.-P. Kwan. "Using GIS and perceived distance to understand the unequal geographies of healthcare in lower-income urban neighbourhoods". In: *Geogr. J.* 178.1 (2012), pp. 18–30.

[154] J. Hewko, K. E. Smoyer-Tomic, and M. J. Hodgson. "Measuring Neighbourhood Spatial Accessibility to Urban Amenities: Does Aggregation Error Matter?" In: *Environment and Planning A* 34.7 (2002), pp. 1185–1206.

[155] M. Hillsdon, J. Panter, C. Foster, and A. Jones. "The relationship between access and quality of urban green space with population physical activity". en. In: *Public Health* 120.12 (Dec. 2006), pp. 1127–1132.

[156] C.-H. Ho. "Risk assessment for the Yucca Mountain high-level nuclear waste repository site: Estimation of volcanic disruption". In: *Mathematical geology* 24.4 (May 1992), pp. 347–364. ISSN: 0882-8121, 1573-8868. DOI: 10.1007/BF00891268.

[157] C. S. Holling. “Resilience and Stability of Ecological Systems”. In: *Annual review of ecology and systematics* 4.1 (Nov. 1973), pp. 1–23. ISSN: 0066-4162. DOI: 10.1146/annurev.es.04.110173.000245.

[158] C. Homer, J. Dewitz, L. Yang, S. Jin, et al. “Completion of the 2011 National Land Cover Database for the conterminous United States–representing a decade of land cover change information”. In: *& Remote Sensing* (2015).

[159] C. Horswell and E. Hegstrom. *Exodus weighs heavily in death toll: 107*. https://www.chron.com/news/houston-weather/hurricanes/article/Exodus-weighs-heavily-in-death-toll-107-1502590.php. Accessed: 2019-5-15. Sept. 2005.

[160] S. Hosseini, K. Barker, and J. E. Ramirez-Marquez. “A review of definitions and measures of system resilience”. In: *Reliability Engineering & System Safety* 145 (Jan. 2016), pp. 47–61. ISSN: 0951-8320. DOI: 10.1016/j.ress.2015.08.006.

[161] S. Hsiao, J. Lu, J. Sterling, and M. Weatherford. “Use of Geographic Information System for Analysis of Transit Pedestrian Access”. In: *Transportation Research Record: Journal of the Transportation Research Board* 1604 (Jan. 1997), pp. 50–59.

[162] Q. X. Huang, C. Y. He, Z. F. Liu, and P. J. Shi. “Modeling the impacts of drying trend scenarios on land systems in northern China using an integrated SD and CA model”. In: *SCIENCE CHINA Earth Sciences* (2014). ISSN: 1674-7313.

[163] Y. Huang and P. H. A. J. M. van Gelder. “Time-Varying Risk Measurement for Ship Collision Prevention: Collision Risk and Prevention”. In: *Risk analysis: an official publication of the Society for Risk Analysis* 37 (Mar. 2019), p. 162. ISSN: 0272-4332. DOI: 10.1111/risa.13293.

[164] T. Hung, D. Uchihama, S. Ochi, and Y. Yasuoka. “Assessment with satellite data of the urban heat island effects in Asian mega cities”. In: *International Journal of Applied Earth Observation and Geoinformation* 8.1 (Jan. 2006), pp. 34–48. ISSN: 0303-2434. DOI: 10.1016/j.jag.2005.05.003.

[165] A. C. Hurlimann and A. P. March. “The role of spatial planning in adapting to climate change”. In: *Wiley Interdisciplinary Reviews: Climate Change* 3.5 (Sept. 2012), pp. 477–488. ISSN: 1757-7780. DOI: 10.1002/wcc.183.

[166] K. I. Sudmeier-Rieux. “Resilience–an emerging paradigm of danger or of hope?” In: *Disaster prevention and management* 23.1 (2014), pp. 67–80. ISSN: 0965-3562.

[167] M. L. Imhoff, P. Zhang, R. E. Wolfe, and L. Bounoua. “Remote sensing of the urban heat island effect across biomes in the continental USA”. In: *Remote sensing of environment* 114.3 (Mar. 2010), pp. 504–513. ISSN: 0034-4257. DOI: 10.1016/j.rse.2009.10.008.

[168] Intergovernmental Panel on Climate Change. *Global Warming of 1.5°C: An IPCC Special Report on the Impacts of Global Warming of 1.5°C Above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty.* en. Intergovernmental Panel on Climate Change, 2018.

[169] International Strategy for Disaster Reduction. *Living With Risk: A Global Review of Disaster Reduction Initiatives.* Tech. rep. 1. United Nations, 2004.

[170] Japan Statistics Bureau. *Population Estimates of Japan 1920 - 2000.* 2011.

[171] J. C. Jiménez-Muñoz and J. A. Sobrino. "A generalized single-channel method for retrieving land surface temperature from remote sensing data". In: *Journal of Geophysical Research, D: Atmospheres* 108.D22 (2003).

[172] R. N. Jones. "An Environmental Risk Assessment/Management Framework for Climate Change Impact Assessments". en. In: *Natural Hazards* 23.2-3 (Mar. 2001), pp. 197–230. ISSN: 0921-030X, 1573-0840. DOI: 10.1023/A:1011148019213.

[173] S. Kaplan, B. J. Garrick - Risk analysis, and 1981. "On the quantitative definition of risk". In: *Wiley Online Library* (1981).

[174] J. X. Kasperson, R. E. Kasperson, B. L. Turner, et al. *Regions at risk.* United Nations University Press, 1995.

[175] D. Kelbaugh. *The Urban Fix: Resilient Cities in the War Against Climate Change, Heat Islands and Overpopulation.* Routledge, 2019.

[176] T. J. Kimpel, K. J. Dueker, and A. M. El-Geneidy. "Using GIS to measure the effect of overlapping service areas on passenger boardings at bus stops". In: *URISA Journal* 19.1 (2007), pp. 5–11.

[177] G. King. *Reconstructing individual behavior from aggregate data: A solution to the ecological inference problem.* Princeton: Princeton University Press, 1997.

[178] M. D. Kipke, E. Iverson, D. Moore, C. Booker, V. Ruelas, A. L. Peters, and F. Kaufman. "Food and Park Environments: Neighborhood-level Risks for Childhood Obesity in East Los Angeles". In: *J. Adolesc. Health Care* 40.4 (2007), pp. 325–333.

[179] R. J. T. Klein, R. J. Nicholls, and F. Thomalla. "Resilience to natural hazards: How useful is this concept?" In: *Global Environmental Change Part B: Environmental Hazards* 5.1 (Jan. 2003), pp. 35–45. ISSN: 1464-2867. DOI: 10.1016/j.hazards.2004.02.001.

[180] E. Klinenberg. *Heat wave: A social autopsy of disaster in Chicago.* University of Chicago Press, 2015.

[181] F. H. Knight. "Risk, uncertainty and profit". In: *New York: Hart, Schaffner and Marx* (1921).

[182] M. Koliou, J. W. van de Lindt, T. P. McAllister, B. R. Ellingwood, M. Dillard, and H. Cutler. “State of the research in community resilience: progress and challenges”. In: *Sustainable and Resilient Infrastructure* (Jan. 2018), pp. 1–21. ISSN: 2378-9689. DOI: 10.1080/23789689.2017.1418547.

[183] J. Koschinsky, E. Talen, M. Alfonzo, and S. Lee. “How walkable is Walker’s paradise?” In: *Environment and Planning B: Urban Analytics and City Science* 44.2 (2017), pp. 343–363.

[184] N. S. N. Lam, M. Reams, K. Li, C. Li, and L. P. Mata. “Measuring Community Resilience to Coastal Hazards along the Northern Gulf of Mexico”. en. In: *Natural Hazards Review* 17.1 (Feb. 2016). ISSN: 1527-6988. DOI: 10.1061/(ASCE)NH.1527-6996.0000193.

[185] J. E. Lamond and D. G. Proverbs. “Resilience to flooding: lessons from international comparison”. In: *Proceedings of the Institution of Civil Engineers - Urban Design and Planning* 162.2 (June 2009), pp. 63–70. ISSN: 1755-0793. DOI: 10.1680/udap.2009.162.2.63.

[186] H. E. Landsberg. *The Urban Climate*. en. Academic Press, Aug. 1981. ISBN: 9780080924199.

[187] M. Langford and G. Higgs. “Measuring Potential Access to Primary Healthcare Services: The Influence of Alternative Spatial Representations of Population”. In: *Prof. Geogr.* 58.3 (2006), pp. 294–306.

[188] K. Larsen and J. Gilliland. “Mapping the evolution of ’food deserts’ in a Canadian city: Supermarket accessibility in London, Ontario, 1961–2005”. In: *International Journal of Health Geographics* 7.1 (2008), p. 16.

[189] L. Larsen. “Urban climate and adaptation strategies”. In: *Frontiers in ecology and the environment* 13.9 (Nov. 2015), pp. 486–492. ISSN: 1540-9295. DOI: 10.1890/150103.

[190] J. Lee and C. Lubienski. “The Impact of School Closures on Equity of Access in Chicago”. In: *Educ. Urban Soc.* (2016), pp. 1–28.

[191] T. L. Lei and R. L. Church. “Mapping transit-based access: integrating GIS, routes and schedules”. In: *Int. J. Geogr. Inf. Sci.* 24.April 2015 (2010), pp. 283–304.

[192] R. J. Lempert. *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. en. Rand Corporation, July 2003. ISBN: 9780833034854.

[193] S. Levine. “Assessing resilience: why quantification misses the point”. In: *Humanitarian Policy Group (ODI) Working Paper* (2014).

[194] X. Li and A. G.-O. Yeh. “Modelling sustainable urban development by the integration of constrained cellular automata and GIS”. In: *International journal of geographical information science: IJGIS* 14.2 (2000), pp. 131–152. ISSN: 1365-8816. DOI: 10.1080/136588100240886.

[195] X. Li, Y. Zhou, G. R. Asrar, M. Imhoff, and X. Li. “The surface urban heat island response to urban expansion: A panel analysis for the conterminous United States”. en. In: *The Science of the total environment* 605-606 (Dec. 2017), pp. 426–435. ISSN: 0048-9697, 1879-1026. DOI: 10.1016/j.scitotenv.2017.06.229.

[196] S. Liang. “Narrowband to broadband conversions of land surface albedo I: Algorithms”. In: *Remote sensing of environment* 76.2 (May 2001), pp. 213–238. ISSN: 0034-4257. DOI: 10.1016/S0034-4257(00)00205-4.

[197] I. Linkov, T. Bridges, F. Creutzig, J. Decker, C. Fox-Lent, W. Kröger, J. H. Lambert, A. Levermann, B. Montreuil, J. Nathwani, R. Nyer, O. Renn, B. Scharte, A. Scheffler, M. Schreurs, and T. Thiel-Clemen. “Changing the resilience paradigm”. In: *Nature climate change* 4 (May 2014), p. 407. ISSN: 1758-678X. DOI: 10.1038/nclimate2227.

[198] I. Linkov, B. D. Trump, and J. Keisler. “Risk and resilience must be independently managed”. en. In: *Nature* 555.7694 (Mar. 2018), p. 30. ISSN: 0028-0836, 1476-4687. DOI: 10.1038/d41586-018-02567-0.

[199] J. M. Links, B. S. Schwartz, S. Lin, N. Kanarek, J. Mitrani-Reiser, T. K. Sell, C. R. Watson, D. Ward, C. Slemp, R. Burhans, K. Gill, T. Igusa, X. Zhao, B. Aguirre, J. Trainor, J. Nigg, T. Inglesby, E. Carbone, and J. M. Kendra. “COPEWELL: A Conceptual Framework and System Dynamics Model for Predicting Community Functioning and Resilience After Disasters”. en. In: *Disaster medicine and public health preparedness* 12.1 (Feb. 2018), pp. 127–137. ISSN: 1935-7893, 1938-744X. DOI: 10.1017/dmp.2017.39.

[200] T. M. Logan, S. D. Guikema, and J. D. Bricker. “Hard-adaptive measures can increase vulnerability to storm surge and tsunami hazards over time”. In: *Nature Sustainability* 1.9 (Sept. 2018), pp. 526–530. ISSN: 2398-9629. DOI: 10.1038/s41893-018-0137-6.

[201] T. M. Logan, T. G. Williams, A. J. Nisbet, K. D. Liberman, C. T. Zuo, and S. D. Guikema. “Evaluating urban accessibility: leveraging open-source data and analytics to overcome existing limitations”. In: *Environment and Planning B: Urban Analytics and City Science* (Nov. 2017). ISSN: 2399-8083. DOI: 10.1177/2399808317736528.

[202] I. S. Lowry. “A short course in model design”. In: *Journal of the American Institute of Planners* 31.2 (May 1965), pp. 158–166. ISSN: 0002-8991. DOI: 10.1080/01944366508978159.

[203] J. Lundberg and B. J. E. Johansson. “Systemic resilience model”. In: *Reliability Engineering & System Safety* 141 (Sept. 2015), pp. 22–32. ISSN: 0951-8320. DOI: 10.1016/j.ress.2015.03.013.

[204] D. Luxen and C. Vetter. “Real-time routing with OpenStreetMap data”. In: *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, Jan. 2011, pp. 513–516.

[205] J. Macedo and M. A. Haddad. “Equitable distribution of open space: Using spatial analysis to evaluate urban parks in Curitiba, Brazil”. In: *Environment and Planning B: Planning and Design* 43.6 (2016), pp. 1096–1117.

[206] R. Mack. “Planning on uncertainty”. In: *Decision making in business and government administration. New York* (1971).

[207] D. MacKinnon and K. D. Derickson. “From resilience to resourcefulness: A critique of resilience policy and activism”. In: *Progress in human geography* 37.2 (Apr. 2013), pp. 253–270. ISSN: 0309-1325. DOI: 10.1177/0309132512454775.

[208] A. K. Magnan, E. L. F. Schipper, M. Burkett, S. Bharwani, I. Burton, S. Eriksen, F. Gemenne, J. Schaar, and G. Ziervogel. “Addressing the risk of maladaptation to climate change”. In: *Wiley Interdisciplinary Reviews: Climate Change* 7.5 (Sept. 2016), pp. 646–665. ISSN: 1757-7799. DOI: 10.1002/wcc.409.

[209] S. Manson, J. Schroeder, D. Van Riper, and S. Ruggles. *IPUMS National Historical Geographic Information System: Version 13.0*. 2018. DOI: D050.V13.0.

[210] S. Manson, J. Schroeder, D. Van Riper, and S. Ruggles. *IPUMS National Historical Geographic Information System: Version 13.0*. 2018. DOI: D050.V13.0.

[211] S. B. Manyena. “The concept of resilience revisited”. en. In: *Disasters* 30.4 (Dec. 2006), pp. 433–450. ISSN: 0361-3666. DOI: 10.1111/j.0361-3666.2006.00331.x.

[212] L. Mao and D. Nekorchuk. “Measuring spatial accessibility to healthcare for populations with multiple transportation modes”. en. In: *Health Place* 24 (Nov. 2013), pp. 115–122.

[213] N. Matin, J. Forrester, and J. Ensor. “What is equitable resilience?” en. In: *World development* 109 (Sept. 2018), pp. 197–205. ISSN: 0305-750X. DOI: 10.1016/j.worlddev.2018.04.020.

[214] A. Matzarakis, F. Rutz, and H. Mayer. “Modelling radiation fluxes in simple and complex environments—application of the RayMan model”. In: *International journal of biometeorology* (2007). ISSN: 0020-7128.

[215] S. Mavoa, K. Witten, T. McCreanor, and D. O’Sullivan. “GIS based destination accessibility via public transit and walking in Auckland, New Zealand”. In: *J. Transp. Geogr.* 20.1 (2012), pp. 15–22.

[216] L.-M. McLachlan. *’We have to react with speed’ - Iwi leaders on climate change*. https://www.radionz.co.nz/news/te-manu-korihi/388691/we-have-to-react-with-speed-iwi-leaders-on-climate-change. Accessed: 2019-5-8. May 2019.

[217] S. Meerow and J. P. Newell. “Spatial planning for multifunctional green infrastructure: Growing resilience in Detroit”. In: *Landscape and urban planning* 159 (2017), pp. 62–75. ISSN: 0169-2046. DOI: 10.1016/j.landurbplan.2016.10.005.

[218] S. Meerow, J. P. Newell, and M. Stults. “Defining urban resilience: A review”. In: *Landscape and urban planning* 147 (Mar. 2016), pp. 38–49. ISSN: 0169-2046. DOI: 10.1016/j.landurbplan.2015.11.011.

[219] S. Meerow and M. Stults. “Comparing Conceptualizations of Urban Climate Resilience in Theory and Practice”. en. In: *Sustainability: Science Practice and Policy* 8.7 (July 2016), p. 701. ISSN: 1548-7733. DOI: 10.3390/su8070701.

[220] H. Merbitz, M. Buttstädt, S. Michael, W. Dott, and C. Schneider. “GIS-based identification of spatial variables enhancing heat and poor air quality in urban areas”. In: *Applied geography* 33 (Apr. 2012), pp. 94–106. ISSN: 0143-6228. DOI: 10.1016/j.apgeog.2011.06.008.

[221] D. Merkel. “Docker: lightweight linux containers for consistent development and deployment”. In: *Linux Journal* 2014.239 (2014), p. 2.

[222] D. Mileti. *Disasters by Design: A Reassessment of Natural Hazards in the United States*. en. Joseph Henry Press, June 1999. ISBN: 9780309261739.

[223] G. Montibeller and D. von Winterfeldt. “Cognitive and Motivational Biases in Decision and Risk Analysis”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 35.7 (July 2015), pp. 1230–1251. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12360.

[224] N. Mori, T. Takahashi, T. Yasuda, and H. Yanagisawa. “Survey of 2011 Tohoku earthquake tsunami inundation and run-up”. In: *Geophysical research letters* 38.7 (2011). ISSN: 0094-8276.

[225] S. Muis, B. Güneralp, B. Jongman, J. C. J. H. Aerts, and P. J. Ward. “Flood risk and adaptation strategies under climate change and urban expansion: A probabilistic analysis using global data”. en. In: *The Science of the total environment* 538 (Dec. 2015), pp. 445–457. ISSN: 0048-9697, 1879-1026. DOI: 10.1016/j.scitotenv.2015.08.068.

[226] P. Murage, S. Hajat, and R. S. Kovats. “Effect of night-time temperatures on cause and age-specific mortality in London”. In: *Environmental Epidemiology* 1.2 (Dec. 2017), e005. DOI: 10.1097/EE9.0000000000000005.

[227] C. Murphy and P. Gardoni. “The role of society in engineering risk analysis: A capabilities-based approach”. In: *Risk analysis* 26.4 (2006), pp. 1073–1083. ISSN: 0272-4332.

[228] K. Murphy. “Australians overwhelmingly agree climate emergency is nation’s No 1 threat”. In: *The Guardian* (May 2019). ISSN: 0261-3077.

[229] C. Nan and G. Sansavini. “A quantitative method for assessing resilience of interdependent infrastructures”. In: *Reliability Engineering & System Safety* 157 (Jan. 2017), pp. 35–53. ISSN: 0951-8320. DOI: 10.1016/j.ress.2016.08.013.

[230] R. Nateghi, J. D. Bricker, S. D. Guikema, and A. Bessho. “Statistical Analysis of the Effectiveness of Seawalls and Coastal Forests in Mitigating Tsunami Impacts in Iwate and Miyagi Prefectures”. en. In: *PloS one* 11.8 (Aug. 2016), e0158375. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0158375.

[231] National Research Council. *Disaster Resilience: A National Imperative*. Washington, DC: The National Academies Press, 2012. ISBN: 9780309261500. DOI: 10.17226/13457.

[232] National Research Council, Division on Earth and Life Studies, Board on Earth Sciences and Resources, Geographical Sciences Committee, and Committee on Needs and Research Requirements for Land Change Modeling. *Advancing Land Change Modeling: Opportunities and Research Requirements*. en. National Academies Press, Mar. 2014. ISBN: 9780309288361.

[233] P. Neis and D. Zielstra. "Recent Developments and Future Trends in Volunteered Geographic Information Research: The Case of OpenStreetMap". en. In: *Future Internet* 6.1 (27 1 2014), pp. 76–106.

[234] S. Netter. "How one man single-handedly opened the only grocery store in one of New Orleans' poorest wards and inspired Ellen DeGeneres". In: *The Washington Post* (Apr. 2016). ISSN: 0190-8286.

[235] B. Newell and R. Wasson. "Social system vs solar system: why policy makers need history". In: *Conflict and Cooperation Related to International Water Resources: Historical Perspectives* 62 (2002), 3ff.

[236] J. Nichol. "Remote Sensing of Urban Heat Islands by Day and Night". In: *Photogrammetric Engineering & Remote Sensing* 71.5 (May 2005), pp. 613–621.

[237] M. Nobles, N. Serban, and J. Swann. "Spatial accessibility of pediatric primary healthcare: Measurement and inference". In: *The annals of applied statistics* 8.4 (2014), pp. 1922–1946. ISSN: 1932-6157, 1941-7330. DOI: 10.1214/14-AOAS728.

[238] L. Noel and U. of Chicago's Center for Spatial Data Science (CSDS). *spatial_access: Compute travel times and spatial access metrics at scale*. 2019–. URL: https://pypi.org/project/spatial-access/.

[239] J.-M. Normandin, M.-C. Therrien, M. Pelling, and S. Paterson. "The Definition of Urban Resilience: A Transformation Path Towards Collaborative Urban Risk Governance". In: *Urban Resilience for Risk and Adaptation Governance: Theory and Practice*. Ed. by G. e. a. Brunetta. Cham: Springer International Publishing, 2019, pp. 9–25. ISBN: 9783319769448. DOI: 10.1007/978-3-319-76944-8_2.

[240] F. H. Norris, S. P. Stevens, B. Pfefferbaum, K. F. Wyche, and R. L. Pfefferbaum. "Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness". en. In: *American journal of community psychology* 41.1-2 (Mar. 2008), pp. 127–150. ISSN: 0091-0562. DOI: 10.1007/s10464-007-9156-6.

[241] Y. Okada. "Surface deformation due to shear and tensile faults in a half-space". In: *Bulletin of the Seismological Society of America* 75.4 (Aug. 1985), pp. 1135–1154. ISSN: 0037-1106.

[242] T. R. Oke. "Street design and urban canopy layer climate". In: *Energy and Buildings* 11.1 (Mar. 1988), pp. 103–113. ISSN: 0378-7788. DOI: 10.1016/0378-7788(88)90026-6.

[243] D. Okrent and N. Pidgeon. "Introduction: dilemmas in intergenerational versus intragenerational equity and risk policy". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 759–762. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206069.

[244] L. N. Oliver, N. Schuurman, and A. W. Hall. "Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands". In: *Int. J. Health Geogr.* 6.1 (2007), p. 41.

[245] N. Onishi. "Seawalls Offered Little Protection against Tsunami's Crushing Waves". In: *New York Times* (2011).

[246] S. Openshaw. "The modifiable areal unit problem". In: Geo Abstracts University of East Anglia, 1984.

[247] OSM. *Unconnected ways - OpenStreetMap Wiki*. http://wiki.openstreetmap.org/wiki/Unconnected_ways. Accessed: 2017-4-18. Jan. 2016.

[248] D. O'Sullivan, A. Morrison, and J. Shearer. "Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach". In: *Int. J. Geogr. Inf. Sci.* 14.1 (2000), pp. 85–104.

[249] M. Pacione. "Access to urban services: the case of secondary schools in Glasgow". In: *Scott. Geogr. Mag.* 105.1 (1989), pp. 12–18.

[250] P. I. Palmer and M. J. Smith. "Model human adaptation to climate change". In: *Nature* 512.7515 (2014), p. 365. ISSN: 0028-0836.

[251] J. Pantelić. "The link between reconstruction and development". In: *Land use policy* 8.4 (Oct. 1991), pp. 343–347. ISSN: 0264-8377. DOI: 10.1016/0264-8377(91)90024-D.

[252] E. Paté-Cornell. "On "Black Swans" and "Perfect Storms": Risk Analysis and Management When Statistics Are Not Enough". In: *Risk analysis: an official publication of the Society for Risk Analysis* 32.11 (Nov. 2012), pp. 1823–1833. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.2011.01787.x.

[253] M. E. Paté-Cornell. "Uncertainties in risk analysis: Six levels of treatment". In: *Reliability Engineering & System Safety* 54.2 (Nov. 1996), pp. 95–111. ISSN: 0951-8320. DOI: 10.1016/S0951-8320(96)00067-1.

[254] D. Paton, L. Smith, and J. Violanti. "Disaster response: risk, vulnerability and resilience". In: *Disaster Prevention and Management: An International Journal* 9.3 (2000), pp. 173–180. DOI: 10.1108/09653560010335068. eprint: https://doi.org/10.1108/09653560010335068.

[255] E. Pawson. "Environmental hazards and natural disasters". In: *New Zealand geographer* 67.3 (Dec. 2011), pp. 143–147. ISSN: 0028-8144, 1745-7939. DOI: 10.1111/j.1745-7939.2011.01207.x.

[256] W. G. Peacock, S. D. Brody, W. A. Seitz, W. J. Merrell, A. Vedlitz, S. Zahran, R. C. Harriss, and R. Stickney. *Advancing Resilience of Coastal Localities: Developing, Implementing, and Sustaining the Use of Coastal Resilience Indicators: A Final Report. Hazard Reduction and Recovery Center.* 2010.

[257] D. Pearce. "Painting the picture: The validity of Walk Score in addressing subjective urban design qualities in the built environment". MA thesis. University of Oregon, 2015.

[258] R. Penchansky and J. W. Thomas. "The concept of access: definition and relationship to consumer satisfaction". In: *Medical care* (1981). ISSN: 0025-7079.

[259] R. Penchansky and J. W. Thomas. "The concept of access: definition and relationship to consumer satisfaction." In: *Medical care* 19.2 (1981), pp. 127–140.

[260] J. Peng, J. Jia, Y. Liu, H. Li, and J. Wu. "Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas". In: *Remote sensing of environment* 215 (Sept. 2018), pp. 255–267. ISSN: 0034-4257. DOI: 10.1016/j.rse.2018.06.010.

[261] S. Peng, S. Piao, P. Ciais, P. Friedlingstein, C. Ottle, F.-M. Bréon, H. Nan, L. Zhou, and R. B. Myneni. "Surface urban heat island across 419 global big cities". en. In: *Environmental science & technology* 46.2 (Jan. 2012), pp. 696–703. ISSN: 0013-936X, 1520-5851. DOI: 10.1021/es2030438.

[262] S. L. Pimm. "The complexity and stability of ecosystems". In: *Nature* 307.5949 (Jan. 1984), pp. 321–326. ISSN: 0028-0836, 1476-4687. DOI: 10.1038/307321a0.

[263] S. Platt. "Planning Recovery and Reconstruction After the 2010 Maule Earthquake and Tsunami in Chile". In: *Urban Resilience for Risk and Adaptation Governance: Theory and Practice.* Ed. by G. e. a. Brunetta. Cham: Springer International Publishing, 2019, pp. 285–304. ISBN: 9783319769448. DOI: 10.1007/978-3-319-76944-8_16.

[264] S. Platt, D. Brown, and M. Hughes. "Measuring resilience and recovery". In: *International Journal of Disaster Risk Reduction* 19 (Oct. 2016), pp. 447–460. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2016.05.006.

[265] A. H. Prieur-Richard, B. Walsh, M. Craig, M. L. Melamed, L. Colbert, M. Pathak, S. Connors, X. Bai, A. Barau, H. Bulkeley, et al. *Extended version: Global Research and Action Agenda on Cities and Climate Change Science.* Tech. rep. IPCC, 2018.

[266] Z. Qin, A. Karnieli, and P. Berliner. "A mono-window algorithm for retrieving land surface temperature from Landsat TM data and its application to the Israel-Egypt border region". In: *International journal of remote sensing* 22.18 (Jan. 2001), pp. 3719–3746. ISSN: 0143-1161. DOI: 10.1080/01431160010006971.

[267] R. Quay. "Anticipatory governance: A tool for climate change adaptation". In: *Journal of the American Planning Association. American Planning Association* 76.4 (2010), pp. 496–511. ISSN: 0194-4363.

[268] S. Raja, C. Ma, and P. Yadav. "Beyond Food Deserts: Measuring and Mapping Racial Disparities in Neighborhood Food Environments". In: *Journal of Planning Education and Research* 27.4 (June 2008), pp. 469–482. ISSN: 0739-456X. DOI: 10.1177/0739456X08317461.

[269] S. Raja, L. Yin, J. Roemmich, C. Ma, L. Epstein, P. Yadav, and A. B. Ticoalu. "Food environment, built environment, and women's BMI: Evidence from Erie County, New York". In: *Journal of Planning Education and Research* 29.4 (2010), pp. 444–460.

[270] T. A. Randall and B. W. Baetz. "Evaluating Pedestrian Connectivity for Suburban Sustainability". In: *Journal of Urban Planning and Development* 127.1 (Mar. 2001), pp. 1–15.

[271] J. Rehmeyer. *Mathematical and Statistical Challenges for Sustainability*. Tech. rep. NSF, 2011.

[272] A. C. Reilly, G. L. Tonn, C. Zhai, and S. D. Guikema. "Hurricanes and Power System Reliability-The Effects of Individual Decisions and System-Level Hardening". In: *Proceedings of the IEEE* 105.7 (July 2017), pp. 1429–1442. ISSN: 0018-9219. DOI: 10.1109/JPROC.2017.2689720.

[273] A. C. Reilly, R. L. Dillon, and S. D. Guikema. "Agent-based models as an integrating boundary object for interdisciplinary research". In: *Risk analysis: an official publication of the Society for Risk Analysis* (2018). ISSN: 0272-4332.

[274] R. Reklaitiene, R. Grazuleviciene, A. Dedele, D. Virviciute, J. Vensloviene, A. Tamosiunas, M. Baceviciene, D. Luksiene, L. Sapranaviciute-Zabazlajeva, R. Radisauskas, G. Bernotiene, M. Bobak, and M. J. Nieuwenhuijsen. "The relationship of green space, depressive symptoms and perceived general health in urban population". In: *Scand. J. Public Health* 42.7 (2014), pp. 669–676.

[275] A. Reséndiz-Vázquez. "Urban Resilience and Post-Disaster Reconstruction. Evidences from Mexico and France". In: *Urban Resilience for Risk and Adaptation Governance: Theory and Practice*. Ed. by G. e. a. Brunetta. Cham: Springer International Publishing, 2019, pp. 267–280. ISBN: 9783319769448. DOI: 10.1007/978-3-319-76944-8_14.

[276] T. Roach, Z. Kapelan, R. Ledbetter, and M. Ledbetter. "Comparison of Robust Optimization and Info-Gap Methods for Water Resource Management under Deep Uncertainty". In: *Journal of Water Resources Planning and Management* 142.9 (Sept. 2016). DOI: 10.1061/(ASCE)WR.1943-5452.0000660.

[277] J.-M. Robine, S. L. K. Cheung, S. Le Roy, H. Van Oyen, C. Griffiths, J.-P. Michel, and F. R. Herrmann. "Death toll exceeded 70,000 in Europe during the summer of 2003". en. In: *Comptes rendus biologies* 331.2 (Feb. 2008), pp. 171–178. ISSN: 1631-0691, 1768-3238. DOI: 10.1016/j.crvi.2007.12.001.

[278] O. Ronneberger, P. Fischer, and T. Brox. "U-net: Convolutional networks for biomedical image segmentation". In: *International Conference on Medical image computing and computer-assisted intervention* (2015), pp. 234–241.

[279] A. Rose. "Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions". In: *Environmental Hazards* 7.4 (Jan. 2007), pp. 383–398. ISSN: 1747-7891. DOI: 10.1016/j.envhaz.2007.10.001.

[280] P. Sandin. "Dimensions of the Precautionary Principle". In: *Human and Ecological Risk Assessment: An International Journal* 5.5 (Aug. 1999), pp. 889–907. ISSN: 1080-7039. DOI: 10.1080/10807039991289185.

[281] S. Y. Sang Lijie, W. Zhu, and F. Su. "Accessibility of urban green spaces in Hangzhou City". In: *Progress in Geography (CN)* 32.6 (2013), pp. 950–957.

[282] W. S. A. Saunders and J. S. Becker. "A discussion of resilience and sustainability: Land use planning recovery from the Canterbury earthquake sequence, New Zealand". In: *International Journal of Disaster Risk Reduction* 14 (Dec. 2015), pp. 73–81. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2015.01.013.

[283] E. Saurman. "Improving access: modifying Penchansky and Thomas's Theory of Access". In: *Journal of health services research & policy* 21.1 (2016), pp. 36–39.

[284] E. Saurman. "Improving access: modifying Penchansky and Thomas's Theory of Access". In: *Journal of health services research & policy* 21.1 (Jan. 2016), pp. 36–39. ISSN: 1355-8196. DOI: 10.1177/1355819615600001.

[285] T. C. Schelling. "Intergenerational and international discounting". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 833–837. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206076.

[286] M. Schlossberg, J. Greene, P. P. Phillips, B. Johnson, and B. Parker. "School Trips: Effects of Urban Form and Distance on Travel Mode". In: *J. Am. Plann. Assoc.* 72.3 (2006), pp. 337–346.

[287] N. Schuurman, R. S. Fiedler, S. C. W. Grzybowski, and D. Grund. "Defining rational hospital catchments for non-urban areas based on travel-time". en. In: *Int. J. Health Geogr.* 5 (Mar. 2006), p. 43.

[288] A. A. Scott, B. Zaitchik, D. W. Waugh, and K. O'Meara. "Intraurban Temperature Variability in Baltimore". In: *Journal of Applied Meteorology and Climatology* 56.1 (Oct. 2016), pp. 159–171. ISSN: 1558-8424. DOI: 10.1175/JAMC-D-16-0232.1.

[289] SEMCOG. *Access to core services in Southeast Michigan.* Tech. rep. The Southeast Michigan Council of Governments, 2016.

[290] N. Sharma, A. Tabandeh, and P. Gardoni. "Resilience analysis: a mathematical formulation to model resilience of engineering systems". In: *Sustainable and Resilient Infrastructure* 3.2 (Apr. 2018), pp. 49–67. ISSN: 2378-9689. DOI: 10.1080/23789689.2017.1345257.

[291] J. E. Sherman, J. Spencer, J. S. Preisser, W. M. Gesler, and T. A. Arcury. "A suite of methods for representing activity space in a healthcare accessibility study". en. In: *Int. J. Health Geogr.* 4 (19 10 2005), p. 24.

[292] K. Sherrieb, F. H. Norris, and S. Galea. "Measuring Capacities for Community Resilience". In: *Social indicators research* 99.2 (Nov. 2010), pp. 227–247. ISSN: 0303-8300, 1573-0921. DOI: 10.1007/s11205-010-9576-9.

[293] T. Shimozono, S. Sato, A. Okayasu, Y. Tajima, H. M. Fritz, H. Liu, and T. Takagawa. "PROPAGATION AND INUNDATION CHARACTERISTICS OF THE 2011 TOHOKU TSUNAMI ON THE CENTRAL SANRIKU COAST". In: *Coastal Engineering Journal* 54.01 (Mar. 2012), p. 1250004. ISSN: 0578-5634. DOI: 10.1142/S0578563412500040.

[294] J. E. Shortridge, S. M. Falconi, B. F. Zaitchik, and S. D. Guikema. "Climate, agriculture, and hunger: statistical prediction of undernourishment using nonlinear regression and data-mining techniques". In: *Journal of applied statistics* 42.11 (Nov. 2015), pp. 2367–2390. ISSN: 0266-4763. DOI: 10.1080/02664763.2015.1032216.

[295] J. E. Shortridge and S. D. Guikema. "Scenario Discovery with Multiple Criteria: An Evaluation of the Robust Decision-Making Framework for Climate Change Adaptation". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 36.12 (Dec. 2016), pp. 2298–2312. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12582.

[296] J. Shortridge, T. Aven, and S. Guikema. "Risk assessment under deep uncertainty: A methodological comparison". In: *Reliability Engineering & System Safety* 159 (2017), pp. 12–23. ISSN: 0951-8320.

[297] K. Shrader-Frechette. "Duties to future generations, proxy consent, intra-and intergenerational equity: The case of nuclear waste". In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (2000), pp. 771–778. ISSN: 0272-4332.

[298] N. Shuto and K. Fujima. "A short history of tsunami research and countermeasures in Japan". In: *Proceedings of the Japan Academy. Series B, Physical and biological sciences* 85.8 (2009), p. 267. ISSN: 0386-2208.

[299] M. Sivapalan and G. Blöschl. "Time scale interactions and the coevolution of humans and water". In: *Water resources research* 51.9 (Sept. 2015), pp. 6988–7022. ISSN: 0043-1397, 1944-7973. DOI: 10.1002/2015WR017896.

[300] P. Slovic, M. L. Finucane, E. Peters, and D. G. MacGregor. "Risk as analysis and risk as feelings: some thoughts about affect, reason, risk, and rationality". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 24.2 (Apr. 2004), pp. 311–322. ISSN: 0272-4332. DOI: 10.1111/j.0272-4332.2004.00433.x.

[301] K. Smith and D. Petley. *Environmental Hazards: Assessing Risk and Reducing Disasters*. New York: Routledge, 2009.

[302] M. J. D. Smith, M. F. Goodchild, and P. Longley. *Geospatial analysis: a comprehensive guide to principles, techniques and software tools*. 2007.

[303] R. B. Smith. "The heat budget of the earth's surface deduced from space". In: *Yale University Center for Earth Observation: New Haven, CT, USA* (2010).

[304] J. M. Sobstyl, T. Emig, M. J. A. Qomi, F.-J. Ulm, and R. J.-M. Pellenq. “Role of City Texture in Urban Heat Islands at Nighttime”. en. In: *Physical review letters* 120.10 (Mar. 2018), p. 108701. ISSN: 0031-9007, 1079-7114. DOI: 10.1103/PhysRevLett.120.108701.

[305] Society of Risk Analysis. *Core Subjects of Risk Analysis.* Tech. rep. Society of Risk Analysis, 2018.

[306] Society of Risk Analysis. *Society of Risk Analysis Glossary.* Tech. rep. 2015.

[307] J. Song, X. Fu, Y. Gu, Y. Deng, and P. Zhong-Ren. “An examination of land use impacts of flooding induced by sea level rise”. In: *Natural Hazards and Earth System Sciences* 17.3 (2017), p. 315. ISSN: 1561-8633.

[308] B. K. Sovacool. “Hard and soft paths for climate change adaptation”. In: *Climate Policy* 11.4 (July 2011), pp. 1177–1183. ISSN: 1469-3062. DOI: 10.1080/14693062.2011.579315.

[309] C. Starr. “The ultimate uncertainty–intergenerational planning”. en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 20.6 (Dec. 2000), pp. 793–800. ISSN: 0272-4332. DOI: 10.1111/0272-4332.206073.

[310] M. Stults and L. Larsen. “Tackling Uncertainty in US Local Climate Adaptation Planning”. In: *Journal of Planning Education and Research* (Apr. 2018), p. 0739456X18769134. ISSN: 0739-456X. DOI: 10.1177/0739456X18769134.

[311] S. Subaiya, C. Moussavi, A. Velasquez, and J. Stillman. “A rapid needs assessment of the Rockaway Peninsula in New York City after Hurricane Sandy and the relationship of socioeconomic status to recovery”. en. In: *American journal of public health* 104.4 (Apr. 2014), pp. 632–638. ISSN: 0090-0036, 1541-0048. DOI: 10.2105/AJPH.2013.301668.

[312] A. Suppasri, E. Mas, S. Koshimura, K. Imai, K. Harada, and F. Imamura. “Developing Tsunami Fragility Curves From the Surveyed Data of the 2011 Great East Japan Tsunami in Sendai and Ishinomaki Plains”. In: *Coastal Engineering Journal* 54.01 (2012), pp. 1250008–1250001. ISSN: 0578-5634. DOI: 10.1142/S0578563412500088.

[313] O. Svenson and G. Karlsson. “Decision-Making, Time Horizons, and Risk in the Very Long-Term Perspective”. In: *Risk analysis: an official publication of the Society for Risk Analysis* 9.3 (Sept. 1989), pp. 385–399. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/j.1539-6924.1989.tb01004.x.

[314] E. Talen. “Neighborhoods as service providers: A methodology for evaluating pedestrian access”. In: *Environment and planning. B, Planning & design* (2003). ISSN: 0265-8135. DOI: 10.1068/b12977.

[315] P. Y. Tan and R. Samsudin. “Effects of spatial scale on assessment of spatial equity of urban park provision”. In: *Landsc. Urban Plan.* 158 (2017), pp. 139–154.

[316] K. Tani. *Past and present map comparison website.* http://ktgis.net/kjmapw/. 2015.

[317] D. R. Tappin, S. T. Grilli, J. C. Harris, R. J. Geller, T. Masterlark, J. T. Kirby, F. Shi, G. Ma, K. K. S. Thingbaijam, and P. M. Mai. "Did a submarine landslide contribute to the 2011 Tohoku tsunami?" In: *Marine geology* 357 (Nov. 2014), pp. 344–361. ISSN: 0025-3227. DOI: 10.1016/j.margeo.2014.09.043.

[318] D. M. Tendall, J. Joerin, B. Kopainsky, P. Edwards, A. Shreck, Q. B. Le, P. Kruetli, M. Grant, and J. Six. "Food system resilience: Defining the concept". In: *Global Food Security* 6 (Oct. 2015), pp. 17–23. ISSN: 2211-9124. DOI: 10.1016/j.gfs.2015.08.001.

[319] The Economist. "The Great Wall of Japan". In: *The Economist* (2014).

[320] G. G. Thompson, L. A. Maguire, and T. J. Regan. "Evaluation of Two Approaches to Defining Extinction Risk under the U.S. Endangered Species Act". en. In: *Risk analysis: an official publication of the Society for Risk Analysis* 38.5 (May 2018), pp. 1009–1035. ISSN: 0272-4332, 1539-6924. DOI: 10.1111/risa.12927.

[321] Tohoku University. *Japan Tsunami Trace Database.*

[322] B. L. Turner. "Vulnerability and resilience: Coalescing or paralleling approaches for sustainability science?" In: *Global environmental change: human and policy dimensions* 20.4 (Oct. 2010), pp. 570–576. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2010.07.003.

[323] B. L. Turner 2nd, R. E. Kasperson, P. A. Matson, J. J. McCarthy, R. W. Corell, L. Christensen, N. Eckley, J. X. Kasperson, A. Luers, M. L. Martello, C. Polsky, A. Pulsipher, and A. Schiller. "A framework for vulnerability analysis in sustainability science". en. In: *Proceedings of the National Academy of Sciences of the United States of America* 100.14 (July 2003), pp. 8074–8079. ISSN: 0027-8424. DOI: 10.1073/pnas.1231335100.

[324] E. Ulutas. "THE 2011 OFF THE PACIFIC COAST OF TOHOKU-OKI EARTHQUAKE AND TSUNAMI : INFLUENCE OF THE SOURCE CHARACTERISTICS". In: (2012), pp. 602–611.

[325] J. Unger. "Intra-urban relationship between surface geometry and urban heat island: review and new approach". In: *Climate Research* 27 (2004), pp. 253–264. ISSN: 0936-577X, 1616-1572. DOI: 10.3354/cr027253.

[326] United Nations Educational, Scientific and Cultural Organization and World Bank. *Culture in City Reconstruction and Recovery.* Paris: UNESCO, Nov. 2018. ISBN: 9789231002885.

[327] U.S. Census Bureau. *2017 TIGER/Line Shapefiles.* 2017.

[328] D. S. Vale, M. Saraiva, and M. Pereira. "Active accessibility: A review of operational measures of walking and cycling accessibility". In: *Journal of Transport and Land Use* 9.1 (2015).

[329] D. B. Van Berkel and P. H. Verburg. "Combining exploratory scenarios and participatory backcasting: using an agent-based model in participatory policy design for a multi-functional landscape". en. In: *Landscape ecology* 27.5 (Mar. 2012), pp. 641–658. ISSN: 0921-2973. DOI: 10.1007/s10980-012-9730-7.

[330] J. Van doninck. “horizon: Horizon Search Algorithm”. In: *R Package* 1.2 (2018).

[331] A. M. Vicedo-Cabrera, M. S. Ragettli, C. Schindler, and M. Röösli. “Excess mortality during the warm summer of 2015 in Switzerland”. en. In: *Swiss medical weekly* 146 (Dec. 2016), w14379. ISSN: 1424-7860. DOI: 10.4414/smw.2016.14379.

[332] J. van Vliet, A. K. Bregt, D. G. Brown, H. van Delden, S. Heckbert, and P. H. Verburg. “A review of current calibration and validation practices in land-change modeling”. In: *Environmental Modelling & Software* 82 (Aug. 2016), pp. 174–182. ISSN: 1364-8152. DOI: 10.1016/j.envsoft.2016.04.017.

[333] J. A. Voogt and T. R. Oke. “Thermal remote sensing of urban climates”. In: *Remote sensing of environment* 86.3 (Aug. 2003), pp. 370–384. ISSN: 0034-4257. DOI: 10.1016/S0034-4257(03)00079-8.

[334] A. Votsis. “Utilizing a cellular automaton model to explore the influence of coastal flood adaptation strategies on Helsinki’s urbanization patterns”. In: *Computers, environment and urban systems* 64 (2017), pp. 344–355. ISSN: 0198-9715.

[335] E. D. Vugrin, D. E. Warren, M. A. Ehlen, and R. C. Camphouse. “A Framework for Assessing the Resilience of Infrastructure and Economic Systems”. In: *Sustainable and Resilient Critical Infrastructure Systems: Simulation, Modeling, and Intelligent Engineering*. Ed. by K. Gopalakrishnan and S. Peeta. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, pp. 77–116.

[336] B. Walker, C. S. Holling, S. Carpenter, and A. Kinzig. “Resilience, adaptability and transformability in social–ecological systems”. In: *Ecology and Society* 9.2 (2004). ISSN: 1708-3087.

[337] W. E. Walker, P. Harremoës, J. Rotmans, J. P. van der Sluijs, M. B. A. van Asselt, P. Janssen, and M. P. Krayer von Krauss. “Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support”. In: *Integrated Assessment* 4.1 (Mar. 2003), pp. 5–17. ISSN: 1389-5176. DOI: 10.1076/iaij.4.1.5.16466.

[338] C. Wang, Z.-H. Wang, C. Wang, and S. W. Myint. “Environmental cooling provided by urban trees under extreme heat and cold waves in U.S. cities”. In: *Remote sensing of environment* 227 (June 2019), pp. 28–43. ISSN: 0034-4257. DOI: 10.1016/j.rse.2019.03.024.

[339] Y. Wang, Q. Zhan, and W. Ouyang. “How to quantify the relationship between spatial distribution of urban waterbodies and land surface temperature?” en. In: *The Science of the total environment* 671 (Mar. 2019), pp. 1–9. ISSN: 0048-9697, 1879-1026. DOI: 10.1016/j.scitotenv.2019.03.377.

[340] J. A. Wardekker, A. de Jong, J. M. Knoop, and J. P. van der Sluijs. “Operationalising a resilience approach to adapting an urban delta to uncertain climate changes”. In: *Technological forecasting and social change* 77.6 (July 2010), pp. 987–998. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2009.11.005.

[341] D. Watson. "Urban lifelines to achieve climate resiliency". In: *Growing Compact*. Routledge, 2017, pp. 51–63.

[342] E. Watt. "South Asia floods: 18,000 schools damaged and thousands of children may never go back". In: (Aug. 2017).

[343] D. L. Wells and K. J. Coppersmith. "New Empirical Relationships among Magnitude, Rupture Length, Rupture Width, Rupture Area, and Surface Displacement". In: *Bulletin of the Seismological Society of America* 84.4 (1994), pp. 974–1002. ISSN: 0037-1106. DOI: <p></p>.

[344] G. F. White. *Changes in urban occupance of flood plains in the United States*. Vol. 57. University of Chicago, 1958.

[345] R. White and G. Engelen. "Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns". In: *Environment and Planning A* 25.8 (1993), pp. 1175–1199. ISSN: 0308-518X. DOI: 10.1068/a251175.

[346] R. White, G. Engelen, and I. Uljee. *Modeling Cities and Regions as Complex Systems*. Cambridge, Massachusetts: MIT Press, 2015.

[347] A. Wicki and E. Parlow. "Multiple Regression Analysis for Unmixing of Surface Temperature Data in an Urban Environment". en. In: *Remote Sensing* 9.7 (July 2017), p. 684. DOI: 10.3390/rs9070684.

[348] W. Willett, J. Rockström, B. Loken, M. Springmann, T. Lang, S. Vermeulen, T. Garnett, D. Tilman, F. DeClerck, A. Wood, M. Jonell, M. Clark, L. J. Gordon, J. Fanzo, C. Hawkes, R. Zurayk, J. A. Rivera, W. De Vries, L. Majele Sibanda, A. Afshin, A. Chaudhary, M. Herrero, R. Agustina, F. Branca, A. Lartey, S. Fan, B. Crona, E. Fox, V. Bignet, M. Troell, T. Lindahl, S. Singh, S. E. Cornell, K. Srinath Reddy, S. Narain, S. Nishtar, and C. J. L. Murray. "Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems". In: *The Lancet* 393.10170 (Feb. 2019), pp. 447–492. ISSN: 0140-6736. DOI: 10.1016/S0140-6736(18)31788-4.

[349] P. R. D. Williams. *Applying Risk Analysis to Two Divisive Topics: Hydraulic Fracking and Marijuana Use*. 2015. DOI: 10.1111/risa.12420.

[350] S. Williams and F. Wang. "Disparities in accessibility of public high schools, in metropolitan Baton Rouge, Louisiana 1990–2010". In: *Urban Geogr.* 35.7 (2014), pp. 1066–1083.

[351] T. G. Williams, D. G. Brown, S. D. Guikema, and A. Agrawal. "Implications of equifinality: a framework for robust model-based policy analysis in complex socio-environmental systems". In: (forthcoming).

[352] T. G. Williams, T. M. Logan, C. T. Zuo, K. D. Liberman, and S. D. Guikema. "Parks and safety: a comparative study of green space access and its inequities in five US cities". In: (forthcoming).

[353] H. C. Winsemius, J. C. J. H. Aerts, L. P. H. van Beek, M. F. P. Bierkens, A. Bouwman, B. Jongman, J. C. J. Kwadijk, W. Ligtvoet, P. L. Lucas, D. P. van Vuuren, and P. J. Ward. "Global drivers of future river flood risk". en. In: *Nature climate change* 6.4 (Apr. 2016), pp. 381–385. ISSN: 1758-678X, 1758-6798. DOI: 10.1038/NCLIMATE2893.

[354] J. Winter and S. Farthing. "Coordinating facility provision and new housing development: impacts on car and local facility use". In: *Evaluating local environmental policy* 1 (1997), pp. 159–179.

[355] J. R. Wolch, J. Byrne, and J. P. Newell. "Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'". In: *Landsc. Urban Plan.* 125 (2014), pp. 234–244.

[356] J. Wolch, J. Wilson, and J. Fehrenbach. "Parks and Park Funding in Los Angeles: An Equity-Mapping Analysis". In: *Urban Geogr.* 26.February 2015 (2005), pp. 4–35.

[357] G. Z. Xian, C. G. Homer, J. Dewitz, J. Fry, N. Hossain, and J. Wickham. "Change of impervious surface area between 2001 and 2006 in the conterminous United States". In: *Photogrammetric Engineering and Remote Sensing* 77.8 (2011), pp. 758–762.

[358] N. Xu, S. D. Guikema, R. A. Davidson, L. K. Nozick, Z. Çağnan, and K. Vaziri. "Optimizing scheduling of post-earthquake electric power restoration tasks". In: *Earthquake engineering and structural dynamics* 36.2 (2007), pp. 265–284. ISSN: 0098-8847.

[359] A. Zautra, J. Hall, and K. Murray. "Community Development and Community Resilience: An Integrative Approach". In: *Community development* 39.3 (July 2008), pp. 130–147. ISSN: 1557-5330. DOI: 10.1080/15575330809489673.

[360] F. Zhao, L.-F. Chow, M.-T. Li, A. Gan, and I. Ubaka. "Forecasting Transit Walk Accessibility : A Regression Model Alternative to the Buffer Method". In: *Transportation Research Record: Journal of the Transportation Research Board* 1835 (2003), p. 16.

[361] G. Zhao, J. Dong, J. Liu, J. Zhai, Y. Cui, T. He, and X. Xiao. "Different Patterns in Daytime and Nighttime Thermal Effects of Urbanization in Beijing-Tianjin-Hebei Urban Agglomeration". en. In: *Remote Sensing* 9.2 (Feb. 2017), p. 121. DOI: 10.3390/rs9020121.

[362] D. Zhou, J. Xiao, S. Bonafoni, C. Berger, K. Deilami, Y. Zhou, S. Frolking, R. Yao, Z. Qiao, and J. A. Sobrino. "Satellite Remote Sensing of Surface Urban Heat Islands: Progress, Challenges, and Perspectives". en. In: *Remote Sensing* 11.1 (Dec. 2018), p. 48. DOI: 10.3390/rs11010048.

[363] D. Zhou, S. Zhao, S. Liu, L. Zhang, and C. Zhu. "Surface urban heat island in China's 32 major cities: Spatial patterns and drivers". In: *Remote sensing of environment* 152 (Sept. 2014), pp. 51–61. ISSN: 0034-4257. DOI: 10.1016/j.rse.2014.05.017.

[364] M. Zook, S. Barocas, D. Boyd, K. Crawford, E. Keller, S. P. Gangadharan, A. Goodman, R. Hollander, B. A. Koenig, J. Metcalf, A. Narayanan, A. Nelson, and F. Pasquale. "Ten simple rules for responsible big data research". en. In: *PLoS computational biology* 13.3 (Mar. 2017), e1005399. ISSN: 1553-734X, 1553-7358. DOI: 10.1371/journal.pcbi.1005399.