Spatio-Temporal Analysis of Terrorism Vulnerability: A Case Study of Central Tokyo, Japan

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Abstract

Terrorism has become and continues to be one of the biggest threats of our time. Large-scale attacks like 1995 in Tokyo, 2001 in New York City, Washington DC, and Pennsylvania, 2004 in Madrid, and 2005 in London are tragic proofs that this is especially true for highly urbanized areas all over the world. The more prevalent such terrorist attacks happen the more scientific papers are written about them. Yet, this increased number of scientific engagement has not lead to more detailed insights into the underpinnings of terrorism. Instead there are many complaints in the terrorism research community about a lack of quantitative data to corroborate the theories made by scholars from various engaged disciplines like the political sciences, psychology, peace and conflict studies, economy, engineering, urban planning, and also geography.

In this study I introduce methodologies for the spatio-temporal micro-scale analysis of terrorism vulnerability in highly urbanized areas to help overcome this limitation. The underlying conceptual framework is based on the selection of appropriate vulnerability factors, their operationalization in measurable real-world phenomena, the calculation of their spatial influence, and finally their weighted combination into an overall vulnerability index. I also present an exemplar application of this framework in a case study for an actual scenario in Tokyo, Japan. Furthermore I provide an interpretation of the empirical results of the case study, and finally discuss the usefulness of the framework and its operationalization as well as opportunities for possible further studies.

The Human Activity Based Vulnerability Concept I developed is based on the activities of people and how these shape the environment into places of different value to them. I argue that these values are what generates disasters from the threats to these places. This concept represents the theoretical foundation for the analysis framework, which consists of a number of components: multiple sources of “hard”, quantitative data, carefully selected vulnerability factors, the factors’ spatial influence, an important concept that allows for the analysis of the impact an object’s vulnerability has on its surroundings, and finally the factors’ weights among themselves.

In a case study for the central part of Tokyo, Japan, the Special 23 Wards, I show the application of the aforementioned framework in a real-world example. The vulnerability factors I employed in this case study are the stationary building population, the pedestrian volumes on the streets, the passenger volumes of train stations and trains, and the symbolic value of places. I used a number of micro-scale datasets to operationalize these vulnerability factors, among them population, employment, and school census data, train passenger volumes, building data, and

data of the road and railway networks of the study area. Furthermore, the inclusion of a micro-scale dataset of people's movements in 1-minute intervals allowed me to enrich the analysis by the introduction of the temporal dimension. In the course of the study I developed a number of novel methodologies for the quantification of vulnerability. These involve the spatio-temporal categorical estimation of building populations, the use of network analysis methods for the estimation of pedestrian flows, and the operationalization of the objects' spatial influence using kernel density estimation and a linear function of the weighted inverse distance.

To my best knowledge this is the first time that such an approach has been developed. It combines traditional terrorism research with a bottom-up vulnerability-based focus using spatially grounded analytic tools. The output of the model introduced here are micro-scale maps of the spatial distribution and agglomeration of vulnerability in highly urbanized areas. These can help with communicating the abstract concept of vulnerability to the broad public, and also provide the hitherto missing quantitative data about vulnerability, which can help governments, municipalities and other involved stakeholders in making educated decisions about the use of limited fundings for the mitigation of vulnerability and other counterterrorism measure.

The interpretation of the case study's empirical results revealed several interesting insights into the connection between the urban spatial structure of Central Tokyo and its terrorism vulnerability and the spatio-temporal constraints involved. First and foremost the commuting movements from the suburban belt into the city center lead to a dramatically higher overall day-time population. This results in larger areas of higher vulnerability during the day than at night. Over the course of the day clusters of highest vulnerability develop in areas with many large office buildings. Second, the concentrated morning commuting period has a strong impact on the vulnerability levels surrounding the railway transportation network. This effect together with the generally high building populations and pedestrian volumes around larger train station hubs create the overall highest vulnerability index values. Furthermore, the monocentric urban spatial structure of Tokyo manifests itself in the agglomeration of most of the places with high symbolic relevance on the one hand, and most of the office districts with high daytime populations on the other hand. Based on these observations the conclusions can be made that from a terrorist's perspective the most attractive location for an attack would be in the city center, preferably inside or near a major train station or near railway tracks. The most attractive time would be during the day, preferably the morning commute.

Keywords: GIS, micro-scale, spatial analysis, terrorism, Tokyo, urban areas, vulnerability

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AAG	Association of American Geographers
ADF	advanced digital file
AHP	Analytic Hierarchy Process
AMeDAS	Automated Meteorological Data Acquisition System
ANRE	Agency for Natural Resources and Energy
ANTEP	Anti-Terrorism Partnership Tokyo
ATM	automated teller machine
BBC	British Broadcasting Corporation
BOJ	Bank of Japan
CBRN	chemical, biological, radiological, nuclear
CRED	Centre for Research on the Epidemiology of Disasters
DHA	Department of Humanitarian Affairs
DHS	Department of Homeland Security
DoD	Department of Defense
EAAJAF	East Asia Anti Japanese Armed Front
ESRI	Environmental Systems Research Institute
Europol	European Police Office
FBI	Federal Bureau of Investigation
FDNY	New York Fire Department
FEMA	Federal Emergency Management Agency
GAO	General Accounting Office
GIS	Geographic Information Systems
GPO	Government Printing Office
GPS	Global Positioning System
GTD	Global Terrorism Database
IAEA	International Atomic Energy Agency
IC	integrated circuit
IEEE	Institute of Electrical and Electronics Engineers
IMTFE	International Military Tribunal for the Far East
IPCC	Intergovernmental Panel on Climate Change
JMA	Japan Meteorological Agency
JMSDF	Japan Marine Self-Defense Forces
JST	Japan Science and Technology Agency
KDE	kernel density estimation

MAFF	Ministry of Agriculture, Forestry and Fisheries
MEP	Mechanical/Electrical/Plumbing
METI	Ministry of Economy, Trade and Industry
MEXT	Ministry of Education, Culture, Sports, Science and Technology
MIC	Ministry of Internal Affairs and Communications
MIT	Massachusetts Institute of Technology
MLIT	Ministry of Land, Infrastructure, Transport and Tourism
MOD	Ministry of Defense
MOF	Ministry of Finance
MOFA	Ministry of Foreign Affairs
MOJ	Ministry of Justice
MPD	Metropolitan Police Department
NCC	National Counterterrorism Center
NGO	Non-governmental Institution
NPA	National Police Agency
NRC	National Research Council
NSTBCM	normalized spatio-temporal betweenness centrality measure
NYPD	New York Police Department
NYSE	New York Stock Exchange
OD	origin-destination
OECD	Organization for Economic Co-operation and Development
PAPD	Port Authority Police Department
PCCIP	President’s Commission on Critical Infrastructure Protection
PSIA	Public Security Intelligence Agency
RAF	German Red Army Faction
RCPS	Rutgers Center on Public Security
Rev.ACDT2011	2011 Revised Academic Consensus Definition of Terrorism
RTM	Risk Terrain Modeling
SI	spatial influence
START	National Consortium for the Study of Terrorism and Responses to Terrorism
TMG	Tokyo Metropolitan Government
TSE	Tokyo Stock Exchange
U.S.	United States

UASI	Urban Areas Security Initiative
UK	United Kingdom
UN	United Nations
UNA	Urban Network Analysis
UNDRO	United Nations Disaster Relief Office (now DHA)
UNISDR	United Nations International Strategy for Disaster Reduction
USA	United States of America
USGS	United States Geological Survey
WNA	World Nuclear Association

1 Introduction

On March 11th, 2011 one of the strongest earthquakes ever measured occurred off the coast of Japan and caused a tsunami that claimed more than 25,000 casualties[1] and caused multiple reactor core meltdowns and explosions at the Fukushima Dai-Ichi nuclear power plant which led to a release of more radioactive material than in the case of the reactor explosion 1986 in Chernobyl (Japan Meteorological Agency 2012; Ministry of Economy, Trade and Industry 2012; International Atomic Energy Agency 2011; von Hippel 2011). Six years earlier on the same day members of the *Abu Hafs al-Masri Brigades*, an Islamic extremist group associated with *al-Qaeda*, detonated ten bombs on crowded commuter trains in Madrid during the morning rush hour causing more than 2,000 casualties[2] (National Consortium for the Study of Terrorism and Responses to Terrorism 2013a; 2013b; 2013c; 2013d), and making this the worst terrorist attack in Europe since the 1988 bombing of PanAm flight 103 over Lockerbie, which killed 270 people (National Consortium for the Study of Terrorism and Responses to Terrorism 2013e). It is dramatic events like these that we keep in our minds for a long time, some of them will even stay with us for the rest of our lives, even though we are not directly affected by them.

I find this especially the case with terrorist attacks as compared to natural disasters. Almost everybody in the world remembers precisely where they have been and what they were doing when the attacks on September 11th, 2001 took place in New York, Washington, DC and Pennsylvania, more than twelve years ago at the time of writing. This can not necessarily be said for enormous natural disasters such as the tsunami following the Indian Ocean Earthquake in 2004, the Haiti Earthquake in 2010, or typhoon *Haiyan/Yolanda* over the Philippines and Vietnam in 2013, which are among the deadliest natural disasters of the past ten years at 230,000, and 227,898 people killed, respectively (United States Geological Survey 2013; 2010), each more than hundred times as many as the aforementioned attacks of September 11th. I believe that this is due to the fact that, while not directly physically affected by a terrorist attack, it can create a feeling of anxiousness and trigger thoughts like “could that have been me?” This creation of fear is what terrorists generally aim for, hence the name for this phenomenon from Latin *terrere*: to frighten. This anxiousness is rooted in the realization that, in contrast to natural disasters, terrorist attacks do not require certain physical preconditions to occur. Contemporary modern societies try hard to avoid these potential dangers, for example by not settling in flood-prone areas or by making buildings earthquake-resistant. Terrorism on the other hand has its foundation in willfully damaging that which is valued the highest by those under attack, that which we strive to establish instead of preventing it.

With this study I hope to be able to contribute in overcoming the scarcity of research and quantitative data about terrorism. I intend to do this by analyzing terrorism not using a risk-based, top-down approach, but instead a vulnerability-based, bottom-up approach. My main intent is to be able to identify and distinguish areas of low and high vulnerability to terrorism inside of highly urbanized cityscapes. To do this I refer to a number of vulnerability factors, their operationalizations as features in the real world and their characteristics as well as the influence they have on their surroundings. I start by defining and discussing key terms in Chapter 2 before presenting my research objectives in Chapter 3. In Chapter 4 I then develop and explain the main spatio-temporal analysis framework, which I apply to a case study of Tokyo, Japan in Chapter 5. I conclude the study by interpreting the results and discussing the frameworks usefulness and also its shortcomings in the final chapter.

In its Final Report the National Commission on Terrorist Attacks upon the United States wrote:

> The lesson of 9/11 for civilians and first responders can be stated simply: in the new age of terror, they—we—are the primary targets. The losses America suffered that day demonstrated both the gravity of the terrorist threat and the commensurate need to prepare ourselves to meet it. The first responders of today live in a world transformed by the attacks on 9/11. Because no one believes that every conceivable form of attack can be prevented, civilians and first responders will again find themselves on the front lines. We must plan for that eventuality. A rededication to preparedness is perhaps the best way to honor the memories of those we lost that day. (2004, 323)

2 Definition of Key Terms

Before explaining in detail what I am striving to accomplish with this research, I believe it is important to provide clear definitions of some of the core terms and principles I use throughout this study. There is a lot of discussion about the definitions of several of the terms I use, to the degree that the attempt to develop clear definitions seems to evolve as a self-contained field of research.

I start with the distinction between “terror” and “terrorism” and a detailed definition of what I regard as terrorism in the scope of this study. I then introduce the current research landscape about terrorism vulnerability analysis and also spatial terrorism analysis. In the following chapters I explain what I mean by “hazard” and “disaster” as well as “risk” and “vulnerability”, including their constituents “probability” and “loss” as well as “exposure”, “resistance”, “resilience” and “attractiveness”, respectively. In the course of the individual definitions I set forth how those components sculpt the overall disaster model I rely on in my research and also the Human Activity Based Vulnerability Concept I developed in the course of my research. I conclude the definitional part of this study by reviewing the current literature about the spatial analysis of vulnerability and focusing on the significance of vulnerability in urban areas.

2.1. Terrorism

2.1.1. Terror and Terrorism

There are as many varying definitions of “terror” and “terrorism” used in the public discussion as well as in the scientific literature as there is confusion about what this term actually denotes. A very extensive collection of definitions and their discussion can be found in Schmid (2011, 99–157), who summarized more than 250 definitions used by governments, alone 20 of these used by various departments within the United States government, in an academic context, and in the public discussion. As a result I regard it as imperative to clearly define what I refer to by “terror”, “terrorism”, and “terrorist attack” in the context of this study.

Simply put I understand “terror” as the mindset of fear among the victims that is created by “terrorism”, activities that exert terror on their victims (Schmid 2011, 41). Those activities are then called “terrorist attacks”. Wilkinson sums this up concisely: “Terrorism is not a philosophy or a movement. It is a method.” (Wilkinson 2011, 17)

But any serious discussion about terror and terrorism also requires a more detailed definition of what those two terms comprise. It is for example imperative to distinguish "terrorism" from similar concepts, such as "war" and also "crime". Kushner (2003, XXIII) identifies unpredictability and secrecy as the main differentiators between state terrorism on the one hand and war or violent law enforcement on the other. Wilkinson lists five characteristics of terrorism:

- It is premeditated and designed to create a climate of extreme fear;
- It is directed at a wider target than the immediate victims;
- It inherently involves attacks on random or symbolic targets, including civilians;
- It is considered by the society in which it occurs as 'extra-normal', that is in the literal sense that it violates the norms regulating disputes, protest and dissent; and
- It is used primarily, though not exclusively, to influence the political behaviour of governments, communities or specific social groups. (Wilkinson 2011, 4)

In my discussion of factors to operationalize the vulnerability to terrorism in Chapter 5.3 I return to some of the basic concepts formulated here, namely the targeting of a broad, civilian audience and the aim for widespread awareness.

More generally the United Nations Security Council established in its *Resolution 1566*

> that criminal acts, including against civilians, committed with the intent to cause death or serious bodily injury, or taking of hostages, with the purpose to provoke a state of terror in the general public or in a group of persons or particular persons, intimidate a population or compel a government or an international organization to do or to abstain from doing any act, which constitute offenses within the scope of and as defined in the international conventions and protocols relating to terrorism, are under no circumstances justifiable by considerations of a political, philosophical, ideological, racial, ethnic, religious or other similar nature. (United Nations Security Council 2004, 2)

Therein it follows the classification of terrorism being the activity that instills a state of terror in those under attack, and it also puts terrorist activities in the context of crime.

Several national governments also incorporated definitions of and legislation regarding terrorism and terrorist activities in their laws, such as the United States in the *United States Code* Title 22 Section 2656f(d) (U.S. Government Printing Office 2010), the United Kingdom in the *Terrorism Act 2000* Part 1, 1.(1)–(3) (The National Archives 2000), and Japan in the *Act on Punishment of the provision of funds etc. for criminal acts of intimidation etc. of the general public* Paragraph 1 (Ministry of Internal Affairs and Communications 2002).

Apart from the two main factors discussed hitherto there is a third dimension that helps to distinguish terrorism from other crimes, namely violence (Kushner 2003, XXIII) or more precisely the *modus operandi* of the perpetrators. Wilkinson (2011, 17) as well as the Federal Emergency Management Agency (FEMA) (2003a) and Willis (2005) provide lists of modes of attack that have either been used by terrorists in the past or should be considered to be potentially employed by terrorists in the future. Yet, the most comprehensive and methodologically arranged compilation is the one underlying the Global Terrorism Database (GTD) by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) as seen in 1. It separates the attack type from the weapon information, which allows for a more precise classification.

All these aspects considered in this study I am going along with Schmid's Revised Academic Consensus Definition of Terrorism (Rev.ACDT2011), which he developed in a tedious process from statements and assessments made by 91 subject matter experts from various academic fields:

> Terrorism refers on the one hand to a doctrine about the presumed effectiveness of a special form or tactic of fear generating, coercive political violence and, on the other hand, to a conspiratorial practice of calculated, demonstrative, direct violent action without legal or moral restraints, targeting mainly civilians and non-combatants, performed for its propagandistic and psychological effects on various audiences and conflict parties. […] At the origin of terrorism stands terror – instilled fear, dread, panic or mere anxiety – spread among those identifying, or sharing similarities, with the direct victims, generated by some of the modalities of the terrorist act – its shocking brutality, lack of discrimination, dramatic or symbolic quality and disregard of the rules of warfare and the rules of punishment. (Schmid 2011, 86)

2.1.2. Terrorism Vulnerability Analysis

The scientific literature on the analysis of vulnerability towards the threat of terrorism and terrorist attacks is significantly smaller than vulnerabilities of natural hazards (cf. Chapter 2.3.2). LaFree and colleagues cite the lack of available statistical data and its low quality as the reasons. They claim that this is a result of three serious limitations: extremely narrow definitions of terrorism in the data sources; definitions influenced by political considerations, since most of the data are collected by government entities; and the exclusion of information about domestic terrorism from all existing publicly available databases at the time of writing, even though it greatly outnumbers international terrorism (LaFree et al. 2006, 5). According to them this led to the fact that “the research literature on terrorism is dominated by books with relatively little statistical analysis” (2006, 4). I am trying to antagonize this lack of quantitative terrorism analysis with this study. Nevertheless a body of publications is available now, mostly published after the complaint by LaFree et al. and largely based on the data edited by them.

Laqueur states that

> war, even civil war, is predictable in many ways; it occurs in the light of day and there is no mystery about the identity of the participants. Even in civil war there are certain rules, whereas the characteristic features of terrorism are anonymity and the violation of established norms. (Laqueur 2001, 3)

Table 1: List of terrorist attack types and weapon information

Attack types	**Weapon information**
assassination	biological
hijacking	chemical
kidnapping	radiological
barricade incident	nuclear
bombing/explosion	firearms
armed assault	explosives/bombs/dynamite
unarmed assault	fake weapons
	incendiary
	melee
	vehicle
	sabotage equipment

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2012, 18–26)

I am convinced that this unpredictability is the best reason against the analysis of terrorism risk and for the analysis of terrorism vulnerability instead. In my definition of risk in Chapter 2.3.1 I include two components: loss and probability. The latter is very problematic in the context of terrorism. Since the occurrence probabilities of terrorist attacks are unknown, the risk for the threat of terrorism can not be determined in a meaningful and reliable fashion. A statement to this effect by Ezell and colleagues that

> while it is perhaps more difficult to spell out [probabilistic] conditions precisely in terrorism risk analysis, there is no fundamental difference in this type of conditioning compared to conditioning probability judgments in the case of natural or engineered systems (Ezell et al. 2010, 578)

was strongly refused by other researchers. Brown and Cox (2011) argue

> that this is importantly incorrect, and that […] calculations based on this idea can be highly misleading, rather than useful, for terrorism risk analysis. In particular, […] conditioning risk estimates on knowledge or beliefs about the future actions of others, who in turn may condition their preferences for alternative actions on what they know about our risk estimates, leads to new problems in terrorism risk analysis that cannot be solved well, if at all, by traditional [probabilistic risk assessment]. (2011, 196)

Tetlock (2005) follows a similar rationale in his monograph *Expert Political Judgement: How Good Is It? How Can We Know?* On a more statistical note Clauset and Woodard show the difficulties in accurately estimating the probability of terrorist attacks due to the "large fluctuations in the [occurrence frequency] distribution's upper tail, precisely where we wish to have the most accuracy" (Clauset and Woodard 2012, 1), and Sandler and Enders (2007) elucidate on the difficulties and shortcomings of applying statistical methods on the forecasting of terrorist attacks.

In comparison to the large body of research about vulnerabilities to natural hazards, which I discuss in Chapter 2.3.2, there is a scarcity of specifically vulnerability-centered research about terrorism vulnerability. That is even more so in the social sciences. The application of the concept of social vulnerability, which I introduce in Chapter 2.3.2, is to my best knowledge and after thorough literature research so far mostly untrodden territory in the realm of terrorism research.

There are several studies on the vulnerability of critical infrastructures and other lifelines to the threat of terrorism. Especially a group of researchers at the Engineering Systems Division and Department of Nuclear Science and Engineering at the Massachusetts Institute of Technology (MIT) has published a number of papers about the vulnerability of infrastructures (Apostolakis and Lemon 2005; Lemon 2004; Michaud 2005; Patterson and Apostolakis 2007) and nuclear power plants (Holt and Andrews 2007; Weil and Apostolakis 2001), as did other authors (Davis et al. 2006; Haimes and Longstaff 2002; Hewitt 2002; Wilson 2007) and also several governmental institutions (Department of Defense 2007; Department of Homeland Security 2007; Federal Emergency Management Agency 2003a; 2003b; 2003c; 2004; 2009; National Research Council 2002). Yet, all these analyses focus exclusively on an engineering perspective in the identification of vulnerabilities, disregarding the humans and social systems involved. Notable exceptions are the papers by Piegorsch et al. (2007) and only recently Perry (2013) who attempt to focus on the social aspects of vulnerability to terrorism.

2.1.3. Spatial Terrorism Analysis

Laqueur (2001, 5) mentions among his six “main features of contemporary terrorism” that terrorism can occur anywhere. While this statement cannot be dismissed, data about the locations of past terrorist attacks show unmistakably that they occur more often in some locations than in others. Hence, a spatial analysis of this fact and the underlying processes should be a matter of course. While Reid and Chen did not include any publications about geographical terrorism research in their “systematic view of terrorism research” (2007, 42)[3], a number of authors have concentrated on this aspect of terrorism.

The anthology *The geographical dimensions of terrorism* by Cutter (2003) is widely regarded as the starting point of engagement with the topic of terrorism in the spatial and geographical sciences. It not only summarized the level of knowledge at that point in time, but also helped to develop the map for future directions of geographical terrorism research. It is also one of the books that sparked the idea for the research I cover in this study.

It should be mentioned, though, that some researchers had published geographic terrorism-related analyses before that. Savitch and Ardashev (2001) are to my best knowledge the first to analyze the social characteristics and target-proneness of cities and compare the past occurrences of terrorist attacks there. Wisner (2002) asked in a panel presentation at the Annual Meeting of the Association of American Geographers (AAG) *Is There a Geographical Theory of Terror?*, reflecting on the multi-faceted past of terrorism research and the role geography could play in this field. It was this panel that formed the group of researchers whose work culminated in the publication of the aforementioned primer in 2003.

In the same year Flint made a statement for a stronger engagement of political geography in the peace and conflict studies. He identified three intersections of geography and terrorist studies:

> The importance of geohistorical context in understanding the causes of contemporary terrorism […]; the spatiality of terrorist networks; and […] the potentially negative efficacy of existing counterterrorist policies given the interaction of terrorist networks and state sovereignty. (Flint 2003, 161)

Mustafa similarly complains that the field of terrorism had so far mostly been covered by non-geographical studies, while geographical hazard studies only focused on natural disasters. He emphasizes that “terrorism is a deeply geographical phenomenon with potentially disastrous consequences for international peace” (Mustafa 2005, 72) and that “terrorism is a phenomenon intricately tied to the concept of place” (2005, 79).

Braithwaite and Li (2007) analyzed transnational terrorism hotspots at the country level. They did this on a worldwide scale to extend the existing literature which only focused on the distribution and diffusion of terrorism among aggregate regions such as Europe and the Middle East. Also, for the first time they facilitated localized spatial statistics, such as local Moran's I, local Geary's C, and Getis and Ord's G_i and G_i^*, to study terrorist violence. Doing so they were able to “identify countries that are located within neighborhoods that are hot spots of terrorist attacks and assess empirically the impact of these hot spots on the countries' subsequent experiences of terrorist incidents.” (Braithwaite and Li 2007, 296)

Piegorsch and colleagues resort to the social vulnerability indices developed in earlier studies (Borden et al. 2007; Cutter, Boruff, and Shirley 2003) which I also introduce in Chapter 2.3.2 in the context of vulnerability to natural disasters. They used it together with historic data from terrorism databases, such as the aforementioned GTD, as a “quantitative methodology to characterize the vulnerability of U.S. urban centers to terrorist attack” (Piegorsch, Cutter, and Hardisty 2007, 1411).

Patterson and Apostolakis (2007) used spatial analysis to derive what they call the “geographic valued worth” of elements within an infrastructure system to determine its vulnerability to terrorism. They do this by assigning them importance measures based on network analysis after deriving the disutility of the loss of each infrastructure's resource (e.g. gas, water, electricity). The geographical aspect of their work lies in the spatial interdependencies of various infrastructural systems, which can enable a perpetrator to affect multiple systems with just one attack in a carefully selected location.

Smith et al. analyzed the activities of terrorists, specifically international and environmental terrorists, spatially and tried to identify spatial and temporal patterns of their pre-incident behavior. These pre-incident activities include criminal acts in the preparation of the actual terrorist attack:

> The spatial analysis from which relationships and patterns can be derived consists of the measurement of the linear distance between points that represent terrorist activities, residences, and the location of the terrorism incident itself. (Smith et al. 2008, 40)

Their analyses provide interesting insights into the spatial and temporal patterns of said behavior.

Rusnak and colleagues (2012) provide a case study of the analysis of terrorism using spatial techniques in cities in Turkey. They developed location quotients to determine how terrorism risk in an area compared to its surroundings in order to assess the relative risk of particular geographic locations. The terrorism risk is operationalized in three dimensions: attractiveness (using the number of assembly members and number of mosques), infrastructure (using socioeconomic development, net trade, city development, and population), and crime (using the number of murder convictions). Doing so they could show "that terrorist incidents within Turkey are not randomly distributed throughout the landscape but rather are concentrated in a statistically significant way among certain high risk cities." (Rusnak et al. 2012, 179)

LaFree and Bersani (2012) analyzed the data from the GTD in multiple ways to answer questions about the geographic concentration of terrorist attacks, the correlation between ordinary crime and terrorism, and whether it is possible to predict terrorist attacks using the traditional predictors of ordinary crime. According to their findings, within the United States terrorism and ordinary crime often occur in the same areas and can partly be predicted by some traditional predictors of ordinary crime. Yet, they conclude that "more work needs to be done to fully understand the relationship between language diversity and terrorism and ordinary crime" (LaFree and Bersani 2012, 28).

Perry and colleagues (2013) focused on the prediction of suicide bombing locations in four Israeli cities using geospatial methods and assessed the benefits of including sociocultural, economic, and political factors in the calculations. While the socioeconomic and demographic factors analyzed are very similar to those employed in the development of the social vulnerability index by Borden et al. (2007), the researchers here also included electoral data, to include political leanings of the inhabitants of certain areas, and sociocultural precipitants, which put terrorist activities in the temporal context of religious holidays or political events (e.g. negotiations or high-profile meetings). Also, an added insight was provided by including the spatial characteristics of terrorists' safe houses, their spatial distribution, agglomerations and distances from each other. Their study shows that

> socioeconomic, demographic, and political data not only have statistically significant relationships with the odds of attack within specific neighborhoods but also explain unique variances in the risk of attack over and above geospatial predictors. (Perry et al. 2013, 53)

Furthermore a notable association between driving distances to terrorist safe houses and attack probability and a robust relationship between the attack frequency and some of the sociocultural precipitants could be proven.

Yet, similar to the studies about the spatial analysis of vulnerability to natural hazards I present in 3 the analyses here are using rather coarse spatial resolutions. Braithwaite and Li (2007) analyze on a country basis, Piegorsch et al. (2007) use cities in the United States, Rusnak et al. (2012) Turkish cities as their spatial unit of reference. Perry et al. (2013) use a meso-scale of statistical areas as defined by the Israeli Central Bureau of Statistics.

I believe that an analysis of terrorism vulnerability on a micro-scale can provide further insight into the spatial distribution of the phenomenon within highly urbanized areas and can also help policy makers and stakeholders to channel mitigation funds more efficiently. This is one of the major motivations for this study.

2.2. Hazard and Disaster

2.2.1. Hazard

A problem in the scientific literature is the definition of the terms “hazard” and “disaster”. Many different definitions and differentiations exist among authors, yet oftentimes they are not clearly defined at all and sometimes even used interchangeably within one publication (Kaplan and Garrick 1981). Since there is no universally accepted definition of those two terms that I could employ, I can ultimately only contribute to the confusion. Hence I believe it is important to provide a clear definition of what I mean by “hazard” and “disaster” in the context of this study. Those two terms are closely related to the two terms “risk” and “vulnerability”, which I talk about in the following chapter.

Yet, before providing a differentiation between “hazard” and “disaster” I would like to introduce another term, namely “threat”. I use it as a synonym for “hazard”. Borden and colleagues, while focusing on natural disasters, define a hazard as “the potential threat from an environmental process, such as a hurricane, tornado, or earthquake” (Borden et al. 2007, 1) and follow this synonymous use of the two terms. Similarly, Cutter defines hazard as “threat to people and the things they value” (Cutter 2001, 2) and Garrick and colleagues, in the context of terrorism, describe it as “the potential intent to cause harm or damage to a system by adversely changing its state” (Garrick et al. 2004, 131). All authors refer to the categories of adverse events (cf. Table 2) that can occur due to certain triggers. Examples are the hazard of an earthquake as a result of the movements of tectonic plates, and the threat of a terrorist attack due to the activities of a group in the pursuance of their political goals.

In my understanding every hazard or threat can cause a disaster. Conversely, each disaster is the materialization of a hazard. Yet not every hazard has to ultimately result in a disaster. Cannon goes along the same lines when he emphasizes the difference between hazards and disasters in the context of his thoughts about whether disasters can be natural in the first place, or whether all disasters are fundamentally caused by human actions: “The hazard is natural; a disastrous outcome is not, and is in many senses largely caused by the vulnerability conditions generated by human systems” (Cannon 1994, 20). While it might be disputable whether the cause of a certain disaster was natural or human-induced (Adger 2006; Cutter 2001; Cannon 1994; World Bank and United Nations 2010), the underlying hazards can generally be assigned to either group. 2 lists a variety of hazards for each category.

One of the most widely accepted and used definitions is that by the United Nations International Strategy for Disaster Reduction (UNISDR) which defines a hazard as

> dangerous phenomenon, substance, human activity or condition that *may* cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage. (United Nations International Strategy for Disaster Reduction 2009, 9, emphasis added)

In this study I follow this definition, by putting a main focus on the word “may”. It implies the possible negative outcome of the materialization of the hazard or threat, which is then defined as a disaster.

2.2.2. Disaster

The Centre for Research on the Epidemiology of Disasters (CRED) defines a disaster as “an unforeseen and often sudden event that causes great damage, destruction and human suffering” (Guha-Sapir, Hoyois, and Below 2013, 7). Whether such a hazardous event will have a disastrous outcome or not is a function of many hazard-related factors: its nature (cf. 2), the scale or magnitude of the hazard, the place, and the time and duration of its occurrence (Gravley 2001, 4). Borden and colleagues also observed that

> variability in natural hazards […] is largely based on site, situation, and the social geography of these places. Spatial differences in these characteristics give rise to vulnerabilities to environmental threats as well as variations in the resilience or the ability to respond and recover from them. (Borden et al. 2007, 1)

Table 2: List of natural and anthropogenic disasters

Natural hazards	Anthropogenic hazards
earthquake	crime
tsunami	war
volcano eruption	terrorist attack
meteorite impact	car accident
tropical cyclone	plane crash
tornado	train derailment
thunderstorm	naval accident
blizzard	fire
heavy snowfall	explosion
avalanche	mining accident
hail	structural collapse
torrential rain	power outage
drought	release of poisonous substance
heatwave	release of biological agent
bushfire, forest fire	release of radioactive material
landslide	
soil liquefaction	
flooding	
epidemic disease	

A small magnitude earthquake for example will most likely not cause a disaster, whereas an M_W 9 (Richter scale) earthquake will. Yet, a M_W 7.0 earthquake caused a major disaster in Haiti in January 2010 (Hayes et al. 2010; United States Geological Survey 2010) while a M_W 7.1 earthquake off Japan in August 2009 caused no significant damage (United States Geological Survey 2009). The reasons are to be found in the different locations (ca. 170 km off-coast and 297 km deep in Japan, while only ca. 25 km from the capital Port-au-Prince and 13 km deep in Haiti) and the different vulnerabilities, both social and in terms of engineering, of Haiti and Japan against earthquakes of such a magnitude. While both these examples and the aforementioned definitions refer to natural hazards, I claim that the same is true for non-natural hazards as well.

Once again I follow the widely accepted definition by the UNISDR in this study. It describes a disaster as "serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources." (United Nations International Strategy for Disaster Reduction 2009, 9)

In summary, my definitions of "hazard" and "disaster" follow the underlying UNISDR concept of a hazard being a *potential danger or threat*, whereas a disaster is the manifestation of this hazard in the form of a *negative event happening*. As shown above this also goes along the lines of a number of scientific publications.

2.3. Risk and Vulnerability

2.3.1. Risk

Equally unclear and disputed as the distinction between "hazard" and "disaster" is the terminology of "risk" and "vulnerability" in the scientific literature. In fact the term "risk" is used in a broad range of disciplines, and can carry a variety of meanings (Kaplan and Garrick 1981; Bankoff, Frerks, and Hilhorst 2004). Originally coined in an engineering context the term has taken on a multitude of meanings once used in different scientific realms, such as the social sciences, political sciences, economic sciences, etc. (Bouchon 2006, 61). In the hazard and disaster context the connotation is exclusively negative (Adger 2006; Bouchon 2006; Kaplan and Garrick 1981).The UNISDR, on which I relied heavily in my description of hazards and disasters, defines risk as "combination of the probability of an event and its negative consequences" (United Nations International Strategy for Disaster Reduction 2009, 25) Furthermore, two distinctive connotations are pointed out:

> In popular usage the emphasis is usually placed on the concept of chance or possibility, such as in 'the risk of an accident'; whereas in technical settings the emphasis is usually placed on the consequences, in terms of 'potential losses' for some particular cause, place and period. (United Nations International Strategy for Disaster Reduction 2009, 25)

Probability

Many authors focus primarily on the probabilistic aspect of risk. For example Burby (1991) states that every risk implies the possibility of suffering a loss, and Borden and colleagues define risk as "a measure of the probability a hazard event will occur and adversely affect a population" (Borden et al. 2007, 1). Yet, oftentimes these probabilities are unknown or at least difficult to estimate (Apostolakis 2004). Kaplan and Garrick (1981) point out that this discussion involves the use of many different terms such as "frequency", and "uncertainty" whose meanings themselves are sometimes not even clearly separated.

The former is a mere equivalent to "probability", yet from another perspective: While probability gives information about how likely something is going to happen (e.g. "A fair dice has a 1/6 or 0.17% probability of rolling a 6."), frequency indicates how often is is going to happen within a certain timeframe (e.g. "A once-in-a-hundred-years event.").

Uncertainty, on the other hand, describes a state of being unclear about something, at least partly, which De Morgan wrote about in his fundamental 19th century monograph *Formal Logic*:

> We have lower grades of knowledge, which we usually call degrees of belief but they are really degrees of knowledge. […] It may seem a strange thing to treat *knowledge* as a magnitude, in the same manner as length, or weight, or surface. This is what all writers do who treat of probability, and what all their readers have done, long before they ever saw a book on the subject. […] By degree of probability we really mean, or ought to mean, degree of belief. […] Probability then, refers to and implies belief, more or less, and belief is but another name for imperfect knowledge, or it may be, expresses the mind in a state of imperfect knowledge. (De Morgan 1847, 172ff, emphasis in original)

These beliefs about probabilities can lead to the underestimation of a threat or its dimensions, and hence be one of the reasons for a hazardous event to cause a disaster. One example is the enormous tsunami—the estimations range from at least 9 m (Japan Meteorological Agency 2012) to 14 m (World Nuclear Association 2011)—that was triggered by a M_W 9 (Richter scale) earthquake off the coast of Japan (Japan Meteorological Agency 2012; United States Geological Survey 2011) and led—amongst other widespread destruction—to severe damage and ultimately a double nuclear meltdown at the Fukushima Dai-Ichi nuclear power plant (International Atomic Energy Agency 2011; Institute of Electrical and Electronics Engineers 2011; OECD Nuclear Energy Agency 2012). The power plant was equipped with protective measures, yet these were not built to withstand a tsunami of such height and strength, since it was not believed an event like that could occur (World Nuclear Association 2011). Another example is the terrorist attacks of September 11th, 2001, which could only be executed in that dimension because of the use of commercial airplanes as weapons. No countermeasure to prevent an attack like that was in place, since it had not been deemed plausible before (Garrick et al. 2004; Savitch and Ardashev 2001). Conversely, these uncertainties can also have the opposite effect and lead to an overprotective state of mind which can be perceived as limiting and restricting personal freedoms (Jenkins 2011; Wilkinson 2011, 75ff).

Especially in the case of large-scale disasters the occurrence probabilities are extremely small. In some cases they cannot be calculated or estimated at all due to non-existing or insufficient data on past events. This is especially the case for those anthropogenic hazards with an underlying malignant intention, i.e. crime and terrorist attacks. Here it is often more meaningful to resort to the attractiveness of a possible target towards the realization of a perpetrator's aims to draw conclusions about the likelihood of an attack (Federal Emergency Management Agency 2009, 2). I explain this approach in more detail in Chapter 2.3.2.

Willis differentiates two types of uncertainty. The first is due to the aforementioned problems introduced by the variability and error in the estimates of the seriousness of a threat and its vulnerabilities:

> Exact knowledge of the threat would require comprehensive intelligence on the plans and capabilities of all terrorist groups. Since this level of precision is not feasible, expert judgments must be substituted for fact, resulting in parameter estimates for threats that are subject to uncertainty or frank disagreements. (Willis 2005, 13)

The second is related to the values attacked by the perpetrators. They may not only be regarded differently by different evaluations, but are generally hard to put into monetary terms (e.g. the “cost” of dead versus injured victims):

> Because this requires value judgments—and potentially contentious ones—it must ultimately be discussed by the public and policymakers. Part of an informed discussion of this judgment rests on an understandable and transparent illustration of the consequences of using alternative values. (Willis 2005, 14)

In his analysis of developments within terrorism and terrorist activities, Jenkins also points out how the missing information and data about the occurrence frequencies and likelihood of terrorist attacks inevitably hamper any risk-focused, probability-based terrorism analysis or prediction of possible future attacks:

> Whereas traditional threat-based analysis assessed an enemy’s intentions and capabilities, today’s vulnerability-based analysis identifies a weakness and hypothesizes a terrorist and a worst-case scenario. Vulnerability analysis is useful for assessing consequences and preparedness, but it relegates the terrorist to a secondary role: the scenario is driven by the vulnerability. Often, such a scenario is reified and becomes a threat: it is successively

> considered possible, probable, inevitable, and imminent. In vulnerability-based assessment, consequences trump likelihood. (Jenkins 2006, 120)

Loss

Coburn and colleagues refer to the definition by the United Nations Disaster Relief Office (UNDRO) (1979) when they postulate that “risk refers to the expected losses from a given hazard to a given element at risk, over a specified future time period” (Coburn, Spence, and Pomonis 1994, 10), thereby focusing strongly on the losses related to a risk.

When talking about those negative outcome of an event two categories of losses have to be taken into account: pecuniary and non-pecuniary. The former describes the damage to buildings, infrastructures and machinery, necessary repairs and rebuilds, business interruption, and litigation, which can be enumerated in economical terms. Opposed to that, the latter describes the deaths and injuries of humans, damage to the ecosystem, and other “social costs” (Cohen 2010). Li et al. (2009, 439) use the terms “structural loss” and “nonstructural loss” to describe the same circumstances and also point out that the latter is oftentimes greater than the former.

Other authors identified more diverse factors that define risk. For example Chapman (1999) understands it as function of the probability of a certain (natural) hazard event on the one hand, and vulnerability of cultural entities on the other hand. These authors specifically pointed out the importance of vulnerability to determine risk in the context of hazards and disasters (Cannon 1994).

2.3.2. Vulnerability

Historically the majority of academic work dealt with risk analysis and risk assessment, while vulnerability-focused endeavors appeared only relatively recently. Cutter (2001, 5ff) provides a very broad overview of the development from the so-called *Hazards Paradigm*, which was initialized by Barrows (1923) and later formalized by White (1986) and by the National Research Council (1983). It was also enhanced by the human adjustment to the natural hazards model (Kates 1971) and to the environmental extremes model (Mileti 1980) and ultimately summarized by White (1994) in multiple comparative case studies. It was only in the mid-90s of the past century that researchers started to consider hazards in their social and political contexts and to emphasize the importance of vulnerability-based hazards studies (Hewitt 1997; Kasperson, Kasperson, and Turner 1995; Wisner et al. 2003).

Many different definitions and understandings of “vulnerability” have been coined over time (Adger 2006; Cutter 2001; Cutter 1996, 351–532; Cutter, Boruff, and Shirley 2003; Dow 1992;

Mileti 1999), which makes a clear definition for the use within this study imperative. In my understanding risk and vulnerability are two components of any hazard. I regard risk as the active component of a hazard, as risk comprises all dimensions that are directly related to the hazard and its resulting disaster. Vulnerability on the other hand has a more passive character in that it describes the characteristics of those assets (humans, built-up structures, and services) that represent certain values to those affected by the disaster. This definition of vulnerability as passive component also enables me to establish the hypotheses as proposed in Chapter 3.2 and to go forward in the operationalization of “vulnerability” as I do in Chapter 5.3.

Several publications use the term “susceptibility” to describe just one component of vulnerability, with “disutility” being the other (Apostolakis and Lemon 2005; Karydas and Gifun 2006; Lemon 2004; Michaud 2005; Patterson and Apostolakis 2007; Weil and Apostolakis 2001). This connotation of disutility is rooted in the perceived value of an object and the negative consequences its defect or missing would have on the overall system under analysis. This goes along the lines of Kaplan and Garrick when they write: “Thus risk is relative to the observer. It is a subjective thing – it depends upon who is looking. Some writers refer to this fact by using the phrase 'perceived risk.'” (Kaplan and Garrick 1981, 12) Kasperson and Kasperson (2005a, 204) similarly point out that vulnerability may be differently perceived by the vulnerable themselves. Yet, as I explain in more detail in Chapter 2.3.1 I consider this perception to be a part of the loss a disaster causes, and thereby a part of the risk component of the underlying threat.

I am using the terms “vulnerability” and “susceptibility” synonymous in this study. This follows the idea underlying the widely accepted definition of vulnerability by the Intergovernmental Panel on Climate Change (IPCC) as “the extent to which a natural or social system is susceptible to sustaining damage” (2001, 89). The aforementioned passive nature of vulnerability is also reflected in the definition by the UNISDR which describes it as “characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard” (United Nations International Strategy for Disaster Reduction 2009, 30). It emphasizes the susceptibility aspect but also mentions that vulnerability is affected by “various physical, social, economic, and environmental factors” (2009, 30).

Similarly Borden et al. (2007) focus on susceptibility as a central component when they refer to vulnerability as “the susceptibility to harm from the risk posed by hazard events at a particular location as well as the potential for social disruption from such events.” (Borden et al. 2007, 1) Equally, Cannon understands vulnerability as

> a characteristic of individuals and groups of people who inhabit a given natural, social and economic space, within which they are differentiated according to their varying position in society into more or less vulnerable individuals and groups. (Cannon 1994, 19)

Both definitions also emphasize the passive nature of vulnerability in the description of a hazard.

This passive nature of vulnerability is a focus of O'Brien et al. (2004) who discuss different perspectives on and interpretations of the term “vulnerability”. One is what Kelly and Adger refer to as “*end point* of a sequence of analyses beginning with projections of future […] trends, moving on to the development of […] scenarios, thence to […] impact studies and the identification of adaptive options.” (2000, 327, emphasis added)A second considers “vulnerability as a *starting point* for analysis. Rather than being defined by future climate change scenarios and anticipated adaptations, vulnerability represents a present inability to cope with external pressures or changes […]. Here, vulnerability is considered a characteristic of social and ecological systems that is generated by multiple factors and processes.” (O’Brien, Eriksen, et al. 2004, 2, emphasis added) It is this definition of “contextual vulnerability” (Adger 2006, 270) that I am referring to in this study.

All aforementioned definitions go along with the “social vulnerability” that has often been referred to in the realm of vulnerability research (Cutter 2001; Borden et al. 2007; Cutter 1996; Cutter, Boruff, and Shirley 2003; Cutter, Mitchell, and Scott 2000; Eakin and Luers 2006; Kasperson and Kasperson 2005b; Kelly and Adger 2000; Luers et al. 2003; O’Brien, Sygna, and Haugen 2004; O’Brien, Leichenko, et al. 2004; Piegorsch, Cutter, and Hardisty 2007; Turner et al. 2003; Uitto 1998; Wisner et al. 2003). It describes both social inequalities, such as poverty, age, gender, and race; and place inequalities (see Chapter 2.3.4) such as the level of urbanization, growth rates, and economic vitality (Cutter, Boruff, and Shirley 2003, 243) and is rooted in three main theorems of vulnerability research, that Cutter et al. (2003, 242f) itemize:

- the identification of conditions that make people or places vulnerable to extreme natural events, an exposure model (Anderson 2000; Burton, Kates, and White 1993)
- the assumption that vulnerability is a social condition, a measure of societal resistance or resilience to hazards (Hewitt 1997; Wisner et al. 2003)
- the integration of potential exposures and societal resilience with a specific focus on particular places or regions (Cutter, Mitchell, and Scott 2000; Kasperson, Kasperson, and Turner 1995)

Those definitions help to identify the three components of vulnerability that define the susceptibility: exposure, resistance, and resilience. Cannon (1994, 19) and Adger (2006, 270) also identified those three main components.

In the context of infrastructural systems Kröger and colleagues define vulnerability as

> flaw or weakness (inherent characteristic, including resilience capacity) in the design, implementation, operation, and/or management of an infrastructure system, or its elements, that renders it susceptible to destruction or incapacitation when exposed to a hazard or threat, or reduces its capacity to resume new stable conditions. (Kröger, Zio, and Schläpfer 2011, 5)

Again the two components of susceptibility and disutility can be found, although Kröger et al. follow the terminology used by Bouchon (2006, 65) who identified three underlying elements: loss and damage, the degree of exposure, and the degree of resilience.

Except the textbook by Kröger et al. (2011) all scientific works cited above are dealing explicitly with natural hazards and the resulting natural disasters. In this study I apply the same concepts to all kinds of objects in their spatial context: humans, buildings, and infrastructures. In Chapter 2.1 I specifically concentrate on the threat of terrorism and the vulnerability of humans towards terrorist attacks. There I also explain the differences between natural hazards and terrorism and the implications this has on the analysis of terrorist attacks. One of the peculiarities of crime and terrorism as opposed to natural and even other human-induced disasters is the underlying malignancy of the perpetrators, which introduces another dimension of vulnerability: that of target attractiveness, a central topic of this study.

Before going on to briefly explain these four components I want to mention an issue pointed out by Bouchon (2006, 60). She remarks that the need for educated decisions regarding the prioritization of grants and loans to developing countries has lead to a bias of scientific papers about vulnerabilities in these countries. The consequence is a dearth of scientific work about vulnerabilities in developing and developed countries. With this study I am trying to fill this gap, by analyzing the vulnerabilities in a highly developed country, namely Japan, and more specifically one of the most highly urbanized areas of the world, the capital Tokyo (cf. Chapter 5.2.1).

Exposure

Adger (2006, 270) describes exposure as "the nature and degree to which a system experiences environmental or socio-political stress" and also points out that these are closely related to the characteristics of hazard or threat under consideration (Burton, Kates, and White 1993; Gravley 2001). Definitions such as Cutter (1996) and Cutter et al. (2003) who regard exposure as the only aspect of vulnerability appear short-sighted, since they neglect the inherent mechanisms of the affected environmental or social systems to cope with the disaster, their "resistance", and to recover from its negative impacts, their "resilience". Adger also points out that "vulnerability is a dynamic phenomenon […] since the biophysical and social processes that shape local conditions [i.e. the exposure] and the ability to cope [i.e. the resistance] are themselves dynamic." (Adger 2006, 274)

I argue that the dynamic of exposure toward a certain hazard is not only temporal in nature, but also spatial. In the definition of exposure within this study I once again follow the UNISDR, which describes it as “people, property, systems, or other elements present in hazard zones that are thereby subject to potential losses” (United Nations International Strategy for Disaster Reduction 2009, 15) In my operationalization (see Chapter 5.3) I also rely on the measures suggested by the UNISDR, namely the number of people and the types of assets in an area(2009, 15).

Resistance

What I call “resistance” in the scope of this study has also been labelled by many other terms in the hazards literature. The IPCC speaks of “sensitivity” when referring to “the degree to which a system will respond to a given change in climate, including beneficial and harmful effects” (Intergovernmental Panel on Climate Change 2001, 89). Adger goes along the same lines when defining it as “the degree to which a system is modified or affected by perturbations” (2006, 270). Both definitions focus on the *ex post*, i.e. changes a system will undergo as a result of the exposure to a disaster.

Both sources also mention the “adaptive capacity”, which Adger defines as “the ability of a system to evolve in order to accommodate environmental hazards or policy change and to expand the range of variability with which it can cope” (2006, 270), while the IPCC speaks of “the degree to which adjustments in practices, processes, or structures can moderate or offset the potential for damage or take advantage of opportunities created by a given change in climate” (Intergovernmental Panel on Climate Change 2001, 89). Here the focus is on the *ex ante*, i.e. the preparedness of a system towards a disaster.

In addition I also feel the need for the inclusion of a more engineering-related dimension of resistance, i.e. the actual structural resistance of an object (e.g. a building, a human, or a lifeline) towards a certain stress, inflicted by a disaster. The FEMA discusses these topics in great detail, especially in regard to the threat of terrorist attacks (Federal Emergency Management Agency 2003a; 2003b; 2004; 2009).

My understanding of resistance contains all three aspects, the preparedness prior to the disaster, the response afterwards, and the engineering dimension. I therefore define it as the degree to which social structure and engineering guidelines can lower the potential for damage and improve the results of the outcome of a disaster.

Resilience

"Resilience" is defined by the UNISDR as

> the ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions. […] The resilience of a community in respect to potential hazard events is determined by the degree to which the community has the necessary resources and is capable of organizing itself both prior to and during times of need. (United Nations International Strategy for Disaster Reduction 2009, 24)

This interpretation aims on the main aspect of restoring the status of a system to that prior to the disaster impact. It overlaps to a certain degree with "response", which UNISDR defines as

> the provision of emergency services and public assistance during or immediately after a disaster in order to save lives, reduce health impacts, ensure public safety and meet the basic subsistence needs of the people affected. (United Nations International Strategy for Disaster Reduction 2009, 24–25)

The focus here is more on the immediate response, whereas resilience relates more general to the post-disaster recovery process.

Bouchon lists three interpretations of resilience from different scientific fields: in physics and engineering resilience refers to the physical property of a material to return to its original shape after deformation; in psychology it is used to describe the ability of people to cope with stress and catastrophes; and in business terms resilience denotes the ability of an organization to sustain the impact of a business interruption and to resume operation (Bouchon 2006, 69).

In the scope of this study I understand resilience, following closely the UNISDR definition above, as the degree to which a social system and its components (humans, built-up structures, processes) can be restored from the negative impact of a disaster in a short amount of time.

Attractiveness

Natural disasters follow the laws of nature, in their type, location, magnitude and frequency. For example, earthquakes are more likely to occur and generally stronger in tectonically active regions, whereas tropical cyclones are more frequent and stronger in the regions 20 degrees north and south of the equator (Henderson-Sellers et al. 1998, 21). Also, natural hazards possess no inherent malignancy, which makes them aim specifically at vulnerable populations or areas. The mechanisms that cause them are generally well understood and operationalized, which makes most of them predictable to a certain degree (Burton, Kates, and White 1993, 30ff).

The same can not be said for crime and terrorism on the other hand. Acts of crime are mostly the result of a decision making process (McCormick 2003) that aims at the maximum possible outcome at the minimum necessary investment, both in terms of material value and risk (Ayyub, McGill, and Kaminskiy 2007). One possible target might be more attractive to a certain terrorist than another target, due to its characteristics, e.g. easier accessibility or a lower level of security measures in place (Li et al. 2009; NRC 2002; Özer and Akbaş 2011; Perry et al. 2013; Rusnak et al. 2012; Sandler and Enders 2007; Shahar 2005; Tsamboulas and Moraiti 2008). Savitch and Ardashev use the term "target-proneness", which they define as "the incentives or values within a city that make it attractive to attack." (Savitch and Ardashev 2001, 2525) The concept of "consequences" by Willis as "the magnitude and type of damage resulting from successful terrorist attacks" (Willis 2005, 8f) goes along the same lines, since these consequences are what the perpetrators usually are striving to maximize.

In the context of a screening methodology for buildings to evaluate terrorism risk the FEMA (Federal Emergency Management Agency 2009) suggests a number of building characteristics that affect its attractiveness. They are in large parts congruent to what Garrick and colleagues write about the attractiveness of targets: "to a terrorist, civilian populations; targets of historical, cultural, and national significance; and infrastructure that underpins the [normal] way of life are all 'fair game.'" (Garrick et al. 2004, 131)

Paté-Cornell and Guikema point out that determining the attractiveness of possible targets for terrorist attacks "based on intent, chances of success given intent, and attractiveness from the point of view of the perpetrators" (Paté-Cornell and Guikema 2002, 5) can be a useful means for prioritization of mitigation activities and the necessary funding (U.S. General Accounting Office 1998). The same point is argued by Caplan and Kennedy (2010a) in the more general context of crime when they state that it "is more manageable for police agencies […] to allocate resources to places that are most attractive to motivated offenders and to where crime is most likely to occur given certain characteristics of the environment" (2010a, 22).

I argue that regarding the threat of terrorism the attractiveness is the most important aspect of a target's susceptibility to become the target of a terrorist attack. As I explain in Chapter 2.1.2, I further believe that it is the most critical dimension in terrorism-related vulnerability analysis. For the scope of this study I define attractiveness as the characteristics of a potential target that make it appear promising to the perpetrator regarding the successful execution of a planned attack.

2.3.3. Disaster Model and Human Activity Based Vulnerability Concept

Following the definitions of the core terms of hazard and disaster research in the previous chapter I developed the disaster model as shown in Figure 1. This disaster model is the foundation of the research within study and will be referred to throughout.

Furthermore I developed a concept of vulnerability that is based on the activities of humans (Fig. 2). It is a spatially grounded causal loop that puts humans and threats in relation. The underlying assumption is that humans perform activities which then shape the environment they are performed in. By doing so, a variety of spaces are created: densely populated urban, sparsely populated rural and (nearly) empty natural ones. All have some importance to the humans interacting with them and within them. In other words these spaces start to represent certain values, which are recognized as such by the humans who created the values by their actions in the first place. This is the first casual loop within this concept. It is important to notice that these values are not assigned uniformly to the different types of spaces. Also this assignment of values can be assumed to differ widely among different groups of humans, based on their cultural and sociodemographic backgrounds.

On the other hand, the environment is not only shaped by human actions but also affected by certain threats and hazards. These will also have direct impact on the various spaces created by the aforementioned human activities. The values that these spaces are believed to represent are what creates their vulnerabilities. Therefore the generation of a disaster does not only require a threat or hazard to materialize, but also the existence of values as recognized by the affected humans. It is only then that these humans are actually put at risk by this particular disaster.

2.3.4. Spatial Vulnerability Analysis

Over the past three decades the interest in the spatial analysis of vulnerability has emerged and produced a reasonable body of literature. It is based largely on the works of Cutter and Solecki (1989) who proposed the *Hazards of Place Model* (Fig. 3) built upon the theory of the hazardousness of places by Hewitt and Burton (1971). Cutter explains it as

> a useful heuristic in understanding the diverse elements that contribute to our understanding of the vulnerability of places. There is an explicit focus on locality within this conceptual framework, for it is place that forms the fundamental unit of analysis for any geographer. (Cutter 1996, 535f)

Cutter and colleagues (2003, 243) introduced the concept of “place inequalities” which are reflected in characteristics of communities and the built-up environment and further contribute to other already well-understood social vulnerabilities. They also fostered the spatial analysis of

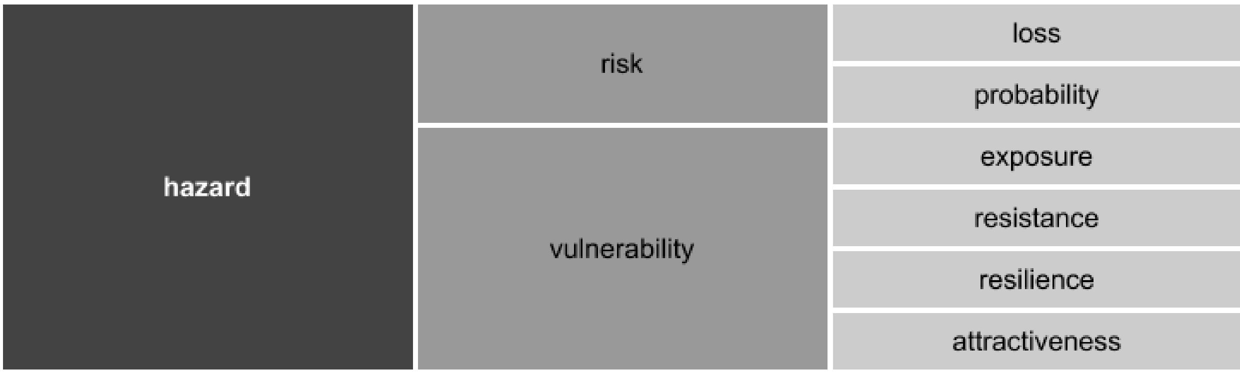

Figure 1: Disaster model used in this study.

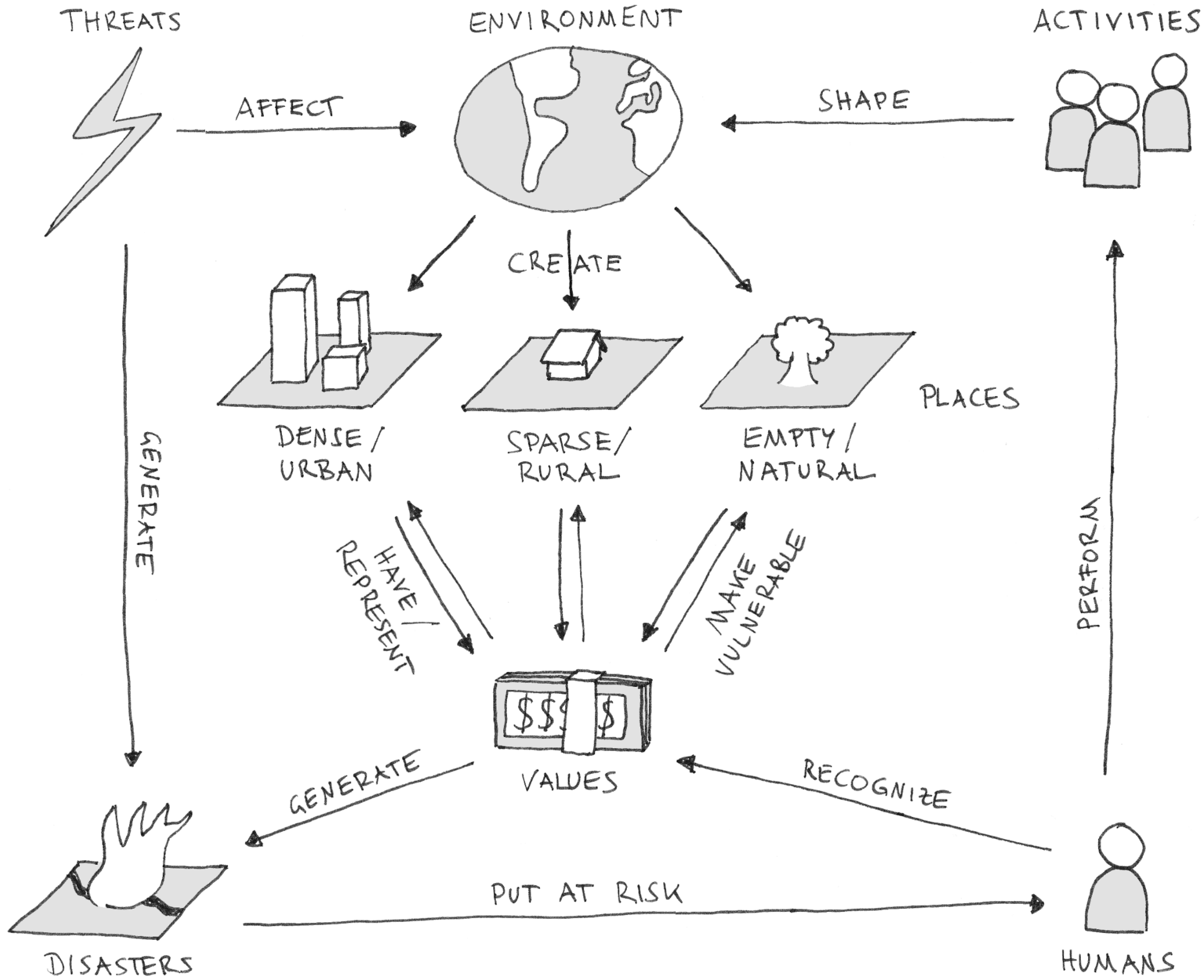

Figure 2: Human Activity Based Vulnerability Concept

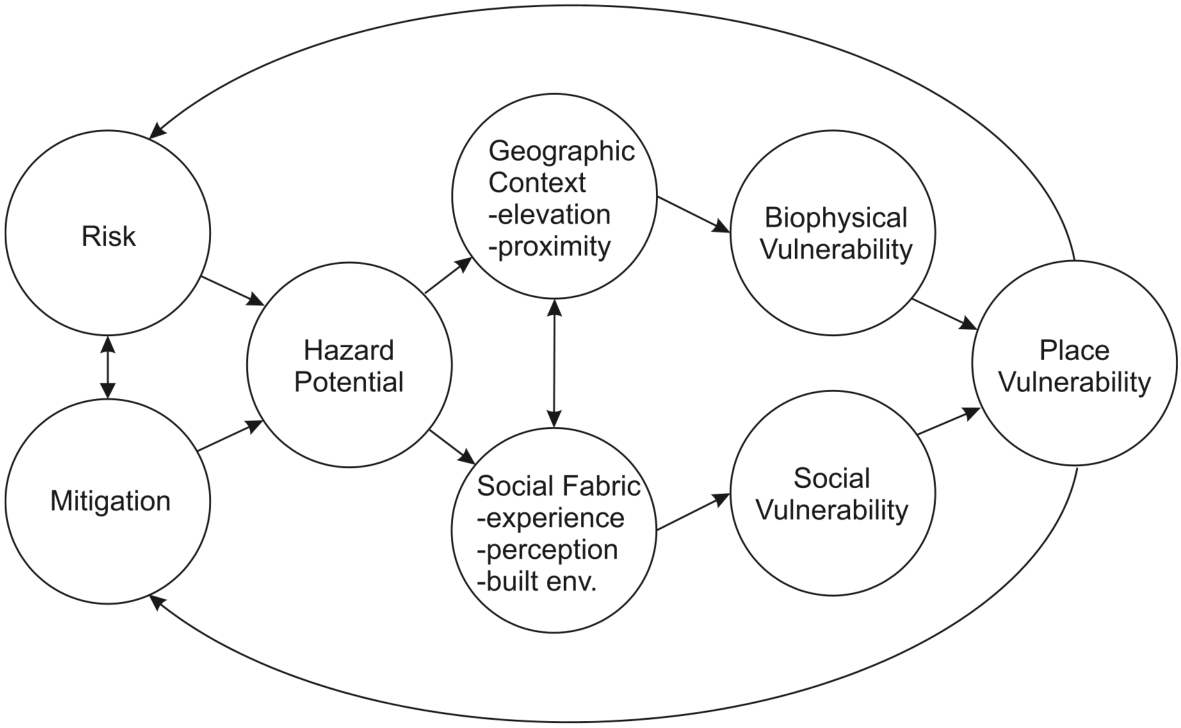

Figure 3: Hazards of Place Model

Source: Cutter et al. (2003, 244)

social vulnerabilities of places in a quantitive way, and also the comparative analysis of vulnerabilities of various places.

Yet, all studies based on the *Hazards of Place Model* and the aforementioned place inequalities have two shortcomings: first, they are all focused exclusively on natural hazards (Cutter 1996; Cutter, Boruff, and Shirley 2003; Cutter, Mitchell, and Scott 2000; Luers et al. 2003; O'Brien, Sygna, and Haugen 2004; O'Brien, Leichenko, et al. 2004; Peterson 2002) with the notable exception of Cutter and Solecki (1989); second, they used rather coarse spatial scales, as 3 shows. Cutter and Solecki (1989) even violated the concept of using the place as the unit of analysis and resorted to an incident-based analysis altogether.

Cutter et al. (2008, 601) also point out the dependency of the scale and unit of analysis of the underlying processes and hazards and how different spatial scales also require different factors and data sources to allow for meaningful conclusions. In this context Turner and colleagues stated that even hazards created by processes on a global scale create locational variations in vulnerability, which emphasizes the importance of place-based analysis, as it "implies a spatially continuous distinctive 'ensemble' of human and biophysical conditions or coupled human-environment systems" (Turner et al. 2003, 8076).

2.3.5. Significance of Vulnerability in Urban Areas

In the explanation of his rationale for a geographical study of vulnerability in urban areas Uitto points out that such an approach has to utilize knowledge that a multitude of disciplines have generated in the past, such as urban geography and planning, hazard research, sociology and anthropology (Uitto 1998, 14). Along the same lines Eriksen and colleagues argue that the key to understand vulnerability lies in the interaction between social dynamics and a social-ecological system and that "at the most abstract level, […] vulnerability can be viewed as a function of the interaction of processes at a given place in time" (Eriksen, Brown, and Kelly 2005, 302).

In accordance to the *Human Activity Based Vulnerability Concept* I introduce in Chapter 2.3.3 the most important reason to analyze the vulnerabilities of urban areas in particular is the large number of values that humans recognize here. The United Nations (UN) Habitat report *State of the World's Cities 2012/13* labelled cities as the "homes of prosperity":

> Cities are where human beings find satisfaction of basic needs and essential public goods. Where various products can be found in sufficiency and their utility enjoyed. Cities are also where ambitions, aspirations and other intangible aspects of life are realized, providing contentment and happiness and increasing the prospects of individual and collective well-being. (United Nations 2012, 4)

Table 3: Different spatial spatial scales of spatial vulnerability analyses in the literature.

Publication	Spatial resolution
Cutter and Solecki (1989)	(event based)
Cutter et al. (2000)	US census blocks
Cutter et al. (2003)	US counties
Luers et al. (2003)	30 * 30 m matrix
Metzger et al. (2005)	10 * 10 arcmin matrix 0.5 * 0.5 deg matrix
O'Brien et al. (2004)	India districts
O'Brien et al. (2004)	Norway nation Norway regions Norway municipalities
Peterson (2002)	60 * 60 m matrix

All aspects of contemporary life can be fulfilled in cities: to work, to play, and to live. The “urban millennium” began—at the latest—a few years ago, when for the first time in history more people lived in cities than in rural areas (UN 2012, 25).

It should therefore not surprise that those prosperous urban agglomerations and the importance they have on our daily lives also introduce a great number of vulnerabilities to a variety of hazards. It is not only the sheer number of objects at risk, which carry important values, but also their spatial layout. As a result I focus on the highly urbanized city centers in this study. As I explain in Chapter 5.2.1 the study area used in this study is located in one of the most populous and also most densely populated areas of the world (Tokyo Metropolitan Government 2012, 7). In addition to the large population figures Tokyo plays an important role as political, economic, and cultural center, not only within Japan but also in the global context of world cities (Sassen 2001; Sassen 2005).

In the context of terrorism Savitch and Ardashev point out many of the implications that risk and vulnerabilities have on urban areas, and why “cities have become the stage on which this tragic drama is played” (Savitch and Ardashev 2001, 2516). They mention the target-richness of cities; their role as economic, communication, and transportation network hubs; the social pluralism of heterogenous social groups in close proximity; and also their symbolic value as the underlying reasons. Statistical analyses show that there have been more terrorist attacks in urban than in rural areas, but that they have also been more violent in terms of injuries, fatalities and structural damage. In the postscript to their paper Savitch and Ardashev aptly sum up the terrorist attacks of September 11th 2001 in New York:

> All told, the terrorists had killed more than 5500 people; they injured many more thousands and they wrought incalculable damage. […] they managed to shut down the stock market for the longest period in its history. For a time, Lower Manhattan was left without telephone service and without water, gas and electric power. The nation's air transport was paralysed and pushed to the brink of bankruptcy; stock markets around the world accelerated their downward spiral and economies faltered. The President of the United States declared the attack to be 'an act of war' and mobilised military forces for action abroad. […] The attack on just 16 acres of one of the world’s greatest cities made this possible and its shock waves changed the course of international events. (Savitch and Ardashev 2001, 2530f)

3 Research Objectives

In this part of the study I make an attempt to explain the objectives of my research about the vulnerability to terrorism in urban areas. I first give a summary of the original problem statement: What are the reasons for starting this research? What are the questions I want to answer, the problems I want to solve? I then state the three basic hypotheses I postulate in this study before setting the aims of this research and covering what I expect to be the outcome of this research. Finally I provide my assessment about which audiences it is targeted at and how they can benefit from it.

3.1. Problem Statement

As I explain above there is a scarcity in scholarly debate and publications about the geographical analysis of vulnerabilities as well as of terrorism in general.[4] The two most comprehensive analyses of the research literature about terrorism are the report by Lum et al. (2006), who surveyed over 14,000 relevant publications, and by Schmid (2011, 457–474). They showed "that only 3-4% of them were based on studies that employed some type of empirical analysis on terrorism data or information" (Cynthia Lum, Kennedy, and Sherley 2006, 491f) and pointed out that "in the absence of empirical data, much of the literature is purely speculative and relies on secondary sources, which are often unreliable […]. Theory is hampered by inability to utilize much closed-source data." (Schmid 2011, 468)

This is even more so in the field of geographical analysis of terrorism. Schmid mentions, among many other shortcomings and *research desiderata* that "there is an essential need to understand the terrorists' operational environment (to know their modus operandi and targeting patterns)" (Schmid 2011, 468). Moreover, to my best knowledge the topic of terrorism vulnerability has not been discussed hitherto from a spatial perspective, at least on a micro-scale within urban areas. Notable exceptions are the recent papers by Rusnak and colleagues (2012) and Perry et al. (2013), who analyzed terrorism and the underlying processes on finer spatial scales. I believe that there are certain characteristics of terrorist attacks that make an analysis on even more precise spatial resolutions necessary and meaningful. These are rooted in the decision making process that precedes all terrorist activities. First is the perpetrator's motivation. McCormick cites two essential types of terrorism movements from the historic terrorism research literature: the "rationalists", who regard terrorist attacks a means to an end, a tool to communicate their matter and raise attention to their cause; and the "expressionists", who understand terrorism as a way for individual expression and redemptive act (McCormick 2003, 477). Both mindsets require a clearly defined goal which it is imperative to reach, and an enemy whom it is essential to fight and ultimately to conquer.

Second is the image and the communicative dimension of terrorism. An early French anarchist is quoted by Leites (1979, 3) saying “if my protest does not attract a scandal which forcibly attracts attention to my grievances, it is as if I am not complaining at all”. Similarly, Ayman Mohammed Rabie al-Zawahiri, then *al-Qaeda*'s operational and strategic commander, purportedly wrote in a letter to *al-Qaeda*'s head in Iraq at the time: “I say to you, that we are in a battle. And more than half of this battle is in the battlefield of the media.” (RAND Center for Terrorism Risk Management Policy 2011, from 29:58). These quotes show the importance of the symbolism of terrorist attacks, and also how well understood it is by the perpetrators. From the earliest beginnings of terrorism it played a central role what Chaliand and Blin describe as the “psychological element” in their view of terrorism as a strategy of insurgence: the propaganda of the deed:

> This meant that the terrorist act was the best herald of the need to overthrow the regime and the torch that would light the way to doing it. The revolutionary terrorists hoped that their attacks would thus transform them from a small conspiratorial club into a massive revolutionary movement. […] Whereas the earlier practitioners were careful to choose symbolic targets, such as heads of state and infamous oppressive governors and ministers, in order to draw attention to the justification of their cause, the more recent brand has turned to indiscriminate attacks aiming to cause multiple casualties. In doing so, they have exchanged the propaganda value of justification for greater shock value, ensuring massive media coverage. (Chaliand and Blin 2007, 33)

Lastly, it must not be forgotten that terrorists do not have unlimited resources at their hands, no different from national governments and supra-national organizations:

> Terrorist groups are small. Their membership ranges from a few individuals to several thousands, and the majority number from the tens to a few hundreds. Even the weakest of governments has a fighting force immensely larger than that of the terrorist insurgents. Under such circumstances, the insurgents cannot expect to win the struggle in any physical way. (Chaliand and Blin 2007, 33)

This calls for an organized strategy and well-planned activities on the part of the perpetrators. Yet, from the perspective of those under attack it also means that the actions of the terrorists might not be as unpredictable as they are often believed to be. If their goals and their *modus operandi* are understood, it should be possible to make educated assumptions about their most likely next targets.

I believe that these three underlying aspects of the terrorists' decision making, the communicative dimension of terrorism, and the terrorists' limited resources can be employed in the context of the *Human Activity Based Vulnerability Concept* I introduce in Chapter 2.3.3. I further believe that any spatial analysis of a vulnerability grounded in this value-based framework has to be performed on a micro-scale basis in order to be meaningful. These beliefs, together with my academic background in the spatial analysis of human-induced processes in urban areas led me to the three hypotheses I am postulating in the following chapter.

3.2. Hypotheses

(1) Vulnerability is not distributed equally over space and time.

I earlier quoted Laqueur's (2001, 5) opinion that terrorism can occur anywhere in Chapter 2.1.3 and also made my point why I do not believe that this is correct. It certainly *can* occur anywhere, but chances are it will not. This is a result of the three aspects of terrorists' decision making, which I explain in the previous chapter. Based on these, some locations make–from a terrorist's point of view–“more sense” to place an attack than others. As a result, a varied landscape of vulnerability exists, which contains both places with high vulnerability and places with low vulnerability.

(2) Factors exist that enhance or mitigate vulnerability.

The aforementioned aspects that structure the terrorists' decision making process are reflected in the values of those under attack (cf. Chapter 2.3.3). If the aims, strategy and abilities–financially and in terms of possible attack types–of a certain terrorist group are known, those values can be evaluated as “vulnerability factors”. Furthermore, these vulnerability factors can be operationalized as attributes of the objects at risk: humans, buildings, and infrastructures (cf. Chapter 4.1).

(3) Vulnerabilities of objects influence their spatial surroundings.

Especially when working on a small spatial scale it is imperative to regard all objects not only in their semantic, but also in their spatial context. It would be misleading to evaluate a single object detached from its systemic and spatial environment. Rinaldi and colleagues define four types of interdependencies: physical, cyber, geographic, and logical (Rinaldi, Peerenboom, and Kelly 2001, 14ff). Some of these only occur within infrastructural networks, but every object in space is affected by objects in its surroundings and will reciprocally also affect objects in its surroundings. This is what Caplan and Kennedy termed “spatial influence” in the formulation of their *Risk Terrain Modeling* methodology (Caplan and Kennedy 2010a; Caplan and Kennedy 2010b) I adopted the use of this term, which I explain in great detail in Chapter 4.2.3.

3.3. Research Aims

The starting point for this research was the desire to develop a methodology to quantify how prone a location is to a certain kind of terrorist attack (cf. Chapter 4.2.1 for the definition of these scenarios), as a result of the attributes of the objects at this location. I believe that there is, on the one hand, a need for such insight, especially on a fine spatial resolution, and on the other hand a scarcity of scientific activity in this direction (cf. Chapter 3.1).

Many risk-based analyses, both in the context of natural and man-made hazards, follow a top-down approach. They start from the assumption of a certain disaster and its occurrence and recurrence probabilities, and continue with an assessment of the losses that can be expected in the case of such a disaster at a certain location. One popular end product of such analyses are the widespread hazard maps that show the spatial characteristics of a certain disaster, for example a tsunami or an earthquake. I believe that these top-down approaches, while certainly having their right to exist, can only provide limited information about the actual situation of a location facing a certain hazard. This is due to the fact that this approach requires *a priori* knowledge about where and when the disaster will strike and detailed information about its magnitude and duration. As I explain in Chapter 2.1.2, this kind of probabilistic information is generally not available in the context of crime and terrorism.

Therefore I am proposing a bottom-up approach in this study, following the ideas of Brantingham and Brantingham (1995; 1981) of an "environmental backcloth", which I explain in detail in Chapter 4.1. The unit of analysis in my research is therefore the geographical space, not the specific outcome of a singular disastrous event. I operationalize the vulnerabilities of locations using the characteristics of the objects that define these locations.

Also, in the course of this research I expect to gain insight in the definition of these object attributes and factors that affect terrorism vulnerability in urban areas. Similar analyses have been undertaken in the realm of spatial crime risk analysis by Caplan and Kennedy (2010a; 2010b) in the course of their proposed *Risk Terrain Modeling* methodology. Similar to the risk terrain maps by Caplan and Kennedy my research allows for the creation of micro-scale vulnerability maps to visualize the spatial distribution of single vulnerability factors as well as overall terrorism vulnerability in highly urbanized areas.

The main goal of this study is to develop both a theoretical framework for the analysis of terrorism vulnerability in highly urbanized areas and quantitatively rooted spatio-temporal methodologies that allow to operationalize terrorism vulnerability for subsequent empirical analyses.

3.4. Target Audience

The outcome and insights gained in this study are of interest for a number of audiences: academia, involved stakeholders, and the general public.

As I illustrate in the preceding chapter, this research, while grounded in existing theories, research practices and methodologies, is novel in its combination of a bottom-up vulnerability-based approach, terrorism vulnerability analysis and the application of spatial analysis tools. This unique combination provides an interesting synthesis of urban geography, social geography, behavioral studies, political studies, and hazard, disaster, risk and vulnerability studies. I hope that this interdisciplinary character will allow for anybody involved in one of the aforementioned realms to gain a more holistic view on this important yet academically underrepresented topic.

In Chapter 3.1 I mention the limited resources at the hands of the perpetrators that affect their decision making. The same is true for the opposite side, too, where those in responsibility for objects, that might become the target of a terrorist attack, have to decide how to use their limited funds to the optimal effect. As Willis writes:

> Ultimately, efficient allocation of homeland security resources would be determined based upon assessment of the cost effectiveness of alternative risk-reduction opportunities. After potentially first addressing obvious and easily mitigated risks, this requires understanding the cost effectiveness of different types and amounts of investment. Neither the methods nor the data are available to answer questions about the effectiveness of available risk-reduction alternatives or to determine reasonable minimum standards for community preparedness. Until these questions are answered, allocating homeland security resources based on risk is the next best approach since areas at higher risk are likely to have more and larger opportunities for risk reduction than areas at lower risk. That is, resources would be allocated roughly proportionally to the distribution of risk across areas receiving funding. (Willis 2005, xvf)

I believe that the vulnerability-based approach presented in this study can help mitigate the shortcomings of current risk-based analyses. This would allow governments, municipalities, building owners and network providers to identify the most vulnerable elements and start mitigating those attributes that cause the vulnerabilities. Previous studies have shown the effectiveness of such an approach (Apostolakis and Lemon 2005; Karydas and Gifun 2006; Lemon 2004; Michaud 2005; Morgan et al. 2000; Patterson and Apostolakis 2007).

Lastly, yet equally important, I believe that the vulnerability maps produced in the course of this research can be beneficial in the task of communicating the abstract concept of vulnerability to a broad audience in the general public. As the proverb goes, “a picture says a thousand words” I hope to be able to provide an opportunity for insight into the processes that create vulnerability to terrorism and how it is distributed in space to the general public.

4 Analysis Framework

In this chapter I introduce the conceptual framework for the spatio-temporal terrorism vulnerability analysis, which also forms the theoretical underpinnings for the applied study I present in Chapter 5.

Before discussing the individual components of the framework I present the objects that this framework covers in Chapter 4.1 and the resulting spatial scale of my analysis. I go on to point out the importance of the definition of attack scenarios as a prerequisite of using the analysis framework in Chapter 4.2.1. I then describe in more detail my spatial vulnerability analysis framework and its different components: starting from the idea of vulnerability factors, which I briefly introduce in the context of my hypotheses in Chapter 3.2, I discuss their selection in Chapter 4.2.2, I continue with explaining the concept of spatial influence in Chapter 4.2.3 before finishing with a description of both the process of assigning weights to represent the varying importance of the single vulnerability factors, and visualizing their spatial distributions as well as that of overall vulnerability using maps in Chapter 4.2.4.

4.1. Objects and Spatial Scale

The main purpose of the framework I introduce in this study is to put the abstract concept of terrorism vulnerability into its spatial context in the real world and to make it quantifiable. As I mention in the context of my three main hypotheses in Chapter 3.2 I do this by analyzing the attributes of real-world objects to operationalize certain vulnerability factors.

Many of the ideas and methods as well as the underlying thought processes and assumptions I am relying on and using in my framework have been developed in the sociological and (later) geographical analysis of crime. Since terrorist attacks constitute a special type of crime (cf. Chapter 2.1), this is a legitimate deduction.

The idea of analyzing crime in the context of space rather than individual criminality is not new: for example Shevky (1972) wrote about the application of social area analysis to the task of assigning social attributes to urban areas in order to be able to describe their propensity to disorder and crime. Similarly Abbott pointed out

> that Chicago [i.e. the Chicago School of sociology] felt that no social fact makes any sense abstracted from its context in social (and often geographic) space and social time. Social facts are located. [...] Every social fact is situated, surrounded by other contextual facts and brought into being by a process relating it to past context. (Abbott 1997, 1152)

Following this idea, many scholars have emphasized the place-based nature of criminogenic opportunities under different names: “routine activity theory”, “opportunity theory”, “environmental backcloth”, and “criminal event perspective” (Block and Block 1995; Brantingham and Brantingham 1995; Cohen et al. 1981; Eck 2001; Eck 2006; Mears, Scott, and Bhati 2007; Sacco 2002). In my framework I am following the rationale by Brantingham and Brantingham which Caplan and Kennedy summarize as follows:

> They referred to the “environmental backcloth” that emerges from the confluence of routine activities and physical structures overlaying urban areas. The Brantinghams suggest that this backcloth is dynamic and, importantly, can be influenced by the forces of “crime attractors” and “crime generators”—both of which contribute to the existence of hotspots. Attractors are those specific things that attract offenders to places in order to commit crime. Generators refer to the greater opportunities for crime that emerge from the collection of more people into areas simply as a result of the increased volume of interaction taking place in these areas. (Caplan and Kennedy 2010b, 11–12)

Accordingly, the vulnerability factors that my framework uses are operationalizations of these crime attractors and crime generators, only in the specific context of terrorist activities.

Caplan and Kennedy (2010a; 2010b) and their research group at the Rutgers Center on Public Security (RCPS) at the Rutgers University School of Criminal Justice in Newark, NJ, have also been amongst the first to approach these concepts and empirical findings by the use of geospatial data and geographic information systems. In the course of this research they developed a crime analysis methodology called *Risk Terrain Modeling (RTM)*, which they describe as

> an approach to spatial risk assessment that utilizes a geographic information system (GIS) to attribute qualities of the real world to places on a digitized map. It operationalizes the spatial influence of crime factors to common geographic units, then combines separate map layers together to produce risk terrain maps showing the compounded presence, absence, or intensity of all factors at every location throughout the landscape. Risk terrain maps show places where conditions are conducive for certain events to occur in the future based on the environmental context for criminogenesis. (Caplan and Kennedy 2010a, 11)

The RTM methodology allows for better strategic decision-making and operational policing by the involved stakeholders than any retrospect approach such as hotspot maps of crimes or terrorist activities ever can, due to the forecasting character of its output. This especially useful in the case of terrorism, which tends to happen only rarely and hence does not produce a significant number of past data to elaborate on. This is one of the most critical aspects of the approach I also employ in this study: “While prediction methods focus on the presence or absence of an event, risk assessments using RTM focus on the dynamic conditions of the environment where a crime could occur. The unit of analysis is the geography, not the event.” (Caplan and Kennedy 2010b, 29)

As I point out in Chapter 2.3.4 previous attempts to spatially analyze vulnerability have always used rather coarse spatial resolutions (cf. 3). Since my analysis is supposed to provide insights into the vulnerability distribution inside highly urbanized areas (cf. Chapter 5.2.1) I decided that it would only make sense to do so on a micro-scale. Caplan and Kennedy recommend a cell size of 100 * 100 ft (30.48 m) as reasonably small regarding the application purpose while accommodating computational limitations:

> 100x100 foot cells were the smallest area that our computers could process reasonably fast and, for the purposes of this risk terrain model, if a risk terrain map could assess the risk of shootings at small (but reasonable) geographic units (e.g. 2 inches would be unreasonable since a person cannot even fit in that space), it would provide the most utility for operational policing compared to larger, less specific, units of analysis. (Caplan and Kennedy 2010b, 48)

I decided to use 10 * 10 m grid cells in my analysis, since I believe that this allows for a more meaningful analysis in my highly urbanized and densely built-up study area (cf. Chapter 5.2.1).

My *Human Activity Based Vulnerability Concept* (cf. Chapter 2.3.3) postulates that the vulnerability factors themselves are spatial operationalizations of the underlying processes happening within urbanized areas as result of the activities that people pursue there. It therefore suggests itself to perform an analysis of these activities on a per-person basis to derive the inherent processes. The activities themselves manifest in the real world both in the form of a precise geolocation of each person, i.e. a pair of X- and Y-coordinates, and by the places that these people populate. Since detailed data about the exact positions of all people within a fairly large study area is impossible to obtain and impractical to process, I resort to more generalized spatial units instead: buildings on the one hand and public space like streets or the train network on the other. Stationary activities, i.e. such that require the actor to stay in one location for a certain elongated period of time, generally take place inside buildings. Examples are “being at home” and “working at the office”. In contrast, transportation activities and short-term activities tend to take place in public space. Examples here are “commuting on the train” or “grocery shopping at the supermarket”.[5]

In addition to the spatial dimension of crime and the underlying criminogenic factors Caplan and Kennedy also elaborate on the temporal dimension: “Risk terrain modeling makes it clear that understanding the spatial-temporal interaction effects of certain qualities of space is key to assessing emergent criminogenic risks.” (2010a, 19) Thereby they refer to the changes that the criminogenic factors undergo over the course of time, which makes it necessary to revisit the same forecasting analyses time and time again. In my analysis I go even further in accommodating temporal variations by introducing a temporal dimension into the vulnerability factors themselves (cf. Chapters 5.3.1, 5.3.2, and 5.3.3).

4.2. Components

Figure 4 shows the complete framework for the spatial analysis of vulnerability as a flowchart. Before explaining all the single components in detail in the upcoming chapters, I want to point out four peculiarities first.

First, I formulated the framework itself and the single components as generic as possible. This also shows that while the framework has been developed in the context of terrorism vulnerability analysis, it is also applicable to the analysis of vulnerabilities to other threats, such as earth-quakes, tsunamis, crime, etc.

Second, the flow chart reveals two different types of data sources: “hard” data and “soft” data. The former comprises all kinds of qualitative and numeric data that can be stored in some kind of digital file or database system. The latter describes input at the discretion of the analyst. These decisions are based on subjective judgements, but affect the computational process significantly. The thought process behind the selection of vulnerability factors is explained in Chapter 4.2.2, the definition of the type and range of spatial influence in Chapter 4.2.3, and the weighting involved in the vulnerability mapping step is presented in Chapter 4.2.4. In addition, Chapters 5.3.1, 5.3.2, 5.3.3, and 5.3.4 show the development of actual terrorism vulnerability factors, Chapter 5.3.6 the calculation of their respective spatial influences, and Chapter 5.3.7 the vulnerability mapping process in the course of an applied case study.

Third, the different representations of the factor maps in Figure 4 originate from two types of vulnerability factors: those with a temporal dimension and those without. While the former (e.g. factor 2) will produce only one vulnerability factor map, which is valid irrespective of the time of day, the latter (e.g. factor 1) will produce a number of vulnerability factor maps, depending on the selected temporal granularity. In the scope of the case study in Chapter 5, three factors have a temporal dimension (stationary building population, mobile pedestrian population and mobile railway population), while one factor does not (symbolic value).

Last, the number of data sources is not limited in any way, it is determined by the type and complexity of the operationalized vulnerability factors. The same holds true for the number of vulnerability factors, with certain limitations, as I explain in Chapter 4.2.2.

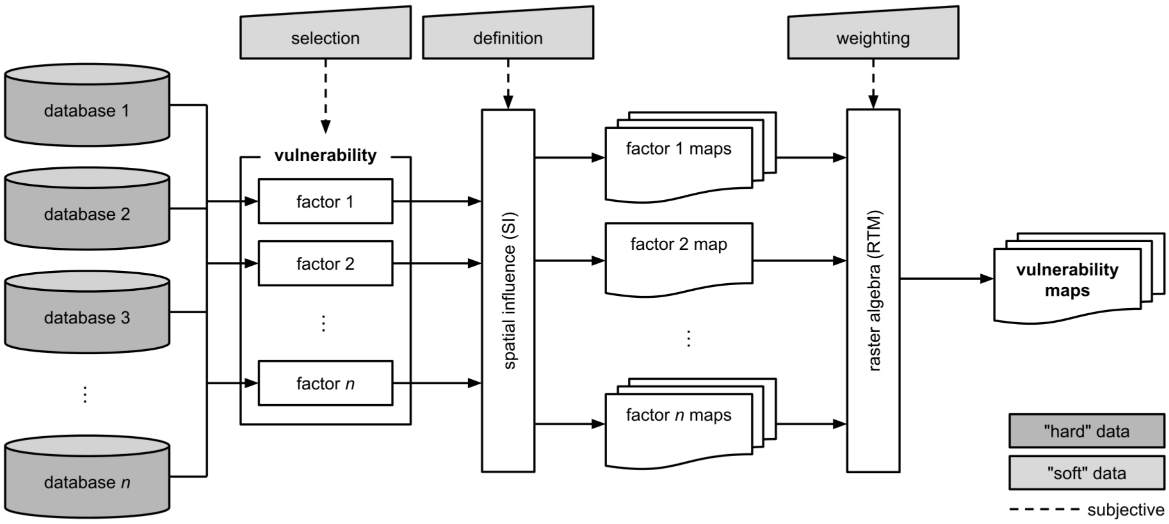

Figure 4: Spatial vulnerability framework developed in this study as stylized workflow.

4.2.1. Scenario

Caplan and Kennedy mention in their introduction to the RTM workflow that

> risk terrain modeling is a form of spatial risk assessment that is specific to the outcome event of interest. […] This might sound impractical, but it is reasonable. For example, the causes of bicycle thefts most likely differ from the causes of shootings, so you would not generally combine bicycle theft and shooting events together to identify mutual risk factors. More generally, it would not be reasonable to use a risk terrain map of murders to forecast the locations of bicycle thefts because the risk factors for each differ. (Caplan and Kennedy 2010b, 72)

The same holds true for the analysis of terrorism vulnerability, too. It is easy to see how terrorist activities are always heavily influenced and determined by three factors, as I explain in Chapter 2: 1) the goals of the terrorists as well as 2) the values of those under attack affect the selection of targets for terrorist attacks; in addition, 3) the available means of the perpetrators define their possible *modus operandi*, therefore limiting the number of outcome scenarios. The determination of an attack scenario therefore has to be the very first step in the application of my vulnerability analysis framework. This scenario comprises two dimensions: a) the exact perpetrator and b) the mode and scale of attack. It heavily influences the input variables marked as “soft” data in Figure 4, which I explain in detail in the following sections.

4.2.2. Vulnerability Factor Selection

The first step is the selection of meaningful vulnerability factors to operationalize the various values that make up possible attack targets for the respective perpetrator. For example, religiously motivated terrorists might be interested in attacking facilities of other religious organizations which they perceive to be infidels or profane. Opposed to that, environmentally motivated activists might be aiming at offices or infrastructures by corporations they believe to be acting in ways harmful to the environment or responsible for an environmental disaster. Accordingly, a suitable vulnerability factor for the former would be “existence of facilities of hostile religious organizations”, while for the latter it would be “existence of buildings or infrastructures belonging to or related to malicious corporations”.

A number of points have to be kept in mind when selecting appropriate vulnerability factors (Caplan and Kennedy 2010b, 77–84):

1) Only the most relevant vulnerability factors should find their way into the final analysis process so not to generalize the outcome result too much.

2) Vulnerability factors can be either aggravating or mitigating, hence amplify an objects vulnerability or ameliorate it.

3) The vulnerability factors have to be independent from each other, so as to avoid a bias or overrepresentation of certain influences.

4) Sufficient quantitative data from reliable sources is necessary to successfully operationalize the vulnerability factors (cf. Chapter 5.3).

I agree with all of these and put great attention to following these guidelines in the selection and development of the vulnerability factors I used in the case study in Chapter 5.

4.2.3. Spatial Influence

The definition of the spatial influence of these vulnerability factors then allows to accommodate for the varying spatial effect *radii* of different modes of attack and their scale. For example the release of a poisonous substance will generally be confined to a certain area, mostly defined by the existing air provision and ventilation systems.[6] Outdoors the diffusion will be affected by climatic conditions such as the wind speed and direction, and by the dilution characteristics of the CBRN agent used as well as the released amount. Similarly an attack using explosives will gain a different outcome according to the amount of explosives used (National Counterterrorism Center 2012). In addition, the outcome result generated by an attack involving the release of a poisonous substance will differ greatly from that involving the detonation of explosives.

Caplan and Kennedy advocate GIS as a tool to visualize the spatial influence of criminogenic factors as “visual narratives of how environmental settings become conducive to crime” (2010a, 22). This allows analysts to abandon the understanding of crime being initiated by the mere existence or non-existence of a certain crime attractor or crime generator, as Brantingham and Brantingham (1995; 1981) originally postulated, and instead to account for the influence of these features to their environment:

> The best way to map crime factors for the articulation of criminogenic backcloths is to operationalize the spatial influence of each factor, acting as crime generators, throughout a common landscape rather than atheoretically mapping the factors as points, lines or polygons in a manner that keeps them disconnected from their broader social and environmental contexts. (Caplan and Kennedy 2010a, 23)

Since the actual location of a terrorist attack does not necessarily have to coincide with the exact pinpoint location of the vulnerable object I follow the suggestions by the original authors of the RTM methodology to use one of two operationalizations of a factor's spatial influence: a) spatial concentration and b) spatial proximity (Caplan and Kennedy 2010a, 25–26).[7]

The former takes into account the fact that the spatial agglomeration of vulnerable objects tends to increase the overall vulnerability of the space they comprise. In the context of terrorism the presence of multiple attractive possible targets amplifies the attractiveness of this location, and hence makes it more vulnerable to a terrorist attack. It is implemented in the computation process as a kernel density estimation (KDE) to estimate the probability density function of the vulnerable objects. The search bandwidth of the KDE needs to be chosen according to the respective vulnerability factor and can be defined separately for each factor.

The latter comes down to the effect radius of the chosen *modus operandi* as I outlined in the beginning of this chapter. From the perpetrators' perspective a location is only suitable for an attack if it is close enough to the actual target to affect it in the intended way and to the planned degree. In GIS terminology this equates to the calculation of a buffer zone of a certain euclidian distance from the vulnerable object. This distance needs to be chosen according to the respective vulnerability factor and can be defined separately for each factor. Deviating from the original RTM approach I decided to implement gradually declining buffers instead of the simplistic dichotomous buffers that Caplan and Kennedy (2010a; 2010b) use, since this represents the correlation of distance and vulnerability more accurately than a pure reproduction of the presence or absence of a vulnerable asset within a certain radius.

4.2.4. Vulnerability Factor Weighting

The last aspect is the appropriate weighting of the single vulnerability factors according to their assumed importance in the perpetrators' decision making process. This regards the selection of their targets as a result of optimal pursuance of their goals on the one hand, and the most effective use of their available means on the other hand.

Since the RTM methodology employs raster maps to represent the spatial influences of the single vulnerability factors, simple raster algebra can be used to combine the vulnerability factor maps into one overall vulnerability map for the study area. I developed the following equation to combine the factors while keeping intact their temporal dimension and at the same time assigning weights:

$$v_t = \sum_{i \in F} w_i \cdot nSI_{i,t} \tag{1}$$

where v_t is the total vulnerability value, F is the set of selected vulnerability factors, w_i is the weight of vulnerability factor i, $nSI_{i,t}$ is the normalized spatial influence value of vulnerability factor i at time t.

This helps to more accurately reproduce the underlying decision-making process of the terrorists and the resulting choices made in the course of their selection of attack targets.

Four important points are to be kept in mind here:

1) This calculation has to be performed for all cells of the raster grid that makes up the study area.
2) The weights w_i of the vulnerability factors have to sum up to a total of 1 or 100%.
3) The calculation of the spatial influence of the single vulnerability factors might generate results on different scales, i.e. the range of cell values of the resulting raster grids can vary. Therefore they need to be normalized to a common scale. The range of this scale can be chosen freely, i.e. [0,1], [0,100], and [0,255] are all valid choices.
4) In the case of vulnerability factors without a temporal dimension the vulnerability factor $f_{i,0}$ has to be used for all time steps, representing the stationarity of the vulnerability factor it operationalizes.

5 Spatio-Temporal Analysis of Terrorism Vulnerability in Central Tokyo, Japan

5.1. Terrorism in Japan

Japan is unarguably not the first country that comes to mind when speaking about terrorism. Before explaining the research I have undertaken in the course of this study in this chapter I will therefore briefly explain my bipartite motivation for doing so nonetheless, by looking at the past on the one hand, and at the present and (possible) future, on the other hand.

5.1.1. The Past

Japan has seen terrorist activities in the past and has even suffered from a number of attacks. The START GTD (National Consortium for the Study of Terrorism and Responses to Terrorism 2013f) lists a total of 386 terrorist incidents in Japan between 1970 and 2009. A temporal analysis reveals five distinct eras of terrorism in Japan (cf. Fig. 5):

1) The years 1974 and 1975 were marked by 12 attacks by the *East Asia Anti Japanese Armed Front (EAAJAF)*, a leftist group inspired by anti-Japanese anarchism. They conducted mainly smaller bombings of police facilities. Their most atrocious and well-known attack was the bombing of the Tokyo head office of Mitsubishi Heavy Industries which left eight dead and almost 400 injured.
2) The years 1977 through 1980 were also dominated by leftist groups. Most notable are the *Revolutionary Workers' Council (Kakurokyo)* and the *Japan Revolutionary Communist League National Committee (Middle Core Faction, Chukakuha)*, purportedly the most powerful Japanese anti-Stalinist far-left revolutionary groups, who organized violent riots and whose terrorist activities consisted mainly of sabotage attacks and assassinations.
3) 1990 was dominated by 25 attacks by the *Japan Revolutionary Communist League National Committee (Middle Core Faction, Chukakuha)*, mainly incendiary attacks on transportation infrastructure and governmental institutions.
4) The highest number of victims in terms of both dead and injured occurred in the years 1994 and 1995 by the hand of *Aum Shinrikyo*, a spiritual doomsday sect. Their deadliest and most well-known attack happened on March 20th, 1995, when five perpetrators synchronously released poisonous sarin gas in subway carriages in the city center of Tokyo

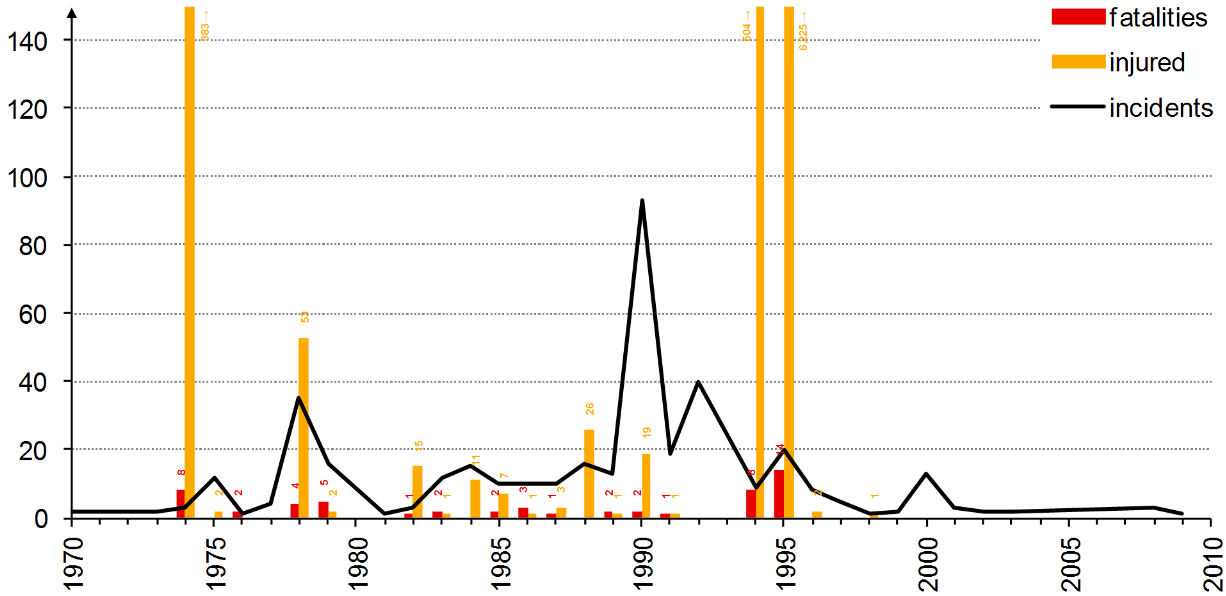

Figure 5: Number of terrorist incidents and the resulting numbers of fatalities and injured in Japan per year (1970-2009).

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2013f)

during the morning rush hour. This attack left 12 people dead and approximately 5,500 people injured (START 2013g). Yet, in the previous year they were also responsible for the release of a smaller amount of sarin gas in the city of Matsumoto, which killed seven and left 500 people injured.

5) The peak in the number of incidents in the year 2000 originates from a number of radiological incidents that happened in June of that year. A single perpetrator by the name of Tsugio Uchinishi mailed envelopes containing a radioactive substance to ten official addresses in Tokyo: the Japanese Imperial Household Agency; the National Police Agency (NPA); the National Public Safety Commission; the Ministry of Education, Culture, Sports, Science and Technology (MEXT); the Ministry of Defense (MOD); the Japan Science and Technology Agency (JST); the Agency for Natural Resources and Energy (ANRE); the Public Security Intelligence Agency (PSIA); the official residence of then Prime Minister Mori; and the then Japanese Home Affairs Ministry (now Ministry of Internal Affairs and Communications). The sender intended to warn government officials about illegal exports of uranium to North Korea (Pate, Ackerman, and McCloud 2001).

Figure 6 shows the different target types that were affected by terrorist incidents, according to the GTD. The two largest groups are governmental, and military targets including non-governmental institutions (NGO) and the police (marked in blue), which together account for 43% of all attacks, and infrastructural targets (airports & airlines, food or water supply, telecommunication, transportation, and utilities) which account for 26.1% in total (marked in orange). Attacks on religious organizations, private citizens, the media and educational institutions appear to have played minor roles in the pursuance of the goals of terrorists in Japan.

One finding from the GTD data is that home-grown terrorism appears to have been the prevalent threat in the past: all but 201 attacks that are registered with an unknown perpetrator have been committed by Japanese terrorist groups. The data also shows that only a few groups have been declared responsible for a greater number of attacks: the *Japan Revolutionary Communist League National Committee (Middle Core Faction, Chukakuha)* committed 61 (15.8% of all attacks in Japan), the *Revolutionary Workers' Council (Kakurokyo)* 24 (6.2%), the *East Asia Anti Japanese Armed Front (EAAJAF)* 12 (3.1%), and the doomsday sect *Aum Shinrikyo* and *Battle Flag (Senkiha)*, another left-wing terrorist group, eight attacks each (2.1%).

When investigating the most prevalent *modus operandi* of terrorists in Japan attacks on infrastructures and facilities and bombings are by far in the majority (Fig. 7). Correspondingly,

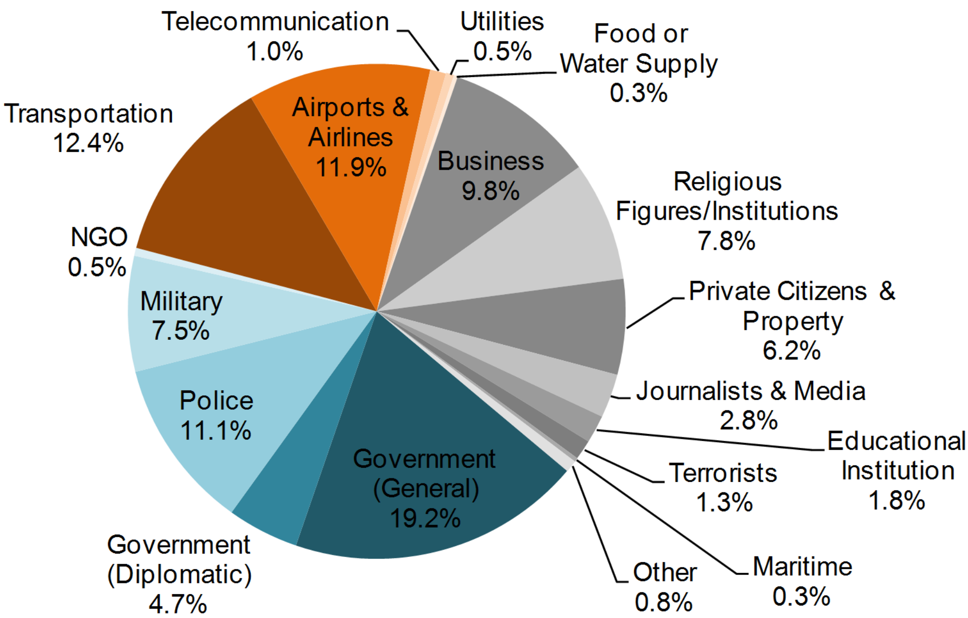

Figure 6: Number of terrorist incidents in Japan (1970-2009) per target type.

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2013f)

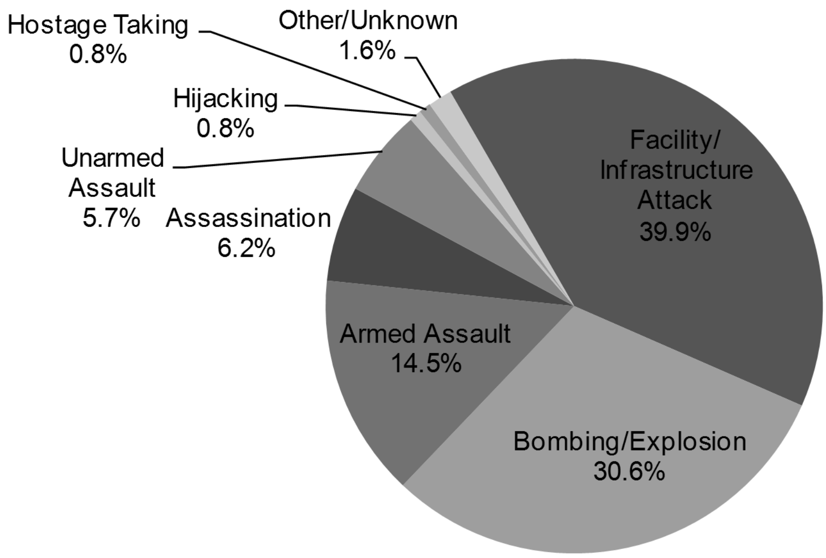

Figure 7: Terrorist incidents in Japan (1970-2009) by attack type.

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2013f)

incendiary devices and explosive materials represent the majority of weapons used in these terrorist attacks (Fig. 8). The fact that the use of CBRN weapons (6.2%) outnumbered the use of firearms (4.1%) in the past is a worrisome development that should be monitored closely and accounted for in future research and counterterrorism measures.

A geographic analysis by place name of the attacks[8] (4) reveals that the major urban agglomerations of Tokyo-Kawasaki-Yokohama and Kyoto-Osaka-Kobe account for the majority of incidents, namely 58.7% and 8.7%, respectively. Other populous cities, such as Nagoya and Fukuoka also appear in the top ten of the list. Narita, the third-most attacked, is the municipality that contains *Narita International Airport.* Its construction and the related relocations and expropriations of local resident homeowners caused a large number of protests and violent riots. Yokosuka, the ninth-most attacked, contains the *United States Fleet Activities Yokosuka*, home port for the *United States Seventh Fleet* and a military port by the Japan Maritime Self-Defense Force (JMSDF), which provoked terrorist activities by anti-US radicals, mainly in the early 1990s.

These descriptive analyses show that Japan is far from the widespread crime- and terrorism-free image. In addition, Matsumoto (2003, 28–29) and Hirose and Miyasaka (2010) provide a Japanese perspective on the history of terrorism in Japan. This eventful history over the past 40 years leads to the conclusion that there is a possibility of terrorist activities in the future, too. The next section focuses on this outlook.

5.1.2. The Present and Future

The Metropolitan Police Department (MPD) writes in an estimation on the threat of international terrorism that Tokyo had been named by *Osama bin Laden* a possible target for Islamist terrorists due to the large number of US-related institutions.[9] In addition it deems the high number of foreigners living in and traveling though Tokyo as a potential opportunity for Islamist extremists to exploit the international community to procure funds and equipment for terrorist activities and for the radicalization of young people (Metropolitan Police Department 2012a) As a result the *Anti-Terrorism Partnership Tokyo (ANTEP)* was founded in 2008 to foster collaboration of administrative organs and private corporations in the prevention of terrorist activities in the Metropolitan Area (Metropolitan Police Department 2012b). Its six main goals are:

1) the implementation of joint training,

2) the implementation of joint patrol campaigns,

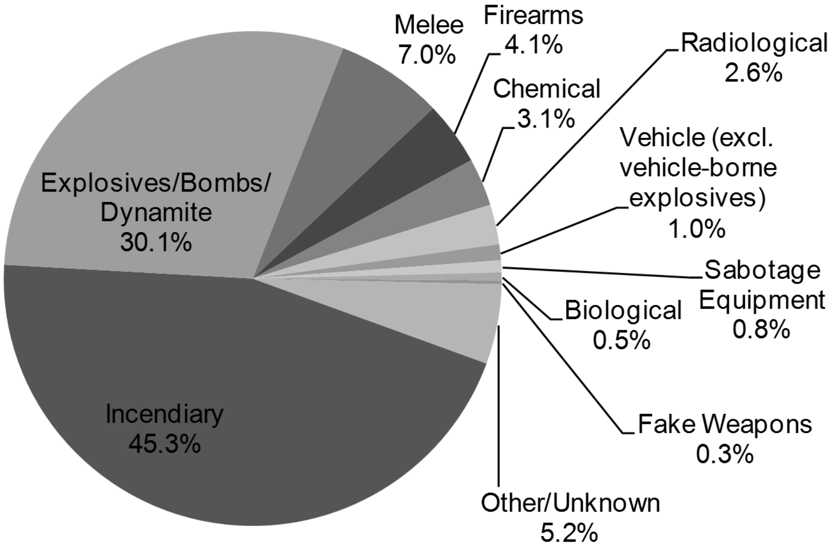

Figure 8: Terrorist incidents in Japan (1970-2009) by weapon type.

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2013f)

Table 4: Terrorist incidents in Japan (1970-2009) by location.

City	Incidents	%	City	Incidents	%
Tokyo	199	54.1	Isesaki	1	0.3
Osaka	21	5.7	Ishibayashi	1	0.3
Narita	17	4.6	Ishikawa	1	0.3
Yokohama	14	3.8	Iwakuni	1	0.3
Kyoto	11	3.0	Izumo	1	0.3
Nagoya	8	2.2	Kamagaya	1	0.3
Chiba	6	1.6	Kariya	1	0.3
Nara	6	1.6	Kashihara	1	0.3
Yokosuka	6	1.6	Katsuta	1	0.3
Fukuoka	5	1.4	Komaki	1	0.3
Omiya	4	1.1	Kumamoto	1	0.3
Kawasaki	3	0.8	Matsudo	1	0.3
Mito	3	0.8	Matsumoto	1	0.3
Nagasaki	3	0.8	Miyaura	1	0.3
Narashino	3	0.8	Mutsuzawa	1	0.3
Okinawa	3	0.8	Okubo	1	0.3
Atsugi	2	0.5	Onjuku	1	0.3
Kimitsu	2	0.5	Sagamihara	1	0.3
Naha	2	0.5	Saitama	1	0.3
Otsuki	2	0.5	Sapporo	1	0.3
Ryufukuji	2	0.5	Takasaki	1	0.3
Tsukuba	2	0.5	Tendo	1	0.3
Urasoe	2	0.5	Tokaimura	1	0.3
Ushiku	2	0.5	Tokushima	1	0.3
Akita	1	0.3	Tomisato	1	0.3
Ashikaga	1	0.3	Urayasu	1	0.3
Gose	1	0.3	Yamatotakada	1	0.3
Hakodate	1	0.3	Zama	1	0.3
Ise	1	0.3	Unknown	25	6.8

Data source: National Consortium for the Study of Terrorism and Responses to Terrorism (2013f)

3) the implementation of investigative commissions, workshops, etc.,

4) the establishment of a terrorism information network,

5) the construction of a video transmission system for times of emergencies, and

6) the conclusion of a mutual agreement for counter-terrorism.

This shows that the TMG perceives the risk of terrorism in Japan as a realistic threat that justifies a significant investment in funds and engagement by all related actors.

Similarly, the Japanese public has a high awareness of the risk of terrorism. In an opinion poll about crisis management in relation to terrorism in 2007 the MPD asked over 2,500 citizens and managers of facilities that could be a target of terrorism about their concerns about terrorism and crisis management with the aim to reflect the various security measures in the future (Metropolitan Police Department 2007).

While a majority of 53.4% of the citizens named earthquakes as their greatest fear, 17.6% said they were most afraid of terrorism, which therefore came out to be the second most feared threat, together with street crime also at 17.6% (Fig. 9). In fact more than two thirds said they were seriously concerned, almost 50% at least somewhat concerned about terrorism (Fig. 10a). On top of that, more than one quarter consider the occurrence of terrorist attacks in Tokyo highly possible, over 50% somewhat possible (Fig. 10b). More than half of the respondents believe strongly or at least somewhat that there is a risk of becoming a victim of terrorism in Japan (Fig. 10c). Among the facility managers a slightly higher number named terrorism their greatest fear, again only exceeded by earthquakes (Fig. 9). They were significantly more concerned about terrorism than the citizens with over 90% seriously or at least somewhat so (Fig. 10d). More than one third strongly believe in the possibility of terrorist attacks in Tokyo, while more than half somewhat think so (Fig. 10e). Two thirds of the respondents are afraid to become a victim of terrorism in Japan, 10% even strongly so (Fig. 10f).

These results show clearly that the threat of terrorism is a topic of concern for Japanese citizens and facility managers and warrants a scientific discourse. The aforementioned study also revealed that young Japanese have a greater anxiety of terrorism, which might seem puzzling, since their generation has not experienced terrorism at home, as opposed to the older population. I understand this as the manifestation of the awareness that Japan in its role as a tantamount member of the global society has inevitably also brought it into the focus of international terrorism. An example is the involvement in the US-led *Operation Enduring Freedom* in Afghanistan

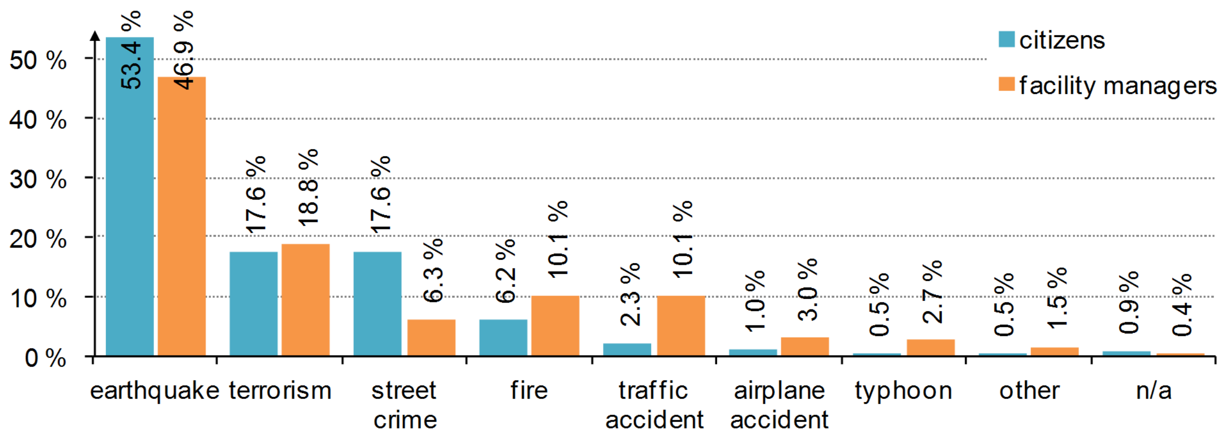

Figure 9: Result of an opinion poll for citizens and facility managers about crisis management in relation to terrorism: "Which incident are you most afraid of?"

Data source: Metropolitan Police Department (2007)

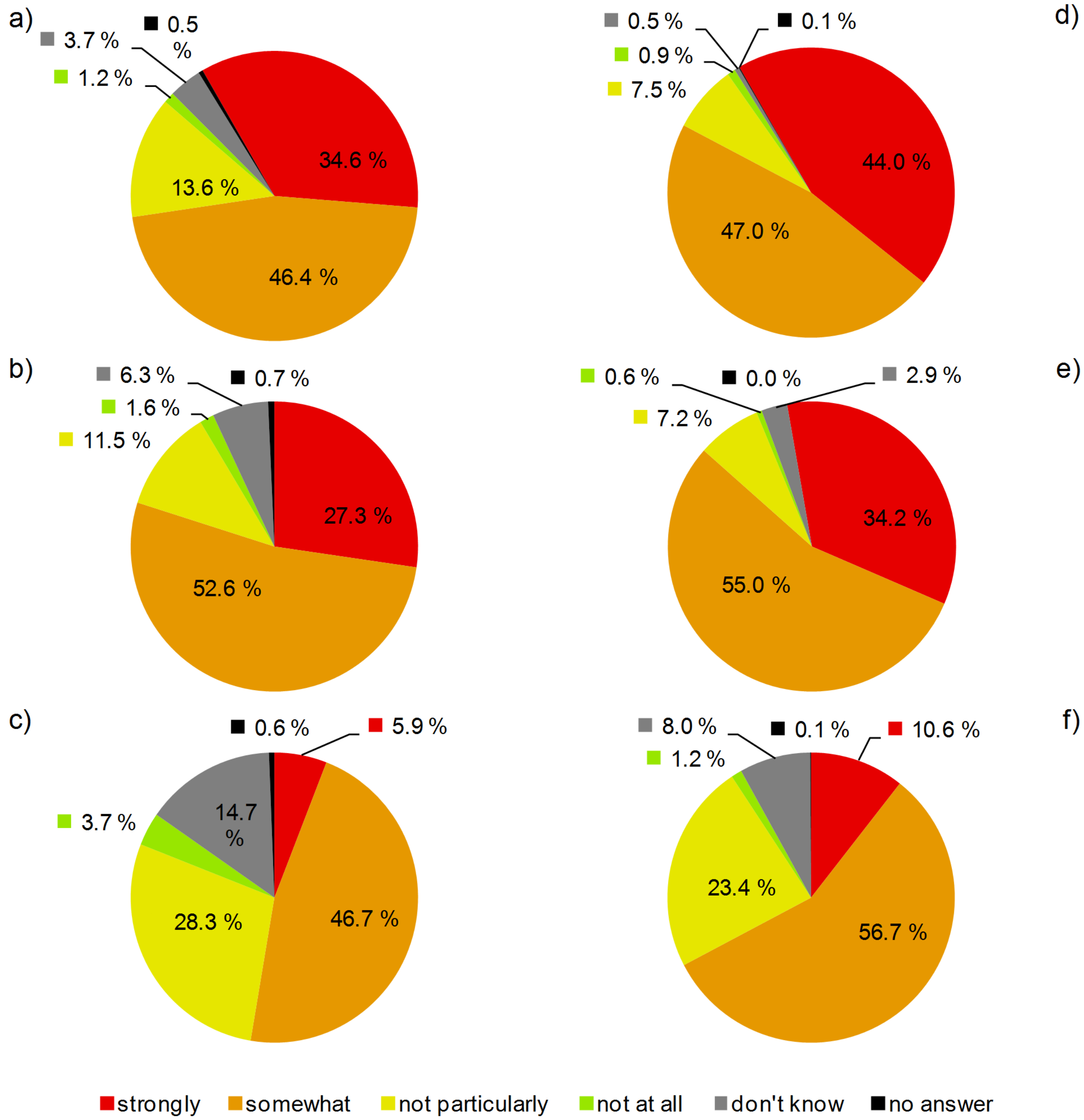

Figure 10: Results of an opinion poll for citizens (a-c) and facility managers (d-f) about crisis management in relation to terrorism: "How concerned are you about terrorism?" (a, d); "Do you think that there is a possibility for terrorist attacks to occur in Japan in the future?" (b, e); "Do you think it is likely for you to become a victim of terrorism in Japan?" (c, f)

Data source: Metropolitan Police Department (2007)

(Ministry of Defense 2007; 2008). While the JMSDF are not participating in ground activities[10], the *Anti-Terrorism Special Measures Law* (Prime Minister of Japan and His Cabinet 2001) issued in 2001, and the *Replenishment Support Special Measures Law* (Ministry of Foreign Affairs 2010a) from 2007 defined the deployment of Japanese vessels in the Arabian Sea with the exclusive purposes of refueling and water supply[11] for allied countries' vessels. Midford notes in this context that

> an unarmed or lightly armed Japan was believed the best way to discourage others from targeting or attacking the nation. This view implied that the more Japan armed itself or involved itself with supporting U.S. military power, the more likely it was to provoke military responses from others [...]. Finally, dispatching the SDF overseas for any purpose was believed to endanger civilian control [...] and likely to provoke other nations, especially those in East Asia with memories of Japan's invasion and occupation [...]. (Midford 2006, 4)

Other possible trouble spots are the ongoing territorial disputes with a number of Japan's neighboring countries, which could possibly escalate in military conflicts as well as violent activities, i.e. terrorist attacks:[12]

- the *Kuril Islands*, also known as *Chishima Islands* or *Northern Territories* in Japanese
- the *Liancourt Rocks*, also known as *Takeshima* in Japanese, and *Dokdo* in Korean
- the *Senkaku Island*s, also known as *Diaoyu Islands* in Chinese

In addition, several authors pointed out that a number of politically and environmentally motivated movements still exist to this day in Japan (Kotani 2006; Library of Congress 2010; McKean 1981; Miyasaka 2009; National Police Agency 2003; Steinhoff 2007). While it would be unjustified to assume *a priori* that these will resort to violent measures, the pure possibility of such home-grown terrorism can not be dismissed, as the past has shown.

5.2. Study Area and Attack Scenario

5.2.1. Study Area

In the upcoming chapters of this study I demonstrate the practical application of the analysis framework I introduced in Chapter 4. I selected the area of the 23 Special Wards of Tokyo (Fig. 11) as my study area for a variety of reasons which I will explain in this section.

First and foremost, as mentioned in Chapter 2.3.5, urban areas combine a large number of values that humans recognize for all aspects of contemporary life and hence introduce a great number of vulnerabilities to a variety of hazards, terrorism being one of them. It is therefore only logical to apply the analysis framework to a highly urbanized area.

Figure 11: Location of the study area, which comprises the 23 Special Wards of Tokyo, within the Tokyo Metropolis and Japan.

The Japanese capital Tokyo plays a major role, not only in the national system of Japanese cities, but also in the global context of world cities (Sassen 2001; 2005). This materializes in a large number of local, prefectural, national and also foreign administrative institutions inside the city, all of which are potentially interesting targets for terrorist activities.

Tokyo, including the surrounding Metropolitan Area, is one of the most populous and most densely populated areas of the world (Tokyo Metropolitan Government 2012, 7). This means that any disaster occurring in the city will undoubtedly affect a large number of people, either directly by becoming a victim (e.g. getting killed or injured), or indirectly by suffering from the damage caused and the resulting constraints in infrastructures and services (e.g. provision with electricity, water, or interruptions in the transportation networks). The 23 wards of Adachi, Arakawa, Bunkyo, Chiyoda, Chuo, Edogawa, Itabashi, Katsushika, Kita, Koto, Meguro, Minato, Nakano, Nerima, Ota, Setagaya, Shibuya, Shinagawa, Shinjuku, Suginami, Sumida, Taito, and Toshima cover 627 km^2 which makes up 31% of the total area of the Tokyo Metropolis.[13] In contrast, according to the 2010 population census they are home to 8.94 million people, which accounts for 66.8% of the total 13.38 million people inhabiting the Tokyo Metropolis. In other words, two thirds of the population of the Tokyo Metropolis are living on only one third of its area. This fact also reflects in the high population density, which amounts to 14,195 ppl/km^2 for the study area, more than four times higher than the 3,231 ppl/km^2 for the remainder of the Tokyo Metropolis.

As I show in Chapter 5.3.1, the study area is also very diverse in its land uses. Pronounced residential areas, office clusters, as well as entertainment and shopping districts can be identified and are distributed across the study area (cf. Fig. 14). In addition, the population densities and building types also vary significantly among the 23 wards (Fig. 12 and 5), which allows for interesting comparative analyses of the results the framework produces.

Other factors for choosing Tokyo over other possible study areas are the abundance of available data about the Tokyo Metropolitan Area and my physical proximity to the city, which allowed for easy data collection and validation by fieldwork as well as personal contact with local experts.

5.2.2. Attack Scenario

The attack scenario I examine in this study is that of a small explosive attack. This was a conscientious decision, based on two facts: First, a study by the MPD revealed that this is the most feared mode of attack: 79.8% of the citizens and 86.3% of the managers of facilities that could be a target of terrorism believe it to be the most likely *modus operandi*.

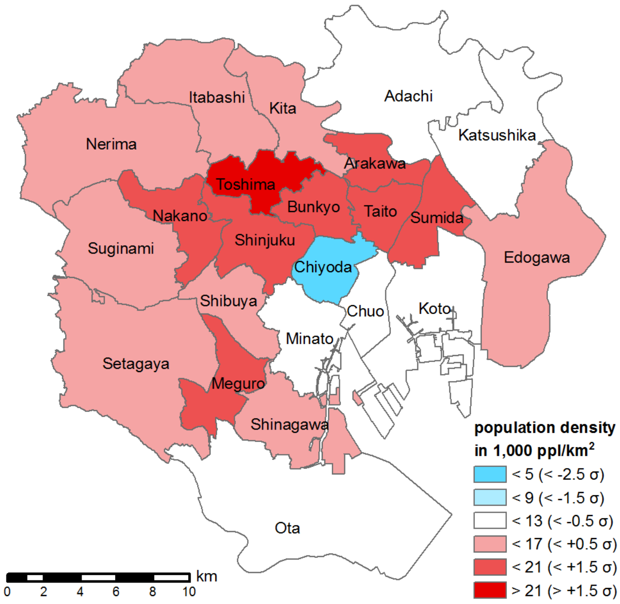

Figure 12: Population densities of the 23 Special Wards of Tokyo as per the 2010 population census.

Data source: Statistics Bureau at the Ministry of Internal Affairs and Communications (2010)

Table 5: Population figures for the 23 Special Wards of Tokyo as per the 2010 population census.

Ward	**Population**	**Area in km^2**	**Population per km^2**
Chiyoda	47,231	11.36	4,156
Chuo	122,762	10.92	11,240
Minato	200,776	20.02	10,030
Shinjuku	326,309	18.27	17,860
Bunkyo	206,626	11.37	18,174
Taito	175,928	10.09	17,443
Sumida	247,606	13.74	18,020
Koto	460,814	39.73	11,600
Shinagawa	365,301	22.42	16,295
Meguro	268,330	14.84	18,079
Ota	693,373	72.96	9,504
Setagaya	877,138	58.12	15,092
Shibuya	204,492	15.12	13,526
Nakano	314,750	15.59	20,195
Suginami	549,569	33.92	16,200
Toshima	284,678	12.97	21,953
Kita	335,544	20.49	16,373
Arakawa	203,296	10.23	19,877
Itabashi	535,824	32.19	16,645
Nerima	716,124	48.14	14,877
Adachi	683,426	53.25	12,834
Katsushika	442,586	34.82	12,710
Edogawa	678,644	49.33	13,756
μ	388,744.7	27.4	15,062.6
σ	217,943.3	17.8	3,964.2

Data source: Statistics Bureau at the Ministry of Internal Affairs and Communications (2010)

Second, an attack using a small explosive device is the most meaningful scenario regarding the spatial analysis of its vulnerability. This stems from the fact that the effect radius is limited, hence the exact location of the blast will be chosen very carefully by the perpetrators. The same can not be said about attacks using large amounts of explosives, the release of CBRN material, incendiary attacks, or shootings.[14] Other terrorist activities, such as sabotage of equipment, kidnappings, hostage takings, barricades, and assassinations follow a completely different reasoning process, since the attack targets in these cases are more confined to single persons or small groups of people, but not the general public. Other forms of terrorism do not have any spatial representation at all, such as cyberterrorism.

Also, for the sake of simplification I decided to assume perpetrators who do not target one specific institution or organization, but who generally regard affecting (i.e. killing or injuring) as many people as possible twice as important as generating attention for their actions.

5.3. Terrorism Vulnerability Evaluation

Any meaningful analysis of terrorism vulnerability and terrorism risk requires detailed and verifiable knowledge about the ideology and goals of the perpetrators as well as information about their available means in terms of money, weapons and intelligence, and their possible and most likely *modus operandi*. Therefore an overarching, universal analysis of terrorism vulnerability per se is an impossible undertaking, which would introduce more generalizations and uncertainties than clarity about the actual vulnerability situation.

Instead, it is advisable to focus on one specific perpetrator, e.g. *Aum Shinrikyo*, the *Japanese Red Army*, *al-Qaeda*, etc.) after performing an *ex ante* analysis of their short- or long-term goals, available means and characteristics of previous attacks. This allows for a precise formulation of vulnerability factors for this specific terrorist group and eliminates most uncertainties regarding their selection of targets for future attacks.

Another option is the analysis of multiple actors that follow certain types of terrorism, e.g. nationalist-separatist, religious, left-wing anarchist, etc. (European Police Office 2013). Although this introduces a higher level of generalization into the analysis, the main motivations and attack scenarios will mostly be similar within these aforementioned groups. This will also allow for the formulation of vulnerability factors that apply to all perpetrators of the respective category.

The vulnerability analysis framework I present in Chapter 4 allows for a theoretically unlimited number of vulnerability factors to be involved in the calculation. Chapter 4.2.2

mentions some criteria that should be considered in the selection of factors and also their number. The model can be highly specialized, to apply for single perpetrators or certain terrorist types if the necessary information and knowledge are available.

This information is mostly collected and developed in military and governmental institutions, crime and anti-terrorism organizations or affiliated think tanks. As a result it is at least difficult, yet mostly impossible to obtain outside of these realms. This unfortunately holds true for me and my analysis, too, which means that I am not able to provide a detailed and fact-based vulnerability analysis for a certain perpetrator at this point in time. I am convinced, though, that analysts at institutions that do have access to such data can utilize my framework to perform meaningful analyses of those terrorist threats they find necessary.

In the case of this study, I had to resort to rather broad assumptions about terrorism vulnerability and factors that increase or mitigate it in the real world. These have to be general enough to apply for most, if not all, types of terrorists and terrorism ideologies. I identified two core ideas that form the foundation of terrorism as "propaganda of the deed", a concept I introduce in Chapter 3.1:

1) Terrorists aim to affect as many people as possible.

2) Terrorists strive to create attention with their actions.

Based on these two ideas I set out to identify possible quantifiable operationalizations.

Obviously, the first idea assumes that areas with large populations, and hence high population densities, are more attractive for terrorists, since an attack with a certain magnitude will affect more victims there than in sparsely populated areas:

> There is a logical link between population-based indicators and terrorism risk. An argument can be made that consequences are correlated with population. However, terrorism risks to a population of 100,000 are clearly different if that population resides in a dense urban area rather than if it is spread across a larger rural area because of the higher probability of many high-profile targets and more people within any given attack footprint. Density-weighted population, i.e., the product of a region's population and its population density, offers one of many possible simple risk indicators that account for this difference. Just as population can be considered correlated with consequences, so too is population density correlated with threat. For example, a terrorist targeting 1,000 people might be more likely to attack a group when they are all within the same city block than if they are dispersed across the country. (Willis 2005, 21f)

Accordingly, the Urban Areas Security Initiative (UASI), a grant program by the US Department of Homeland Security (DHS), is using a population-based approach to distribute funds for counter-terrorism activities in American cities and urban agglomerations (Department of Homeland Security 2013).

The second idea is based on the assumption that terrorists are also interested in the publicity a successful attack can generate for their cause. The psychosocial approach to explain terrorism and terrorist activities argues that “terrorism must not be seen as a syndrome but as a method of social and political influence” (de la Corte 2007, 2):

> Many minority groups conduct terrorist activities as a way to bring about social change. (Kruglanski and Webster 1991). Usually, these groups represent beliefs and positions on political and religious issues which are not readily accepted by the majority. These terrorists are what some social psychologists define as 'active minorities' (Moscovici et al. 1991; Moscovici et al. 1996). According to research conducted by experimental social psychologists, minorities attempt to gain influence by persuading majority members to consider their point of view. Effective persuasion depends on the minority member's ability to clearly communicate their positions over several different occasions. Through such persistence, a minority may be able to change or influence the majority position. Terrorism is not much different from this process because the spreading of fear or terror through violence has a communicative dimension. Remember the relationship between terrorism and propaganda: after all, terrorist violence is a means to direct people's attention to certain problems (real, exaggerated or fictitious) and publicize the terrorist's political or religious demands. (de la Corte 2007, 2)

I therefore argue that terrorists will select their targets with certain symbolic connotations in mind, as this will give their deeds the aspired attention.

For the scope of this study I defined four factors to operationalize the aforementioned generalized terrorism vulnerability within highly urbanized areas:

1) the number of people inside buildings[15],

2) the number of people populating the urban space outside of buildings as pedestrians,

3) the number of people within the public railway transportation network, and

4) the symbolic value of places.

As population figures in highly urbanized areas vary significantly over time, I incorporated the temporal dimension in the calculation of the first three factors. In contrast, the symbolic value of an object does not change over the course of one day, so it was not necessary to consider this additional dimension in the case of the fourth factor.

The operationalization methodologies for these four factors constitutes the core objective of this study. I will therefore discuss them in great detail in the upcoming sections. The central focus while doing so is on the spatial characteristics of urban space that determine the emergence of vulnerability. To my best knowledge this has not been done in the past, which underlines the originality of my scientific approach.

5.3.1. Stationary Building Population

Introduction

Detailed population information is crucial for the micro-scale modeling and analysis of human behavior and processes in urban areas. Ideally it should be based on individual persons, yet, for privacy reasons such data is generally not available. Therefore it has become necessary to derive estimated data from aggregated datasets such as census data.

Wu et al. (2005) provided an extensive summary of a variety of approaches and methodologies that have been published in the past. Since it has now become somewhat outdated, I first provide a brief overview of some of the major achievements in the field of population estimation methodologies and focus on those studies that have been the most influential in the development of the approach I developed in the course of this study.

Tobler et al. (1997) suggest their *Gridded Population of the World* as a macro-geographic approach for population estimation on a global scope. They argue that "the average daily activity space of individuals is dependent upon culture, environment, social, and urban-rural status, but averages more than 15 km in western societies." (Tobler et al. 1997, 207) In their calculations they rely on population data aggregated on secondary administrative levels and ultimately produce worldwide population figures "interpolated to a 5- by 5-minute grid using a smoothing algorithm developed by Tobler (1979)." (Sutton et al. 2003, 546)

The *LandScan Global Population Project* at the Oak Ridge National Laboratories (Bhaduri et al. 2007; Dobson et al. 2000) also attempts to provide worldwide population figures, albeit on a finer spatial scale of 30 by 30 second grid cells, and more recently even with a 90 by 90 m resolution for the USA. They do this by improving the pycnophylactic and dasymetric interpolation algorithms that had traditionally been employed, using additional ancillary spatial data, such as roads, slope, land use, urban areas, nighttime lights (Elvidge et al. 1997; Sutton et al. 2001), and coastlines. In addition, they also incorporate diurnal nighttime and daytime populations to account for the variations in population distributions as a result of different underlying activities.

Similarly, McPherson and Brown (2004) focus on the shifts in populations in their work at the Los Alamos National Laboratory. They argue that "the 1-kilometer resolution used in that [i.e. the LandScan] dataset is insufficient for urban exposure analyses." (McPherson and Brown 2004, 2) and provide nighttime residential, daytime residential, and daytime workplace population data on a 250 by 250 m grid for the continental United States and Hawaii. In their model they rely on a number of datasets, including nighttime population census data, a business directory and a *Census County to County Journey to Work* dataset by the US Census Bureau containing the numbers of people moving from their homes to their workplaces. This approach bears some similarity to the one I introduce in this study, but it is more simplistic and uses a coarser spatial scale.

Along the same lines Martin (1996) and Martin et al. (2009) developed a model for the estimation of

> 24-hour gridded population models of the UK [...] based on an existing adaptive kernel density approach for building gridded population models (Martin 1996), which is now being extended to become a spatio-temporal kernel density estimation method. (Martin et al. 2009, 1)

To my best knowledge this marks the first attempt to overcome the diurnal model of daytime and nighttime populations and to provide an insight into the differences in population distributions over the course of a day. They achieve this by not relying exclusively on the available census data, but by incorporating additional secondary datasets, such as employee numbers, traffic and passenger flow data, as well as counts of prison inmates, hospitalized people and tourists (Martin et al. 2009, 3). This is a fundamental parallel to the methodology I present in this study, but my approach overcomes the limitations regarding the availability of dynamic population data that Martin and colleagues deplore.

Ahola et al. (2007) attempt to overcome the coarse spatial resolutions of the aforementioned studies, which preclude their application in the micro-scale context of highly urbanized areas. They were able to do this by using population census data on the building level for their case study. In order to represent the dynamic characteristics of the population distribution they employed a spatial decision support framework (Malczewski 1999) using several data and *a priori* assumptions:

> (1) basic static data on the population and infrastructure (municipal and governmental registers); (2) time-series data on the trends in various phenomena (data from the statistics); (3) spatio-temporal knowledge (spatio-temporal model of population); and (4) strategies on preparedness (governmental statements about the threats and the preparedness for them). (Ahola et al. 2007, 938)

They identified 14 individual time periods over the course of a week as a result of the modeled activities, but mention that “more detailed information about the temporal behaviour of different population groups could also improve the quality of the model.” (Ahola et al. 2007, 952) This one of the major aspects I pursued with the development of the estimation approach introduced in this study.

As Martin and colleagues remark

> grid-based population models have considerable advantages for population representation, offering more meaningful representation of settlement and neighbourhood pattern, including the geography of unpopulated areas, and providing stability through time. As a result, gridded models have seen extensive use where population must be integrated with environmental phenomena. (Martin et al. 2009, 1)

On the downside these grids are normally too generalized in their spatial resolution to be able to adequately represent facts and processes within highly urbanized areas. Another shortcoming of the models introduced above is the temporal scale, which is either left out completely, or defined as a two-stage process that opposes the situations during the day and at night. A notable exception is the approach by Martin et al. (2009), but their assumption of all people of a certain demographic group being engaged in a certain activity (and hence being present at certain corresponding locations) at a certain time appears me to be too generalizing, which again makes spatio-temporal micro-scale analyses unreliable.

Two approaches have been published recently that attempt to ameliorate these two short-comings. Lwin and Murayama (2009) suggested a variety of calculation methods to estimate populations on a building basis, including areametric and volumetric approaches. In addition Horanont (2012) suggested and exemplified the use of person trip data in the modeling of dynamic populations.

In this part of my study I present a novel approach for a spatio-temporal micro-scale population estimation on a building basis. It incorporates multiple datasets, namely population census data, employment data, student data, address point data and, following Horanont's (2012) suggestion, movement data. As a result the model provides fine-grained results of the estimated populations within different usage categories for each building on a given time-scale.

I first explain the necessary data and describe the datasets I employed in the exemplar calculations for my study area (cf. Chapter 5.2). I then explain and discuss the basic methodology, which builds the foundation for my enhanced approach, as well as the extensions I made to the model. I then go on to explain in detail the newly introduced dimensions of usage categories and temporal fluctuations derived from movement data. In addition I discuss the validation of the model as well as its output, before summarizing and pointing out some shortcomings in the final section.

Data

All datasets required for the estimation calculation I propose here together with their required attributes are shown in 6.

Table 6: Necessary datasets for the spatio-temporal building population estimation methodology and datasets used in this study.

Dataset	Attributes	Dataset name and source	Date
building data	footprint area number of floors	Zmap-TOWNII by Zenrin Co., Ltd.	2008/09
census data	residential population (i.e. population census information)	Population census by the Statistics Bureau at the Ministry of Internal Affairs and Communications	2010
	employment population (i.e. business or economic census information)	Employment census by the Statistical Institute for Consulting and Analysis	2009
	student population (i.e. school census information)	School census by the Department of Statistics Population at the Tokyo Metropolitan Government Bureau of General Affairs	2010
address point data	spatial location of each address point category of the person or business represented by each data point	Telepoint Pack! by Zenrin Co., Ltd.	2011
population movement data	spatial location of each individual at each time step trip purpose / activity means of transportation	PersonFlow data by the University of Tokyo Center for Spatial Information Science	2008

Since I am aiming to derive population figures for single buildings, detailed data about these buildings is necessary. The 2008/09 *Zmap-TOWNII* data by Zenrin Co., Ltd., one of the biggest Japanese providers of geospatial data[16], contains exact building footprints and information about the number of floors for most buildings. It has to be mentioned, though, that this data is by no means complete and free of errors: of the 1,899,953 buildings in the study area, 67.8% do not contain floor data, hence I had to perform all calculations using the remaining 571,922 buildings. Their area can be easily determined in GIS software from their footprint polygons.

A second source of data for my population estimation model are census datasets. These data can be obtained easily in most parts of the world. Their respective aerial unit refers to the level of aggregation of the underlying population data. It depends on the dataset used and can range from large-scale units like states or metropolitan area to smaller units like census tracts or even micro-scale units like census blocks or building blocks. In this study I used the population census data collected by the Statistics Bureau at the Japanese Ministry of Internal Affairs and Communications for the year 2010 on the spatial aggregation level of census tracts.

While its general availability is a positive aspect of population census data, two obvious shortcomings are its exclusive focus on residential populations, discounting other activities such as working or studying, and its missing temporal scale. Many authors have emphasized how census data does never portray the actual population distribution, but can, at its best, only represent the so-called "nighttime population" (Ahola et al. 2007; Bhaduri et al. 2007; Dobson et al. 2000; Martin et al. 2009; McPherson and Brown 2004; Schmitt 1956). In this context Wu and colleagues note that census data are "mainly concerned with residential populations and the daytime population distribution can be very different from that described by the census." (2005, 70) Thus the data will be especially misleading in areas with minor residential use and a great number of other usages. Prime examples are highly urbanized city centers, which have undoubtedly high populations during daytime, but almost no residents. Whether or not they are completely deserted during the night depends on the presence of employees at night, for example due to globalized business activities at all times, and on the existence of other land uses, such as entertainment facilities. Figure 13 shows a map of the central part of the Tokyo Metropolitan Area with the residential population density figures for each census tract according to the aforementioned 2010 census data. It is obvious how the population density in the core city of Tokyo is significantly lower than in the surrounding suburban belts, which reach far into the neighboring prefectures of Saitama to the north, Chiba to the east and Kanagawa to the south.

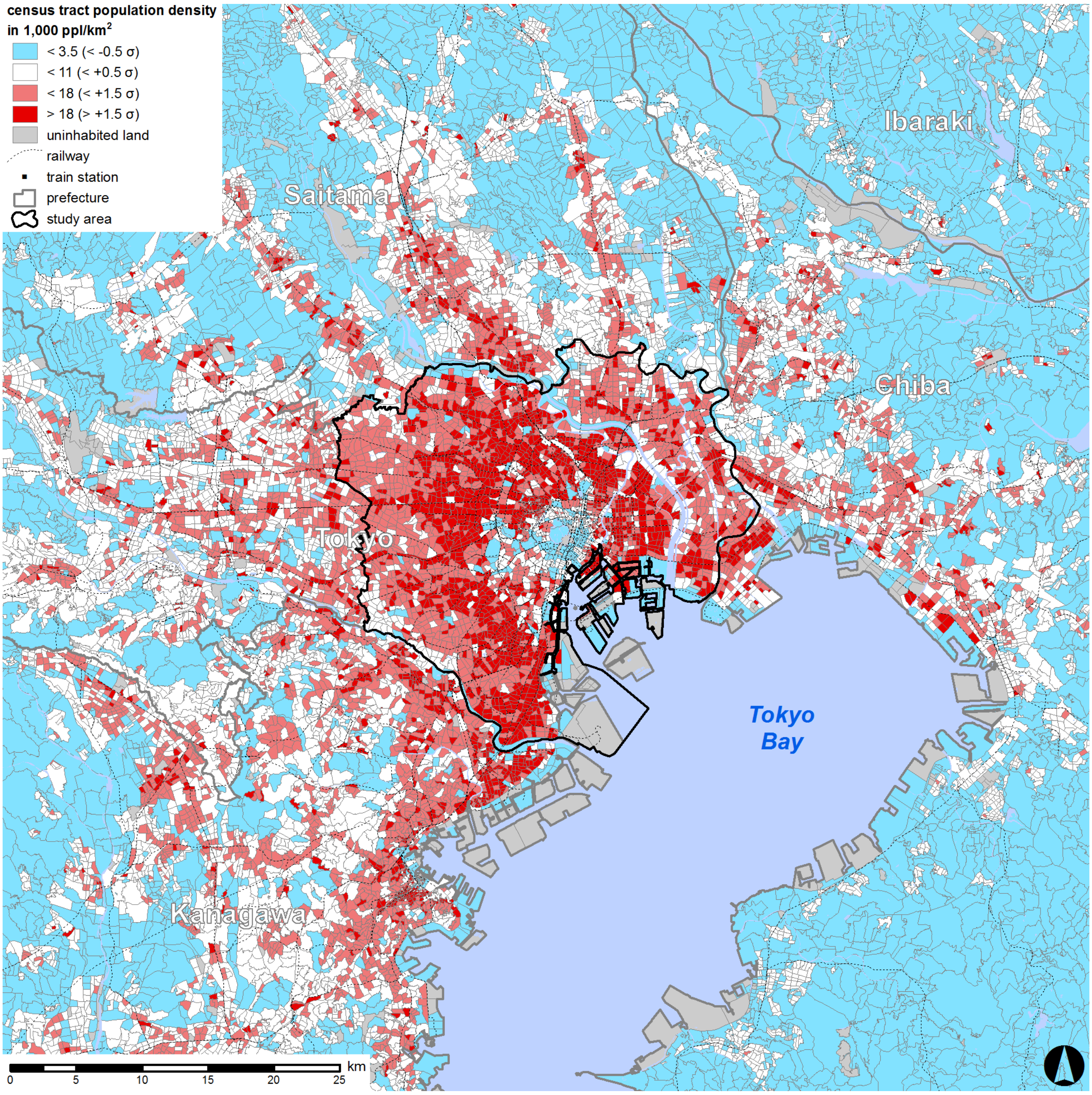

Figure 13: Population density per census tract as per the 2010 population census dataset for parts of the Tokyo Metropolitan Area.

Data source: Statistics Bureau at the Ministry of Internal Affairs and Communications (2010)

It is imperative to amend these two shortcomings, the exclusive focus on residential populations and the missing temporal scale of all population datasets, in order for micro-scale population data to be useful for my vulnerability assessment. Sutton and colleagues argue that “useful measures of population density must be made at appropriate, application specific, spatial and temporal scales.” (Sutton et al. 2003, 545) Hence it was necessary to utilize additional datasets to incorporate both the multiple usage categories and the inherent temporal differences that affect building populations in highly urbanized areas in my enhanced model.

Similar to the normal population census data, which represents the residential or “nighttime” population, employment census data contains information about the number of employees in different business categories. In this study I used the employment census data on the spatial aggregation level of census tracts by the Statistical Institute for Consulting and Analysis, which had originally been collected by the Statistics Bureau at the Japanese Ministry of Internal Affairs and Communications for the year 2009. This dataset contains detailed data about the number of employees and businesses, together with some socio-demographic details about the employees. The data are grouped in 16 employment categories, which are originally defined by the Japanese Ministry of Health, Labour and Welfare. In order to be able to combine them with other datasets, I generalized the 16 categories from the original dataset to five usage categories, which 7 shows.

I developed these five non-residential usage categories by defining all activities that are pursued in urban areas. I did this by largely emulating the classifications by Axhausen et al. (2002), Bowman and Ben-Akiva (2001), and Jiang et al. (2012). Since these activities have to be mapped to multiple other datasets from different sources in the course of the modeling process, I formulated them as general as possible while keeping intact their distinct characteristics. To derive them I used a dataset of address points, which contained not only the spatial location but also an indicator of the usage for each data point. Starting from a total of 2,208 indicators I aggregated them to these six categories for use in this study, as 8 explains. The colors for these six usage categories are used consistently throughout this study.

In addition to these two census datasets I also used the 2010 school census data by the Department of Statistics at the TMG Bureau of General Affairs. In contrast to the two aforementioned datasets, this data is only available at the spatial resolution of wards. It contains a number of attributes about the numbers of schools, students and teachers for ten different school types, of which I only implemented the number of students in this model as 9 shows. The teachers are already represented by the employment census in the category “education” (cf. 7).

Table 7: Assignment of the original employment categories in the employment census data to the generalized usage categories used in the population estimation model.

Employment categories as per 2009 employment census dataset	**Usage category**
Agriculture & forestry	business & office
Fisheries	
Mining and quarrying of stone and gravel	
Construction	
Manufacturing	
Electricity, gas, heat supply and water	
Information and communications	
Transport and postal activities	
Finance and insurance	
Real estate and goods rental and leasing	
Government, except where classified	
Scientific research, professional and technical services	education
Education, learning support	
Wholesale and retail trade	retail & service
Living-related and personal services and amusement services	
Compound services	
Accommodations, eating and drinking services	leisure & hotel
Medical, health care and welfare	public institution
Services not elsewhere classified	

Table 8: Six usage categories used in the population estimation model and some exemplar real-world usages from the address point dataset.

Category		Exemplar usages as per address point dataset
1	home	private households
2	business & office	all types of offices and places of manual labor (e.g. factories, agricultural, forestry and fishery) excluding those aiming predominantly at service tasks
3	education	kindergarten, elementary schools, junior high schools, senior high schools, vocational schools, schools for the disabled, universities, research institutes, libraries
4	retail & service	all types of shops, department stores; all types of service institutions (e.g. gas stations, cleaning shops, branch banks, post offices, etc.)
5	leisure & hotel	restaurants, coffee shops, entertainment facilities (e.g. bars, movie theaters, concert halls, etc.), sports facilities, hotels
6	public institution	police departments, fire departments, hospitals, clinics, nurseries, public assembly halls

Table 9: Number of students for different school types per ward in the study area as per the 2010 school census dataset.

Ward	kindergarten	elementary school	junior high school	senior high school	secondary education	special assis-tance education	vocational school	university	junior college	technical college
Chiyoda	1,057	4,578	7,117	11,166	857		17,563	136,151	2,889	
Chuo	1,399	4,631	1,404	959			876	509		
Minato	2,658	7,422	9,057	12,881		270	4,112	25,162	335	
Shinjuku	2,244	8,825	6,120	7,751		34	28,401	73,274	617	
Bunkyo	2,775	9,636	8,731	15,834	798	358	5,477	75,337	535	
Taito	2,341	6,437	2,985	4,867			3,768	3,162	65	
Sumida	1,786	9,606	5,336	5,803		249	2,717			
Koto	4,691	19,821	7,761	6,747		407	2,204	4,206	129	
Shinagawa	4,015	13,237	8,194	9,058		45	1,726	14,487	119	1,595
Meguro	3,312	9,461	4,510	8,644	785		1,348	7,317		
Ota	9,244	29,123	10,873	9,848		553	8,073	1,258		
Setagaya	10,694	36,043	19,509	25,550		448	4,308	69,488	2,824	
Shibuya	1,908	7,325	4,934	9,019			22,264	28,502	3,672	
Nakano	3,002	9,629	5,569	9,595	706	326	5,809	190	803	
Suginami	6,407	19,020	10,270	16,254		537	3,239	6,889	1,289	
Toshima	1,509	8,633	7,773	12,185		162	14,669	35,771	560	
Kita	4,906	12,965	7,434	10,392		619	3,559		670	
Arakawa	1,177	8,018	4,200	2,759			2,963	1		
Itabashi	6,440	22,918	11,963	11,178		561	3,329	31,643	1,846	
Nerima	10,672	35,124	15,366	9,127	443	463	989	5,594		
Adachi	9,678	32,343	14,643	8,504		519	595	1,183		
Katsushika	6,454	20,796	9,400	5,193		589	1,711	559		
Edogawa	11,338	38,087	16,572	9,058		589	7,131		101	
μ	4,769.8	16,246.8	8,683.5	9,668.4	717.8	395.8	6,384.0	26,034.2	1,096.9	1,595.0
σ	3,423.4	10,952.0	4,516.5	5,013.8	162.8	189.0	7,333.3	36,240.9	1,166.7	./.

Data source: Tokyo Metropolitan Government Bureau of General Affairs (2010)

To account for the temporal fluctuations in the distribution of populations it is necessary to obtain spatio-temporal data representing the movements of people in the respective study area. In the case of this study I included the 2008 *PersonFlow* data by the University of Tokyo Center for Spatial Information Science (CSIS), which contains movement data of 576,806 individuals in the Greater Tokyo Metropolitan Area. It comprises the Tokyo Metropolis, the prefectures Kanagawa and Chiba, as well as Southern parts of Saitama and Ibaraki prefectures, an area of 15,712 km^2. Since, according to the 2010 census, this area is home to 41,371,181 people, the sample represents 1.39% of the total population. The underlying data were originally collected by the Tokyo Metropolitan Area Transportation Planning Council using paper questionnaires. The dataset contains not only the location and time stamp of the start and end of trips, but also the mode of transportation, the purpose of the trips, and several socio-demographic details about the individuals, such as gender, age, and occupation (Tokyo Metropolitan Area Transportation Planning Council 2013). I reclassified the 15 trip purposes as per the questionnaires to match the aforementioned six usage categories, as 10 shows.

The data were collected on Thursday, October 1st, 2008, and hence represent a regular working day during the week, outside of all relevant holiday or festival periods. Also, the AMeDAS weather data provided by the Japanese Meteorological Agency shows no precipitation during the day and comfortable temperatures ranging from 17.3ºC to 20.9ºC (Japan Meteorological Agency 2008). The data from the questionnaires had been further processed using various multi-modal routing algorithms by a research group at CSIS, who were able to synthesize it into point positions in one minute intervals from 12am to 11:59pm (Sekimoto et al. 2011; Usui et al. 2009). This results in 1,440 point positions per individual, amounting to 830,600,640 datasets in total.[17]

While this massive person trip dataset allows for the analysis of person flows and single trips, I filtered it for the time spans of stationarity between trips, where the individuals were not moving in space. Since these stationarity events themselves were not assigned a purpose in the dataset, I classified them according to the purpose of the immediately preceding trip. If for example an individual started a trip with the purpose of "going to work", then I classified the subsequent stationarity event as "work" activity, if it was "going home", I classified it as "home" activity. This allowed me to extract the number of people in each location at each point in time pursuing in each of the six usage categories. One data issue were the first stationary events in the morning, as they were coded "other, n/a" for all individuals. A quick analysis revealed that only 3,704 of the sample individuals (0.64%) indicated "going home" as the purpose of their second trip (i.e. their first non-stationary event). I therefore assumed for the remaining 573,102 persons

Table 10: Assignment of the trip purposes in the Person Trip questionnaire data to the generalized usage categories used in the population estimation model.

Trip purposes as per 2008 *Person Trip* questionnaire dataset	**Usage category**
going home	home
going to work	business & office
delivery purpose (work)	
business purpose (work)	
service purpose (work)	
agricultural purpose (work)	
other work related purpose	
going to school	education
going shopping	*retail & service*
going for meal, leisure, social interaction	*leisure & hotel*
sightseeing	
going to hospital	*public institution*
running an errand	
dropping somebody off	
other, n/a	./.

Note:
Italics mark usage categories that are not incorporated in the spatio-temporal building population estimation calculation due to their transient character (cf. Chapter 5.3.5).

that they were at home at midnight and assigned the respective usage category to these stationary events. The remaining persons, most likely coding errors or people working in night-shifts, kept the purpose “other, n/a” and were not included in the population estimation process until their first meaningfully encoded trip started.

It is important to note here that in the spatio-temporal stage of the estimation process three activities represent the six categories I defined above: the activity “home” corresponds to the usage category “home”, the activity “work” contains the employees of all five remaining categories ("business & office", "education", "retail & service", leisure & hotel", and "public institution"), and the activity “education” contains the students present at educational institutions. People engaging in these activities outside of their occupation, for example as customers of a shop or guests at a restaurant, can not be captured by this method and are therefore not contained in the resulting population estimation figures (cf. Chapter 5.3.5).

Methodology

The population estimation methodology I developed in the course of this study is an extension of the paper by Lwin and Murayama (2009). There the authors introduced both areametric and volumetric methods for the estimation of residential building populations. Both methods assume an equal distribution of the population over the available floorspace within all the residential buildings in a study area, but they differ in the method to derive this total floorspace area: while the areametric method refers exclusively to the buildings' footprint areas, the volumetric method takes the number of floors per building into account in addition to that. The former is owed to the possible unavailability of comprehensive data about the number of floors per building. While it still allows for an estimation of the building populations, the authors remark that “the Areametric method is suitable for low-rise buildings especially in rural areas while the Volumetric method is suitable for high-rise buildings, especially in downtown areas.” (Lwin and Murayama 2009, 404) A shortcoming of their approach is the exclusive focus on residential buildings, which neglects all other building uses, such as offices, shops, schools, etc. This limitation is especially striking in highly urbanized areas, such as my study area, which are characterized by a mix of usages over space (cf. Fig. 14) and sometimes even within buildings.

The volumetric building population estimation methodology introduced by Lwin and Murayama (2009) uses equation (2) to calculate population figures for all buildings. They point out that buildings with non-residential use and reasonably small footprint areas have to be excluded from the calculation. They also statistically derived the optimal minimum footprint area to be

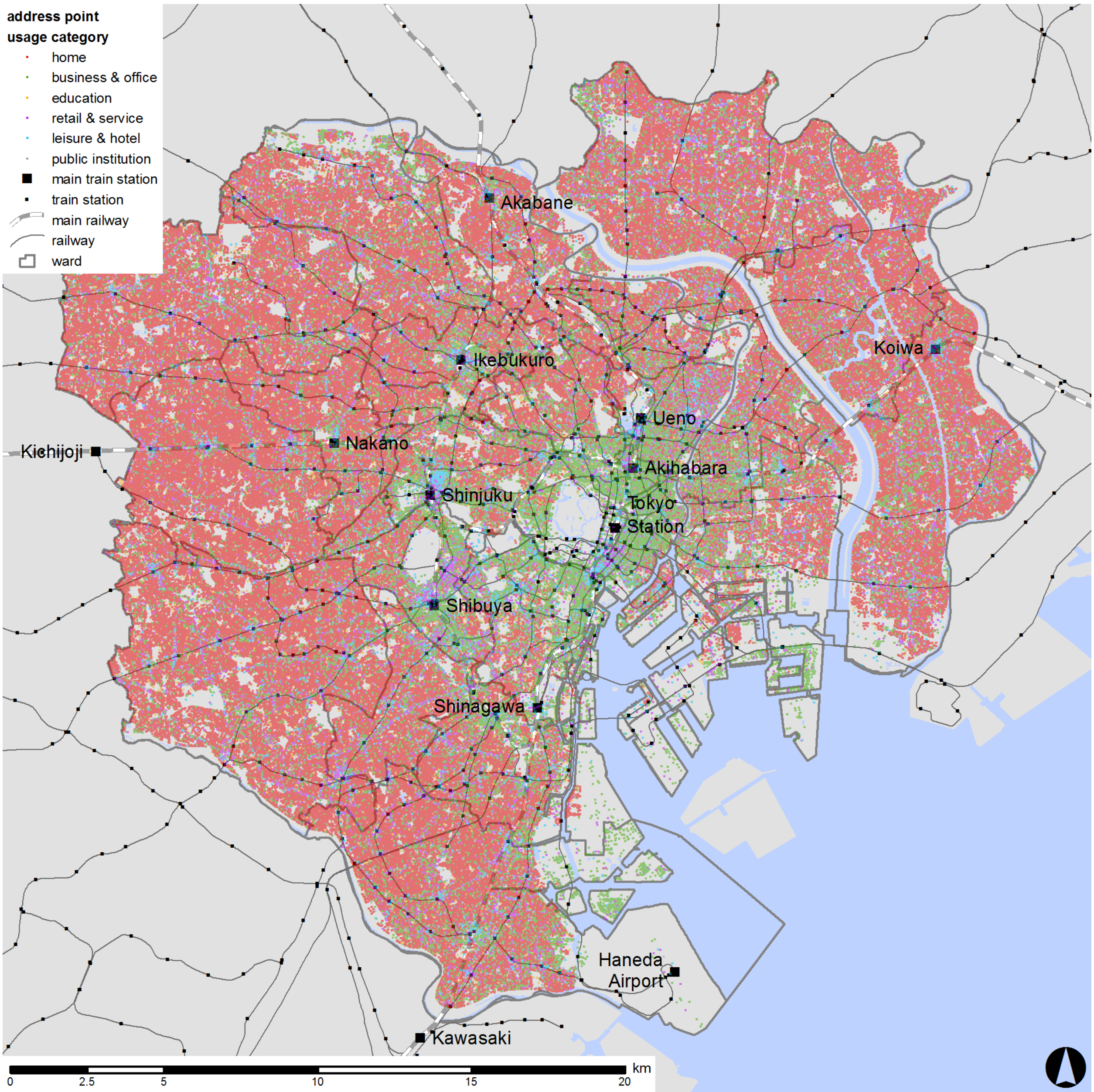

Figure 14: Spatial distribution of the six usage categories within the study area as per the 2011 Telepoint! Pack dataset.

Data source: Zenrin Co., Ltd. (2011)

25 m², which "is probably the average single-unit living space in the study area." (Lwin and Murayama 2009, 410)

$$BP_i = \left(\frac{CP}{\sum_{k=1}^{n} BA_k \cdot BF_k} \right) \cdot BA_i \cdot BF_i \tag{2}$$

where BP_i is the estimated population of building i, CP is the population of the aerial unit that contains building i, BA_i is the footprint area of building i, BF_i is the number of floors of building i, and n is the number of buildings that meet the user-defined criteria regarding residential usage and minimum footprint area and that are located inside the same aerial unit as building i. (modified from Lwin and Murayama 2009, 403)

A validation in the original study showed a statistical correlation between the calculated building populations and the actual building population figures of $R^2 = 0.94$. This led me to believe that the underlying assumption of the population being equally distributed over the available total floorspace allows for a sufficiently precise estimation of building populations. Yet, the limitations in the suggested method regarding the usage types (the authors only accounted for the residential population) and the missing temporal dimension incited me to extend and further develop their basic approach into an enhanced methodology that can represent more realistically the underlying real-world processes that are the result of the human actions happening, especially in urban areas.

Hence I developed the enhanced spatio-temporal building population estimation methodology, which equation (3) shows in a formalized fashion. In the course of this section I will explain the underlying assumptions, datasets and calculation steps in great detail.

$$SBP_{i,c,t} = \left(\frac{AP_{A_{i,c,t}}}{\sum_{k \in A_{i,c}} BA_k \cdot BF_k} \right) \cdot BA_{i,c} \cdot BF_i \tag{3}$$

where $SBP_{i,c,t}$ is the stationary population of building i in category c at time t, $AP_{Ai,c,t}$ is the total population of category c at time t of the census tract that contains building i, A is the set of all census tracts, BA_i is the footprint area of building i, $BA_{i,c}$ is the footprint area of building i in category c, BF_i is the number of floors of building i.

The calculation process itself is split into two main parts: first the categorical volumetric building population estimation process, which estimates the building population per usage category. This part of the estimation process produces meaningful results on its own, if the additional temporal dimension is not of interest or the necessary data are not available. In this case, equation (3) has to be applied without the notation of the time t, producing $SBP_{i,c}$ as the stationary population of building i in category c. The actual spatio-temporal volumetric building population estimation process, which includes the temporal dimension, is explained in detail afterwards.

Categorical Volumetric Building Population Estimation Process. I first assigned the total number of address points as well as the number of address points in each of the six usage categories to each building. Figure 14 shows that the different usage categories are not distributed equally within the study area and instead reveal several patterns: the aforementioned suburban residential belt can be seen spreading from just outside the tracks of the Yamanote Line loop.[18] In contrast, the center-most area is dominated by business and office usage, starting roughly near Iidabashi Station north of the Imperial Palace grounds and stretched alongside the Yamanote Line tracks until Shinagawa Station and from the eastern side of Tokyo Station northwards until Ueno Station. The business areas along the coast of Tokyo Bay are dominated by logistics and cargo companies and their warehouses. The largest shopping areas can be identified in the northeast of Shibuya Station, where the upscale Omotesando Street and the alternative Harajuku quarters are located, as well as in the Ginza neighborhood, south of Tokyo Station, and around Akihabara Station, which is dominated by electronics and duty-free shops. The agglomerations of restaurants and entertainment facilities around practically all train stations shows the importance these transportation hubs have in the day-to-day lives of the Tokyoites. In addition, the infamous entertainment quarters of Kabukicho, northeast of Shinjuku Station, as well as in Shibuya and Roppongi can be seen.

A closer look at the area inside the loop of the Yamanote Line tracks in Figure 15 reveals some residential clusters on the small artificial island of Tsukishima southeast of Tokyo Station and in south-western Minato ward, northwest of Shinagawa Station. Also, the agglomeration of offices to the west and to the east of Shinjuku Station are visible. Additional clusters of leisure facilities south of Ueno (Ameyayokocho), in Yurakucho and Akasaka, south of Hibiya Park, around Ebisu Station and Gotanda Station between Shibuya and Shinagawa on the Yamanote Line, as well as in Kinshicho and Nakano on the eastern and western edges of the map, respectively.

Due to the mix of usage categories prevalent not only over space but even within buildings in highly urbanized areas, it was necessary to implement these mixed uses in the estimation model. An analysis of the dataset used in this study revealed that 35% of all buildings contained address

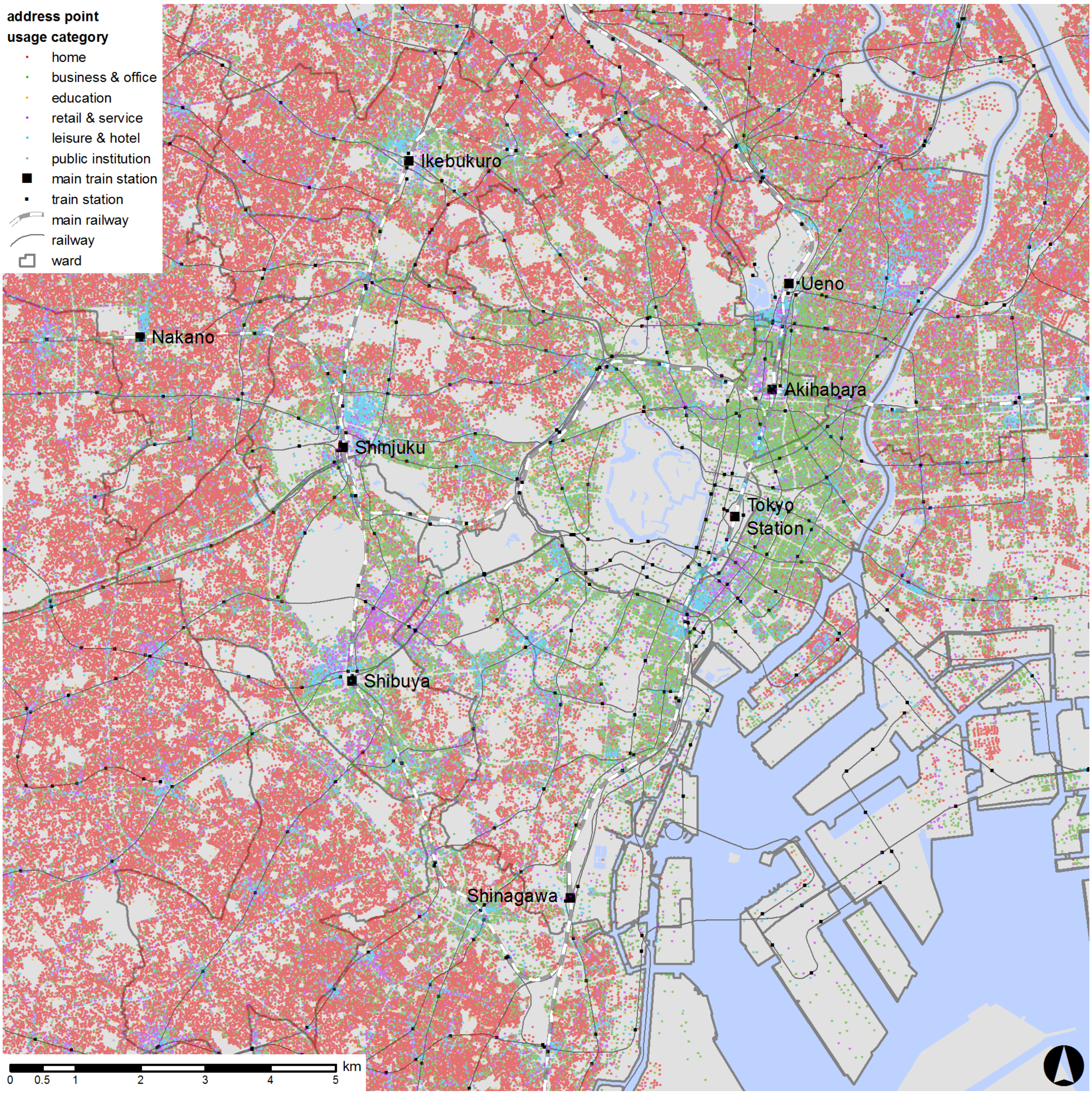

Figure 15: Spatial distribution of the six usage categories within the central part of the study area, inside the tracks of the Yamanote Line loop as per the 2011 Telepoint! Pack dataset.

Data source: Zenrin Co., Ltd. (2011)

points of more than one category. Since detailed information about the actual floorspace occupancy per category within a building is usually not available, the model uses the relative ratio of address points per category per building as an approximation. Figure 16 shows examples of this relative ratio of usage three exemplar usage categories in a small portion of the study area around Tokyo Station. The numbers show the percentage of floorspace of each building that is occupied by a certain usage category. The Kyobashi Plaza Building for example, which is marked in Figure 16, contains 19 address points over all six categories on its 19 floors, eleven of which are “home”, four are “business & office”, and one each is “education”, “retail & service”, “leisure & hotel”, and “public institution”. Therefore, category “home” is assigned 57.9%, “business & office” 21.1%, and the other categories 5.3% each of the total floorspace of 46,064 m^2. It is obvious how the relative occupation of residential use is decreasing towards Tokyo Station, while the office occupancy rate per building is high across this part of the study area. Again, the main shopping area of Ginza is easily identifiable in the southwestern corner of Figure 16c. Also, the big Takashimaya Department Store in Nihombashi north of the center of the map as well as the numerous shopping opportunities in the highrise office buildings west of Tokyo Station are clearly visible.

Next I derived the total floorspace in m^2 for each building from its footprint area and the number of floors as suggested in the preliminary approach by Lwin & Murayama (2009). In addition I was able to calculate the absolute floorspace occupied by each usage category within each building, using both the information about each building's total floorspace and the relative ratio of usage per category within each building based on the existent address points. This introduces two possible errors that will ultimately also affect the building population figures. First, missing address point data can skew the floorspace percentages per usage category significantly. If for example a building with a total floorspace of 300 m^2 contains one address point each for “home” and “business & office” use, both categories would be assigned 150 m^2 floorspace each. A missing address point in either category, for example another office, would mean a significant deviation from these numbers, since in this case the actual floorspace would be 100 m^2 and 200 m^2, respectively. The model would thereby over- respectively under-estimate the floorspace by 50 m^2. Second, my approach assumes an even split of the available floorspace area within a building between the existing usage categories. This can be problematic in cases where one category occupies a larger portion of the space than others. If for example a building with five floors at 100 m^2 each contains one office and one convenience store, both categories would be assigned 250 m^2 each. Yet in reality the convenience store only occupies the ground

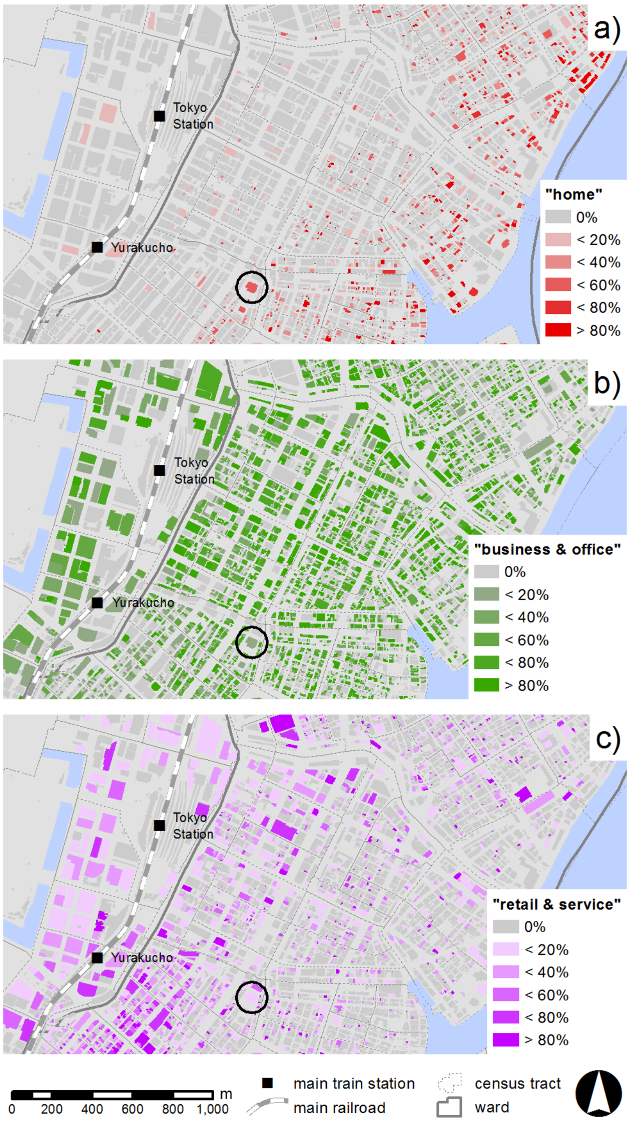

Figure 16: Floorspace occupancy ratios for the usage categories a) "home", b) "business & office", and c) "retail & service" in a small part of the study area derived from the 2009 employment census.

Data source: Statistical Information Institute for Consulting and Analysis (2009) floor, whereas the office spreads across the other four floors, amounting to an effective split of 100 m^2 and 400 m^2, respectively, which again introduces significant over- and under-estimations of the two categories. While I am aware of these shortcomings I have been unable to ameliorate them given the available data.

In order to match the floorspace per category per building with the categorical population data as introduced in the original estimation model I then calculated the total floorspace per category for all buildings within each census tract. Doing so I relied on the aforementioned assumption of assigning the population of each census tract to the buildings it contains according to their ratio of floorspace in the cumulative floorspace of all buildings within it. My enhanced model does this separately for each of the six usage categories. To achieve this I used different data sources for the calculation of the populations within each usage category, as mentioned above: while regular population census data represents the residential population, also known as the "nighttime population", the employment census contains information about the number of employees in the five different business categories (cf. 7). This allowed me to put the number of employees per category per census tract into context with the relative floorspace ratio of each category across each building within this census tract. In addition, the use of the school census dataset allowed me to account for the number of students. Accordingly, the aforementioned building population estimation formula has to be employed once for the residential population (usage category "home"), once for each of the five remaining categories ("business & office", "education", "retail & service", "leisure & hotel", "public institution"), and once for the student populations using the respective population figures and floorspace ratios. As a result, I could then assign an estimated population per usage category to each building. In this context it should be mentioned again, that the current estimation model does only account for the number of residents, employees and students within the buildings, but not for the number of people pursuing other activities there. Other, more transient populations like customers, guests and visitors can not be estimated in this fashion, and are therefore left out of the calculation.

Since the number of employees per category varies both per building and per census tract, it is necessary to perform the aforementioned calculations for all five employment categories and once each for the residential and student populations. This way the connection between the address point dataset and the residential, employment, and student census datasets, respectively, is maintained throughout the model. It should also be mentioned that due to the separated calculation processes for the different usage categories (residential, non-residential, education) the spatial representations (e.g. "census tracts") of the underlying population datasets do not necessarily need to be identical and can vary in their levels of generalization. This is true since all upcoming steps of the modeling process will work on the building level.

I would also like to point out another shortcoming of this estimation process here, which is a result of the available datasets. With the assignment of residents, employees and students to the buildings based on the percentage floorspace ratio within their respective census tract we assume that all occurrences of a usage category accommodate an equal number of people per m^2. In reality there are quite big variations in the space requirements even within usage categories. For example, some offices are rather cramped and hold a large number of employees on little space, while others have rather spacious layouts and house fewer employees. The same holds true for different forms of residential units (e.g. single-room apartments, mansions, lofts, etc.). They are all assumed to be equal by my estimation process, which can potentially introduce significant errors. With the available data I have not been able to circumvent this shortcoming.

In a last step these categorical building population figures can then be summed up to the total estimated building population of each building. Figure 17 shows the result of this final step. These numbers can be understood as $SBP_{i,c}$, the estimated total stationary building population of building i in category c. They represent the maximum number of people that, according to the underlying assumptions and data sources used in the modeling, are present within each respective building. This figure does most likely not reflect reality, as can be easily understood by the example of a building containing both residential and commercial use: while the residents are likely to leave their homes during the course of a day and tend to return in the evening, the employees would rather enter the building in the morning and leave in the late afternoon, as I will prove in the upcoming section. As a result it is highly unlikely that 100% of the populations of both categories would be present in the building at the same time. This renders the current model output questionable, since it grossly overestimates the actual building population. I therefore deemed it imperative to include the temporal dimension into the estimation process.

Adding the Temporal Dimension. The outcome so far extends the original methodology by Lwin and Murayama (2009) by the introduction of five additional usage categories over their one-dimensional approach of residential populations. As mentioned above, this does not account for the fact that populations are not stationary over time, but move in space according to the routine activities performed by people in the urban space.

To account for this it was necessary to obtain spatio-temporal data representing the movements of people in the respective study area. In the case of this study I used the aforementioned CSIS *PersonFlow* dataset (Center for Spatial Information Science 2008).

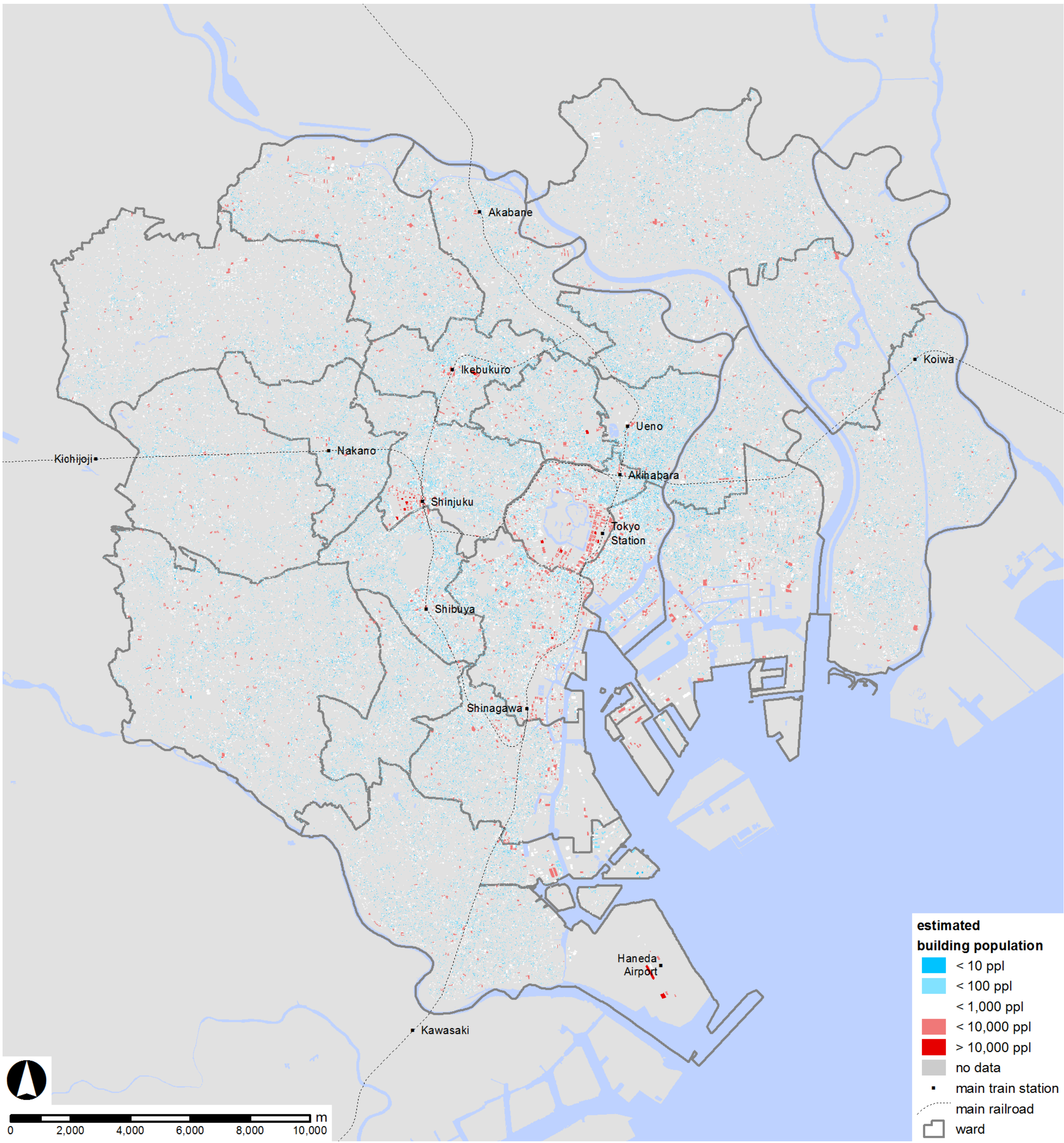

Figure 17: Estimated total stationary building population SBPi,c for all buildings in the study area. The data is the result of the stationary building population estimation methodology using a number of data sources from 2008-2011.

Due to privacy reasons the team at CSIS had to anonymize the exact spatial locations of the addresses provided in the original questionnaires. Therefore I was not able to assign the locations of the stationarity events (or the last location of the preceding trip) to the exact building locations, which would have made the subsequent population estimation process significantly simpler. Instead, the stationarity locations of all individuals within one areal unit, the so called "person flow zones", had been generalized to random locations within that areal unit. It is worth mentioning that these person flow zones are not identical to the census tracts used by the population and employment census datasets, or the wards used by the school census dataset, and are generally larger in area than the former but smaller than the latter. Again, the fact that at this point in the estimation workflow I had already established categorical population figures for each single building makes the use of such different spatial units possible.

In order to make the information about the stationarity events useable in the context of my estimation methodology I aggregated the number of distinct stationarity events within each person flow zone to hourly time steps, ranging from 0 to 23. I did this by counting each event from the time step it started in until the time step it ended in. If for example an event started at 12:15pm and ended at 5:45pm it is represented in my aggregated data as lasting for six time steps from 12 through 17. These aggregated data can be understood as an hourly census of people within the sample population pursuing each activity within each person flow zone.

By defining the maximum population per category and person flow zone over 24 hours as a 100% index I went on to calculate which proportion of this maximum population was present in each person flow zone at each given time step. This relative population ratio can then be plotted as a graph showing the temporal fluctuation of population within each person flow zone, census tract or even building, per activity over time. Figure 18 shows an example of such data for a census tract on the artificial island of Tsukishima, which is characterized by a comparatively large residential population. It clearly shows how most people leave their homes in the morning between 7am and 9am and return in the evening starting from around 5pm. It also reveals the main working hours from roughly 8am and 9am to between 5pm and 7pm and thereby proves both assumptions I made at the end of the previous section.

In the second to last step I combined the output data of these calculations with the output result of the penultimate step from the previous section. I assumed that the temporal variations of the proportional populations for each category, which I just calculated, are valid for everything within the respective person flow zone. In other words, if a person flow zone has its maximum working population at 10am and only 50% of that population at 5pm, the same is assumed to be

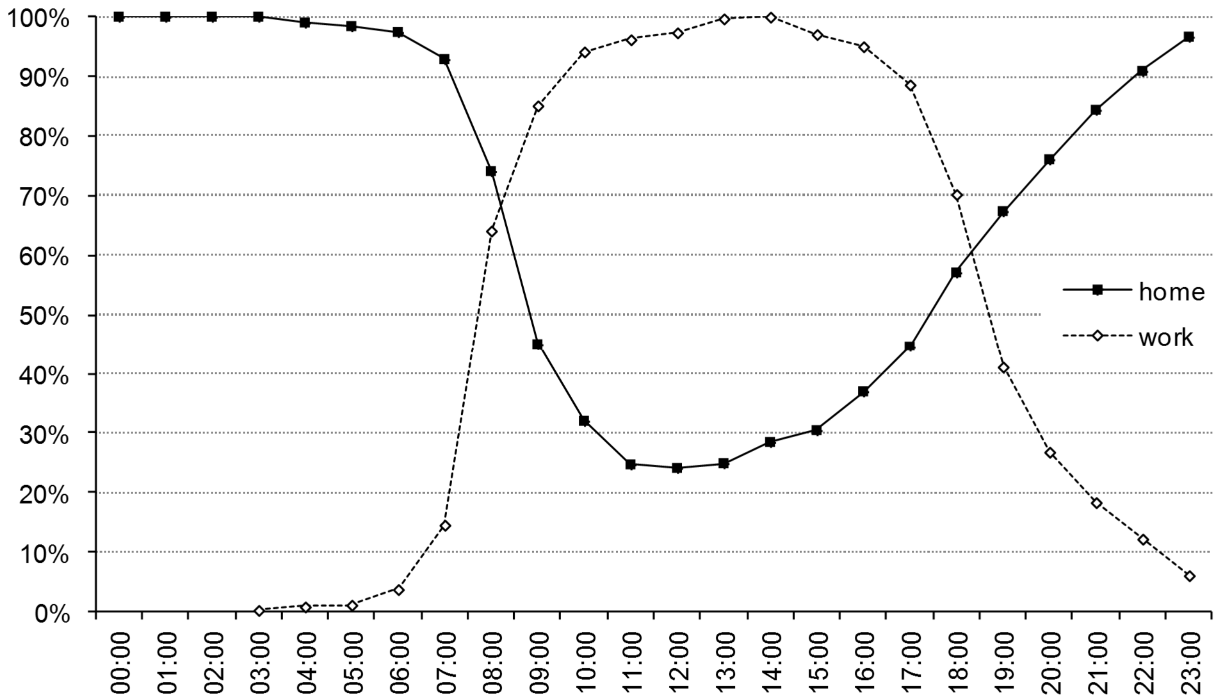

Figure 18: Temporal fluctuation of the populations within the two activity categories "home" and "work" for an exemplar census tract within the study area.

the case for all buildings within this person flow zone. In terms of calculation I applied the percentage of the total population per activity at each time step within each person flow zone to the estimated categorical population figures of each building. If for example a building has been estimated with a residential population of 100 people at the end of the previous section, and the calculation above has shown that the equivalent of 20% of the daily maximum “home” population within the respective person flow zone are present at 1pm, then this building would be assigned a temporally corrected estimated building population of 20 people at 1pm. Figure 19 shows the results for the activities “home” and “work” at two different times of the day for a small part of the study area.[19] It clearly reveals that a large number of people enters the study area during the day to pursue work there.

In a final step I then added up the temporally corrected estimated population figures of the three activities “home”, “work”, and “education” for each building and each time step. This makes it possible to analyze the estimated total number of people per building over time. Figure 20 shows an example of a map of the total estimated stationary building population within the study area at 1pm. Appendix A contains the maps for all 24 time steps.

Validation

Since no data about the actual building populations are available, the model output is difficult to validate. The only viable option appeared to be a manual count of the numbers of people entering and leaving a number of selected buildings, which allows for the calculation of the building populations. Performing this strategy for several buildings within the study area produced the results shown in Figure 21. The graphs show the absolute numbers of people entering and leaving the buildings within each hour as bars. The cumulative building populations based on the count at each time step are shown as solid lines, while the dotted lines represent the numbers derived by the estimation model. In addition I also included the absolute number of people that the model overestimated (positive numbers) or underestimated (negative numbers).

The data were collected for seven hours each, between 7am and 2pm on July 2nd (buildings A and B) and 3rd (building C), 2013. All three buildings are located in the area around Tokyo Station. In their selection I paid close attention to the number and locations of entrances, i.e. the number of doors as well as the existence of underground passageways and parking garages. These features, more precisely their non-existence, severely limited the number of applicable buildings. Also the small number of buildings as well as the brief observation times are owed to the limited time and resources available. Even with those limitations I deem the validation imperative for a meaningful discussion of the usefulness of my proposed estimation approach. To

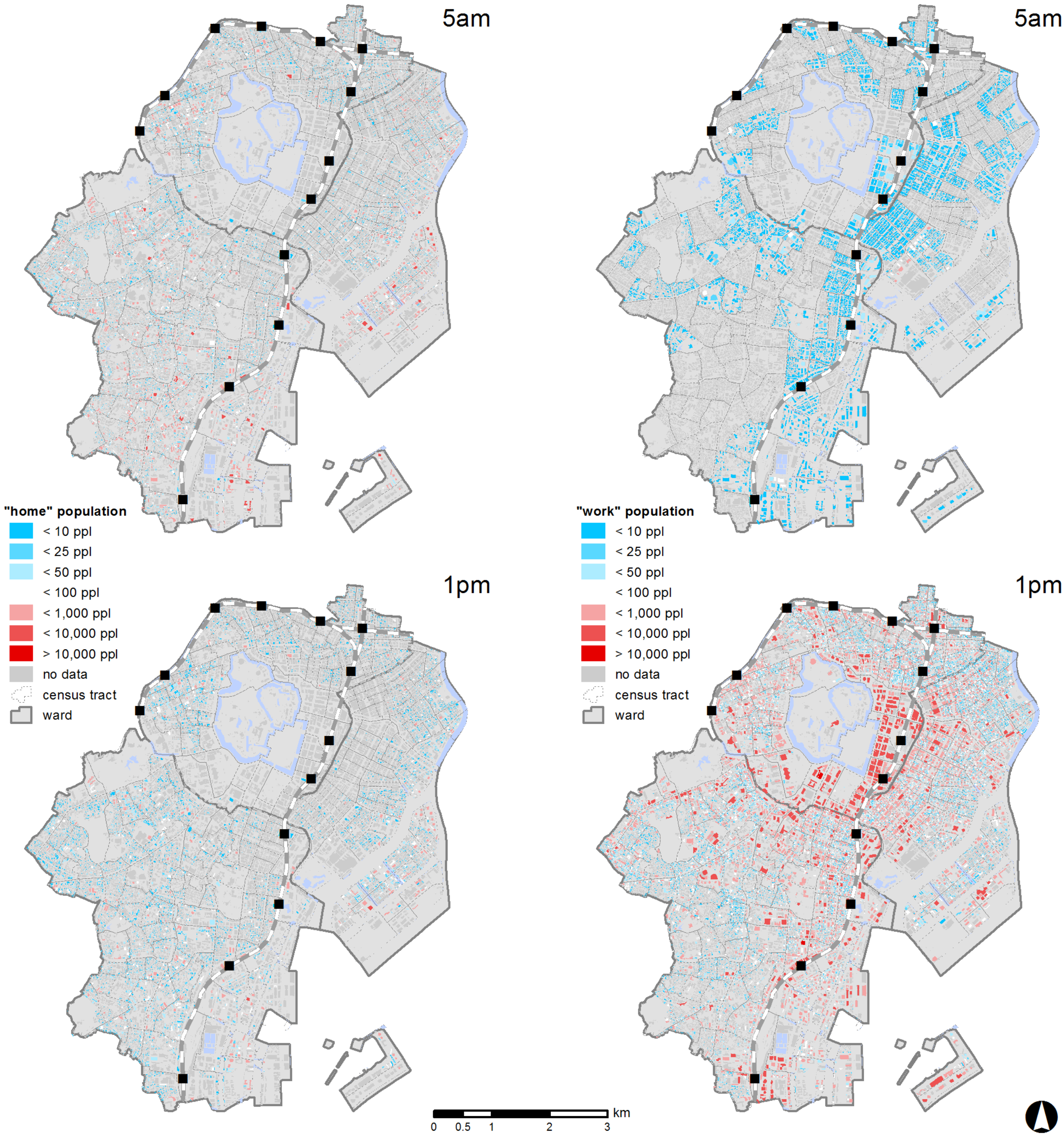

Figure 19: Comparison between the estimated building populations for the activity categories "home" (left) and "work" (right) for 5am (top) and 1pm (bottom) for a part of the study area. The data is the result of the stationary building population estimation methodology using a number of data sources from 2008-2011.

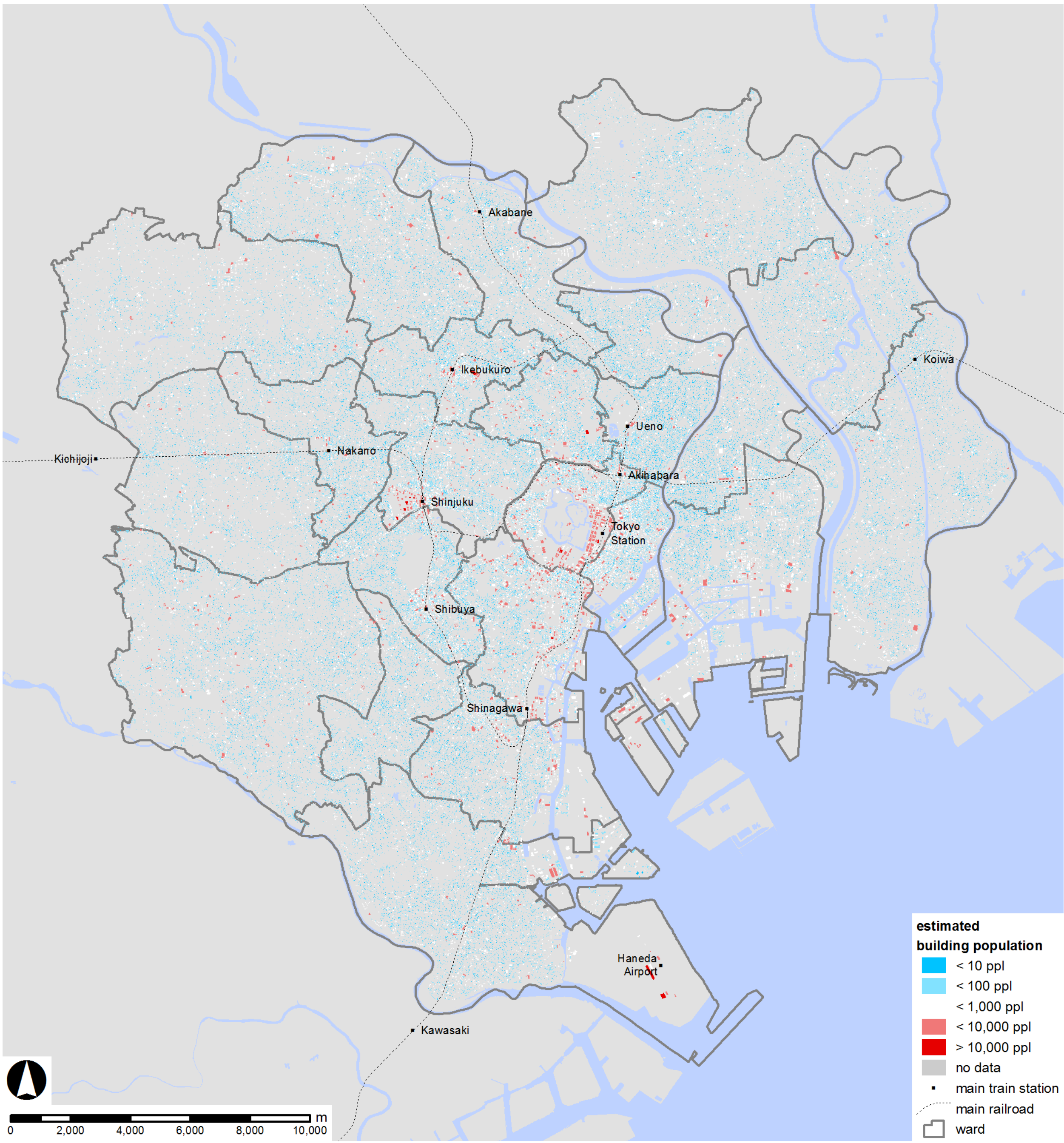

Figure 20: Total estimated stationary spatio-temporal categorical building population within the study area at 1pm. The data is the result of the stationary building population estimation methodology using a number of data sources from 2008-2011.

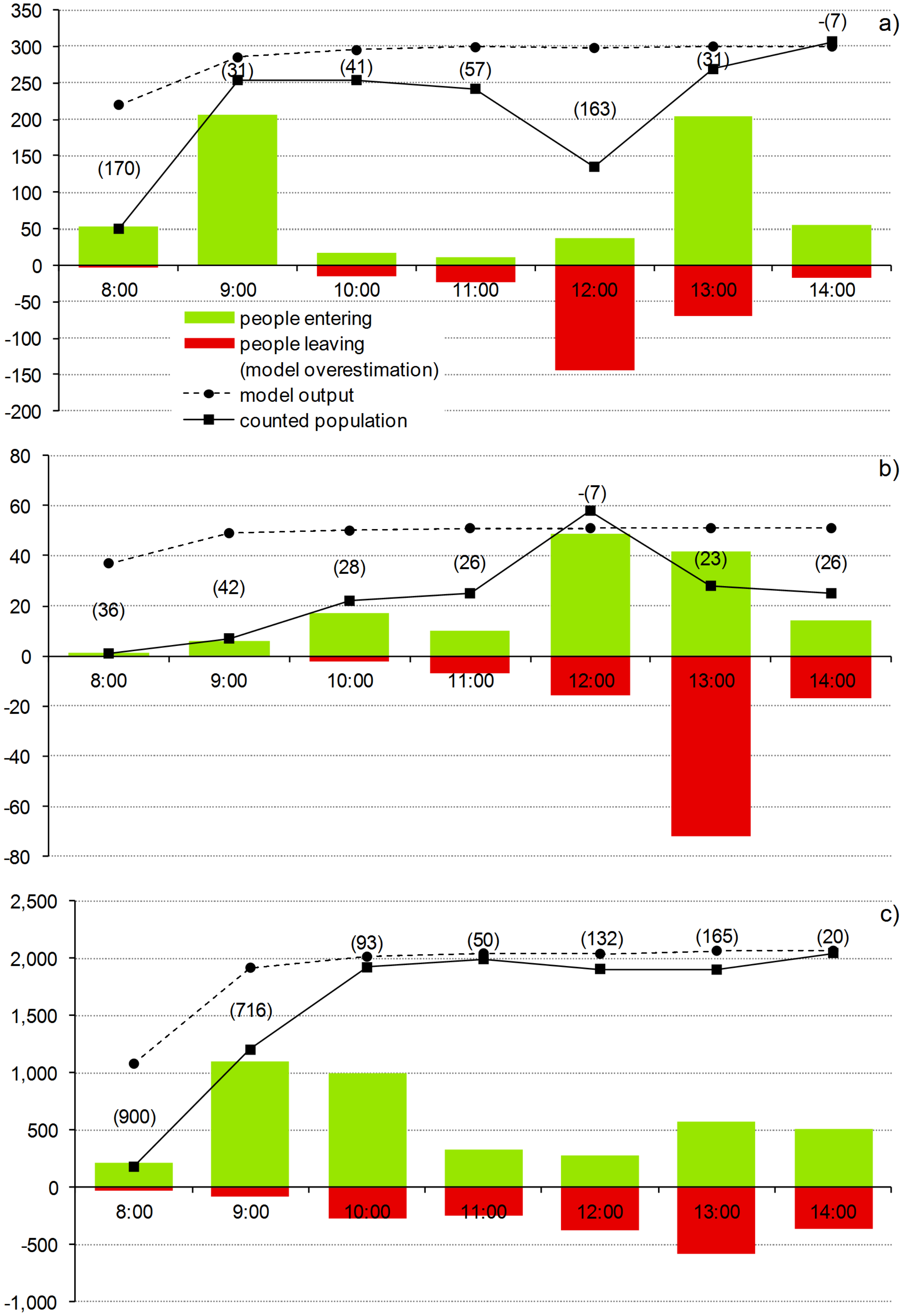

Figure 21: Validation of the stationary building population estimation methodology using door counts for three exemplar buildings within the study area.

my best knowledge this is the first published validation of a spatio-temporal micro-scale population estimation model.

Building A (Fig. 21a) is a pure office building with one tenant over ten floors and only one door. Building B (Fig. 21b) is an eight-story mixed use building with five offices, one retail store and a restaurant and has a total of three doors. Building C (Fig. 21c) is a highrise office building with 26 floors, containing 39 offices, five shops, six restaurants, and a total of six doors. It is worth noting that I purposefully did not include buildings that contain residential uses, since the number of people inside the building at the start of our counting period (7am) would not be obvious. The same holds true for employees who worked overnight or arrived before 7am, but due to the domestic nature of the companies in these three buildings I deem this effect negligible. While the model overall produces results close to the actual measured building populations, there are some obvious variances, which I discuss in the following section.

The employees of all buildings arrive later for work than my model predicted, mostly between 7am and 8:59am, therefore the model overestimates the number of people present in the buildings for those times greatly. As Figure 22 shows, the deviations are at 340%, 3,600% (not shown in the graph), and 503%, respectively. I attribute this to the fact that the movement data I used had originally been collected using paper questionnaires. The given start and end times of trips therefore do not necessarily represent the precise times in reality, but rather the more generalized perceived or memorized times. This becomes obvious in an analysis of the structure of the timestamps that represent the start of work for the sample individuals. A detailed analysis of the underlying data shows that 88% of those stationary working activities supposedly started at round numbered minutes such as ":00", ":10", ":15" etc. 27% were apparently started exactly at the full or half hour marks. This becomes especially problematic when these numbers are grouped by hour, as is the case in my methodology. If for example an employee started working at 8:47am but entered 9:00am in the questionnaire, he would fall into the 8am group in my door count, but in the 9am group in the movement data.

Buildings A and C show comparatively high numbers of people leaving these buildings during the whole observation period and from as early as 9am. These numbers can be attributed to short-term visitors, who entered the buildings for the purpose of business meetings or deliveries. In the case of building C another major factor is the existence of a convenience store and a coffee shop on the ground floor, which attracted large numbers of customers starting from 8am. None of these populations are captured in the estimation model.

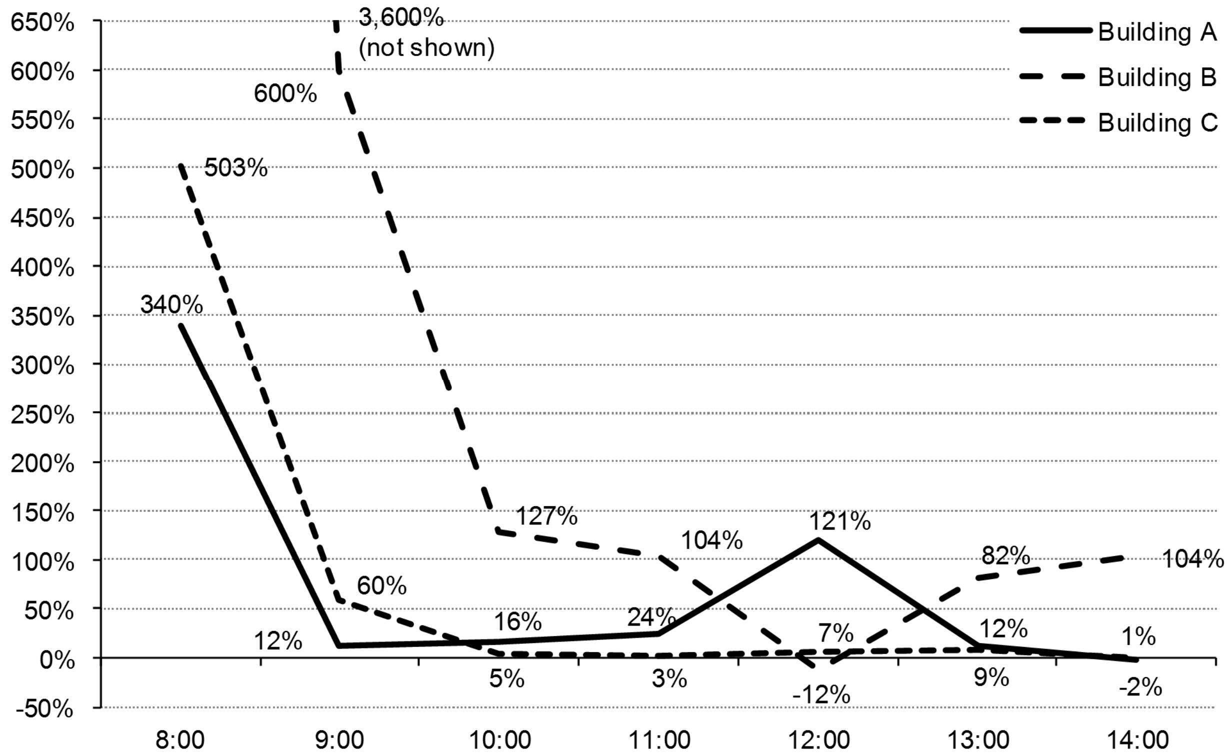

Figure 22: Overestimation of the stationary building population estimation model for three validation buildings.

Figure 22 shows the over- and underestimation of the model in percent compared to the actually observed numbers for all three buildings. In comparison to the other two, building B shows generally a higher deviation. This can be attributed to the comparatively small number of people in the building, which amplifies the model's uncertainties. The other two sample buildings are within 60% deviation from 9am and below 25% after 10am (building C even below 5%) with the exception of the lunch hour between 12pm and 1pm. Here building A is greatly overestimated (+121%), which can be attributed to the coarse temporal resolution of hourly steps in the modeling process. People who leave and reenter the building within a short timespan (such as a 30 minute lunch break) can not be covered by the model, which looks only at the two activities of “home” and “work”. If for example employees leave their workplace at 12:30pm they would be counted pursuing activity “work” for the hour from 12:00pm to 12:59pm. If they return by 1:15pm they would again be counted pursuing activity “work” for the hour from 1:00pm to 1:59pm. The fact that they have actually left the building in the meantime is not reflected in the model, but only in the door count. The same effect can also be seen in the numbers of building B, albeit in the opposite direction: here I counted a great number of people entering the building in the time from 12pm to 1:59pm to have lunch in the restaurant there. Since these customers do not show up in the model, it underestimates the actual number by 12%. Building C does not show either of these two effects to a greater degree, since the number of employees leaving the building during lunch time and the number of customers entering the building to have lunch in one of the building's restaurants almost even each other out.

Ahola et al. mention that “more detailed information about the temporal behaviour of different population groups could also improve the quality of the model.” (2007, 950–951) I believe that the inclusion of spatio-temporal movement data of a large sample population achieves this improvement, as it provides data about the exact locations of each individual at any time and ameliorates the *a priori* assumptions that Ahola and colleagues had to rely on in their modeling approach. I therefore believe that my model can indicate the actual changes in building populations over time more precisely than previous approaches had been able to. Nevertheless, the modeling accuracy could be further improved by using a finer time scale, e.g. 30 minutes, 15 minutes or even 1 minute intervals, and by including short-term populations from the remaining four activities in the modeling process, such as customers, guests and visitors.

Summary

The enhanced spatio-temporal building population estimation approach I introduce in the preceding section can be used to produce a variety of output data and products. First, the geolocated address point data allow for an overview of the spatial distribution of different activity categories and the locations that facilitate these activities (Figs. 14 and 15). While this is not an outcome of the estimation model as such, I want to emphasize how even the simple first step of defining broad activity categories and the visualization of just one dataset can provide a meaningful insight into the urban structure defining the spatio-temporal effects the model elaborates on in its further steps.

Second, the first part of my proposed model extends the preliminary estimation approach by Lwin and Murayama (2009) by a number of usage categories over the one-dimensional focus on residential building populations. This alone can help to get a more realistic representation of the population of each building in a study area. As mentioned above, this is especially important when analyzing areas whose primary land use is not residential. A prime example are highly urbanized city centers, which are characterized by a multitude of different land uses gathering in close spatial proximity to each other, and often even mixed within single buildings. My enhanced approach covers these peculiarities and maps the underlying real-world processes to the buildings under analysis. A closer look at the spatial distribution of buildings with a high number of usage categories reveals that they are mainly clustered in the business districts, which are also the locations of most of the highrise buildings in the study area (e.g. in Marunouchi west of Tokyo Station, around Shinbashi, Mita, and Shinagawa Stations, as well as west of Shinjuku Station, east of Ikebukuro Station and in Akasaka in northern Minato ward). These agglomerations of multiple usage categories can be understood as a result of the need for multiple activities in the close surroundings of the workplace. They allow employees to perform all their daily routine activities within one building, which is convenient in terms of both travel time and cost.

Third, the introduction of the temporal dimension to the estimation of building populations allows for a micro-scale analysis of the actual population figures according to the underlying human activities and the datasets used in the process. I believe that this is the most interesting characteristic of the proposed estimation methodology, since for the first time it allows for a reliable estimation of building populations even for large study areas with justifiable requirements in terms of both necessary input data and computational expense. I formulated the calculations shown in the two sections above as a series of SQL statements that process a multitude of tables within a PostgreSQL database with the PostGIS extension installed to make use of geographical functionalities.

The output result of the spatio-temporal model can be used in a multitude of ways. Examples for visualizations are graphical representations of the population figures over time for single buildings or aerial units (Fig. 18), and maps of the population distribution at a certain point in time (Fig. 19 and 20) or as time series maps (see Appendix A). In addition the output data can be used for further quantitative analyses, such as population density calculations for certain points in time. In this study I use it as a factor that heightens the vulnerability to terrorist attacks, based on the assumption that highly populated places have a greater attractiveness for attacks by terrorists (cf. Chapter 5.3).

Other than that, these micro-scale building populations could be used in a risk and hazard context to identify realistic starting scenarios for multi-agent-based tsunami evacuation simulation models like those introduced by Mas and colleagues (Mas, Adriano, and Koshimura 2013; Mas et al. 2013). It can also be used as input for other quantitative models, such as traffic volume estimations in an urban planning or risk assessment context (cf. Chapters 5.3.2 and 5.3.3), or customer volume estimation models in an economic geographical context.

The population estimation approach I introduce has several shortcomings inherent in the model, that have to be kept in mind when using the output data in further analyses. So far the spatio-temporal model does only take into consideration three activities: "home", "work", and "education". All other daily routine activities pursued by the people in highly urbanized areas, such as shopping, recreation, daily errands, etc., are not reflected. This effect became obvious in the low accuracy during the office lunch time hours between 12pm and 1:59pm, where the populations of the three sample buildings were greatly under- or overestimated according to the existence or non-existence of restaurants in the respective buildings. So far the model focuses only on the long-term activities, where people would stay within the same building over an extended amount of time. These populations can be called "stationary populations". Short-term activities such as the aforementioned are completely neglected, the respective "transient populations" are not reproduced in the model. Therefore the main amendment to the model has to be the inclusion of the remaining transient population categories, i.e. "shopping", "entertaining", and "errand" (cf. Chapter 5.3.5).

Also, model inaccuracies in the morning hours can be attributed to the collection method of the underlying movement data. Since these were obtained using paper questionnaires, a strong tendency to round number minutes in the time stamps was introduced. In connection with the coarse temporal resolution of our population model, this led to severe estimation errors. Therefore, two more modifications to improve the model accuracy have to be 1) the use of more temporally precise movement data, possibly collected in an automated process using GPS-enabled devices, and 2) the use of a temporal scale finer than the hourly intervals I used in this study. I also want to mention that the nature of the data used in this paper did not allow for a comparison of different temporal cycles, such as weekdays as opposed to the weekend, holiday periods versus normal school and working terms[20], or seasonal changes[21], which would undoubtedly all provide further interesting insights into the spatio-temporal changes in human activity patterns.

On a different note, some shortcomings of the model in regard to the modeling precision can be attributed to the underlying data and their deficiencies. While all datasets used in this area are amongst the best available in their respective realms, they impaired the model calculation by missing and incomplete data. Especially missing address points, buildings with missing attribute information and the aforementioned flaws of the person trip data have had significant implications on the overall model output. I am confident that it can be improved significantly if these deficiencies were amended. Also, several generalizations in my estimation model can possibly have an effect on the calculation results. These generalizations are inherent in the assumptions of 1) an equal split of a building's floorspace among the contained usage categories and 2) equal floorspace use within each usage category, neglecting differences among various residential types, as well as office and store layouts. Both can lead to skewed distributions and therefore biased outcomes but are impossible to quantify or eliminate given the available data.

5.3.2. Mobile Pedestrian Population

Introduction

In the preceding chapter I introduce a spatio-temporal methodology to quantify the estimated number of people inside buildings at various time of the day. This comprises people being at home, working at their workplace (e.g. an office, factory, shop, or entertainment facility), and studying at school or university.[22] In addition to people sojourning inside buildings people also spend time outside of buildings, in public places such as streets and parks and in transportation means.

I believe that this mobile population is equally important for identifying the most populous, crowded places, since it helps to identify vulnerable places inside urban areas regarding one of the three generic goals of terrorist perpetrators I present in the introduction of Chapter 5.3: crowded places. It can be seen as the logical extension of the spatio-temporal estimation of stationary building populations I introduce in the preceding chapter.

The reason to focus this estimation process exclusively on pedestrians (cf. this chapter) and railway passengers (cf. Chapter 5.3.3) is to be found in the modal split of transportation within my study area and the composition patterns of transportation chains (Tables 11 and 12). Of the almost 900,000 single trips within the study area over the 24 hours of data collection 82.5% have been taken either by foot or on trains (i.e. monorail, railway, and subway), with the majority of 51.9% on foot. All individual modes of transportation (i.e. moped, motorcycle, car, and minivan) together only account for 4.9% of all trips, about half of the amount of bicycle trips. Other public modes of transportation also play only minor roles in the composition of traffic within the study area, with taxis under 1% and buses (private and public) at only 3%. This can be explained by the very convenient provision of public transportation railway services in the study area, which is characterized by a dense network of stations, manifold and redundant connections between train lines and a high service frequency and succession of trains.

Most trips do in fact consist of a number of different modes of transportation, they are so-called multi-modal trips. For example a person might ride a bicycle from their home to the train station, ride a train and ultimately walk to their office. This constitutes a multi-modal trip using three different modes of transportation: bicycle, railway, and walking. A detailed analysis of these trip chains showed that the largest number of transfers happened between the "walking" and "railway, subway" modes of transportation: 80.6% of the people walking boarded a train afterwards, while 80.3% of train passengers continued their trip on foot (cf. 12).

These data led me to the conclusion that the majority of people in public spaces are either on-board trains or walking. In this chapter I introduce my methodology for the micro-scale spatio-temporal modeling and estimation of mobile pedestrian populations on the streets within the study area. In the following chapter I introduce a similar methodology for the micro-scale spatio-temporal modeling and estimation of mobile railway populations (cf Chapter 5.3.3). The outcome of both models are fine-grained results of the estimated populations for all road segments and railway links within my study area on a given time-scale. I have to mention here that the resulting figures do not reflect the absolute numbers of pedestrians or passengers, but an index of how crowded each road segment or railway link is. To my best knowledge there have been no published attempts to perform such an analysis on the fine spatial and temporal scales I present here.[23] Therefore, I introduce a novel approach for a spatio-temporal micro-scale population estimation on a street segment basis in this part of my study. It builds upon the estimated building population figures I produce in Chapter 5.3.1 and a number of other datasets, which I describe first. I then explain and discuss the methodology I employed in my model. I

Table 11: Modal split of trips within the study area over 24 hours.

Mode of transportation	Trips	Percent
walking	463,411	51.9%
bicycle	69,416	7.8%
moped	2,832	0.3%
motorcycle	3,128	0.4%
taxi	6,143	0.7%
car	33,998	3.8%
minivan	3,666	0.4%
lorry	8,748	1.0%
private bus	3,604	0.4%
bus	23,028	2.6%
monorail	2,828	0.3%
railway, subway	271,760	30.4%
total	892,562	100%

Data source: Center for Spatial Information Science (2008)

Table 12: Matrix showing the composition patterns of transportation chains as transfers of modes of transportation within the study area over 24 hours.

		to											
		walking	**bicycle**	**moped**	**motorcycle**	**taxi**	**car**	**minivan**	**lorry**	**private bus**	**bus**	**monorail**	**railway, subway**
from	**walking**		1,317	143	59	320	2,142	341	88	1,373	68,311	4,007	324,372
	bicycle	1307		14	4	9	107	30	19	172	787	375	31,633
	moped	143	6		2		7	4	3	2	34	6	2,037
	motorcycle	74	7	4		1	4		2	2	6	4	353
	taxi	224	13	1			5			4	36	7	1,239
	car	2,567	130	15	3	3		5	8	102	172	58	7,970
	minivan	408	30	5	1	1	3		3	20	30	6	972
	lorry	91	18	3	1	1	4	4			4	1	122
	private bus	1,339	155	1	2	3	81	16	1		157	38	4,156
	bus	68,388	733	35	6	91	140	22	2	149		217	31,962
	monorail	3,976	359	10	6	14	44	9	1	43	210		2,862
	railway, subway	324,730	29,362	1,894	342	2,466	5,468	762	70	4,161	32,094	2,835	

Data source: Center for Spatial Information Science (2008) then go on to explain in detail the temporal fluctuations derived from the movement data, before summarizing and pointing out some shortcomings in the final section.

Data

All datasets required for the estimation calculation I propose here together with their required attributes are shown in 13.

The methodology builds upon the estimated building population figures generated by the estimation model introduced above. In addition it requires the numbers of passenger transfers at each train station within the study area. I obtained these in the form of the numbers of daily passenger transfers per train station from the MLIT National Land Information Division, National and Regional Policy Bureau. This dataset from 2010 is derived from the same OD data by the Tokyo Metropolitan Area Transportation Planning Council (Tokyo Metropolitan Area Transportation Planning Council 2013) that was used by CSIS to synthesize the point positions in one minute intervals (Sekimoto et al. 2011; Usui et al. 2009). The numbers therefore do not show the actual passenger counts per day, but the number of sample individuals passing through each respective train station. In addition the data itemizes the numbers of transfer processes by the mode of transportation the respective person changed to or from at this station. This allowed me to extract only the number of pedestrians. Since the data are not broken down into temporal units, I had to once again make use of the 2008 CSIS *PersonFlow* data.

Lastly I also needed data showing the train stations in their spatial context, which I was able to obtain for 2011 from the MLIT National Land Information Division, National and Regional Policy Bureau, and detailed street network data to perform the pedestrian volume analysis on. For this purpose I used the 2010 *Advanced Digital Road Map Database (ADF)* by Sumitomo Electric System Solutions Co., Ltd., which is a comprehensive digital road network dataset for all of Japan. It contains 96 attributes for the street segments (links) and 90 attributes for the nodes in the network spread out over a multitude of files. Of these attributes I only used the information whether a road segment is accessible to pedestrians or not, thereby filtering out all city highways in my study area. I also created a logical routing network for use in ESRI ArcGIS using the Network Analyst extension.

Methodology

The process of estimating the degree of pedestrians traffic per street segment contains a total of three steps, which I explain in detail in the upcoming sections:

Table 13: Necessary datasets for the spatio-temporal mobile population estimation methodology and datasets used in this study.

Dataset	**Attributes**	**Dataset name and source**	**Date**
building data (cf. Chapter 5.3.1)	*footprint area* *number of floors*	*Zmap-TOWNII by Zenrin Co., Ltd.*	*2008/09*
census data (cf. Chapter 5.3.1)	*residential population (i.e. population census information)*	*Population census by the Statistics Bureau at the Ministry of Internal Affairs and Communications*	*2010*
	employment population (i.e. business or economic census information)	*Employment census by the Statistical Institute for Consulting and Analysis*	*2009*
	student population (i.e. school census information)	*School census by the Department of Statistics Population at the Tokyo Metropolitan Government Bureau of General Affairs*	*2010*
address point data (cf. Chapter 5.3.1)	*spatial location of each address point* *category of the person or business represented by each data point*	*Telepoint Pack! by Zenrin Co., Ltd.*	*2011*
population movement data (cf. Chapter 5.3.1)	*spatial location of each individual at each time step* *trip purpose / activity* *means of transportation*	*PersonFlow data by the University of Tokyo Center for Spatial Information Science*	*2008*
railroad data	spatial locations of all train stations	Railroads (time series data) by National Land Information Division, National and Regional Policy Bureau	2011
road network data	linear representations of all road segments accessibility of road segments for pedestrians spatial locations of all road network nodes	Advanced Digital Road Map Database (ADF) by Sumitomo Electric System Solutions Co., Ltd.	2010
traffic flow volume data	number of daily passenger transfers per train station	Traffic flow volume (passenger transfers at stations) by National Land Information Division, National and Regional Policy Bureau	2010

Note:
Italics mark datasets explained in detail in Chapter 5.3.1, since they are necessary for the calculation of the building population figures.

1) calculation of building access

2) calculation of train station usage, and

3) calculation of road network betweenness centrality

Calculation of building access. The aim of this first preparatory step is the assignment of each building to the street segment that provides access to the building. Since the 2008/09 Zenrin *Zmap-TOWNII* building dataset does not contain information about the locations of entrances of the buildings, and the total number of buildings was too large for a fieldwork data collection, I needed to approximate the most likely entrance locations. I did this by implementing the simplified assumption that every building is accessible from the street network closest to it, which has been employed in previous studies (Sevtsuk and Mekonnen 2012b).

Obviously this introduces some error, since in some cases a building might be located closer to a street from where it is not accessible. This has also been pointed out by Sevtsuk and Mekonnen (2012b), but I was able to improve the rate of correctly assigned buildings by referring not only to the building centroids, as they did, by analyzing the actual building footprints. Yet, this still does not solve the issue of wrongfully assigning buildings with multiple entrances. These are very common in highly urbanized areas like my study area and therefore introduce a quite significant source of error.

Figure 23 shows examples for both issues: the buildings marked green have their entrances to the larger connector street, also marked green (example A), the buildings marked blue have their entrances to the main street marked blue (example B). In addition all three buildings marked blue (example B) have secondary entrances to the connector streets and backstreets. Without additional data, i.e. a detailed database of building entrance location, I will not be able to overcome this error.

In my estimation model the centrality calculation itself will not be performed for the single buildings, but for each street segment. The estimated stationary building populations developed in the preceding chapter will be used as weights for the centrality calculation. Therefore the population figures need to be assigned to their adjacent street segments in this first step. Hence the sum of the absolute estimated populations of all buildings that are accessible from a certain street segment are assigned to this street segment. The centrality calculation algorithm, which I present in detail in the section after the next, requires weighted point locations as input data. This can be achieved by assigning half of the "virtual" population of each street segment to its two constituent nodes, as equation (4) shows:

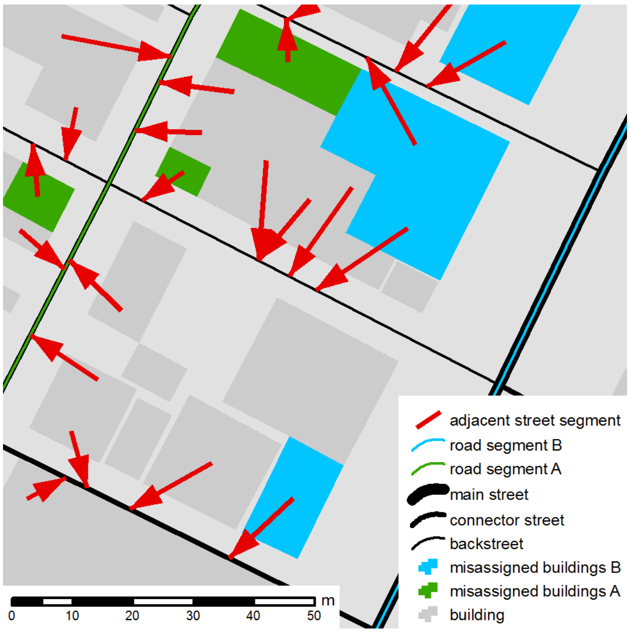

Figure 23: Example of erroneous assignments of buildings to street segments based on shortest straight-line distances.

$$VP_{n,t} = \frac{\sum_{l \in L_n} \sum_{b \in B_l} SBP_{b,t}}{2} \tag{4}$$

where $Vp_{n,t}$ is the virtual population of road node n at time t, L_n is the set of road links that connect to road node n, B_l is the set of buildings that are adjacent to road link l, $SBP_{b,t}$ is the estimated stationary building population of building b at time t.

This process allows for the provision for the temporal dimension in the stationary building population and creates virtual accumulated road node populations for all time steps. These time steps have to be either the same or a subset of those selected during the building population estimation process.

Calculation of train station usage. As I mention in the introduction to this chapter, the passenger transfer data do not account for temporal fluctuations during the day and provides only the total number of transfers over the course of 24 hours. Therefore I had to offset it against the population movement data from the 2008 CSIS *PersonFlow* dataset.

I did this by extracting all those point locations from the database that met the following three criteria:

- final point location of one subtrip, starting point of another[24]
- ending mode of transportation is “railway, subway” or “monorail”[25]
- starting mode of transportation of the subsequent subtrip is “walking”

This produces a table of point locations where people from the sample population got off trains and started walking. Since the *PersonFlow* data carries time stamps this allows for a temporal analysis of transfers per train station per time step. In order to do so I performed a spatial join between these transfer points and the train station point locations to assign them the respective station names. This allows to derive the number of total transfers as well as the hourly transfers per station regarding the sample population.

I then calculated how much percent of the total number of passenger transfers, as per this data, took place within each hour and assigned the respective percentage from the 2010 MLIT data. If for example the *PersonFlow* data showed 1,822 transfers from “train” to “walking” for Kanda Station of which 765 were registered between 8:00am and 8:59am, this means that 42.0% of the daily passenger transfer volume there took place during this hour. In contrast, only 50 transfers were registered there between 3:00pm and 3:59pm, which equates to 0.3% (Fig. 24). As we know the total number of passengers at each station from the MLIT data, it is then possible to

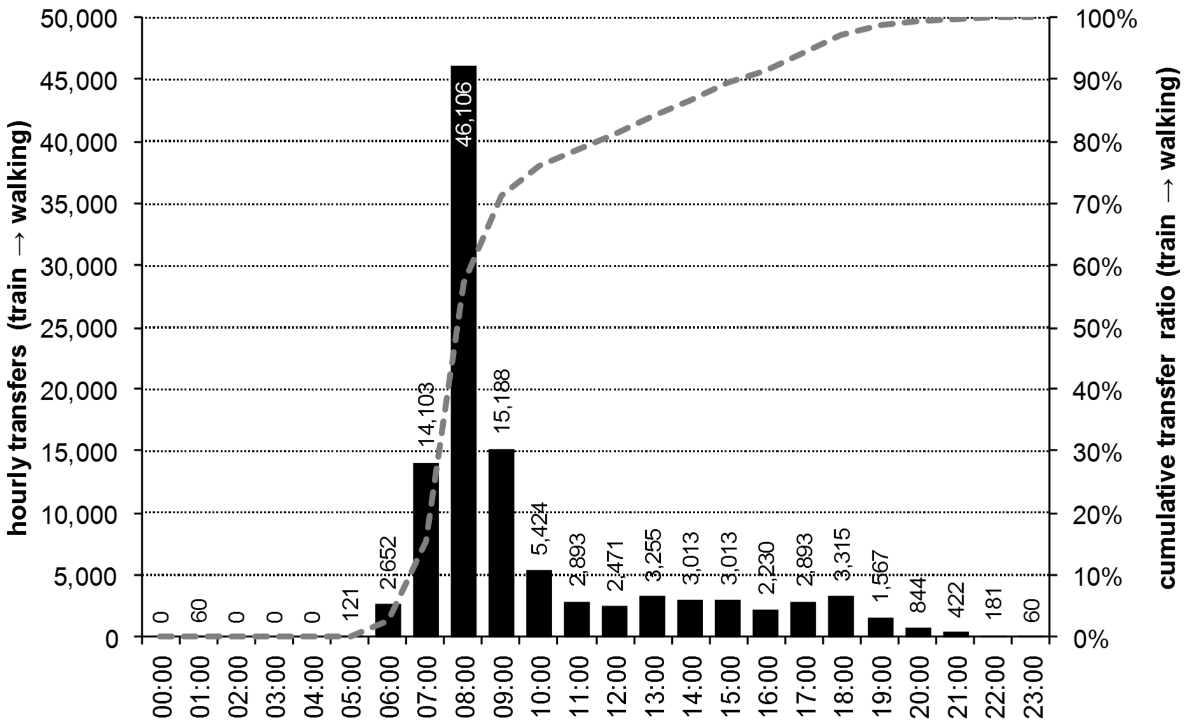

Figure 24: Hourly passenger transfers and cumulative passenger transfer ratio at Kanda Station.

Data sources: National Land Information Division, National and Regional Policy Bureau (2010), Center for Spatial Information Science (2008) calculate the temporally corrected number of pedestrians leaving the train stations by referring to the aforementioned percentage. In the case of Kanda Station this means that 42.0% of the total 109,811 passengers who leave by foot over the course of the day, did so between 8:00am and 8:59am, namely 46,106 people. In contrast, between 3:00pm and 3:59pm it were only 3,013 people.

In my model I do account only for those pedestrians that start from a train station and walk towards a building, not the other way around. This is possible because the model does not calculate the actual number of pedestrians per street segment, but the mere degree of pedestrian traffic. Hence the directionality of the walks has no impact on this calculation.

I also had to account for the fact that the passenger transfer data shows only one figure per train station, even if the station itself consists of a number of affiliated stations (cf. 14). Since there is no data available about the distribution of passengers on the different affiliated stations, I had to assume an even distribution. This is most likely a wrong assumption, but since I have no numerical way to ameliorate the falsifying effect, I have to accept the error it introduces into the calculation. Hence I divided the result from the previous calculation step by the number of affiliated stations for each train station. Of the 457 train stations within the study area, 91.3% had only one or two affiliated stations, which should keep the emerging error small, but these together account only for 64.8% of the total number of passenger transfers. In contrast, Tokyo Station and Shinjuku, the only train stations with eight affiliated stations, represent only 0.4% of the total number of train stations, but together account for 6.5% of all passenger transfers in the study area. This is especially significant as both stations extend widely with their connected underground walkways, which spread their respective exits over large areas.

Calculation of pedestrian traffic volume. In order to calculate the volume of pedestrian traffic per street segment I avail myself of a methodology from graph theory, namely the *betweenness centrality*. It is one of a multitude of centrality measures, which Freeman generally defines as “a function of the sum of the minimum distances between [a] point and all others” (1977, 35). Centrality measures are used in all types of network analyses, from social networks to communication networks, organizational networks, urban growth and, as in my case, spatial networks (Bavelas 1950; Beauchamp 1965; Moxley and Moxley 1974; Porta et al. 2009; Sabidussi 1966). In the aforementioned article by Freeman he introduced the betweenness centrality as a new methodology to measure the betweenness of points, building on the works of Shaw (1954) and Leavitt (1951), who started regarding the physical distances between the network nodes as determinants in their centrality to the whole network.

Table 14: Distribution of stations with multiple affiliated stations and respective passenger transfers.

Affiliated stations	Stations within study area		Passenger transfers	
	absolute	relative	absolute	relative
1	344	75.3%	4,684,026	43.0%
2	73	16.0%	2,372,967	21.8%
3	22	4.8%	1,344,692	12.4%
4	10	2.2%	693,883	6.4%
5	4	0.9%	516,820	4.7%
7	2	0.4%	570,946	5.2%
8	2	0.4%	704,025	6.5%

Data source: National Land Information Division, National and Regional Policy Bureau (2010)

In my model I use the implementation of the betweenness centrality by Sevtsuk and Mekonnen (2012a) in their Urban Network Analysis (UNA) toolbox for ArcGIS. It uses a highly optimized algorithm by Brandes (2001) to calculate the betweenness centrality measure, which is defined as "the fraction of shortest paths between pairs of other buildings in the network that pass by building *i*" (Sevtsuk and Mekonnen 2012a, 11, emphasis in original). Equation (5) shows the mathematical implementation.

$$BTW^{r}_{i,t} = \sum_{j,k \in G-i, d[j,k] \leq r} \frac{n_{i,j,k}}{n_{j,k}} \cdot w_{j,t} \tag{5}$$

where $BTW_{i,t}^{r}$ is the betweenness of building i at time t within the search radius r, $n_{i,j,k}$ is the number of shortest paths from node j to node k that pass by node i, $n_{j,k}$ is the total number of shortest paths from node j to node k, $w_{j,t}$ is the weight of node j at time t, with nodes j and k lying within the network radius r from node i. (modified from Sevtsuk and Mekonnen 2012a, 11)

As Sevtsuk and Mekonnen (2012a) mention, this betweenness centrality measure can be used to estimate the potential of passersby at different buildings on the network. Since it allows to introduce the weights $w_{j,t}$ in the calculation it is possible to represent the temporal fluctuations in the passenger flows over the course of a day. This time dimension is my addition to the model by Brandes (2001) and thereby represents to my best knowledge the first spatio-temporal betweenness centrality measure.

The resulting values represent a dimensionless indicator of the estimated pedestrian traffic volume on each street segment based on the aforementioned assumptions and specifications. While the values for the single street segments are comparable amongst each other for the same time step, the same is not the case across multiple time steps. Therefore the data need to be normalized.[26] In order to do so I queried the database for the greatest value over all street segments and all 24 hours and calculated each value's percentage of that maximum value. I label the resulting figures the *normalized spatio-temporal betweenness centrality measure (NSTBCM)* for the street segments (Fig. 25). Appendix C contains the maps for all 24 time steps.

Summary

The spatio-temporal mobile population estimation approach I introduce in the preceding section can be used to calculate an index showing the pedestrian traffic volume on single street segments, divided into deliberately chosen time steps. This is especially useful in the spatial

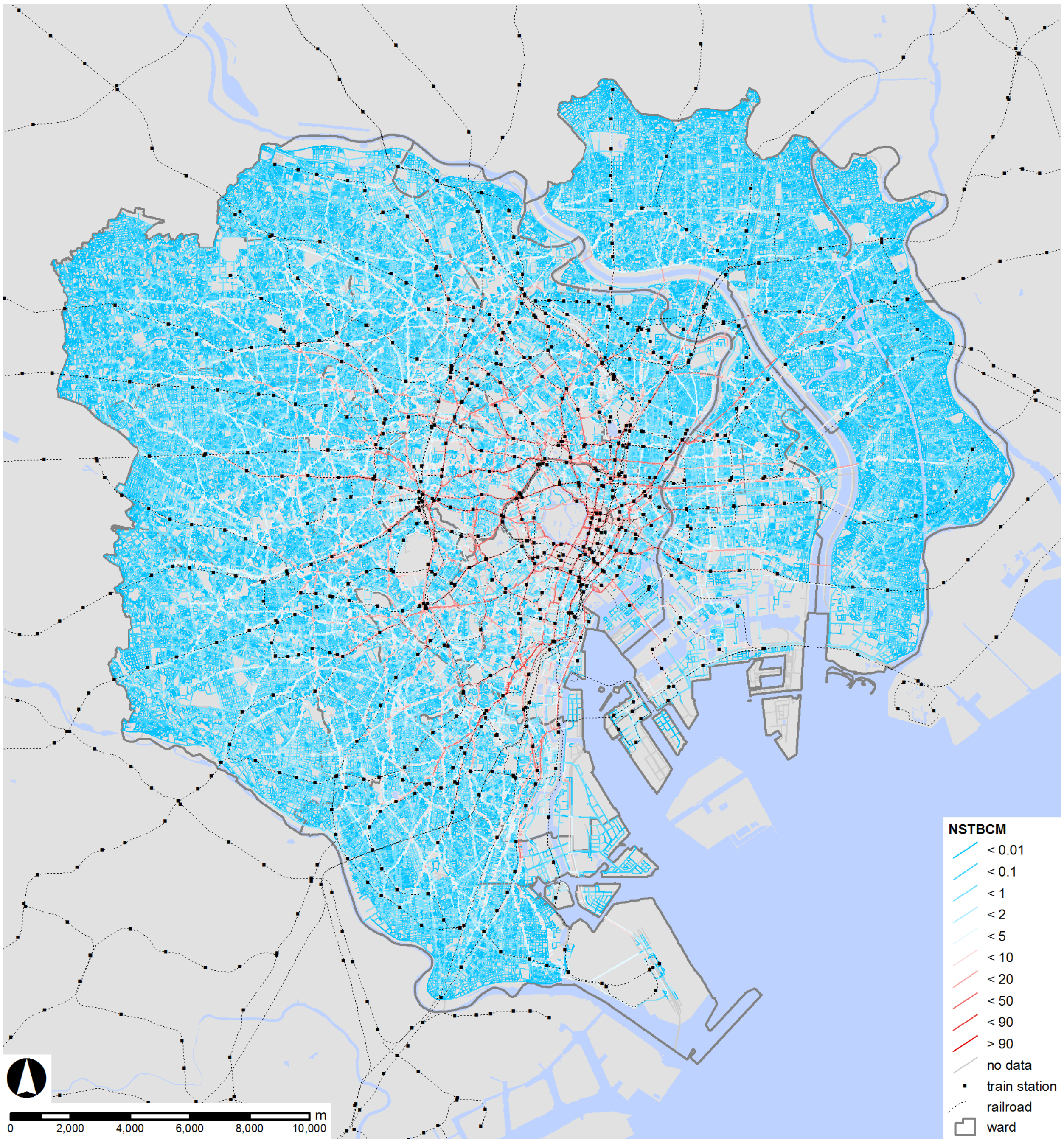

Figure 25: Normalized spatio-temporal betweenness centrality measure (NSTBCM) for all street segments within the study area at 9am.

context of highly urbanized areas, as it provides the populations in public space as a complementary element to the figures of the population inside buildings (cf. Chapter 5.3.1).

I achieve this by employing a graph theory methodology, namely that of betweenness centrality, on a number of datasets that provide information about building populations and train station passenger transfers segregated both spatially and by time.

The introduction of the temporal dimension to the estimation of populations in public space allows for a micro-scale analysis of the actual population figures according to the underlying human activities and the datasets used in the process. I believe that this is the most interesting characteristic of the proposed estimation methodology, since for the first time it allows for a reliable estimation of mobile populations even for large study areas with justifiable requirements in terms of both necessary input data and computational expense.

The output result of the spatio-temporal model can be used to visualize the amount of pedestrians on the streets of a chosen study area. While the data do not represent the absolute numbers of pedestrians, they do reflect the traffic volume and allow for a comparison of crowdedness among all street segments within the study area. In addition the output data can be used for further quantitative analyses, such as population density calculations for certain points in time. In this study I use it as a factor that heightens the vulnerability to terrorist attacks, based on the assumption that highly populated places have a greater attractiveness for attacks by terrorists (cf. Chapter 5.3).

Yet, the population estimation approach I introduced has several shortcomings inherent in the model, that have to be kept in mind when using the output data in further analyses. Since I currently do not have access to the exact numbers and locations of building entrances I had to make the *a priori* assumption that every building is only accessible from the street segment that has the shortest straight-line distance to the building's footprint. This can obviously lead to erroneous assignments of building populations to wrong street segments. Without the availability of such a dataset it is impossible to overcome this shortcoming, which led me to conscientiously accept the introduced error.

Also, since the volumes of passenger transfers were only given per train station in the available dataset, I had to make the generalizing assumption that these passenger volumes are distributed equally to all affiliated train stations. This does not reflect the reality and will greatly over- and underestimate certain train stations, but is impossible to overcome without the introduction of additional data.

As I use the same population movement dataset as in the preceding chapter, the same resulting model inaccuracies can be attributed to this data as explicated in Chapter 5.3.1. Generally, most shortcomings of the model in regard to the modeling precision can be attributed to the underlying data and their deficiencies. While all datasets used in this area are amongst the best available in their respective realms, they impaired the model calculation by missing and incomplete data. I am confident that it can be improved significantly if these deficiencies were amended.

5.3.3. Mobile Railway Population

Introduction

In the introduction to the preceding chapter I explain in detail my reasoning behind employing the volumes of pedestrians on the streets and passengers in public railway transportation to identify crowded and therefore vulnerable places. At 271,760 subtrips the usage of railway is second only to the number of pedestrian subtrips (cf. 11). Therefore the number of people on board the trains poses a significant factor in the identification of populated places in addition to the estimated pedestrian traffic flows (cf. Chapter 5.3.2).

In 2007 the MPD asked over 2,500 citizens and facility managers in an opinion poll about their concerns about terrorism and crisis management. There 62.5% of the citizens noted that they use trains on a daily basis (Metropolitan Police Department 2007, 16) and 59.5% expressed their fear of becoming a victim of a terrorist attack while on a train (2007, 21). This shows the value and importance of public railway transportation to the people in the study area and underlines that it is of critical importance in the process of the identification of crowded and hence vulnerable places.

Data

All datasets required for the identification of the spatial distribution of symbolic value together with their required attributes are shown in 15. A search for exact, time-stamped trips by train within my study area unfortunately did not produce any results. Due to the widespread use of rechargeable contactless IC smart cards in Japan, such data is constantly being collected in the form of ticket gate readings by the railway corporations and has already been used in scientific publications (Yabe and Kurata 2013). While I had been able to contact the authors of the aforementioned journal article and also a contact person at East Japan Railway Company (JR East), I have not been able to obtain the data on the grounds that these are confidential and only to be used in-house by JR East and affiliated research groups. As a result I had to resort to the movement data of train passengers in the 2008 CSIS *PersonFlow* dataset and the 2010 traffic

Table 15: Necessary datasets for the spatial identification of railway link importance and datasets used in this study.

Dataset	Attributes	Dataset name and source	Date
building data (cf. Chapter 5.3.1)	*footprint area* *number of floors*	*Zmap-TOWNII by Zenrin Co., Ltd.*	*2008/09*
underground passage data (cf. Chapter 5.3.1)	footprint area	Zmap-TOWNII by Zenrin Co., Ltd.	2008/09
population movement data (cf. Chapter 5.3.1)	*spatial location of each individual at each time step* *trip purpose / activity* *means of transportation*	*PersonFlow data by the University of Tokyo Center for Spatial Information Science*	*2008*
railroad data (cf. Chapter 5.3.2)	*spatial locations of all train stations*	*Railroads (time series data) by National Land Information Division, National and Regional Policy Bureau*	*2011*
traffic flow volume data (cf. Chapter 5.3.2)	*number of daily passenger transfers per train station*	*Traffic flow volume (passenger transfers at stations) by National Land Information Division, National and Regional Policy Bureau*	*2010*

Note:
Italics mark datasets explained in detail in preceding chapters.

flow volume data by the MLIT National Land Information Division, National and Regional Policy Bureau in my modeling process.

The traffic volume dataset contains the names of the train stations and the number of people getting on or off trains at each train station according to the CSIS *PersonFlow* data (cf. Chapter 5.3.1). The figures therefore do not represent the actual numbers of passenger transfers but allow for a comparison of the passenger volumes among all train stations contained in the dataset. The numbers are divided into 14 modes of transportation that passengers arrived by at the stations or by which they continued their trips on from there: bus, car, light automobile, truck, private bus, taxi, motorcycle, motorized bicycle, bicycle, walking, aircraft, ship, other and unknown (cf. Chapter 5.3.2 and 11).

The 2011 railroad dataset by the MLIT National Land Information Division, National and Regional Policy Bureau consists of two datasets, one about train stations and one about railroad tracks. The former contains the spatial locations of all train stations and a large number of attributes, such as the name of the station, name of the serving train line, the name of the operational company, and the years that service was commenced or ended.[27] The latter contains line features representing the course of the railroad tracks as well as the same attributes as mentioned above. Since unfortunately the railroad dataset and the traffic volume dataset do not contain a common identifier for the train stations, I had to join them based on the station names.

Methodology

I split the estimation of the mobile railway population in two parts: the usage of train stations on the one hand, and the ridership of railway links on the other hand. This comprises all types of rail-bound passenger traffic, including heavy rail, light rail, and monorail, both track-bound and on rubber tires.

Train Station Usage: The train stations within the study area consist of both overground and underground portions, which are oftentimes combined to larger train station complexes. In several cases these station complexes comprise multiple separate train stations with differing names in addition to the affiliated train stations serving multiple train lines under the same name. All these combinations had to be taken care of in the calculation of the populations present within each train station complex over the course of the day. To do this I relied on the 2010 traffic flow volume data by the MLIT National Land Information Division, National and Regional Policy Bureau and the 2008 CSIS *PersonFlow* dataset, a process I describe in detail in Chapter 5.3.2.

In order to assign these hourly passenger volumina I also had to delineate the aforementioned train station complexes from the 2008/09 Zenrin *Zmap-TOWNII* dataset, which contains both the building footprints and the footprints of underground passages including underground train stations. Yet, since the datasets do not contain the information about the affiliation of certain buildings or underground passages to a train stations, I had to do this manually for all 405 unique train stations in the study area. After doing so I ended up with two datasets: one with the train station buildings, and another one with the underground train stations, both including the information about their affiliation to a certain train station. I was then able to merge these two datasets and dissolve the resulting polygon features, which resulted in a dataset with one polygon feature per train station as Figure 26 shows for a detail of the study area.

In cases where one underground passage is used by two or more train stations this process ended up with multiple congruent polygons. In Chapter 5.3.6 I introduce the methodology of estimating the spatial influence of this vulnerability factor which ensures that these congruent polygons mutually aggravate their importance regarding the vulnerability of the respective places. I then joined these polygon features with the hourly passenger flow figures I derive in Chapter 5.3.2. This allows me to generate a map showing the estimated usage for each train station complex in the study area for each time of the day. It is important to note that the resulting figures do not represent the actual number of passengers but an index value indicating the relative usage of each train station in comparison to the others within the study area. Figure 27 shows the resulting data for 8am. Appendix E contains the maps for all 24 time steps.

Railway Link Ridership: Since railway trips have to start and end at train stations I define a railway link as the direct connection between two train stations. Since unfortunately no detailed data about the actual number of passengers between train stations are available I had to resort to the 2008 CSIS *PersonFlow* data for this vulnerability factor as well. I did this by evaluating the closest railway link for each point location in the *PersonFlow* dataset that indicates the use of public railway transportation in its “transportation mode” attribute. As the *PersonFlow* data contains a point location for every individual in 1-minute intervals I then had to aggregate the number of points per unique person and hour for all railway links in the study area. This allows for the creation of maps of the estimated railway link ridership as shown in Figure 28. It is important to note that the resulting figures do not represent the actual number of passengers but an index value indicating the relative usage of each railway link in comparison to the others within the study area. Appendix G contains the maps for all 24 time steps.

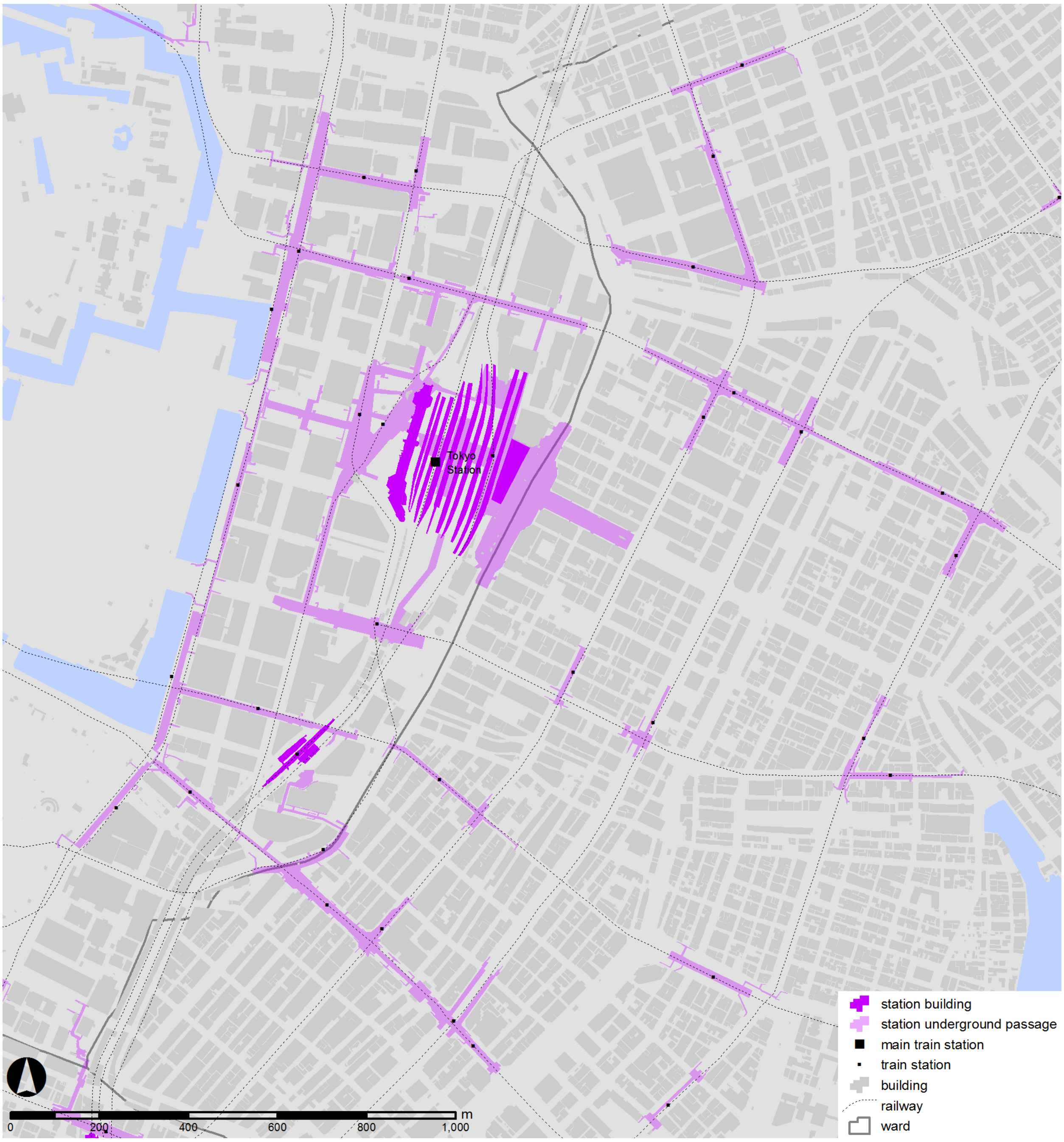

Figure 26: Train station complexes including overground buildings and underground passages around Tokyo Station as per the 2008/09 Zenrin Zmap-TOWNII dataset.

Data source: Zenrin Co., Ltd. (2008)

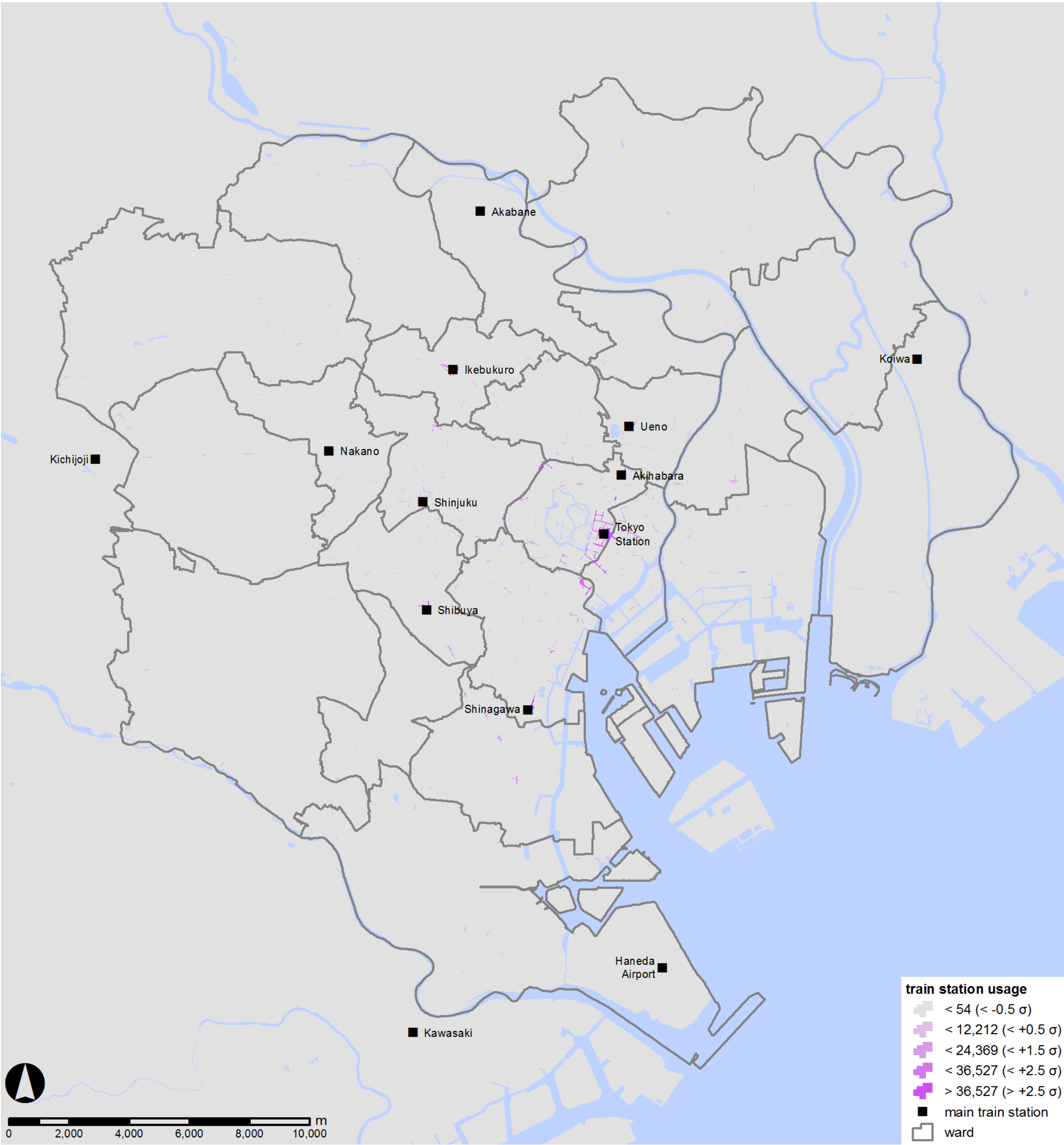

Figure 27: Estimated train station usage at 8am. The data is the result of the train station usage estimation methodology using a number of data sources from 2008-2011.

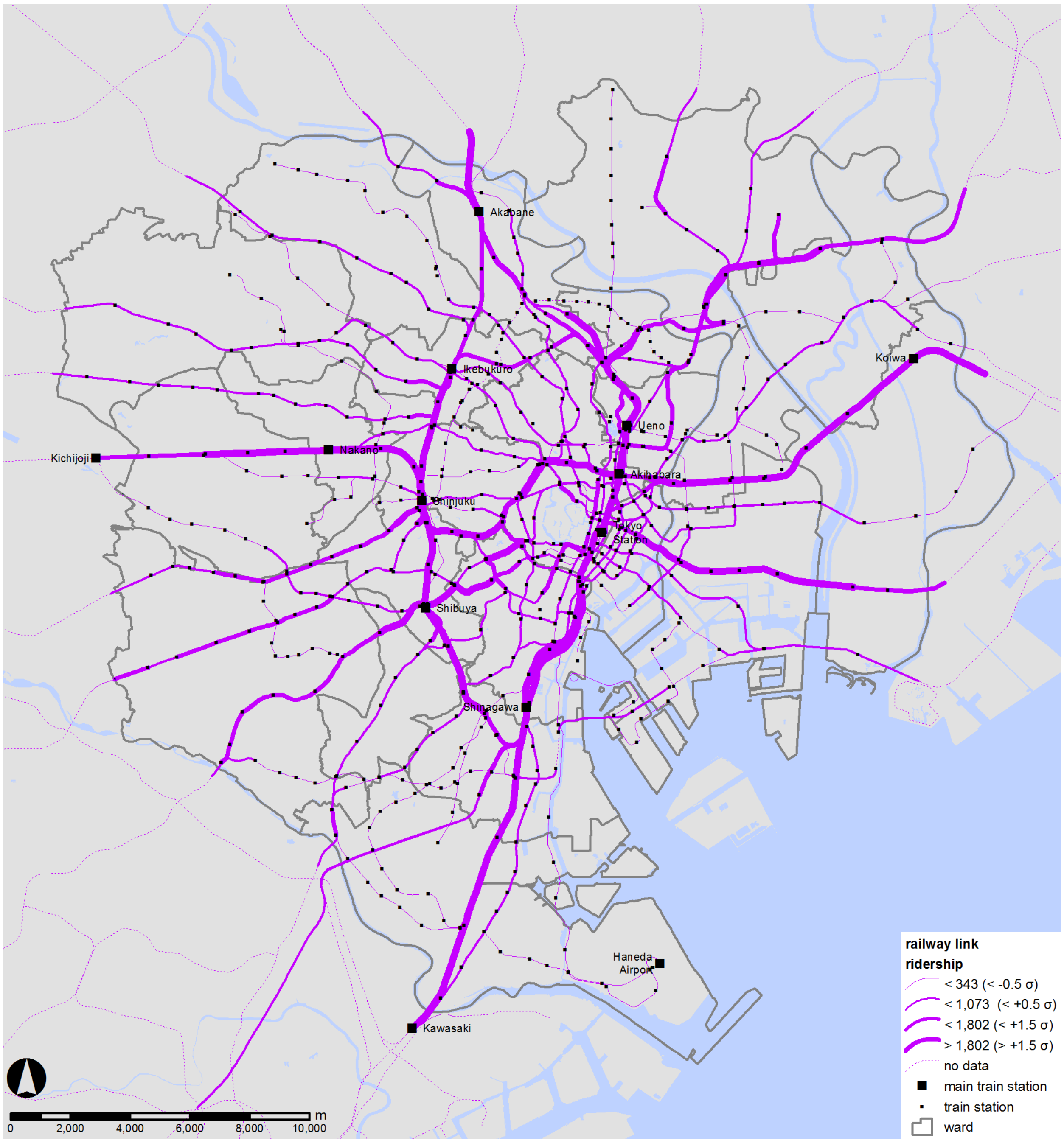

Figure 28: Estimated railway link ridership at 8am. The data is the result of the railway link ridership estimation methodology using a number of data sources from 2008-2011.

Due to the dense network of train lines there are many instances of two or more of them running in parallel over extended sections. In my calculation process I handle these as separate from each other. The methodology of estimating the spatial influence of this vulnerability factor in introduce in Chapter 5.3.6 ensures that these spatially adjacent yet logically separated train lines mutually aggravate their importance regarding the vulnerability of the respective places.

Summary

In the preceding section I introduce two novel spatio-temporal approaches for the estimation of the mobile population within the railway network of a study area. It contains two components: the train station usage and the railway link ridership. Both can be used to calculate indices showing the traffic volumes within single train station complexes and on single street segments, respectively, divided into deliberately chosen time steps. In the same way as the estimation of the mobile pedestrian population (cf. Chapter 5.3.2) this is especially useful in the spatial context of highly urbanized areas, as it provides the populations in another public space, i.e. public transportation, as a complementary element to the figures of the population inside buildings (cf. Chapter 5.3.1).

I achieve this by employing a number of data, foremost the 2008 CSIS *PersonFlow* dataset, and their combination with infrastructural data such as train station buildings, underground train stations and railway links between these train stations. Together they provide information about the relative mobile railway populations segregated both spatially and by time.

The introduction of the temporal dimension to the estimation of populations in public space allows for a micro-scale analysis of the actual population figures according to the underlying human activities and the datasets used in the process. I believe that this is the most interesting characteristic of the proposed estimation methodology, since for the first time it allows for a reliable estimation of mobile populations even for large study areas with justifiable requirements in terms of both necessary input data and computational expense.

The output result of the spatio-temporal model can be used to visualize the amount of passengers moving inside the public railway transportation network of a chosen study area. While the data do not represent the absolute numbers of passengers, they do reflect the traffic volumes and hence allow for a comparison among the train stations and the railway links. In addition the output data can be used for further quantitative analyses, such as population density calculations for certain points in time. In this study I use it as a factor that heightens the vulnerability to terrorist attacks, based on the assumption that highly populated places have a greater attractiveness for attacks by terrorists (cf. Chapter 5.3).

Yet, the population estimation approach I introduced has several shortcomings inherent in the model, that have to be kept in mind when using the output data in further analyses. Since the volumes of passenger transfers were only given per train station in the MLIT dataset, I had to make the generalizing assumption that these passenger volumes are distributed equally to all affiliated train stations. This does not reflect the reality and will greatly over- and underestimate certain train stations, but is impossible to overcome without the introduction of additional data.

As I use the same population movement dataset as in the preceding chapters, the same resulting model inaccuracies can be attributed to this data (cf. Chapters 5.3.1 and 5.3.2). Generally, most shortcomings of the model in regard to the modeling precision can be attributed to the underlying data and their deficiencies. While all datasets used in this area are amongst the best available in their respective realms, they impaired the model calculation by missing and incomplete data. I am confident that it can be improved if these deficiencies were amended.

5.3.4. Symbolic Value

Introduction

Apart from affecting a large number of people with their attacks, terrorists will generally also strive for maximum attention about their actions. As mentioned in the introduction to Chapter 5.3, the symbolic value of possible attack targets therefore serves as the fourth aggravating terrorism vulnerability factor in the scope of this study.

The quantification of an abstract concept such as “symbolic value” is obviously significantly more difficult than that of quantifiable measures such as stationary or mobile populations. The main problem is the definition of what actually has a symbolic value. I understand the symbolism of a place or an object (cf. Chapter 4.1) as the result of two valuations: 1) that of the perpetrator, and 2) that of those under attack.

Terrorists will generally aim at targets that have some context with their ultimate political goals or that are directly involved in their fight for these goals. Examples are *al-Qaeda*'s bombings of the United States Embassies in Nairobi, Kenya, and Dar es Salaam, Tanzania. On August 7th, 1998, two truck bombs detonated simultaneously in front of the embassy buildings in these two East African capital cities. The attacks left 235 people dead and more than 4,000 injured (National Consortium for the Study of Terrorism and Responses to Terrorism 2013g;

2013h). Since the date of the attack coincides with the anniversary of the American invasion in Saudi-Arabia, the attacks are widely believed to be a response to these activities and also the alleged mis-treatment of four members of an affiliate organization of *al-Qaeda*, the *Egyptian Islamic Jihad*, in American captivity:

> On August 5, 1998, […] in what was beginning to take on the aura of a very personal vendetta, an Arab-language newspaper in London published a letter from [al-]Zawahiri threatening retaliation against the United States—in a "language they will understand." He warned that America's "message has been received and that the response, which they hope they will read carefully, is being prepared." Two days later the U.S. embassies in Kenya and Tanzania were blown up, killing 224 people. (Mayer 2008, 114)

In addition, terrorists will also aim to select targets that represent certain values amongst those under attack. Again, one of the most well-known examples is an attack attributed to *al-Qaeda*, namely the series of attacks on September 11th, 2001. On that day terrorists were able to hijack four passenger planes and subsequently used them as missiles when flying them into the two towers of the World Trade Center in New York City, as well as the Pentagon and the United States Capitol in Washington, D.C. Even though the last impact could be avoided, more than 3,000 people are estimated to have lost their lives as a direct result of the attacks, the number of injuries and long-term damages is unknown (National Consortium for the Study of Terrorism and Responses to Terrorism 2013i; 2013j; 2013k; 2013l). These attacks were aimed directly at US American economic, military and political landmark buildings: the World Trade Center[28], the US Department of Defense and the meeting place of the US Congress.

Thornton was amongst the first political scientists and terrorism researchers to emphasize the symbolism of terrorist activities in his definition of terrorism as “the deliberate creation of fear, usually through the use (or threat of use) of *symbolic acts of violence*, to influence the political behaviour of a target group.” (1964, 73, emphasis added) These dimensions, the deliberate character, the violence and the inherent symbolism also help to discern terrorism from other forms of political violence:

> It highlights the violent quality of most terrorist acts, which distinguishes a programme of terror from other forms of non-violent propagation, such as mass demonstrations and boycotts. It also stresses the particular quality of terrorist violence. Thornton referred to it as 'extra-normal'; that is, for a certain level of organized political violence to be called terrorism, it must go beyond the norms of violent political agitation accepted by a given society. Finally, and perhaps most importantly, Thornton's definition emphasizes the symbolic nature of the violent act. An act of terrorist violence will attempt to *convey a message to a target audience* rather than secure a piece of territory (as in conventional war) or extinguish a people or ethnic group (as in genocide). (Neumann 2009, 8, emphasis added)

In the context of how contemporary terrorists more and more effectively exploit modern communication technologies, Jenkins notes that

> for terrorists, the most significant technology is not weapons but direct communication with their multiple audiences. Terrorism, to repeat, was originally aimed at the people watching. Victims were threatened or killed to make a point, not only to the terrorists' foes but above all to the terrorists' own constituents. Technological developments in the 1960s and 1970s—the ubiquity of television, more portable television cameras, communications satellites, uplinks to remote news crews, global news networks—allowed terrorists to reach audiences worldwide almost instantaneously. By carrying out visually dramatic acts of violence, terrorists could virtually guarantee coverage, intensifying the terror and inflating their own importance. (Jenkins 2006, 125)

As I explain in the course of the development of my *Human Activity Based Vulnerability Concept* in Chapter 2.3.3, the values of those threatened by a hazard are imperative in discerning disasters from non-disastrous hazard events. The characteristic that differentiates terrorism from natural hazards is the underlying malevolent intent, in other words the aim at harming people and creating a disastrous outcome.

My attempt at operationalizing the symbolic value of places follows mostly the ideas formulated by Caplan and Kennedy (2010a) in their *Risk Terrain Modeling* framework. There they introduce a number of criminogenic features of spaces (e.g. bus stops, liquor shops, ATMs, etc.) and methods to operationalize them as well as their spatial influences (cf. Chapter 4.2.3). As opposed to the aforementioned population-based vulnerability factors (cf. Chapters 5.3.1 and 5.3.2), which used density maps to operationalize the spatial influence of highly populated places, I use a distance-based approach here. This allows to rather identify vulnerable *radii* around those places that carry a symbolic value than to identify their spatial agglomeration.

The first step, though, has to be the definition of what constitutes symbolic value and the identification of the associated places that represent these values in the study area. In the following sections I describe the data I used and explain these steps in detail.

I want to mention at this point that this vulnerability factor and its operationalization are highly subjective. The definition of "symbolism" in the upcoming sections follows my personal perception of what constitutes a symbolic value in the context of terrorism attractiveness, based on the published literature where referenced. Another researcher would possibly define it in a different way, which would lead to the selection of different places that represent this symbolism. As a result, the spatial distribution of "symbolic value" would also be different from that which I develop in the following sections.

One might argue that this subjectivity introduces ambivalence in the quantitative analysis of terrorism vulnerability, which I attempt to achieve with the approach and framework developed in this study. I agree that there is some ambivalence inherent in this part of the analysis. But I am strongly convinced that this ambivalence is ameliorated by the conscientious selection of symbolic places by the person performing the analysis. This selection is optimally based on the subject matter expertise, quantitative results and information about the respective perpetrator and a precise attack scenario (cf. Chapter 4.2.1). Every analysis employing my framework therefore not only will but **has to** produce a different result, since the underlying assumptions are also different.

Data

All datasets required for the identification of the spatial distribution of symbolic value together with their required attributes are shown in 16. These datasets and their attributes have been explained in detail in the preceding chapters.

Methodology

I defined three different categories of places that carry symbolic values for the public for different reasons, which I explain in the upcoming sections:

1) large train stations,
2) symbolic institutions, and
3) landmarks

In comparison to the methodologies for the estimation of stationary building populations and mobile populations, the processes I describe here are largely of manual nature, albeit they obviously make use of various spatial analysis techniques.

Large Train Stations. The symbolism of large train stations originates not from the fact that they are frequented by a large number of people, but rather from the degree of popularity that arises out of those masses of users. This popularity can be more than local (i.e. known to the surrounding population) or national (i.e. known all over Japan) and broaden to an international level (i.e. known around the world).

I decided to operationalize this popularity by selecting those train stations that constitute the 95th percentile of the overall distribution of passenger volumes in the study area. To identify these I used the 2010 traffic flow volume data by the National Land Information Division, National and Regional Policy Bureau, which contains the exact number of passenger transfers at all train stations in Japan. The average passenger volume of all stations in the study area was 52,085 passengers with a standard deviation of 80,366. 39 train stations had passenger volumes greater than the resulting passenger volume threshold per day of 132,451, as shown in 17.

Table 16: Necessary datasets for the spatial identification of symbolic value and datasets used in this study.

Dataset	Attributes	Dataset name and source	Date
building data (cf. Chapter 5.3.1)	*footprint area* *number of floors*	*Zmap-TOWNII by Zenrin Co., Ltd.*	*2008/09*
underground train station data	footprint area	Zmap-TOWNII by Zenrin Co., Ltd.	2008/09
address point data (cf. Chapter 5.3.1)	*spatial location of each address point* *category of the person or business represented by each data point*	*Telepoint Pack! by Zenrin Co., Ltd.*	*2011*
road network data (cf. Chapter 5.3.2)	*linear representations of all road segments*	*Advanced Digital Road Map Database (ADF) by Sumitomo Electric System Solutions Co., Ltd.*	*2010*
railroad data (cf. Chapter 5.3.2)	*spatial locations of all train stations* *linear representations of all railroad tracks*	*Railroads (time series data) by National Land Information Division, National and Regional Policy Bureau*	*2011*
traffic flow volume data (cf. Chapter 5.3.2)	*number of daily passenger transfers per train station*	*Traffic flow volume (passenger transfers at stations) by National Land Information Division, National and Regional Policy Bureau*	*2010*

Note:
Italics mark datasets explained in detail in preceding chapters.

Table 17: Train stations within the study area constituting the 95^{th} percentile of the passenger volumes of train stations within the study area as per the 2010 traffic flow volume dataset.

Station name	**Affiliated stations**	**Daily passenger volume**
Shinjuku†‡	8	940,176
Shibuya†‡	7	638,872
Ikebukuro†‡	7	595,866
Tokyo†‡	8	516,431
Shinbashi†‡	5	422,530
Shinagawa†	4	389,850
Tamachi†	1	290,354
Otemachi‡	5	260,861
Akihabara†‡	4	260,131
Iidabashi†‡	5	248,332
Ueno†‡	4	222,926
Yurakucho†‡	2	221,048
Kanda†‡	3	220,130
Hamamatsucho†	1	216,396
Takadanobaba†‡	3	208,347
Ebisu†‡	2	204,117
Ochanomizu†‡	3	197,836
Kamata†	3	196,783
Ichigaya†‡	4	194,502
Ginza‡	3	179,378
Nihonbashi‡	3	178,154
Gotanda†‡	3	176,468
Kinshicho†‡	2	176,179
Kasumigaseki‡	3	175,922
Omori†	1	172,755
Osaki†	2	165,245
Ogikubo†‡	2	164,029
Yotsuya†‡	3	161,503
Nakano†	2	153,769
Suidobashi†‡	2	150,755
Meguro†‡	4	150,013
Kitasenju†‡	5	145,509
Kayabacho‡	2	144,491
Akabane†	2	144,222
Roppongi‡	2	143,223
Toyocho‡	1	139,204
Jinbocho‡	3	139,031
Toranomon‡	1	135,896
Kudanshita‡	3	134,929

Notes:

† Overground platforms.
‡ Underground platforms.

Data source: National Land Information Division, National and Regional Policy Bureau (2010)

Most of these stations are located along the Yamanote Line loop and inside of it, Others are major transit points and gateways for commuters from the residential areas surrounding the Tokyo Metropolis: Shinjuku and Shibuya Stations are fed mostly by commuters from the western Tokyo Metropolis, Akabane and Ikebukuro Stations from the northwest (i.e. Saitama prefecture), Kitasenju and Akihabara Stations from the northeast (i.e. Chiba and Ibaraki prefectures), while Kinshicho and Toyocho Stations receive extensive amounts of commuters from the east (i.e. Chiba prefecture), and Kamata, Omori and Osaki Stations from the south (i.e. Kanagawa prefecture including the nearby cities of Yokohama and Kawasaki), respectively. In addition, most of these stations are located in areas with a large number of offices, shops and restaurants, which serve as destinations for the commuter traffic.[29]

I related this selection to the train station point dataset by the National Land Information Division, National and Regional Policy Bureau. Among these 39 train stations Hamamatsucho, Omori, Tamachi, Toranomon, and Toyocho Stations are served by only one train line[30], while all other stations consist of multiple affiliated train stations serving different train lines under the same station name. It is also noteworthy that Akabane, Hamamatsucho, Kamata, Nakano, Omori, Osaki, Tamachi, and Shinagawa Stations have exclusively overground platforms, while Ginza, Jinbocho, Kasumigaseki, Kayabacho, Kudanshita, Nihonbashi, Otemachi, Roppongi, Toranomon, and Toyocho Stations consist entirely of underground platforms.

As a next step I used a spatial join to extract all buildings from the 2008/09 Zenrin *Zmap-TOWNII* data that intersect with these train stations, represented by the point features from the aforementioned railway dataset, marked red in Figure 29. Since the point features insufficiently represent the actual shape of the trains stations I then had to manually extend these selections to contain all buildings that belong to the train station buildings in the real world. I verified these selections of buildings, marked blue in Figure 29, using fieldwork in the study area. I did the same with the underground train station data from the same Zenrin *Zmap-TOWNII* dataset to account for the underground portions of the train stations, which are marked green in Figure 29.

Finally I dissolved the multiple buildings and underground portions of each train station into one feature per station, which allows for an easy creation of the straight-line distance buffer to represent the nine station complexes' spatial influence later in the process.

Symbolic Institutions. Next I identified the locations of institutions that might have some kind of symbolic value to either terrorists or the broad public. These institutions are shown in 18. Overall I was able to extract twelve different categories of institutions matching this criterion. Eight of these represent political offices of any kind. In addition I selected all

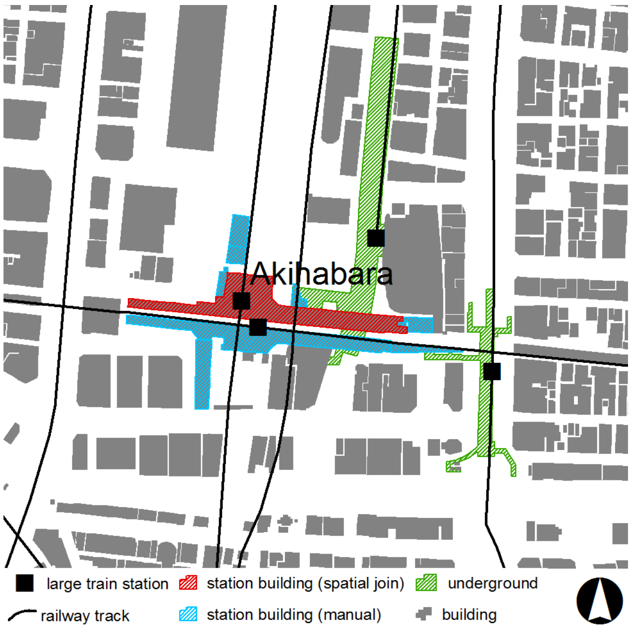

Figure 29: Semi-automated selection of over- and underground train station complexes from the train station point feature dataset using the example of Akihabara Station.

Table 18: Categories of symbolic institutions and corresponding address points within the study area.

Institution	Address points
airport	(1)
cabinet, cabinet office*	20
court of justice*	281
fire department, fire station	68
foreign embassy, consulate*	228
ministry, state authority*	542
municipal authority*	1,891
parliament*	9
police department, police station, police box	189
political organization*	256
prefectural authority*	787
religious group	659

Note:
* Political office.

institutions related to the police, the fire department, offices of religious groups and airports. These categories were taken directly from Zenrin's 2011 *Telepoint Pack!* dataset. I created a group for all state authorities and ministries from the original twelve categories: “Ministry of Agriculture, Forestry and Fisheries (MAFF)”, “Ministry of Defense (MOD)”, “Ministry of Economy, Trade and Industry (METI)”, “Ministry of Education, Culture, Sports, Science and Technology (MEXT)”, “Ministry of Finance (MOF)”, “Ministry of Foreign Affairs (MOFA)”, “Ministry of Health, Labour and Welfare”, “Ministry of Internal Affairs and Communications (MIC)”, “Ministry of Justice (MOJ)”, “Ministry of Land, Infrastructure, Transport and Tourism” (MLIT), “Ministry of the Environment”, and “other state authority”. 18 also shows the number of address points within each category, 4,931 in total. At 81.4% most of them are political offices, marked with an asterisk in the table. Even though the complete area of *Tokyo Haneda International Airport* is located inside the study area, no address points of category “airport” are contained in it. Therefore I manually added one address point.

Finally I used a spatial join to extract all buildings from the aforementioned building dataset that intersect at least one of the filtered address points from the previous step. Since many of the buildings contain more than office, this resulted in 2,361 buildings. As the address point category “airport” was not present in the filtered institutions, I also manually added the two passenger terminal buildings of Haneda Airport. Thereby I identified 2,363 buildings that contain institutions with some kind of symbolic value.

Landmarks. The Merriam-Webster online dictionary (2013) defines a landmark as “an object or structure on land that is easy to see and recognize”. I identified three different categories of landmarks: 1) economic, 2) political, and 3) touristic. In my selection of landmarks, which 19 shows, I tried to be as general as possible, while still establishing a meaningful selection of features. One necessary requirement was that the landmarks have to have symbolic value both for Japanese citizens and for people abroad, in order to be of interest for terrorists, given that these pursue an international agenda.

Both the Bank of Japan, domicile of the central bank of Japan, and the Tokyo Stock Exchange represent institutions with significant influence on the national and international economic markets. Terrorist attacks in their immediate vicinity could be seen as a strong statement against the finance and credit markets, globalized economies, and the monetary policies of the Japanese cabinet and other governments abroad. In addition, successful terrorist activities in their vicinity can and will lead to business interruptions that are most likely to have significant repercussions on the Japanese economy and the global stock markets. This effect could be observed in the

Table 19: 25 landmarks in the study area and their categories.

Category	**Landmark name**
economic	Bank of Japan (BOJ)
	Tokyo Stock Exchange (TSE)
political	National Diet Building
	Yasukuni Shrine†
touristic	*Asahi Beer Hall*
	Ginza‡
	Meiji Shrine (incl. surrounding forest)†
	Mori Tower (Roppongi Hills)
	Rainbow Bridge‡
	Sensoji Temple (incl. Nakamise Street)†
	Shibuya Crossing†
	Ryogoku Sumo Hall
	Sunshine 60 Building
	Tokyo Big Sight (Tokyo International Exhibition Center)
	Tokyo Station Building
	Tokyo Dome
	Tokyo Imperial Palace (incl. outer gardens)†
	Tokyo International Forum
	Tokyo Metropolitan Central Wholesale Market (Tsukiji Fish Market)†
	Tokyo Metropolitan Government Building (Tokyo City Hall)
	Tokyo Skytree
	Tokyo Tower
	Tokyo World Trade Center
	Ueno Park†
	Zojoji Temple†

Notes:
† Broad area, manually digitized.
‡ Linear feature, 15 m straight-line buffer around road.
Italics mark TripAdvisor (2013) as source.

aftermath of the terrorist attacks in New York City on September 11th, 2001, which forced the New York Stock Exchange (NYSE) and other stock market places in the world to close down and adjourn trade for multiple days. The resulting economic damage can not be numeralized, but is believed to be immense (Makinen 2002).

Most of the landmarks that carry a political symbolism are already covered in the list of symbolic institutions in the previous section. For reasons of completeness I deemed it necessary to complete these by landmarks that do represent some kind of political symbolism, yet do not necessarily fulfill any political function at the same time. The National Diet Building serves as the building where the Diet of Japan meets, including both the House of Representatives and the House of Councillors. Beyond that it also stands out by its unique architectural appearance which makes it an easily recognizable building both for Japanese citizens and foreign tourists. Yasukuni Shrine is a Shinto shrine that commemorates almost 2.5 million men, women and children who died in the service of Japan during military conflicts, such as the Boshin War, the Seinan War, the Sino-Japanese and Russo-Japanese wars, World War I, the Manchurian Incident, the China Incident and World War II (Yasukuni Shrine 2013). While religion and state are strictly separated in Japan by the model of *State Shinto*, this shrine's political symbolism originates from the enshrinement of more than 1,000 convicted war criminals as per the *International Military Tribunal for the Far East (IMTFE)*:

> Analysts say that because the main wars it commemorates are those with China and the US, it appears to the political left to symbolise foreign invasions. To the right, it is a symbol of patriotism. (British Broadcasting Corporation 2012)

Regularly visits by members of the Japanese government, including the prime minister, are causing tensions between Japan and its neighbors and former war enemies, especially China, South Korea and North Korea. These governments regard the visits as provocation, since according to their belief “the shrine represents Japan's past militarism–something for which they feel it has not fully apologised.” (British Broadcasting Corporation 2012)

During the, admittedly very subjective, selection process I tried to employ third-party data to derive a general idea about which landmarks carry a symbolic value. In the case of touristic landmarks I consulted the list of attractions in Tokyo compiled by the users of *TripAdvisor*, one of the biggest travel advice websites and communities on the internet (TripAdvisor 2013). The landmarks I took from this list are written in italics in 19, the others are my personal, subjective selection.

I encountered three different spatial types of landmarks: buildings, broad areas, and areas that are defined by a linear feature. As in the two previous cases of the large train stations and the symbolic institutions I used a spatial join to identify the buildings that contained the 15 non-areal landmarks. In addition I manually digitized the areas for the eight landmarks that comprise a broad area: Yasukuni Shrine, Meiji Shrine, Sensoji Temple, Shibuya Crossing, Tokyo Imperial Palace, Tokyo Metropolitan Central Wholesale Market, Ueno Park, and Zojoji Temple. For the two linear features, namely Ginza and the Rainbow Bridge, I created 15 m straight-line distance buffers around the line features that symbolize the middle lines of the respective roads. Thereby I created a total of 25 polygon features that represent the landmarks in my study area.

Summary

In this chapter I introduce the operationalization of another vulnerability factors, that differs greatly from the three previously factors (cf. Chapters 5.3.1, 5.3.2, and 5.3.3). The main differentiator is that it is a highly subjective operationalization that follows my personal perception of what constitutes a symbolic value in the context of terrorism attractive-ness. I want to reiterate that I don't perceive the ambivalence this subjectivity introduces in the quantitative analysis of terrorism vulnerability as a shortcoming, but rather a unique feature and advantage over other estimation models, since it requires a very detailed and differentiated approach by the respective analyst in the formulation of what constitutes symbolic value, the central element of the underlying *Human Activity Based Vulnerability Concept* I introduce in Chapter 2.3.3.

The definition of three different categories of places that carry symbolic values for the public for different reasons, namely large train stations, symbolic institutions, and political, economical or touristic landmarks allows for the identification of the respective places in the real world (i.e. buildings, streets, etc.) that represent these symbolic values.

I was able to identify 39 building complexes that represent large, and therefore well-known train stations, 2,363 buildings that contain institutions with some kind of symbolic value, and 25 buildings or areas that represent landmarks in my chosen study area. Figure 30 shows the spatial distribution of these symbolic places of all three categories within the study area.

5.3.5. Disregarded Vulnerability Factors

In the course of developing this approach and the selection of possible vulnerability factors I developed a number of other factors. I will briefly explain why I did not end up using these in my study.

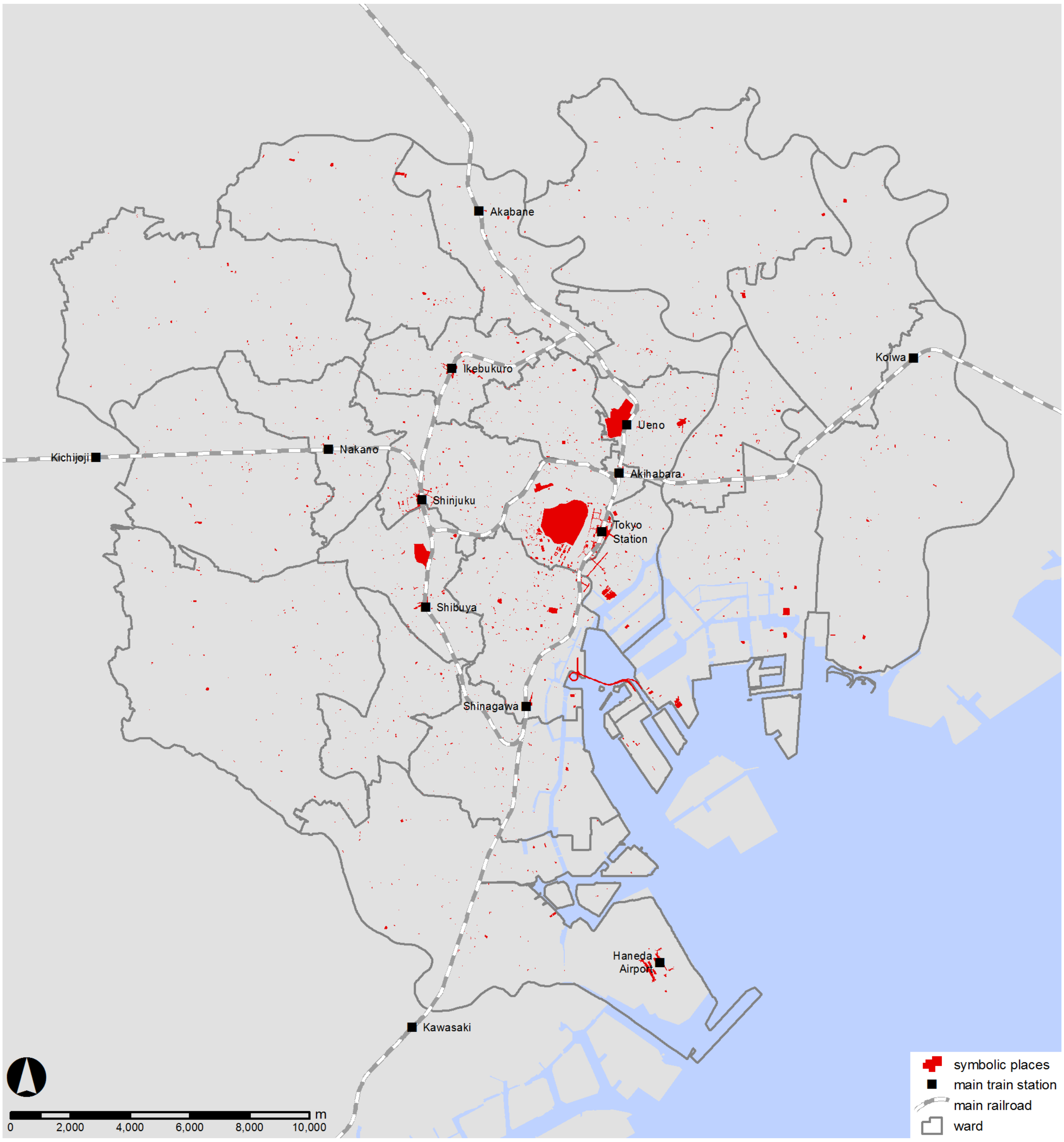

Figure 30: Spatial distribution of symbolic places of all three categories within the study area.

Infrastructural Networks

As I lay out in Chapter 4.1, infrastructural networks are an essential part of urban areas. They provide services, without which the urban system can not function properly, hence their disruption will inevitably cause major disutilities to the affected population. The provision with electricity, gas, heat[31] and water, the drainage of wastewater, as well as the connections that communication and transportation networks provide have become essential elements of modern urban life.

All the aforementioned infrastructural networks, in the form of pipes and cables, and the related plants, distributors, converters, stops and stations are located in the urban space and integrated among other buildings. The effect of a malicious tampering is two-fold: first, an attack on a building will inevitably also affect the infrastructural elements contained in, connected to, or located close to this building (Apostolakis and Lemon 2005; Karydas and Gifun 2006; Lemon 2004; Michaud 2005; Patterson and Apostolakis 2007); second, an attack that is aimed primarily on an infrastructural element will affect surrounding buildings and will also cause trickle-down effects within the affected infrastructure (e.g. an overload in the electricity network) or on physically or logically interdependent infrastructural networks (e.g. a communication network that needs electricity to work) (Rinaldi, Peerenboom, and Kelly 2001).

The reason for not analyzing the vulnerability of infrastructural networks in this study is to be found in the data availability. In order to perform such kind of analysis it is necessary to have access to detailed information about the network, both in terms of their functional connections (i.e. a network graph or schema) and their actual locations in the real world (i.e. maps showing the course of pipes and cables). Both are generally very difficult to obtain, since the network operators have a legitimate interest in keeping such information from the broad public to protect them from any malicious tampering. While I got in contact with the Bureau of Waterworks at the TMG in a very early stage of my research, I have not been able to obtain the necessary datasets.

Building Attributes

The physical attributes of buildings have an effect on their resistance towards the forces they might be exposed to. Kappes and colleagues (2012) point out the importance of a hazard-specific approach when analyzing vulnerability indicators in the context of physical vulnerability. They refer to a number of studies that concentrate on the development of such relative vulnerability towards different hazards as a result of building characteristics (Birkmann, Schneiderbauer, and Ehrlich 2013; Collins, Grineski, and de Lourdes Romo Aguilar 2009; Cutter, Mitchell, and Scott 2000; Dao and Peduzzi 2003; Dilley 2005; Granger et al. 1999; Lazarus 2011; Papathoma and

Dominey-Howes 2003; Papathoma-Köhle et al. 2007; Puissant, Malet, and Maquaire 2006; United Nations Development Programme and Bureau for Crisis Prevention and Recovery 2004; Wisner et al. 2003). Some of the building vulnerability indicators they developed for tsunami and landslide threats are: material of the building, number of floors of the building, characteristics of the slope side wall, condition of the ground floor, building surroundings, row of the building, presence of sea defense, and width of intertidal zone in front of the building (Kappes, Papathoma-Köhle, and Keiler 2012, 579).

In the context of terrorism vulnerability the FEMA suggests the following six building characteristics in its *Handbook for Rapid Visual Screening of Buildings to Evaluate Terrorism Risks*[32] (Federal Emergency Management Agency 2009, 44–101):

- site (e.g. perimeter boundary, unobstructed view, storage of hazardous materials, adjacent structures)
- architecture (e.g. building height, footprint area, building configuration, lobby/retail location, loading dock, vehicular penetration)
- building envelope (e.g. window support type, total percent of window area, glass type, security film, wall type)
- structural components and systems (e.g. wall reinforcements, column spacing, column height, column accessibility, structural enhancements)
- mechanical, electrical, plumbing (MEP) systems (e.g. external air intake conditions, internal air distribution system, location of critical utilities)
- security (e.g. intrusion detection, video surveillance, security guards, vehicle access control, pedestrian access control)

I implemented features from the former two characteristics in my assessment framework by the use of spatial analysis methodologies. The latter four require either a detailed screening procedure (as suggested in the aforementioned FEMA document) or documentation by the building owners.

Yet again the security relevant nature of these kind of information made it impossible for me to obtain them. In addition, the sheer number of ca. 1.9 million buildings in my study area (cf. Chapter 5.2.1) made it impossible to inquire for the data from all related building owners. At the same time, the amount of data that would need to be collected also made a fieldwork approach impracticable. As a result I had to leave the physical attributes of buildings outside the scope of my analysis.

Temporary Building Population

In Chapter 5.3.1 I introduce a methodology for the estimation of building populations at different times during the day. I labeled this the stationary building populations, since I can only regard those periods of time where the individuals stay at one location to perform certain activities. These activities are “being at home”, “working”, and “studying”. The methodological reasons for this limitation are explained in detail in Chapter 5.3.1.

Yet, I do acknowledge that there is a large number of other activities that people pursue in urban areas, apart from the three listed above. These activities are often characterized by a short duration, such as “shopping”, “eating at a restaurant”, or “running an errand”. The data I am using for the calculation in the stationary building population estimation does not allow this kind of analysis on the required fine temporal scale.

Therefore I decided to take a different approach, as suggested by Bosserhoff (2005a; 2005b) in his analyses of socio-demographic data for the estimation and prediction of traffic volumes. I adapted the central idea of assuming a certain consumption of floorspace per usage category and that the knowledge about the available floorspace and the usage type allow me to derive the maximum number of temporary visitors (e.g. customers of a shop or restaurant). For example a convenience store of a certain size can contain a certain maximum number of customers at a time, while another convenience store of twice the size can contain twice as many customers at a time. Similarly, a restaurant of the same size as a convenience store will contain a smaller number of customers than the convenience store due to the different activities being pursued at each, and the resulting different store layouts.

Based on these assumptions I developed the following equation for the estimation of the temporary building population:

$$TBP_{i,c,t} = FS_{c,i} \cdot \gamma_c \cdot \beta_{c,t} \tag{6}$$

where $TBP_{i,c,t}$ is the temporary building population of building i in category c at time t, $AP_{Ai,c,t}$, $Fs_{c,i}$ is the cumulative floorspace of category c in building i, γ_c is the customer floorspace ratio of category c, $\beta_{c,t}$ is a binary variable showing whether category c is in operation at time t.

I developed a number of values for γ_c based on the figures that Bosserhoff (2005a; 2005b) generated. Since these data were used in the context of traffic volume estimations in Germany I needed to transpose them to more realistic values for the use in Japanese urban areas. In addition I was planning to derive the values for $\beta_{c,t}$ from clustered movement profiles as has been suggested in a number of publications (González, Hidalgo, and Barabási 2008; Horanont 2012; Jiang, Ferreira, and González 2012). As a first step I defined some rough values myself, based on general observations I had made during the analysis of the movement profile data I am using in Chapter 5.3.1. 20 shows the resulting preliminary data. Experimental calculations with these values showed that the results did not provide any new insights, as the changes in the population figures did not vary significantly from those I derived using only the stationary building population estimation methodology. This fact together with the enormous computational investment involved and the high degree of additional uncertainty introduced by the *a priori* estimations and guesses regarding the values of γ_c and $\beta_{c,t}$ led me to the conclusion to abandon this subject and focus on other, more reliable vulnerability factors instead.

5.3.6. Spatial Influence Estimation

In Chapter 4.2.3 I introduce the concept of spatial influence (SI) as one of the main components of the analysis framework I develop in the course of this study. It is a spatial representation of the fact that objects influence their surroundings by their own attributes and states. This means that a place that is otherwise not vulnerable towards being the target site of a terrorist attack can be vulnerable nevertheless due to the fact that it is spatially close to a place of high vulnerability.

In Chapter 4.2.3 I also introduce two possible operationalizations of spatial influence: spatial concentration and spatial proximity as suggested by Caplan and Kennedy (2010a, 25–26). In the context of the attack scenario of a small explosive attack (cf. Chapter 5.2.2) and the four vulnerability factors (cf. Chapters 5.3.1 through 5.3.4) I chose for the purpose of this study I use both of these operationalizations, as 21 shows.

I selected the bandwidth of 250 m for the KDE smoothing following the argumentation by Caplan and Kennedy in their operationalization of the spatial influence of criminogenic factors for shootings in US american cities: “A 1,000 foot bandwidth was selected because it seemed a reasonable sphere of influence for shooters—the average blockface is approximately 350 feet.” (2010b, 48) Given the chosen attack scenario of a small explosive attack I also followed the recommendations by the National Counterterrorism Center (NCC) and the FEMA for stand-off distances in the context of explosive devices. The NCC (2012) recommends a mandatory evacuation distance of 46 m and a preferred evacuation distance of at least 564 m for explosive devices up to 23 kg TNT equivalent, which constitutes a briefcase bomb. Similarly, the FEMA

Table 20: Preliminary data for the estimation of temporary building populations.

Category c	**Ratio γ_c**	**Hours (for $\beta_{c,t}$)**		**Category c**	**Ratio γ_c**	**Hours (for $\beta_{c,t}$)**	
kindergarten	0.2	08:00	15:00	fitness center	0.2	08:00	22:00
library	0.4	08:00	20:00	hotel	0.2	15:00	10:00
school	0.1	08:00	15:00	movie theater	0.5	15:00	01:00
university	0.1	08:00	20:00	museum	0.2	10:00	19:00
convenience store	01	00:00	24:00	night club	0.5	22:00	06:00
department store	0.5	09:00	20:00	restaurant	0.5	11:00	22:00
retail	0.5	09:00	20:00	sport facility	0.1	08:00	22:00
service	0.2	09:00	17:00	theater	0.2	19:00	22:00
supermarket	1	09:00	20:00	governmental	0.15	09:00	15:00
entertainment	0.5	17:00	02:00	hospital	0.15	00:00	24:00
café	0.5	07:00	20:00	doctor	0.15	09:00	15:00
disco	1.5	22:00	06:00	religious	0.5	08:00	18:00

Notes:
The ratio γ_c denotes the number of people per m^2 inside the respective usage category.
The hours show the opening and closing times of all outlets of the respective usage category.

Extended from original data sources: Bosserhoff (2005a; 2005b)

Table 21: Operationalization of the spatial influence of the four vulnerability factors in this study.

Vulnerability factor	SI operationalization	Details
stationary building population	spatial concentration	• kernel density estimation (KDE) • bandwidth of 250 m • weighted by the estimated population per building
mobile pedestrian population	spatial concentration	• kernel density estimation (KDE) • bandwidth of 250 m • weighted by the NTSBCM per street segment
mobile railway population (train station usage & railway link importance)	spatial concentration	• kernel density estimation (KDE) • bandwidth of 250 m • weighted by the usage per train stations and the riderhip per railway link, respectively
symbolic value	spatial proximity	• buffer • euclidian distance of 100 m • weighted by the symbolic relevance

(2003b) defines luggage bombs to contain ca. 26-100 lbs (11.8-45.4 kg) of TNT equivalent and estimates minor wounds by glass fragments to be sustained from standoff distances between 67 and 122 m (220-400 ft) as Figure 31 shows. Since these values depend heavily on factors such as size and characteristics of the explosive device as well as the location of the explosion inside or outside of a building or within a confined space such as an underground train station, I opted for a radius larger than these values and therefore settled at 250 m.

Since the spatial influence estimation will produce smooth raster surfaces over the complete study area it is important to choose an appropriate cell size. Caplan and Kennedy remark in this context:

> 100x100 foot cells were the smallest area that our computers could process reasonably fast and, for the purposes of this risk terrain model, if a risk terrain map could assess the risk of shootings at small (but reasonable) geographic units (e.g. 2 inches would be unreasonable since a person cannot even fit in that space), it would provide the most utility for operational policing compared to larger, less specific, units of analysis. (Caplan and Kennedy 2010b, 48)

I argue that in the context of a micro-scale analysis of a highly urbanized area such as the study area of this study (cf. Chapter 5.2.1) a cell size of 30 m (≈ 100 ft) is still too generalized and unspecific. Under the constraint of being able to do so within a feasible timeframe I decided to calculate the spatial influence as raster surfaces with 10 * 10 m cells. Given the size of the study area this results in raster datasets of 3,221x3,295 pixels (i.e. 10.6 megapixels), which can easily be created and processed on a contemporary computer. In the following sections I explain the details about the calculation of the spatial influence for each of the four vulnerability factors.

Stationary Building Population

In Chapter 5.3.1 I describe the process of calculating the estimated population of the buildings in the study area in bespoke time steps over the course of a day. The output result is a table of 24 population figures for each building, one per hour, which can be visualized in thematic maps (cf. Fig. 20 and Appendix A). Using the aforementioned KDE smoothing algorithm with a 250 m bandwidth and these estimated hourly building population figures it is possible to produce raster surfaces of the study area with a 10 m cell size to operationalize and visualize the spatial influence of the buildings on their immediate surroundings.

In order to be able to compare the data for the single time steps it is then necessary to normalize the raster surfaces to a scale of 0-100, where the maximum value of 100 represents the maximum cell value over all 24 hourly raster surfaces. I call the resulting value the *normalized spatial influence (nSI)* of the respective vulnerability factor. Figure 32 shows a side-to-side comparison of the estimated building population values and the resulting nSI distribution for a

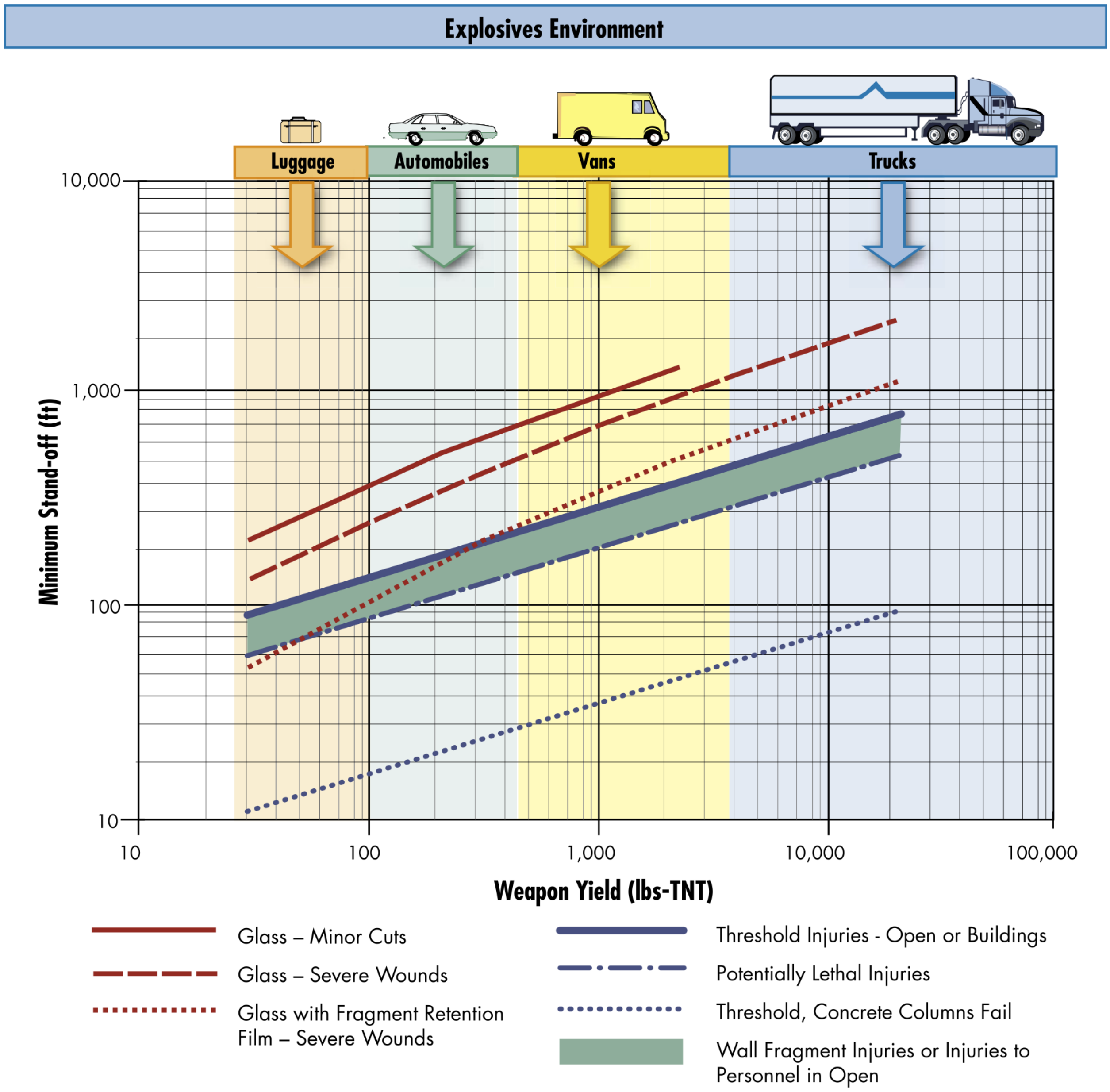

Figure 31: Recommended minimum standoff distances in relation to the size of an explosive device.

Source: Federal Emergency Management Agency (2003b, 4–11)

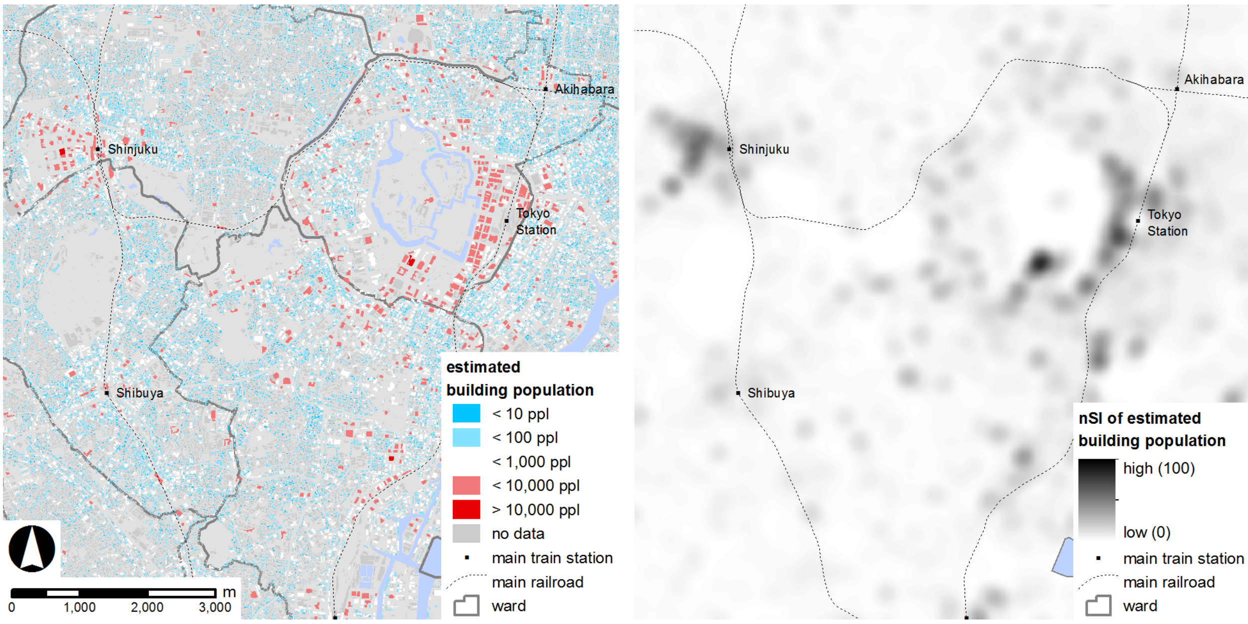

Figure 32: Comparison of the estimated population figures per building (left) and the resulting raster surface representing the normalized spatial influence (nSI) (right) for a detail of the study area at 9am.

detail of the study area at 9am. It is obvious how the highly populated highrise office buildings in Marunouchi, west of Tokyo Station, as well as west of Shinjuku and the large governmental office buildings in Hibiya, south of the Imperial Palace, have a great influence on their immediate surroundings. Appendix B contains all 24 maps of the study area showing the nSI raster surfaces for each time step.

Mobile Pedestrian Population

The process of calculating the spatial influence of the estimated mobile population follows mostly that of the estimated building population I outline above. It starts from the pedestrian volume per street segment, expressed by the *normalized spatio-temporal betweenness centrality measure (NSTBCM)*, whose calculation process I describe in Chapter 5.3.2. Since this vulnerability factor also has an inherent temporal dimension, each street segment is assigned 24 population figures, one per hour, which can be visualized in thematic maps (cf. Fig. 25 and Appendix C). Once again the KDE smoothing algorithm with a 250 m bandwidth over these estimated hourly mobile population figures produces raster surfaces of the study area with a 10 m cell size to operationalize and visualize the spatial influence of more or less crowded street segments on their immediate surroundings.

Similarly to the process of calculating the spatial influence of the stationary building population it is necessary to normalize the raster surfaces to a scale of 0-100 to allow for comparisons over the temporal dimension. The end result are 24 raster surface maps showing the *normalized spatial influence (nSI)* of the respective vulnerability factor. In the comparison of a map of the original NSTBCM and the resulting nSI for a detail of the study area at 8am in Figure 33 it can easily be seen how the most crowded street segments can be found around train stations. This can be attributed to the fact that public train transportation is the most common mode of transportation for people working in Tokyo and mostly commuting there from their homes in the residential belt around the core city (cf. Fig. 13). Appendix D contains all 24 maps of the study area showing the nSI raster surfaces for each time step.

Mobile Railway Population

The process of calculating the spatial influence of the mobile railway population follows those of the estimated stationary building and mobile pedestrian population, since I used the operationalization of spatial concentration again. The initial values are the train station usage and the railway link ridership, whose calculation I describe in detail in Chapter 5.3.3. Both components of this vulnerability factor have an inherent temporal dimension, hence each train station and

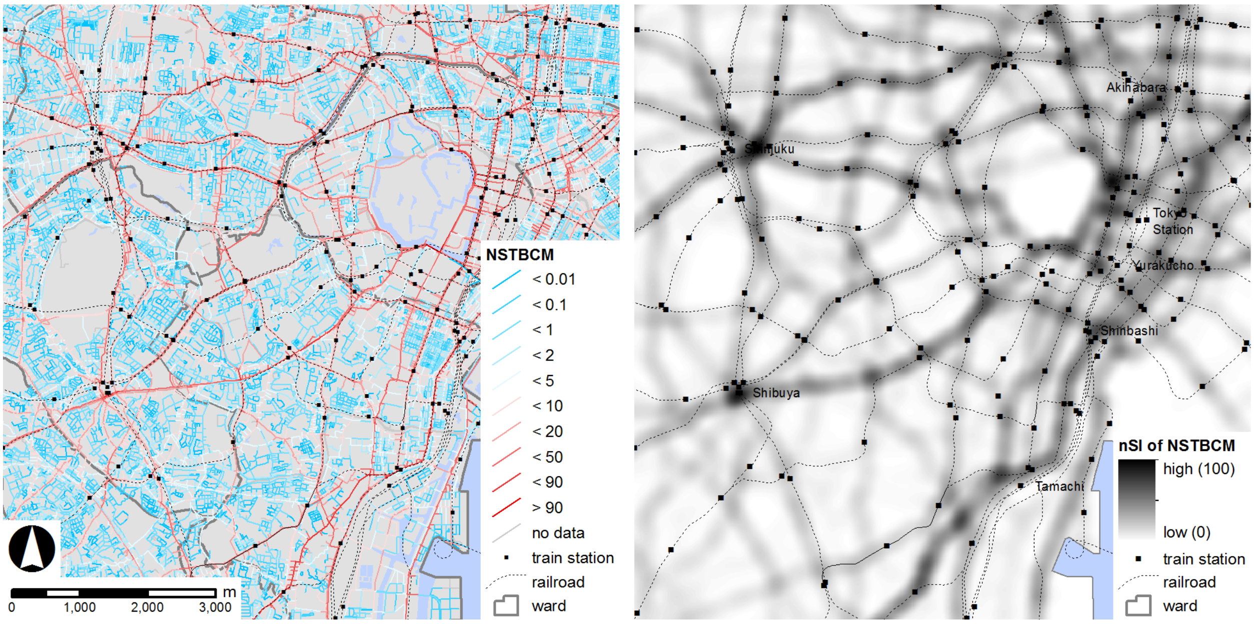

Figure 33: Comparison of the estimated population figures per street segment (left) and the resulting raster surface representing the normalized spatial influence (nSI) (right) for a detail of the study area at 8am.

railway link is assigned 24 population figures, one per hour, which can be visualized in thematic maps (cf. Figs. 27 and 28 as well as Appendix E and Appendix G). Once again the KDE smoothing algorithm with a 250 m bandwidth over these estimated hourly mobile population figures produces raster surfaces of the study area with a 10 m cell size to operationalize and visualize the spatial influence of more or less crowded train stations and railway links on their immediate surroundings.

Following the examples of the processes of calculating the spatial influence of the stationary building population ans mobile pedestrian population it is necessary to normalize the resulting raster surfaces to a scale of 0-100 to allow for comparisons over the temporal dimension. This results in 24 raster surface maps showing the normalized spatial influence (nSI) of the respective vulnerability factor, namely the train station usage and the railway link ridership. The comparison between a map of the original estimated train station usage data and the resulting nSI for a detail of the study area at 8am in Figure 34 shows how the most crowded train station complexes have quite widespread influence. In the eastern part the contiguous underground passages connecting Tokyo Station and Yurakucho Station as well as the subway stations Otemachi, Nijubashimae, Hibiya, Ginza, and Higashiginza span an area of roughly 1.5 by 1km. Similarly in the western part the station complex that connects Shinjuku Station as well as the train and subway stations Seibushinjuku, Shinjukunishiguchi, Nishishinjuku, Tochomae, and Shinjukusanchome comprise a nearly circular area of 1km diameter.

In contrast the comparison of a map of the railway link ridership and the resulting nSI for a detail of the study area at 8am in Figure 35 shows how the linear railway tracks differ in their estimated passenger volumes. The figures are the highest near major train stations such as Tokyo Station and Shinjuku Station and along sections where multiple train lines run in parallel. This is for example the case between Kanda Station, south of Akihabara Station and Tokyo Station, and even more so between Shinbashi Station and Shinagawa Station where some of the most heavily used train lines converge: the Chuo Main Line, the Yamanote Line, Keihin-Tohoku Line, and the Tokaido Main Line as well as a number of long distance trains (the Tohoku Shinkansen, Yamagata Shinkansen, Akita Shinkansen, Joetsu Shinkansen, and Nagano Shinkansen lines, and the Tokaido-Sanyo Shinkansen, respectively). Appendix F contains all 24 maps of the study area showing the nSI raster surfaces of the train station usage for each time step, Appendix H does the same for the railway link ridership.

Since I divided the operationalization of the mobile railway population into two parts (i.e. the estimated train station usage and the estimated railway link ridership) it also became necessary to

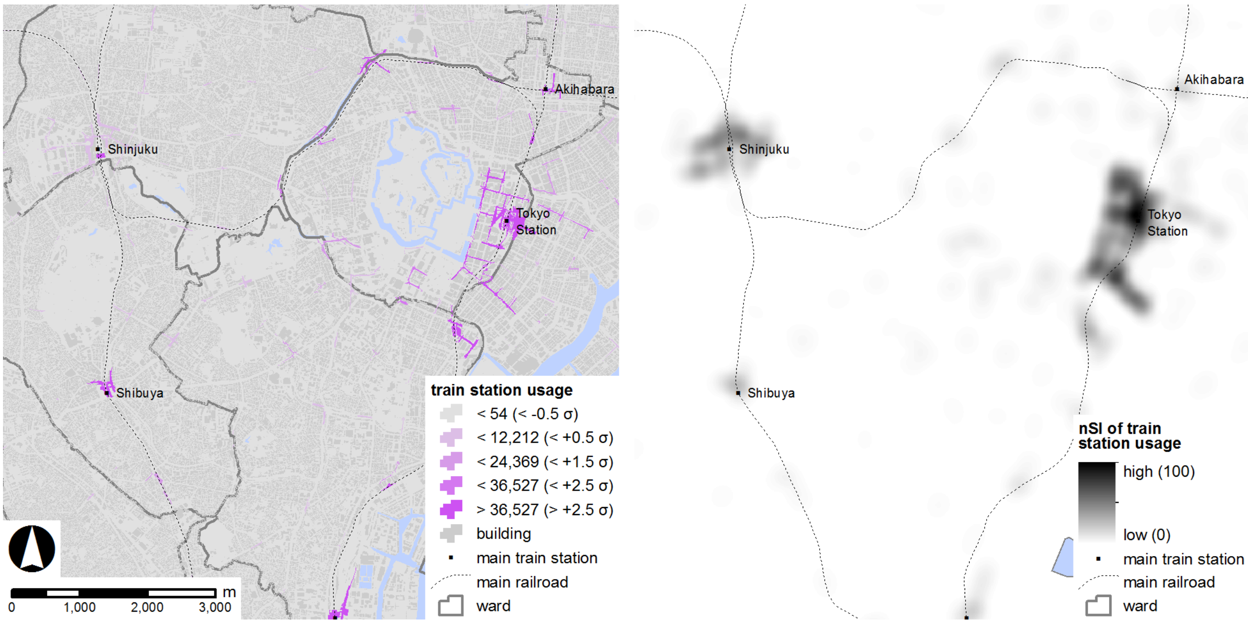

Figure 34: Comparison of the estimated train station usage (left) and the resulting raster surface representing the normalized spatial influence (nSI) (right) for a detail of the study area at 8am.

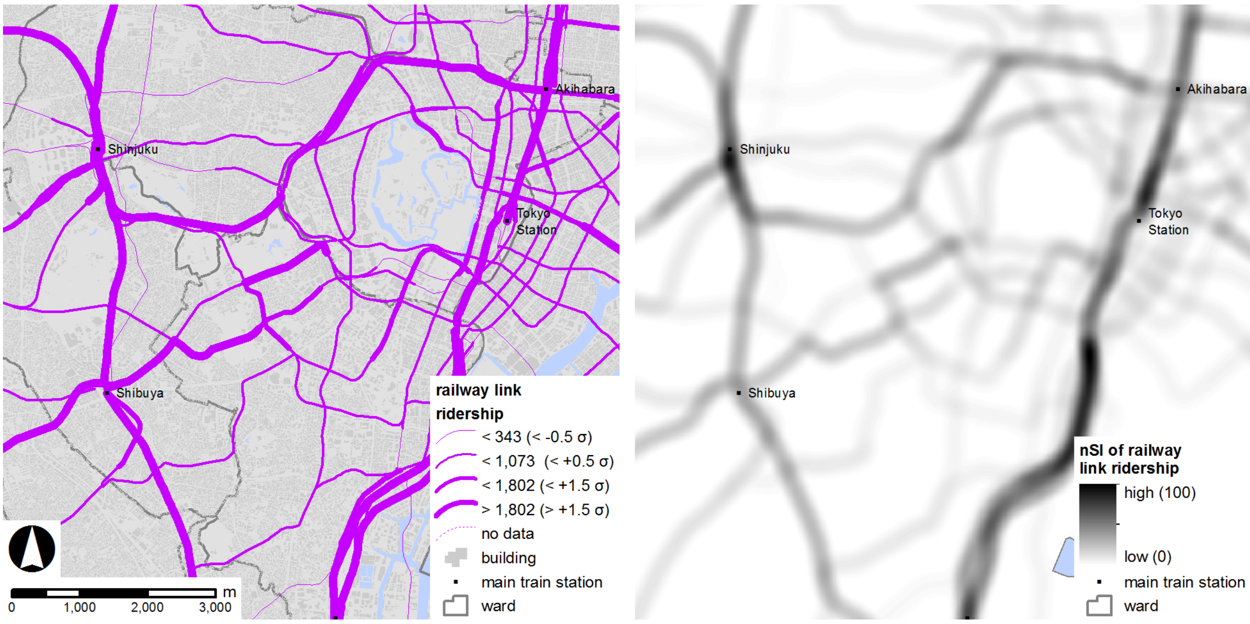

Figure 35: Comparison of the estimated railway link ridership (left) and the resulting raster surface representing the normalized spatial influence (nSI) (right) for a detail of the study area at 8am.

combine the two resulting nSI raster surfaces for each of the 24 time steps into one combined map showing the normalized spatial influence of the mobile railway population. I did this by using equation (1), which I explain in detail in the context of the overall vulnerability map creation. Here I assigned both components an equal importance, but the formula allows for a weighting as deemed appropriate by the analyst (cf. Chapter 5.3.7). Appendix I contains the resulting 24 maps of the study area showing the nSI raster surfaces of the mobile railway population.

Symbolic Value

The process of calculating the spatial influence for the symbolic value differs from the aforementioned processes for the other three vulnerability factors. The spatial operationalization methodology in this case is not that of spatial concentration to evaluate the existence of hot spots of highly accumulated features of a certain kind, but that of spatial proximity. This allows to account for the fact that a terrorist attack is more likely to be associated with a certain symbolic location or object the closer it happens to it.

The starting point are the locations of the symbolic places, which I describe in Chapter 5.3.4. In addition I also included a dimension of symbolic relevance to account for the fact that not all symbolic locations bear the same symbolic value. This measure of symbolic relevance allows for a weighting of more or less symbolic relevance according to the subjective perceptions of the analyst and of those under attack.

Just like the selection of symbolic locations in the first place, this weighting step is highly subjective since the definitions of symbolic relevance in this section follows my personal perception. Another researcher would possibly define it in a different way, which would lead to a different weighting of places that bear more or less symbolic value. As a result, the distribution of the symbolic locations' spatial influence would also be different from that which I develop in this section. Again, one might argue that this subjectivity introduces ambivalence in the overall quantitative analysis of terrorism vulnerability, and I cannot negate this fact. But I am strongly convinced that this ambivalence is ameliorated by the conscientious selection of symbolic places by the person performing the analysis. This selection is optimally based on the subject matter expertise, quantitative results of questionnaires or an AHP-based process and information about the respective perpetrator and a precise attack scenario. Therefore I postulate again that every analysis employing my framework will inevitably produce a different result, since the underlying assumptions are also different.

In the case of the large train stations I assigned the symbolic relevance on the basis of the actual numbers of passenger transfers at each of these 39 stations. Shinjuku Station, at 940,176 transfers the most highly frequented station, was assigned a value of 100, while the remaining stations were assigned their relative ratio of this value. For example Meguro Station with 150,013 transfers was assigned a symbolic relevance of 16. 22 shows the symbolic relevance for all 39 stations.

For the remaining two categories of symbolic institutions and landmarks I decided to use a tripartite scale of “low”, “medium”, and “high”. In order to be able to use this ordinal scale in the quantitative calculation of the spatial influence I then assigned the actual weights on a scale of 0-100 based on the relative rank of the ordinal scale values (i.e. at “low” at 33.3, “medium” at 66.7, and “high” at 100). For the scope of this study I decided to assume a perpetrator that aims predominantly at high value targets. Therefore I assigned all symbolic institutions a “low” symbolic relevance. These targets would more likely be attractive for terrorists who seek to have an impact on the government, public services like the police or fire fighters, or religious groups. To determine the values for the economic, political, and touristic landmarks I decided to use their relative recognition in the local, national (i.e. Japanese), or international community I equated these to the three aforementioned levels of symbolic relevance, as 23 shows. Figure 36 also shows the symbolic places and their assigned symbolic relevance.

In contrast to the other three vulnerability factors the symbolic value of a location does not change with the time of day, hence only one map of symbolic places is sufficient. This is due to the fact that within the scope of this study and the analysis framework I developed (cf. Chapters 3.1 and 5.3) the symbolic value is an operationalization of the terrorists' aim to create attention with their actions, whereas the other two vulnerability factors represent their goal to affect as many people as possible. For example a terrorist attack near Tokyo Tower will create attention in the national and international media irrespective of the actual time of the attack. Obviously the perpetrators would be able to achieve both goals if they perform the attack at a time where they can also affect a larger number of people, but this dimension of the decision making process is covered by the remaining, population based vulnerability factors. In order to keep the vulnerability factors independent as required by the guidelines for electing appropriate vulnerability factors in Chapter 4.2.2 it is imperative to not erroneously introduce the temporal dimension here in the context of the symbolic value.

Table 22: Symbolic relevance of large train stations based on their daily passenger traffic volume.

Station name	Daily passenger volume	Symbolic relevance	Station name	Daily passenger volume	Symbolic relevance
Shinjuku	940,176	100	Nihonbashi	178,154	19
Shibuya	638,872	68	Gotanda	176,468	19
Ikebukuro	595,866	63	Kinshicho	176,179	19
Tokyo	516,431	55	Kasumigaseki	175,922	19
Shinbashi	422,530	45	Omori	172,755	18
Shinagawa	389,850	41	Osaki	165,245	18
Tamachi	290,354	31	Ogikubo	164,029	17
Otemachi	260,861	28	Yotsuya	161,503	17
Akihabara	260,131	28	Nakano	153,769	16
Iidabashi	248,332	26	Suidobashi	150,755	16
Ueno	222,926	24	Meguro	150,013	16
Yurakucho	221,048	24	Kitasenju	145,509	15
Kanda	220,130	23	Kayabacho	144,491	15
Hamamatsucho	216,396	23	Akabane	144,222	15
Takadanobaba	208,347	22	Roppongi	143,223	15
Ebisu	204,117	22	Toyocho	139,204	15
Ochanomizu	197,836	21	Jinbocho	139,031	15
Kamata	196,783	21	Toranomon	135,896	14
Ichigaya	194,502	21	Kudanshita	134,929	14
Ginza	179,378	19			

Data source: National Land Information Division, National and Regional Policy Bureau (2010)

Table 23: Symbolic relevance of the 25 economic, political and touristic landmarks.

	Symbolic relevance	
Landmark name	**Rank**	**Value**
Asahi Beer Hall	medium	66.7
Bank of Japan (BOJ)	high	100
Ginza	high	100
Meiji Shrine (incl. surrounding forest)	high	100
Mori Tower (Roppongi Hills)	medium	66.7
National Diet Building	high	100
Rainbow Bridge	high	100
Ryogoku Sumo Hall	medium	66.7
Sensoji Temple (incl. Nakamise Street)	high	100
Shibuya Crossing	high	100
Sunshine 60 Building	low	33.3
Tokyo Big Sight (Tokyo International Exhibition Center)	medium	66.7
Tokyo Dome	medium	66.7
Tokyo Imperial Palace (incl. outer gardens)	high	100
Tokyo International Forum	medium	66.7
Tokyo Metropolitan Central Wholesale Market (Tsukiji Fish Market)	high	100
Tokyo Metropolitan Government Building (Tokyo City Hall)	high	100
Tokyo Skytree	high	100
Tokyo Station Building	medium	66.7
Tokyo Stock Exchange (TSE)	high	100
Tokyo Tower	high	100
Tokyo World Trade Center	low	33.3
Ueno Park	medium	66.7
Yasukuni Shrine	high	100
Zojoji Temple	high	100

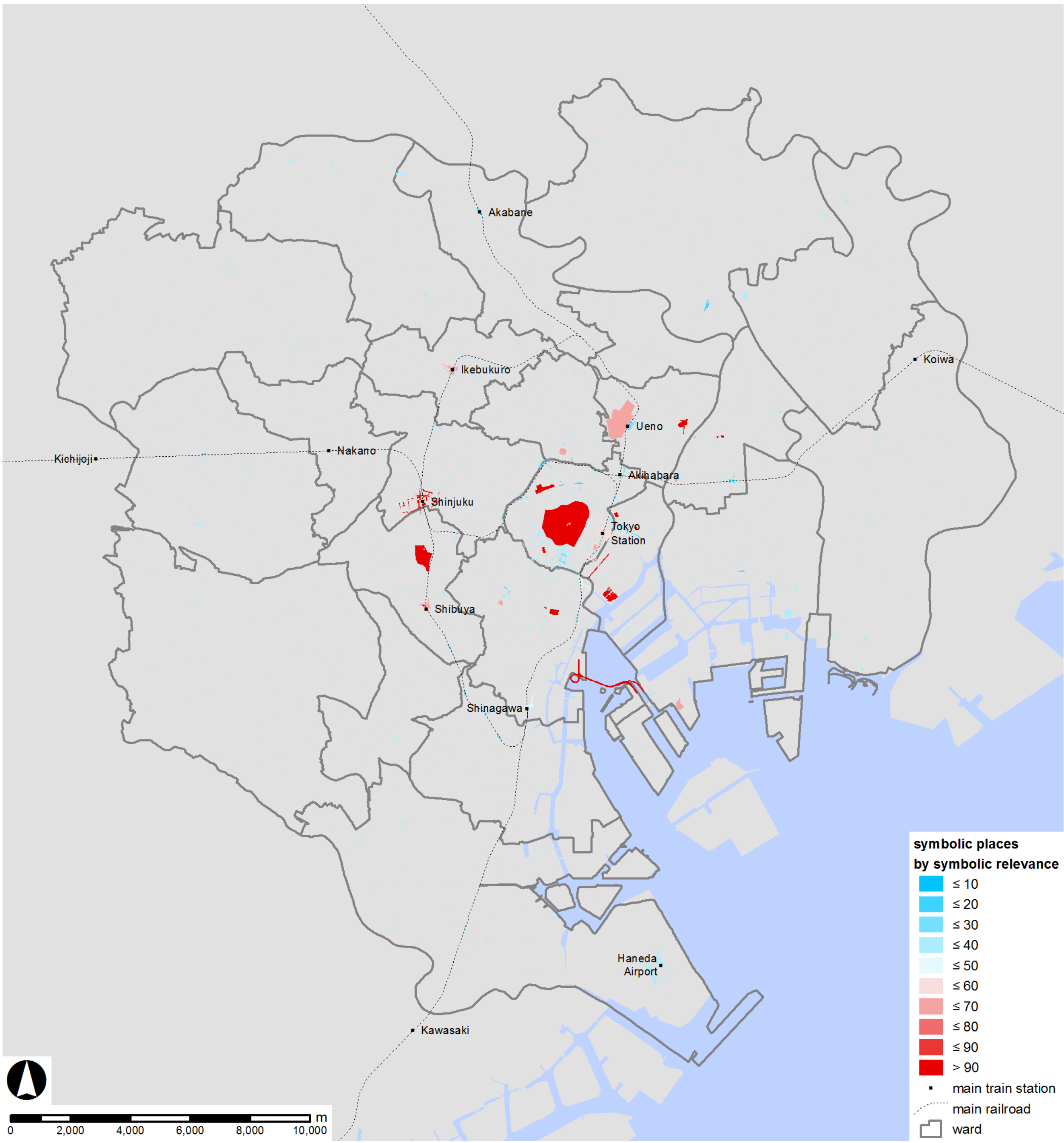

Figure 36: Spatial distribution of symbolic places within the study area and their symbolic relevance.

In cases where the spatial influence is operationalized as the spatial proximity from the objects of interest it represents a linear function of the weighted inverse distance from the objects as shown in equation (7):

$$nSI_{\delta} = \begin{cases} 0 & \forall \delta \geq \rho \\ \rho - \delta \cdot \left(\frac{\rho}{\delta_{max}}\right) & \forall \delta < \rho \end{cases} \tag{7}$$

where nSI_{δ} is the normalized spatial influence at distance δ, ρ is the symbolic relevance, δ_{max} is the maximum distance.

This calculation process creates a raster surface as shown in Figure 37 which compares a map of the original symbolic places and their symbolic relevance with the resulting normalized spatial influence (nSI) for a detail of the study area. Appendix J contains the map of the complete study area showing the nSI raster surface of the symbolic value.

5.3.7. Vulnerability Map Creation

In the preceding chapters I introduce the operationalization of four vulnerability factors: estimated stationary building population (cf. Chapter 5.3.1), estimated mobile pedestrian population (cf. Chapter 5.3.2), estimated mobile railway population (cf. Chapter 5.3.3), and symbolic value (cf. Chapter 5.3.4). These all produce spatial representations of their respective features (i.e. buildings, street segments, train station complexes, railway links, and symbolic places) which are materialized as vector objects (i.e. polygons and lines). Subsequently I introduce the operationalization of these vulnerability factors' spatial influence (cf. Chapter 5.3.6), which denotes the influence objects have on their surroundings' vulnerability as a result of their own vulnerability. This spatial influence, which needs to be normalized to a continuous scale of 0-100 for comparison between factors, is materialized as continuous raster surfaces for the complete study area. Furthermore, since the vulnerability factors can also have a temporal dimension, multiple raster maps of their nSI at various times of the day can be produced.

The concept for the vulnerability map creation approach I present here originates from the *Risk Terrain Modeling* (RTM) methodology introduced by Caplan and Kennedy (2010a; 2010b). There the authors use it for the combination of risk map layers, which represent the existence of certain criminogenic factors that aggravate or mitigate the risk of a certain type of crime evolving, using simple raster algebra. The approach I developed in this study is shown in equation (1) and has a number of improvements over the methodology introduced by Caplan and Kennedy:

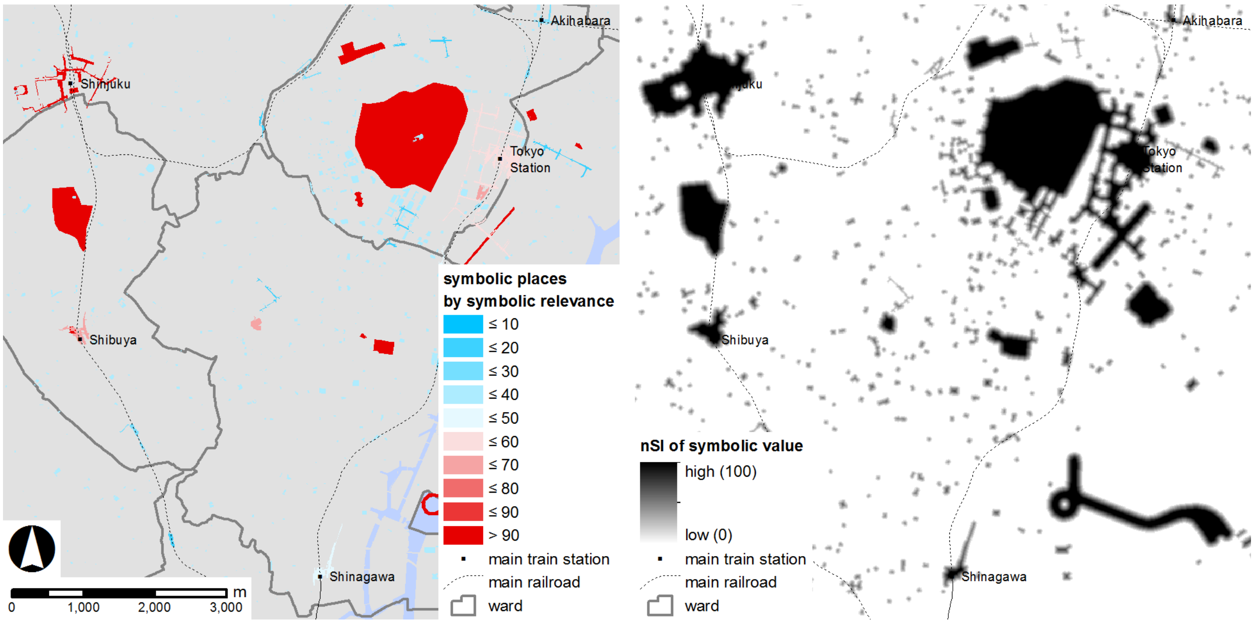

Figure 37: Comparison of the symbolic places including their symbolic relevance (left) and the resulting raster surface representing the normalized spatial influence (nSI) (right) for a detail of the study area.

1) a gradient between vulnerability values as compared to discrete classified values,

2) the inclusion of the temporal scale where meaningful, and

3) an improved methodology for the weighting of vulnerability factors.

The definition of the vulnerability factor weights is equally critical for the meaningfulness of the overall analysis process as the selection of the vulnerability factors in the early steps of the analysis framework (cf. Chapter 4 and Fig. 4). Yet, at the same time it is also highly subjective since it is based solely on the perceived importance of the vulnerability factors from the viewpoint of the analyst. One possibility to ameliorate this potential bias is the employment of a standardized procedure to produce the factor weights, such as the Analytic Hierarchy Process (AHP) as introduced by Saaty (1980; 2006; 2008) and, in the context of GIS, Malczewski (1999). Yet, I argue that these methods would have only a limited influence on minimizing the bias for four reasons: first, the samples for both regular questionnaires and those used for AHP would have to be sufficiently large to be representative, which is at least a difficult undertaking in the case of subject matter experts necessary for AHP. Second, in order to be able to represent an overall perception of general values by the population the samples would also need to reflect all perceptions of these values that exist among the population. I argue that such a generalized overall perception of values does neither exist, nor is it possible to guarantee that a sample covers all its aspects. Third, the relevant perspective in the selection of the weights and thereby the importance of the vulnerability factors should not be that of those under attack, but in turn the perpetrators' perception of these. In other words, terrorists will most likely not select their targets by choosing something that represents a certain value in their own opinion, but rather something they believe to represent a value in the eyes of those they aim to attack (McCormick 2003; Abrahams 2008; Bakker 2012). It is therefore imperative to ask the question "if I were a terrorist, I would..." (Apostolakis and Lemon 2005, 365) and thereby to imitate the perpetrators' mindset and decision making process. Last, all these considerations abstract away from the moment of surprise that terrorists might use for their advantage, for example by doing something that was not deemed to make sense from their perspective or that has not been evaluated as providing them a benefit. Whichever standardized method is chosen to define these vulnerability factor weights can therefore at best only provide a misleading sense of certainty, at worst it can lead to bad decisions under the wrongful impression of being based on quantifiable facts.

For the scope of this study I defined the weights of the four vulnerability factors at my own discretion as shown in 24. I derived them by following the scenario I defined for the scope of this case study (cf. Chapter 5.2.2): a twice as important aim at affecting as many people as

Table 24: Weighting of the four vulnerability factors for the scope of this case study.

Vulnerability factor	**Weight w_i**
estimated stationary building population†	0.22
estimated mobile pedestrian population†	0.22
estimated mobile railway population†	0.22
symbolic value	0.33

Note:

† Including temporal dimension.

possible than at attracting maximum attention. The 66.7% that the total weight of the population-based vulnerability factors need to account for were split evenly between the three respective factors (i.e. stationary building population, mobile pedestrian population, and mobile railway population), as the scenario provides no details about the terrorists' preferences for rather attacking buildings, trains, or people on the streets. These types of information exist for real terrorist groups, and could therefore be implemented into the framework at this point to provide an analysis tailored specifically at a certain group.

The weighted summation of the vulnerability factors needs to be performed for all cells of the input raster surfaces. These have to have the same spatial resolution for this purpose, otherwise they must be interpolated to line up with each other. The same holds true for those vulnerability factors that include a temporal dimension. The time steps either have to be identical (e.g. hourly as in the case of this study) or must be interpolated to line up.

In a last step the resulting vulnerability maps then have to be normalized once again to stretch the summarized vulnerability index values to a scale of 0-100. The calculation ultimately produces one map of the overall weighted vulnerability index per time step, as can be seen in Figure 38 for the example of 8am. Appendix K shows all 24 vulnerability maps for the complete study area. In Chapter 6 I will discuss the hourly results in more detail.

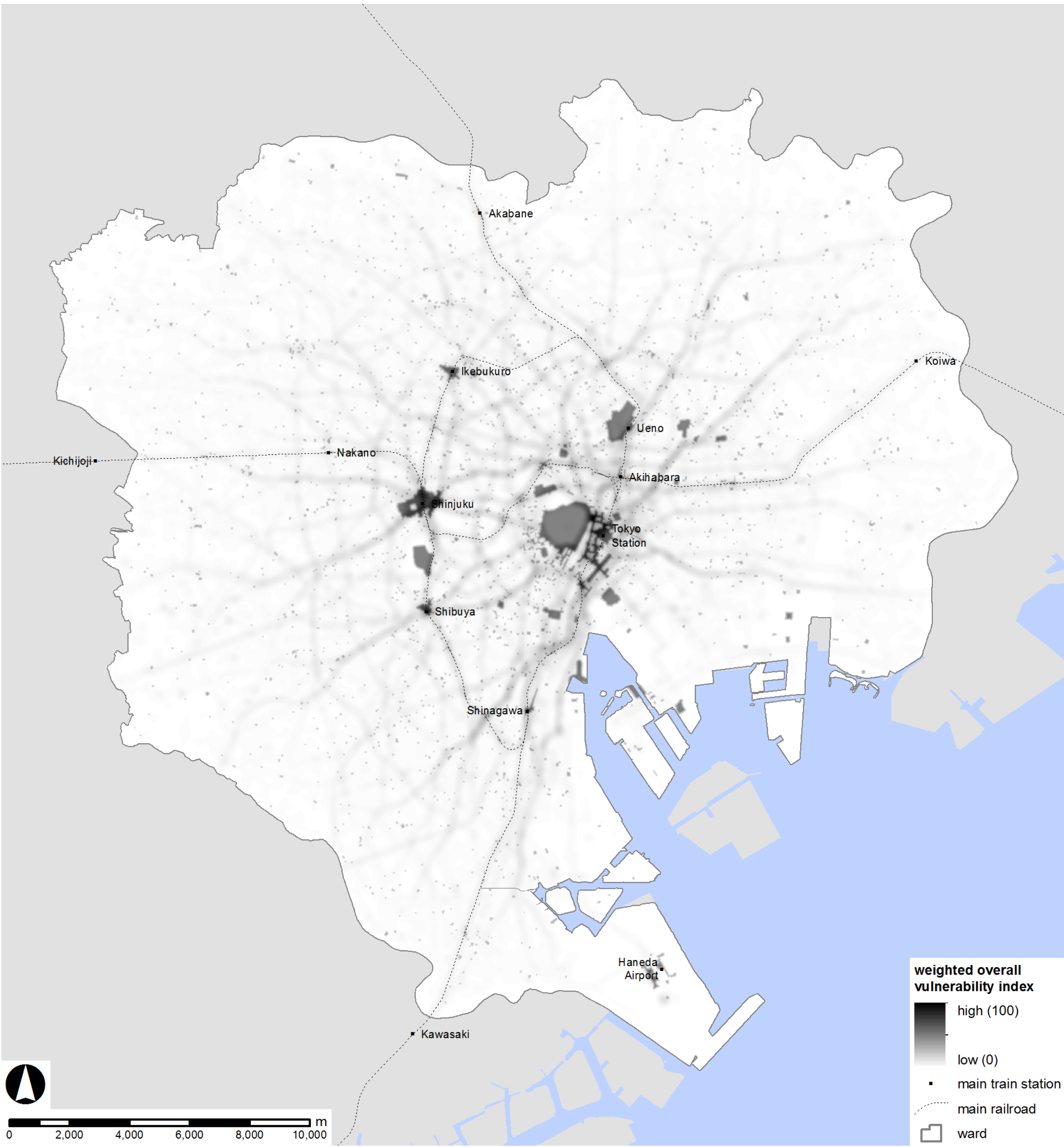

Figure 38: Spatial distribution of the overall vulnerability at 8am based on the four selected vulnerability factors and their weights.

6 Interpretation and Discussion of Results

6.1. Introduction

Before going into the details of analyzing the quantitative result that the vulnerability assessment produced in the case study in Chapter 5 I want to emphasize once again an important point I already mentioned in the introduction of the conceptual framework in Chapter 4, namely that of the inevitably inherent subjectivity. The subjective decision of the analyst applying this framework come to play in four dimensions:

1) the selection of the scenario,
2) the selection of vulnerability factors and their operationalization,
3) the definition of the spatial influence and its operationalization, and
4) the weighting of the vulnerability factors.

I mention this again here, since the statements I make here are conclusions based on the conscientious decision I made regarding these four dimension in the course of this study. I chose the attack scenario of a small explosive attack for a number of reasons, which I explain in detail in Chapter 5.2.2, the most important of them being that this is the most feared mode of attack according to an opinion poll among citizens of the study area (Metropolitan Police Department 2007). The process of selecting appropriate vulnerability factors was lengthy and commanded by three major criteria:

1) the independence of the vulnerability factors in order to avoid bias,
2) the availability of appropriate quantitative data to operationalize the vulnerability factor using appropriate spatial and temporal scales, and
3) the existence or possibility for development of quantitative methodologies for the computational of the operationalization of the vulnerability factors.

The resulting four vulnerability factors (i.e. estimated stationary building population, estimated mobile pedestrian population, estimated mobile railway population, and symbolic value) as well as some other factors, which I rejected for one or many of the aforementioned reasons, are explained in detail in Chapters 5.3.1 through 5.3.4 and 5.3.5, respectively. The operationalization of the symbolic value is particularly subjective, as I explain in the relevant chapter. Along the same lines the assignment of weights for all four vulnerability factors, which I elucidate in Chapter 5.3.7, bears a significant subjectivity, as it is based entirely on my personal perceptions. Therefore the results and their interpretations, which I present in this chapter, are based on these circumstances. A different analyst, using different vulnerability factors, a different operationalization of their spatial influence, and also a different weighting of the factor maps will inevitably come to a different result, and therefore to different conclusions. I perceive this not as a flaw of the framework I developed, but in contrast as one of its strengths. I strongly believe that there can be no right or wrong in the scientific discussion of a topic as defined by subjective perceptions and values as terrorism. Instead, this framework and its results should allow for the first time for a thorough, quantitatively founded discussion of terrorism vulnerability in highly urbanized areas.

In the context of my research objectives I mention in Chapter 3 the statement by Schmid who had to say about the scientific engagement in the field of terrorism research that "in the absence of empirical data, much of the literature is purely speculative and relies on secondary sources, which are often unreliable" (Schmid 2011, 468). With the research I undertook in the course of this dissertation I aim at ameliorating this shortage of empirical data and to discuss, to my best knowledge for the first time[33], the topic of terrorism vulnerability from a spatial micro-scale perspective within urban areas. Thereby I hope to help overcome the scarcity in scholarly debate and publications about the geographical analysis of terrorism vulnerability.

In Chapter 3.2 I postulate three hypotheses:

1) Vulnerability is not distributed equally over space and time.

2) Factors exist that enhance or mitigate vulnerability.

3) Vulnerabilities of objects influence their spatial surroundings.

The conceptual framework I developed on top of these hypotheses together with the empirical operationalization I describe in Chapter 4 and 5 have produced an interdisciplinary methodology to quantify how prone a location is to a certain kind of terrorist attack as a result of the attributes of the objects at this location. This ultimately allows for the creation of micro-scale vulnerability maps to visualize the spatial distribution of single vulnerability factors as well as overall terrorism vulnerability in highly urbanized areas.

These provide, to my best knowledge for the first time, a detailed overview and insight into the rather abstract concept of vulnerability and its representation in the real-world, and therefore are useful for all three target audiences I outline in Chapter 3.4: academia, involved stakeholders, and the general public.

In addition to their visual message these maps also allow for subsequent quantitative analyses. Here I introduce two examples of how the vulnerability data produced by my framework and model can help answer questions regarding the threat of terrorist attacks in highly urbanized areas, more specifically within the study area I present in Chapter 5.

Limited resources at the hands of the perpetrators affect their decision making, as I mention in Chapter 3.1. Therefore they will be driven to make conscious decisions about where, when and how to attack. The same is true for the opposite side, too, where those in responsibility for objects that might become the target of a terrorist attack, have to decide how to use the limited funds at their hands to the optimal effect (Willis 2005; Willis and Al-Shahery 2014). I believe that the vulnerability-based approach presented in this study can help mitigate shortcomings of the current risk-based analyses and instead allows governments, municipalities, and other stakeholders to identify the most vulnerable elements and start mitigating their vulnerabilities.[34]

6.2. Quantitative Interpretation of Estimated Vulnerability

6.2.1. Identification of Vulnerable Areas

The raster surfaces I present in Chapter 5.3.7 and Appendix K as the final output of the vulnerability assessment model provide a good visual overview and impression of the spatial distribution of the terrorism vulnerability over the study area based on the four selected vulnerability factors, their operationalization and weighting. It is therefore worthwhile to analyze how these estimated overall vulnerability values correspond with the spatial structure of the study area. For further quantitative analyses it is advisable to group the gradient vulnerability values into five vulnerability levels: “low”, “rather low”, “medium”, “rather high”, and “high”. Each vulnerability level makes up for 20% of the vulnerability index scale of 0-100. Appendix L contains maps of these classified vulnerability indices for all 24 hours of the day for the complete study area.

Caplan and Kennedy suggest to test for the statistical validity of all maps that were produced using their RTM methodology since “this gives [a] model empirical credibility and allows for the estimation of future events with a certain degree of confidence” (Caplan and Kennedy 2010b, 99). While I whole-heartedly agree with this aspect, it proves to be problematic in the context of terrorism. The reason therefore lies in the necessity of existing data that describes past events of the attack scenario of the respective study. While this is normally not an issue in the field of crime analysis (where the RTM methodology originated), the situation is difficult in the case of terrorist attacks. It might be a feasible undertaking in areas with a high number of past events, such as terrorism hot spots in Iraq, Afghanistan, or Syria, but is impossible in the study area for this study, which has experienced only a small number of terrorist attacks in the past (cf. Chapter 5.1.1). While not empirically grounded, it is still worthwhile to put the quantitative findings of the vulnerability analysis in context with other terrorist attacks in similar highly-urbanized areas in industrial countries.

While maps provide a good overview of the spatial distribution of the vulnerability levels, a quantitative analysis of the total area each vulnerability level comprises can reveal interesting trends in the data. As Figure 39 shows, the percentage of the relative area these vulnerability levels comprise change over the course of the day. The first fact that strikes from these data is the high percentage of areas in the lowest vulnerability level. The numbers are so high (97.3-98.3%) that they are not shown in the graph for clarity. The remaining vulnerability levels account for only 1.7-2.7%. It is only during the day, from 8am to 6pm, when areas with "high" vulnerability exist. Even then they make up only 0.003-0.05% of the study area, which equals 18,800-308,500 m^2.

This can be explained by the higher absolute number of people inside the study area during the day compared to the nighttime, which is a result of the spatial distribution of residential areas in the Tokyo Metropolitan Area. As I explain in Chapter 5.2.1, the 23 Special Wards of Tokyo, which comprise the study area, are surrounded by a suburban residential belt that extends far into the neighboring prefectures (Figs. 12 and 13). Therefore the three population-based vulnerability factors, which together account for 66.7% of the overall vulnerability index, have a more significant impact. This is especially true for the main commuting period in the morning around 8am and lesser so in the late afternoon and evening around 6pm, where spikes in the percentages of all four vulnerability levels other than "low" emerge. It is especially the crowded morning rush hour where the highest number of people on trains and walking on the streets occurs, which results in the highest percentages within the aforementioned vulnerability levels. Particularly the areas with "rather high" and "high" vulnerability are the largest at this time with 0.25% and 0.05%, respectively.

This result matches a number of terrorist attacks using the same attack scenario as in this case study: the train bombings in Madrid on March 11th, 2004, a coordinated series of ten explosions on commuter trains, which killed 191 people and wounded more than 1,800, occurred between 7:37 and 7:42am (National Consortium for the Study of Terrorism and Responses to Terrorism 2013a; 2013b; 2013c; 2013d); similarly four bombs detonated onboard trains and a bus in Lon-

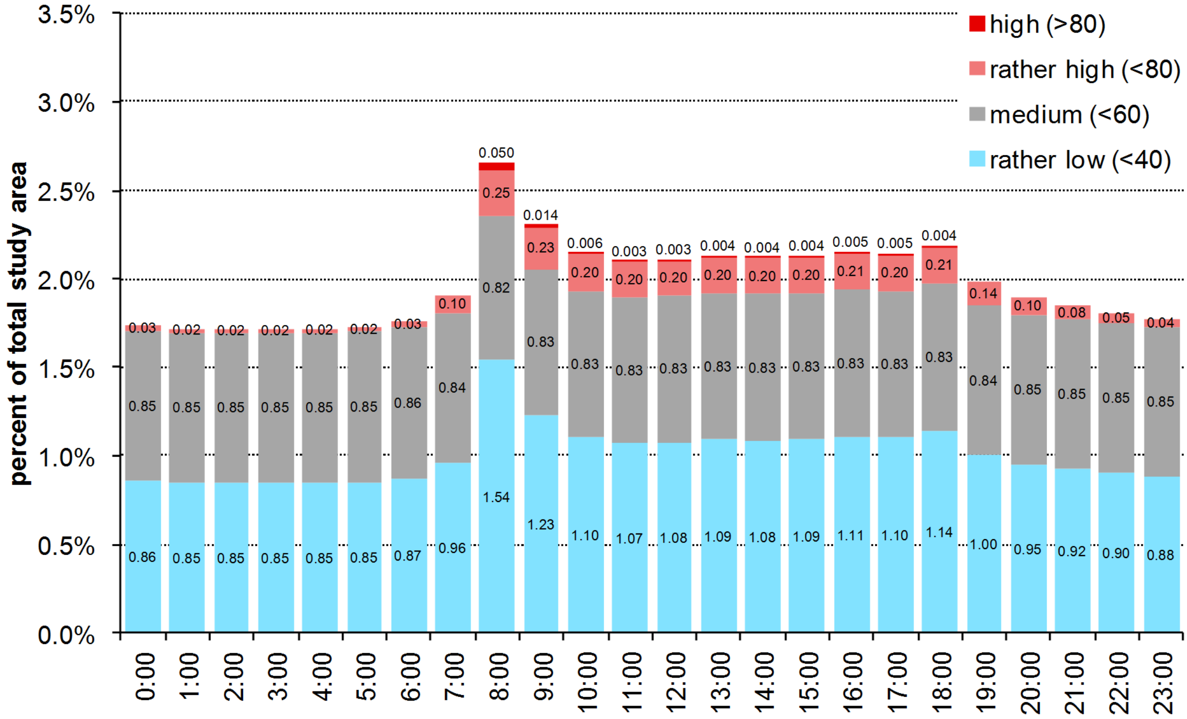

Figure 39: Percentage of the relative area of the study area over the course of 24 hours of four vulnerability levels (level "low" not shown).

don on July 7th, 2005 at 8:50 am and 9:47, respectively, and as a result killed 54 and left more than 700 wounded in total (National Consortium for the Study of Terrorism and Responses to Terrorism 2013m; 2013n; 2013o; 2013p).

Another interesting fact is the almost constant area with “medium” vulnerability, which varies only between 0.82% and 0.86%. This can be explained by the fact that all areas that represent symbolic values fall in this level, unless their vulnerability is enhanced by other factors. This especially true for the large areas of Meiji Shrine (incl. surrounding forest), the Tokyo Metropolitan Central Wholesale Market (Tsukiji Fish Market), Tokyo Tower with Zojoji Temple, Ueno Park, Yasukuni Shrine, and especially the Tokyo Imperial Palace (incl. outer gardens). Figures 38, 40, and 41 show these large areas and also reveals that they are located mainly in the center of the study area. As I explain in Chapter 5.3.4 the symbolic value of places does not vary over time, hence these areas stay on the same vulnerability level throughout the day.

A spatial analysis of the distribution of highly vulnerable places for the time of the morning commute reveals that at 8am the major railway hubs of Ikebukuro, Shibuya, Shinagawa, Shinjuku, Tokyo, and Ueno Stations exhibit the largest clusters of “rather high” and “high” vulnerability (cf. Fig. 40). In addition these clusters also comprise the office districts in the greater perimeter of these train stations. As Figure 41 shows these vulnerability clusters in areas with a high density of offices buildings persist throughout the working hours of the day (i.e. from 9am to 5pm). Figure 42 shows how the vulnerability level is “rather high” in the area east of Shinjuku Station due to the number of people present in this well-known night life area, how it reaches a “high” level during the morning commute as a result of the enormous number of people coming through Shinjuku Station, and how the vulnerability of the whole perimeter of Shinjuku Station is “rather high” during the day as a result of the many workers present in the numerous office buildings both east and west of the station.[35]

This matches the narratives of the terrorist attacks on the buildings of World Trade Center in New York City on February 26th, 1993 and September 11th, 2001, and on the *Alfred P. Murrah Federal Building* in Oklahoma City on April 19th, 1995, both characterized by a high number of office workers present there at the time of the attacks. The attacks on the World Trade Center[36] occurred at 12:17pm (Federal Bureau of Investigation 2008) and between 8:46am, when the North Tower was hit, and 9:03am, when the South Tower was hit (National Consortium for the Study of Terrorism and Responses to Terrorism 2013i; 2013j), the explosion in Oklahoma City happened at 9:02am (National Consortium for the Study of Terrorism and Responses to Terrorism 2013q). It also matches the locations of the two largest terrorist attacks that took place

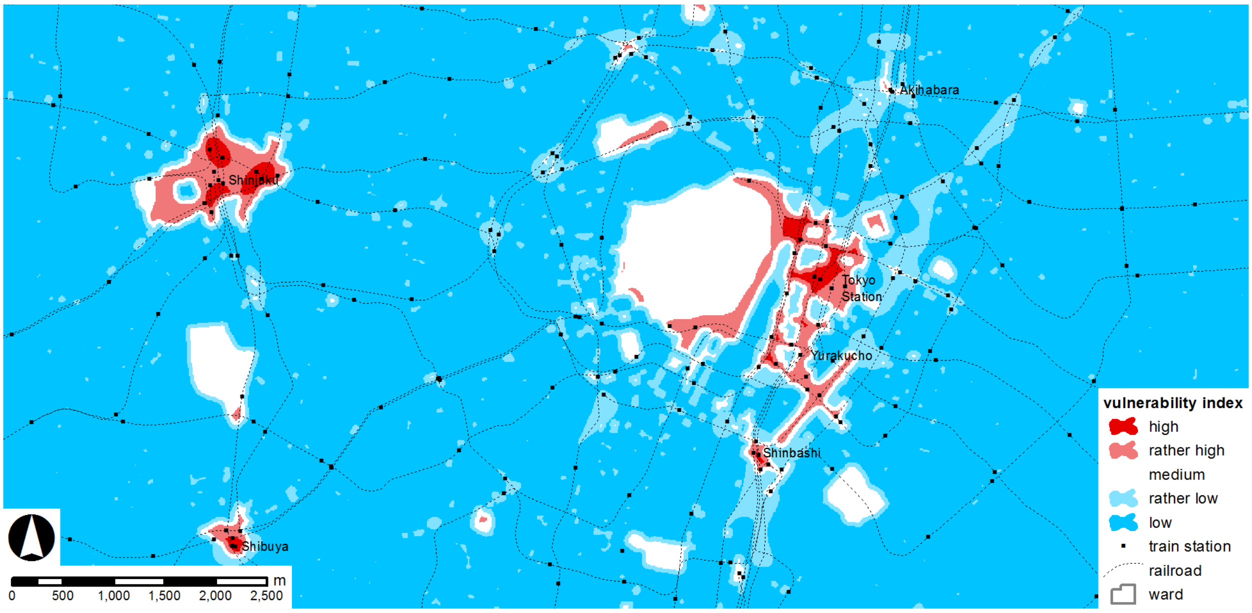

Figure 40: Spatial distribution of the vulnerability index at 8am in the center of the study area.

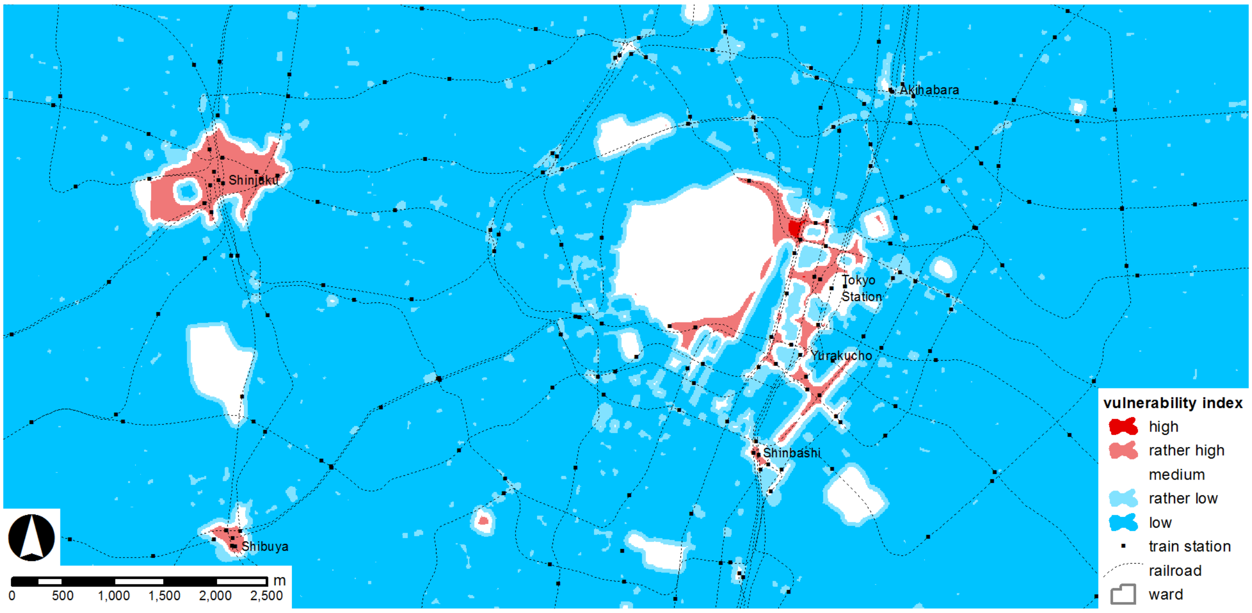

Figure 41: Spatial distribution of the vulnerability index at 12pm in the center of the study area.

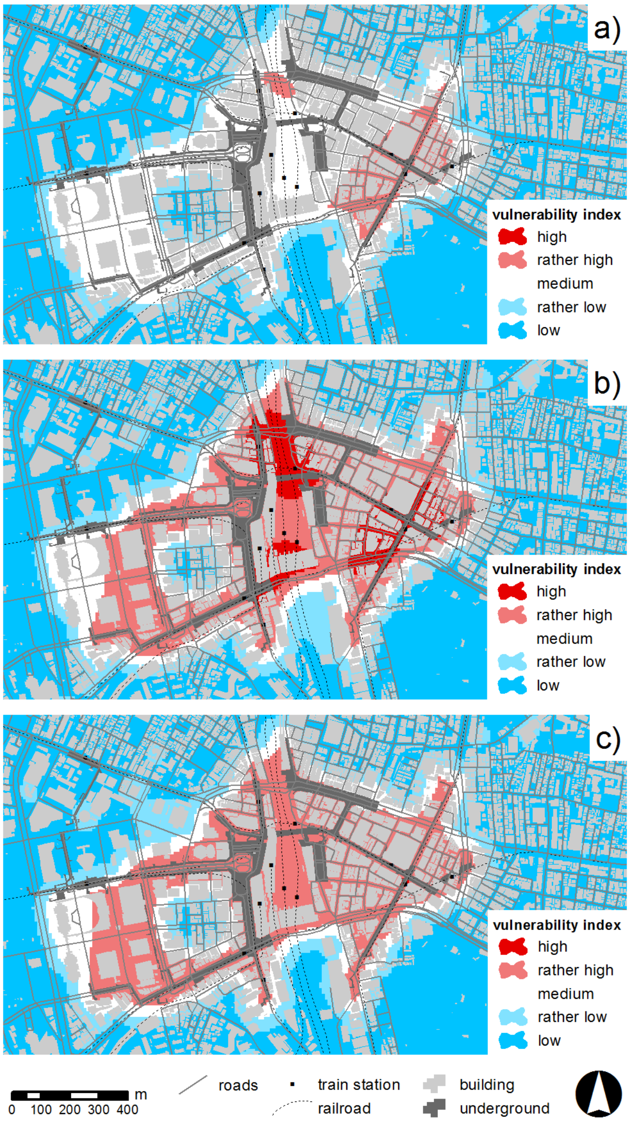

Figure 42: Variation of the vulnerability index as a result of stationary and mobile populations in Shinjuku at a) 2am, b) 8am, and c) 12pm.

within the study area in the past. The Tokyo head office of *Mitsubishi Heavy Industries* which was attacked in a bombing by the *EAAJAF* on August 30th, 1974, an event that left 8 people dead and 376 wounded is located in Marunouchi (Matsushita 1997). Also, while initiated in different locations onboard a number of subway trains, the area most heavily hit, and also targeted by the perpetrators of the *Aum Shinrikyo* doomsday sect was the area around the subway stations Kasumigaseki and Kokkaigijidomae south-east of the Imperial Palace, which is home to a number of high-profile political institutions, including the National Diet Building and the Residence of the Prime Minister (National Consortium for the Study of Terrorism and Responses to Terrorism 2013g).

The vulnerability maps can also reveal some unexpected findings. As an example the combination of the politically symbolic landmark of Yasukuni Shrine, the underground tracks of the Tokyo Metro Shinjuku Line and Hanzomon Line which exist in parallel, the nearby subway station and the crowded Yasukuni Dori street running alongside it raise the vulnerability of this area from the "medium" level to the "rather high" level during the morning rush hour between 8am and 10am (Fig. 43). Also, single crowded buildings or building clusters can generate a raise in the vulnerability level. This can be seen in Figure 44 in three instances: on the left side of the map the cluster of three buildings (*Ote Center Building*, *Risona Maru Biru*, and the *Mitsubishi Tokyo UFJ Bank Otemachi Building*) maintains a "rather high" vulnerability level throughout the day, from 8am to 6pm it raises the vulnerability of its surrounding to the "high" level (Fig. 44a); in the center of the map the *Marunouchi North Building* and the connected *Marunouchi Oazo* create an area of "rather high" vulnerability from 7am through 11pm and "high" vulnerability from 8am to 9am (Fig. 44b); in the top right corner of the map the Bank of Japan (BOJ) raises the "medium" vulnerability it generates by its symbolic value to a "rather high" level from 8am to 6pm as a result of the number of people inside the building and passing it outside (Fig. 44c).

6.2.2. Total Population in Vulnerable Areas

In the previous section I outline the levels of vulnerability in highly populated areas, both in terms of stationary populations inside buildings and mobile populations on foot or in trains. It should not surprise that areas with higher populations also possess higher vulnerability, since three of the four vulnerability factors I used in this case study refer to population figures and their spatio-temporal fluctuations. Together these three factors account for 66.7% of the overall vulnerability index.

Figure 43: Raise of the vulnerability index as a result of overlapping vulnerability factor influences at Yasukuni Shrine at a) 8am, b) 9am, and c) 10am.

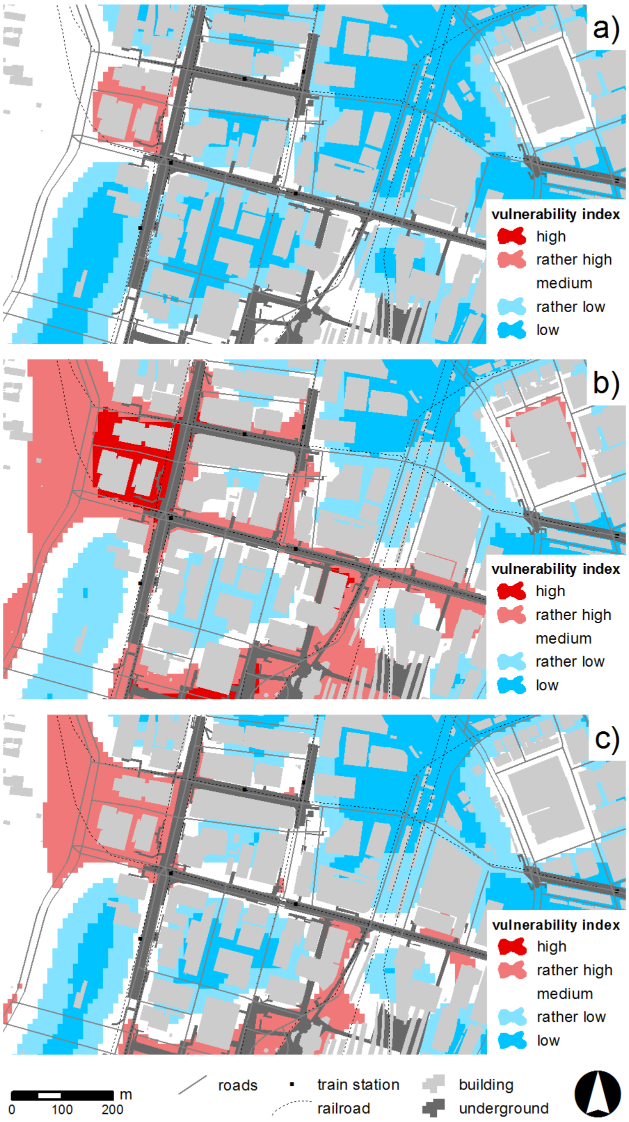

Figure 44: Raise of the vulnerability index as a result of single crowded buildings and building clusters in Marunouchi and Otemachi at a) 3am, b) 9am, and c) 7pm.

That said it is still worthwhile to examine the actual number of people present in the areas of higher vulnerability. These data can shed light on the number of people to be possibly affected by a terrorist attack in a certain location and at a certain time. This can ultimately help in the preparation for these disasters, for example by providing sufficient emergency routes from buildings and underground walkways and regarding the establishment of shelters and emergency care institutions. In addition this information can be of great value in the event of an actual attack, when it provides emergency services an understanding of the number victims to be expected.

Figure 45 shows how the stationary building population figures in the areas of different vulnerability levels change over the time of the day. As in the preceding analysis of the total area of these vulnerable areas (cf. Fig. 39) it comes as no surprise that the highest numbers of people are present in all four vulnerabilities other than "low" can be found between 7am and 8pm, which comprises the regular working hours plus commuting times in the morning and evening.[37]

The absolute numbers are impressive nevertheless. Between 9am and 5pm, which equates roughly the regular working hours in most Japanese offices, the estimated number of people present in areas with "rather high" vulnerability is at around 200,000. The same holds true for the estimated population of the "medium" high vulnerability level where the figures vary between 250,000 and 375,000 people. This number also stays higher than 100,000 until 8pm. The peak in the curve for "rather low" vulnerability can be explained by the aforementioned morning rush hour, which is characterized by a high number of people onboard trains and walking on the streets of the study area to get to their offices, which elevates the vulnerability of the buildings' surroundings. This also explains the peak of the population in "high" vulnerability areas at 8am. Over the course of the day the stationary building populations in "high" vulnerability areas varies between 4,000 and 21,000 people between 8am and 6pm.

These high populations figures should come as no surprise if one once again recalls past terrorist attacks in similarly highly urbanized areas. The terrorist attacks on the buildings of the World Trade Center in New York City on September 11th, 2001 alone killed 1,382 people and wounded an unknown number (National Consortium for the Study of Terrorism and Responses to Terrorism 2013i; 2013j). Similarly, the explosion in front of the *Alfred P. Murrah Federal Building* in Oklahoma City left 168 dead and more than 650 wounded (National Consortium for the Study of Terrorism and Responses to Terrorism 2013q).

Due to the operationalization methodology and constraints of the available data, which I describe in detail in Chapter 5.3.2 and 5.3.3, I was not able to numeralize the actual estimated

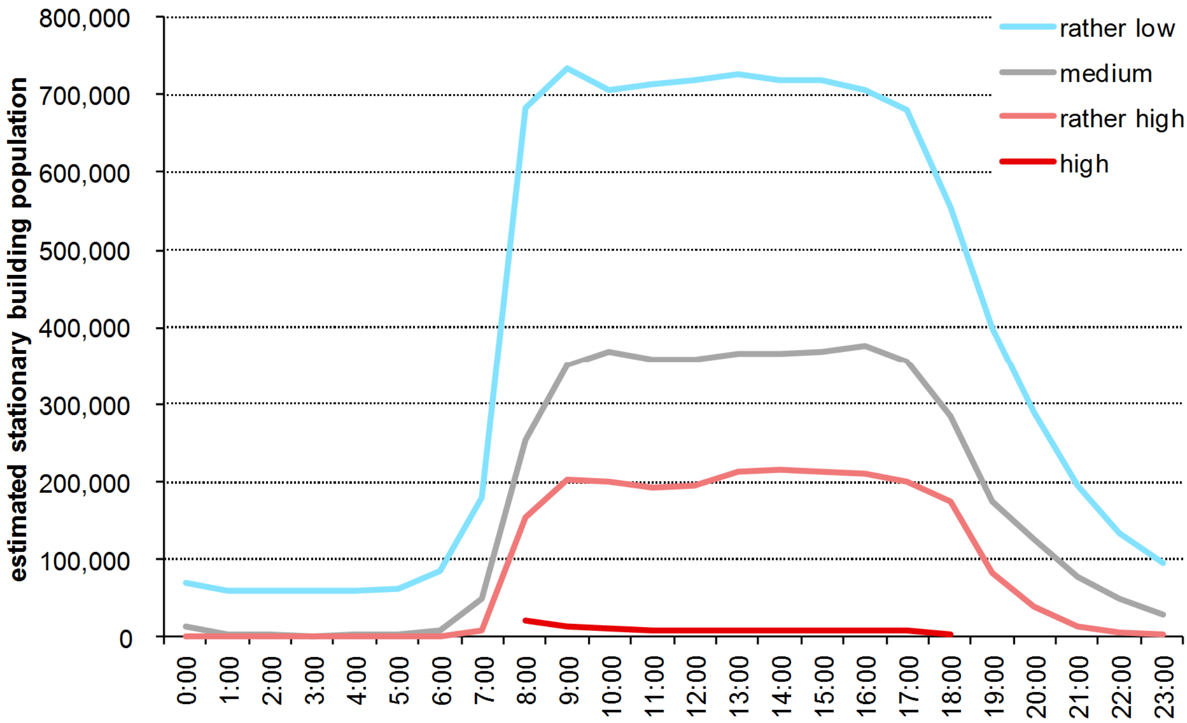

Figure 45: Total estimated stationary building population in the vulnerable areas of the study area over the course of 24 hours.

number of people walking on the streets and onboard trains. The numbers in Figures 46, 47, and 48 do therefore not show the absolute count of pedestrians and people at train stations or onboard trains, but their respective dimensionless index values instead.

All three metrics show clearly the higher populations during the time period of the morning commute between 7am and 9am. This matches the events of the attacks in Madrid and London, where terrorists set off explosive devices onboard crowded commuter trains and a public bus. It also matches the attack by *Aum Shinrikyo* in 1995 where perpetrators released sarin gas in five trains of the Tokyo Metro subway and ultimately killed 12 and injured over 5,500 people (National Consortium for the Study of Terrorism and Responses to Terrorism 2013g). In addition, all graphs also show a distinct peak during the evening rush hour from 5pm to 8pm, albeit on significantly lower levels. This is due to the fact that while the beginning of the regular working day in many Japanese offices starts at the same time, the ending times are more spread out and after work activities are very common, which also disperses the pedestrians and train passengers accordingly over time.

The morning rush hour is also the time that has the largest mobile populations in the areas with a “high” vulnerability level. In addition the mobile pedestrian population reveals a small degree of people present in areas of “high” vulnerability from the morning until the late afternoon.

Lastly, the null values of the train station usage and the railway link importance (Figs. 47 and 48) in the middle of the night from 2am to 3am are attributed to the closing hours of most railway lines in the Tokyo Metropolitan Area.

6.2.3. Sensitive Infrastructures in Vulnerable Areas

From a risk management and emergency planning perspective it is critical to have detailed information not only about the number of people (possibly) affected by a certain incident, but also the urban structure of the area of the attack. This is especially so in the case of so-called *sensitive infrastructures*. I coined this term to distinguish these institutions from *critical infrastructures*. The latter are defined by the US President's Commission on Critical Infrastructures (PCCIP) as

> a network of independent, mostly privately-owned, man- made systems and processes that function collaboratively and synergistically to produce and distribute a continuous flow of essential goods and services. […] Certain of our infrastructures are so vital that their incapacity or destruction would have a debilitating impact on our defense and economic security. (President’s Commission on Critical Infrastructure Protection 1997, 3)

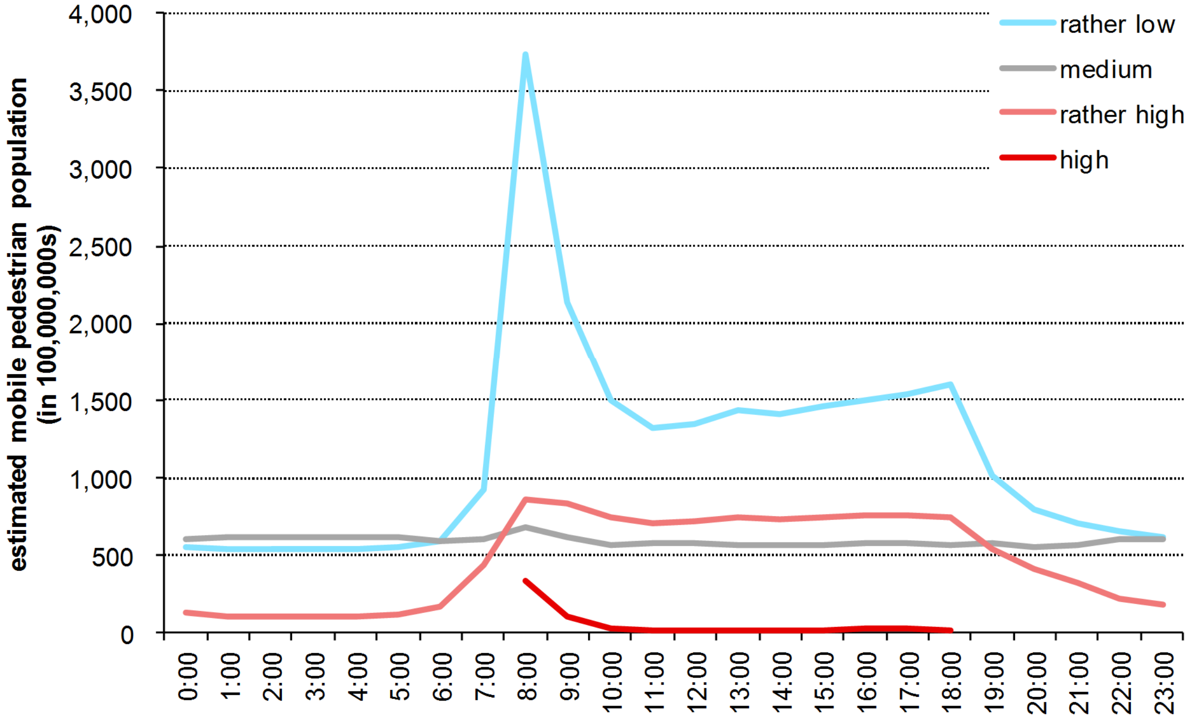

Figure 46: Estimated mobile pedestrian population in the vulnerable areas of the study area over the course of 24 hours. The values do not represent absolute people but dimensionless index values.

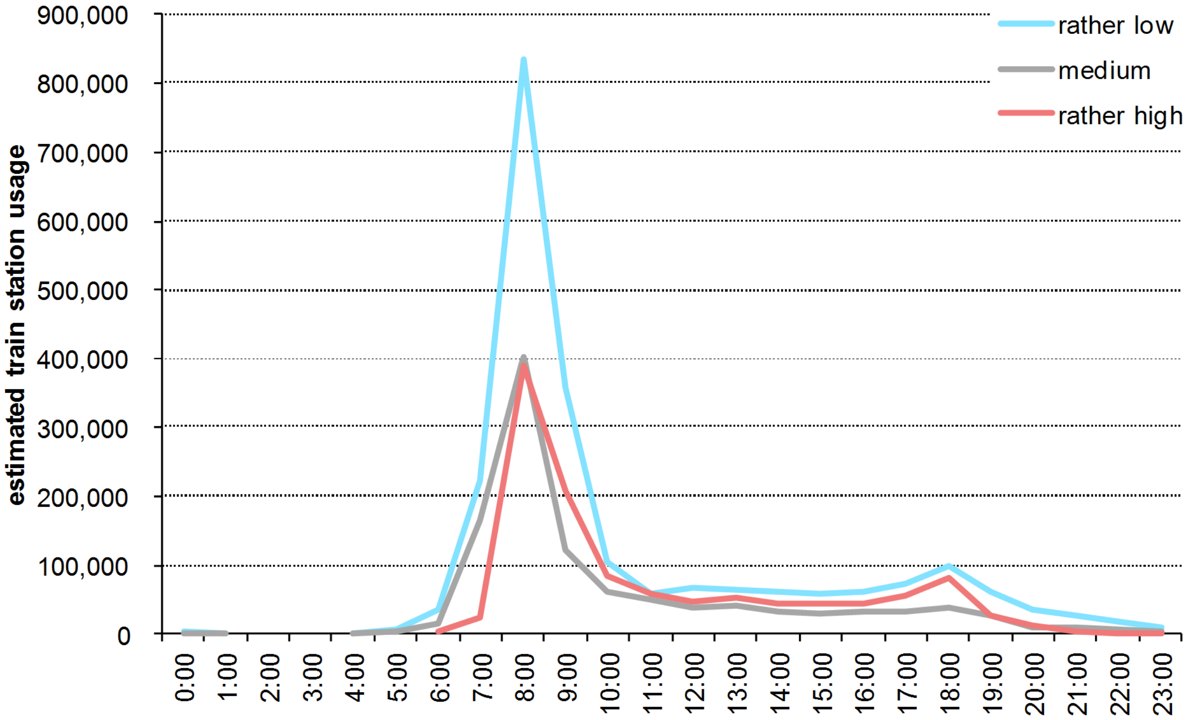

Figure 47: Estimated train station usage in the vulnerable areas of the study area over the course of 24 hours. The values do not represent absolute people but dimensionless index values.

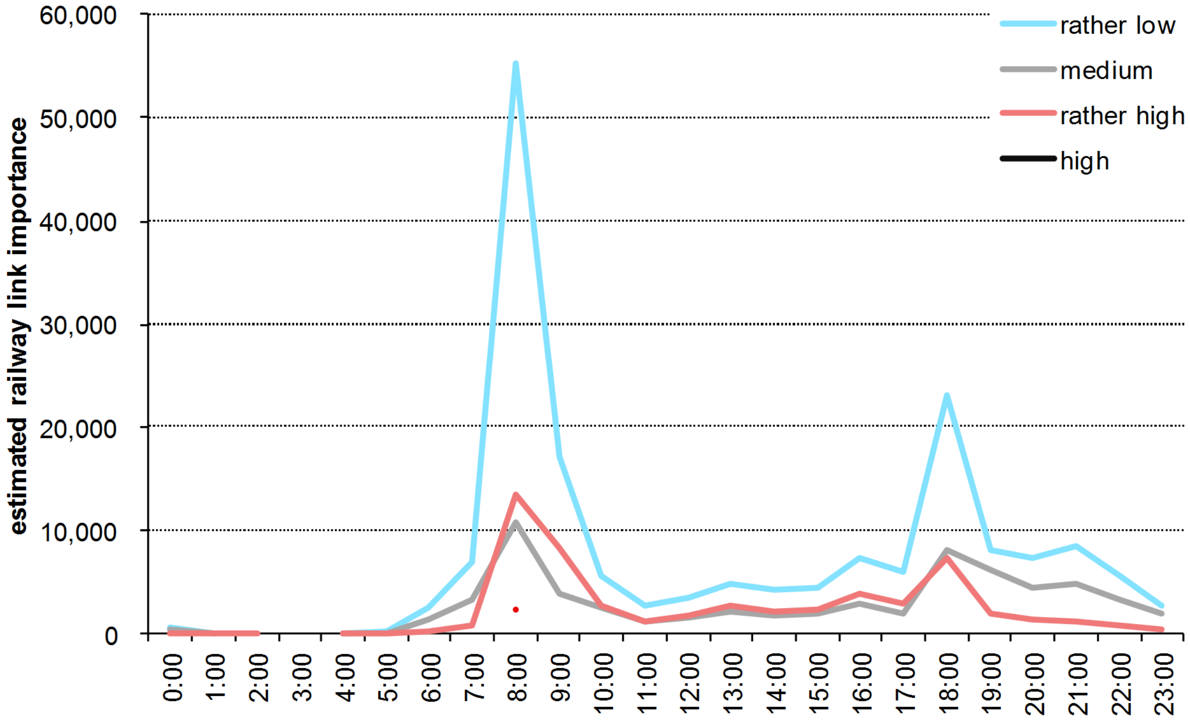

Figure 48: Estimated railway link importance in the vulnerable areas of the study area over the course of 24 hours. The values do not represent absolute people but dimensionless index values.

This includes transportation networks as well as water, gas, electricity and communication networks (Rinaldi, Peerenboom, and Kelly 2001; Haimes and Longstaff 2002; DHS 2007). I outline in Chapter 5.3.5 why I did not focus on these types of infrastructural networks in this study. Yet, above these infrastructures that are essential for the provision of services necessary for the functioning of the city and its systems, the sensitive infrastructures which I focus on in this section are of such nature that they are either 1) of great importance in the aftermath of a disaster or represent something that is either highly valued by the public or necessary in the case of a disaster, or 2) something that poses significant problems regarding the possible necessity of an evacuation.

Examples of the former are hospitals, which can provide medical care for victims, as well as police and fire stations, whose services are of critical importance in the immediate aftermath of a terrorist attack. The hampering of these services can help to exacerbate the disastrous effects of a terrorist attack, both immediately and in the long run. The most striking example are the over 400 members of the rescue authorities who were killed in the course of the attacks on the World Trade Center in New York City on September 11th, 2001 (National Commission on Terrorist Attacks upon the United States 2004).[38] This number does not account for the considerably higher number of officers and fire fighting personnel who are suffering from the physical and psychological time dependent effects of the collapse of the towers to the degree of service disability or death.

Examples of the latter are nurseries, kindergarten, all types of schools, colleges and universities, cram schools[39], and homes for the elderly. They are all populated by population groups which either require general support, such as in the case of nurseries for infants and retirement homes for elderly people, or which are more heavily affected by the disturbing effects a terrorist attack might have, such as school children.

The map in Figure 49 shows that these sensitive infrastructures are generally dispersed over the whole study area. A closer analysis of the data reveals that there are some spatial characteristics in the location and distribution of some of the infrastructure types (cf. 25).

Most nurseries, elementary, and junior high schools as well as schools for the disabled are located in areas characterized by residential use. Since these areas are generally not distinguished by large working populations, major traffic hubs or railway lines, or symbolic places, their vulnerability levels are comparatively low. As a result none of these institutions are located in areas of "medium" or higher vulnerability levels. Similarly, at maximum only nine homes for the elderly are located in areas with a higher than "rather low" vulnerability, that equals 1%. All of

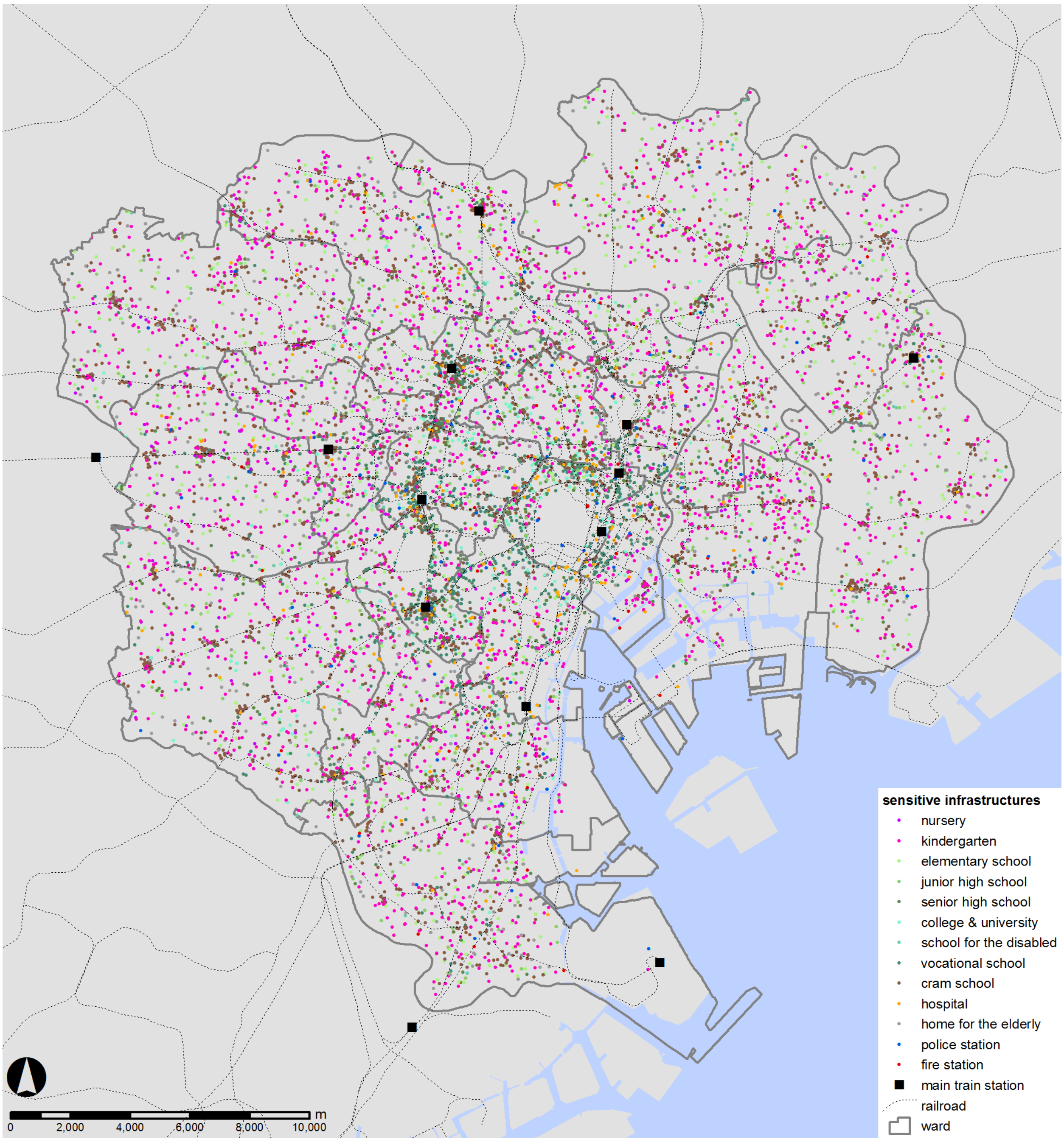

Figure 49: Spatial distribution of sensitive infrastructures over the study area.

Data source: Zenrin Co., Ltd. (2011)

Table 25: Number of various sensitive infrastructures within the vulnerable areas over the course of 24 hours.

	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
nursery																								
⊖⊖	416	417	417	417	417	417	415	414	409	412	413	414	414	414	415	413	412	413	412	415	415	415	414	416
⊖	71	70	70	70	70	70	72	73	78	75	74	73	73	73	72	74	75	74	75	72	72	72	73	71
⊙																								
⊕																								
⊕⊕																								
kindergarten																								
⊖⊖	2,696	2,696	2,696	2,696	2,696	2,696	2,696	2,687	2,672	2,682	2,685	2,685	2,685	2,685	2,685	2,685	2,685	2,685	2,684	2,686	2,691	2,695	2,696	2,696
⊖	82	82	82	82	82	82	82	91	102	93	92	92	92	92	92	92	92	92	93	92	87	83	82	82
⊙	7	8	8	8	8	8	7	6	8	7	7	7	7	7	7	7	7	7	6	6	6	6	6	7
⊕	1						1	2	3	4	2	2	2	2	2	2	2	2	3	2	2	2	2	1
⊕⊕									1															
elementary school																								
⊖⊖	1,320	1,321	1,321	1,321	1,321	1,321	1,320	1,318	1,314	1,317	1,318	1,321	1,321	1,321	1,319	1,318	1,320	1,318	1,318	1,318	1,318	1,320	1,320	1,320
⊖	33	32	32	32	32	32	33	35	39	36	35	32	32	32	34	35	33	35	35	35	35	33	33	33
⊙																								
⊕																								
⊕⊕																								

Vulnerability level: ⊖⊖ low; ⊖ rather low; ⊙ medium; ⊕ rather high; ⊕⊕ high

(continued on the following page)

Table 25 (continued): Number of various sensitive infrastructures within the vulnerable areas over the course of 24 hours.

	0:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
junior high school																								
⊖⊖	839	839	839	839	839	839	837	837	835	835	837	837	837	837	839	837	837	837	835	837	837	837	837	839
⊖	19	19	19	19	19	19	21	21	23	23	21	21	21	21	19	21	21	21	23	21	21	21	21	19
⊙																								
⊕																								
⊕⊕																								
senior high school																								
⊖⊖	557	557	557	557	557	557	555	553	544	549	551	551	551	551	553	551	551	551	549	553	553	554	555	557
⊖	11	11	11	11	11	11	13	15	24	19	17	17	17	17	15	17	17	17	19	15	15	14	13	11
⊙	1	1	1	1	1	1	1													1	1	1	1	1
⊕								1	1	1	1	1	1	1	1	1	1	1	1					
⊕⊕																								
college & university																								
⊖⊖	1,817	1,817	1,817	1,817	1,817	1,817	1,817	1,816	1,795	1,796	1,796	1,796	1,796	1,796	1,796	1,796	1,796	1,796	1,798	1,798	1,816	1,817	1,817	1,817
⊖	55	55	55	55	55	55	55	56	61	59	61	61	62	61	61	61	61	61	59	70	56	55	55	55
⊙	37	37	37	37	37	37	37	36	9	19	17	17	16	17	17	17	17	17	17	10	36	36	36	37
⊕								1	44	35	35	35	35	35	35	35	35	35	35	31	1	1	1	
⊕⊕																								

Vulnerability level: ⊖⊖ low; ⊖ rather low; ⊙ medium; ⊕ rather high; ⊕⊕ high.

(continued on the following page)

Table 25 (continued): Number of various sensitive infrastructures within the vulnerable areas over the course of 24 hours.

	0:00	**1:00**	**2:00**	**3:00**	**4:00**	**5:00**	**6:00**	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**
school for the disabled																								
⊖⊖	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54	54
⊖	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
⊙																								
⊕																								
⊕⊕																								
vocational school																								
⊖⊖	2,138	2,140	2,140	2,140	2,140	2,138	2,138	2,123	1,994	2,059	2,070	2,075	2,074	2,071	2,073	2,070	2,070	2,076	2,078	2,112	2,119	2,133	2,133	2,138
⊖	120	122	122	122	122	120	120	128	232	173	164	166	166	168	167	169	166	162	159	135	133	121	121	120
⊙	50	47	47	47	47	51	49	48	36	34	37	34	33	32	31	32	35	33	34	40	48	46	46	48
⊕	3	2	2	2	2	2	4	12	46	44	40	36	38	40	40	40	40	40	40	24	11	11	11	5
⊕⊕									3	1														
cram school																								
⊖⊖	2,978	2,978	2,978	2,978	2,978	2,978	2,977	2,967	2,896	2,940	2,948	2,950	2,950	2,949	2,949	2,949	2,947	2,946	2,940	2,958	2,970	2,973	2,973	2,974
⊖	60	60	60	60	60	60	60	68	128	89	81	79	79	80	80	80	82	83	89	75	64	63	64	63
⊙	29	29	29	29	29	29	30	24	21	22	24	24	24	24	24	24	24	24	22	24	26	26	28	30
⊕								8	20	16	14	14	14	14	14	14	14	14	16	10	7	5	2	
⊕⊕									2															

Vulnerability level: ⊖⊖ low; ⊖ rather low; ⊙ medium; ⊕ rather high; ⊕⊕ high.

(continued on the following page)

Table 25 (continued): Number of various sensitive infrastructures within the vulnerable areas over the course of 24 hours.

	0:00	**1:00**	**2:00**	**3:00**	**4:00**	**5:00**	**6:00**	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**
hospital																								
⊖⊖	383	383	383	383	383	383	383	383	366	370	373	373	373	373	373	373	373	373	378	382	383	383	383	383
⊖	33	34	34	34	34	33	33	31	42	39	37	37	37	37	37	37	37	37	31	30	31	33	33	33
⊙	7	6	6	6	6	7	7	8	8	9	9	9	9	9	9	9	9	9	10	10	8	6	6	7
⊕								1	7	5	4	4	4	4	4	4	4	4	4	1	1	1	1	
⊕⊕																								
home for the elderly																								
⊖⊖	838	838	838	838	838	838	838	834	819	830	835	835	835	835	835	835	834	834	835	835	836	837	837	838
⊖	55	55	55	55	55	55	55	59	65	61	58	58	58	58	58	58	58	59	57	58	57	56	56	55
⊙									9	2							1		1					
⊕																								
⊕⊕																								
police station																								
⊖⊖	6	6	6	6	6	6	6	6	3	3	3	3	3	3	4	3	3	3	3	4	6	6	6	6
⊖	166	183	183	183	183	183	183	164	158	160	162	162	162	162	161	162	160	162	160	163	163	163	166	166
⊙	17							19	26	24	24	24	24	24	24	24	26	24	26	22	20	20	17	17
⊕									2	2														
⊕⊕																								

Vulnerability level: ⊖⊖ low; ⊖ rather low; ⊙ medium; ⊕ rather high; ⊕⊕ high.

(continued on the following page)

Table 25 (continued): Number of various sensitive infrastructures within the vulnerable areas over the course of 24 hours.

	0:00	**1:00**	**2:00**	**3:00**	**4:00**	**5:00**	**6:00**	**7:00**	**8:00**	**9:00**	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**
fire station																								
⊖⊖	5	5	5	5	5	5	5	3	2	4	5	5	5	5	5	5	5	4	3	3	4	4	5	5
⊖	63	63	63	63	63	63	63	64	58	57	57	58	58	57	57	57	57	58	59	64	63	64	63	63
⊙								1	8	7	6	5	5	6	6	6	6	6	6	1	1			
⊕																								
⊕⊕																								

Vulnerability level: ⊖⊖ low; ⊖ rather low; ⊙ medium; ⊕ rather high; ⊕⊕ high.

these are located near train stations, which explains their elevated vulnerability levels between 8am and 9am as well as at 4pm and 6pm in the afternoon.

In contrast, several kindergartens, senior high schools as well as colleges and universities, and vocational schools are located in areas with “medium”, “rather high”, or in the case of one kindergarten and up to three vocational schools even “high” vulnerability. For institutions of higher education easily accessible and prestigious locations in the city center are highly desirable, while at the same time longer commuting times and farther distances from home have generally lesser impact on these older students compared to elementary and high school students. This in turn also puts them in areas that are crowded during the day, especially the morning rush hour, which results in higher vulnerability levels in their vicinity.

Similarly, cram schools are oftentimes located near train stations, as can be seen clearly from the map in Figure 49. While this makes them easily accessible for the students it also places them in areas of higher vulnerability, due to the vicinity to highly populated train stations, the rail way links leading to and from these, and also the roads that distribute the train passengers to and from the stations as pedestrians. As a result two cram schools are located in areas with “high” vulnerability, Late in the afternoon at 6pm, when the cram schools are very well frequented, 12.6% of those outside of areas with “low” vulnerability are located in areas with “rather high” vulnerability.

For the analysis of medical institutions I focused exclusively on hospitals, since they play a major role in the aforementioned scenario of medical assistance for victims of terrorist attacks. While doctor’s offices are more common throughout the study area and both their medical staff, facilities, and drugs can be of help in these cases, I don’t regard them as particularly sensitive in the sense of my definition of sensitive infrastructures above. Most of the 423 hospitals in the study area are located in areas with “low” to “medium” vulnerability. At maximum only 1.7% of them are in areas with “rather high” vulnerability, none them in areas with “high” vulnerability. I believe that this bodes well for the medical care within the study area in the case of a terrorist attack, they are located in areas which appear not attractive for terrorists to attack.

Both police stations and fire stations are located mostly in areas of “rather low” vulnerability. This differs from all other categories of sensitive infrastructures in introduce, which are all most prevalent in the large areas of “low” vulnerability. This can be explained by the fact that both police and fire fighters are purposefully positioned exactly where most people are, since lots of people mean both a higher probability of crime and accidents. Both police and fire stations are also classified as symbolic institutions (cf. 18) and hence contribute to the vulnerability of their surroundings themselves. Yet, only two police stations and none of the fire stations are in areas with “rather high” vulnerability, none of them in areas with “high” vulnerability. This bodes well for the provision of their services after an attack, since they are not in areas of heightened interest for terrorists and will hence be able to continue to work.

7 Conclusion

In this study I introduced a methodology for spatio-temporal terrorism vulnerability analysis. Its conceptual framework is based on the selection of appropriate vulnerability factors, their operationalization in measurable real-world phenomena, the calculation of their spatial influence, and finally their weighted combination into an overall vulnerability index. I also presented an exemplar application of this framework in a case study for an actual scenario in Central Tokyo, Japan. In this conclusion I interpret the result of the case study and also discuss the usefulness of the framework and its operationalization as well as their shortcomings and the opportunities for future studies.

I started this research from the desire to develop a spatially grounded methodology to quantify vulnerability in order to find out how prone a location is to terrorist attacks as a result of the attributes of the objects at this location. My motivation stems from the belief that there is both a scarcity of scientific activity in the micro-scale geographical analysis of terrorism and a need for more insight into terrorism vulnerability and its spatio-temporal representation in the real world. I am convinced that the three characteristics of terrorist attacks I elucidated in Chapter 3.1, the underlying terrorists' decision making, the communicative dimension of terrorism, and the terrorists' limited resources, are summarized in the *Human Activity Based Vulnerability Concept* I introduced in Chapter 2.3.3. The empirical results presented in Chapter 6 are testimony of the successful quantifiability of the abstract concept of “vulnerability” by the use of the conceptual framework I introduced in Chapter 4 and its operationalization. The model's output data ultimately allowed for a detailed analysis of the distribution of vulnerabilities in highly urbanized area, both spatially and temporally.

The framework's usefulness lies in its variability which allows for the implementation to the desire of the analyst. First of all the focus on a certain outcome event and scenario sets the agenda for the upcoming steps of the analysis. In the case study in Chapter 5 I decided for the analysis of the vulnerability to a terrorist attack using a small explosive device. Yet, any other *modus operandi* of terrorists, for example large explosive devices like truck bombs, the release of poisonous substances, or shootings can be analyzed, as long as they have measurable representations in the real world. I also want to point out that the research framework can not only be used in the context of terrorism, but all types of disasters, both anthropogenic and natural (cf. 2). It should be kept in mind, though, that crime and terrorism are the only threats that follow a malicious intent and therefore contain a component of attractiveness as part of their vulnerability. As a result the disaster model and the derived *Human Activity Based Vulnerability Concept* I develop in Chapter 2.3.3 do not apply in these cases. Similarly, it can be applied to lesser urbanized areas, but the framework's computational intricacies would probably make the vulnerability evaluation more complicated than the results can justify.

Second, the selection of vulnerability factors to be represented in the vulnerability assessment is at the analyst's discretion. This provides leeway in the provision for factors according to the beliefs and perceptions of the analyst, but also demands extensive subject matter expertise on his end regarding the factors' completeness, meaningfulness and independence.

Third, the operationalization of the chosen vulnerability factors poses both great freedom and one of the biggest challenges in the use of this framework and hence is the central part of this study. It requires the analyst to identify real-world phenomena that represent the selected vulnerability factors, to develop methodologies and algorithms to quantify them, and to find reliable, complete and consistent data sources that can be used as input data for these calculations. Consequently the vulnerability of certain objects then also needs to be put in context with the space these objects are located within, which requires the analyst do develop methods to formulate their spatial influence.

Finally, the resulting vulnerability factor maps have to be combined into an overall vulnerability map. This allows the analyst to account for the importance of each factor as opposed to the other factors by the use of weights. These factor weights can be derived using a standardized process like AHP to incorporate another level of expert knowledge into the analysis.

In addition to these aforementioned dimensions of how the analysis framework introduced in this study is useful for the analyst, it also ultimately produces results that bear great value for a number of audiences. These results can be used to communicate the topic of vulnerability to the broad public and raise an awareness for and informed public discussion about this important topic. As outlined in Chapter 6.2 the results can also be used as input data for consecutive analyses: they can help to identify vulnerable areas in their spatio-temporal context and to enumerate the number of people or sensitive infrastructures in these vulnerable areas.

In Chapter 5 I presented a case study of the framework's application in Central Tokyo, Japan. The interpretation of the empirical results I produced in Chapter 6.2 reveals several interesting insights into the connection between the urban spatial structure of Central Tokyo and its terrorism vulnerability. These findings, which are only possible due to the chosen spatio-temporal operationalization of vulnerability, are one of the most distinctive features of this study, since for the first time they provide detailed insights into the spatio-temporal constraints between terrorism vulnerability and the respective urban spatial structure.

First and foremost the commuting movements from the suburban belt of Tokyo into the city center, i.e. into the study area from the outside, lead to a dramatically higher overall population during the day than at night. Owing to the three population-based vulnerability factors this results in generally larger areas of higher vulnerability during the day than at night. Over the course of the day this also results in clusters of the highest vulnerability in areas with many large office buildings, such as Ikebukuro, Kasumigaseki, Marunouchi/Otemachi, Roppongi, Shibuya, Shinagawa, and Shinjuku. In contrast the vulnerability levels at night are overall lower than during the day.

In addition, the concentrated morning commuting period causes a strong impact on the vulnerability levels surrounding the railway transportation network, both in terms of train stations and railway tracks. This effect together with the generally high building populations and pedestrian volumes around the larger train station hubs create the overall highest vulnerability index values. This is especially true for the stations along the Yamanote Line, where many commuters from the surrounding prefectures and the residential areas of western Tokyo arrive and change trains. Also, the major train lines such as the Chuo Line, Sobu Line, Saikyo Line, and Yamanote Line contribute to heightened vulnerability levels during the day by their high passenger numbers. This is especially the case during the morning commute, but also late in the evening, when many people are on the way back to their homes outside of the study area after work or subsequent activities.

The monocentric urban spatial structure of Tokyo also manifests itself in the agglomeration of most of the symbolic places with high symbolic relevance on the one hand, and most of the by day highly populated office districts on the other hand.

Based on these observations and results the following conclusions can be made regarding the vulnerability towards a terrorist attack with a small explosive device within the study area:

1) The most attractive time from a terrorist's perspective would be during the day, preferably the morning commute.
2) The most attractive location would be in the city center, preferably inside or near a major train station or near railway tracks.

As I explained in Chapter 6.2.2 these findings coincide with the occurrences of terrorist attacks in highly urbanized areas in the past. While this must not be misinterpreted as a validation of the model, it can be understood as a confirmation for the meaningfulness of the output results.

There are also several shortcomings involved in the use of this framework. Most of these are regarding methodological issues or shortcomings with the data as I explained in the corresponding sections of Chapter 5.3. One of the most important aspects that should be discussed in this context is the overall subjectivity of the analysis. As I stated repeatedly throughout this study I don't understand this as a shortcoming of the framework but instead one of its biggest strengths. It would be a fallacy to believe that there is *one correct way* to operationalize terrorism vulnerability and hence *one universally valid* terrorism vulnerability map. Instead I understand the opportunity for the use of a cornucopia of possible vulnerability factors, their operationalization and weighting as one of the most intriguing promising aspects on the way to a deeper overall understanding of terrorism vulnerability. I believe that multiple perspectives from a variety of cultural and scientific backgrounds as well as different experience levels are an essential precondition for a holistic understanding of this phenomenon, which continues to pose one of the biggest challenges of our time.

I therefore hope for the this spatio-temporal vulnerability analysis framework to be employed in future studies. It will be very interesting to compare not only vulnerability assessments of different scenarios of terrorist attacks, but also the selection, operationalization, and weighting of other vulnerability factors than the ones introduced in this study and their spatial influence. Due to the normalization inherent in the calculation of the overall vulnerability index it is possible to compare these maps and quantify the difference that the aforementioned changes have on the overall result. Lastly, I would also be thrilled to see this vulnerability analysis framework employed in different thematic contexts than terrorism and also in studies around the world.

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Notes

1) Officially over 15,850 were killed, over 3,250 are missing, and over 6,000 got injured (Ministry of Economy, Trade and Industry 2012, 2).
2) The official tally is at 191 killed and over 1,800 injured.
3) This omission is ironic since the title of Reid and Chen's research paper is *Mapping the contemporary terrorism research domain*.
4) For exceptions see Chapters 2.1.3 and 2.3.4.
5) Chapter 5.3.1 provides a deeper insight into the definition of these activity categories.
6) During the sarin gas attack by *Aum Shinrikyo* on the Tokyo subway system on March 20th, 1995, the spread of the gas was mostly confined to the train carriages, where it had been released, and the platforms where the respective trains ultimately stopped for evacuation.
7) Caplan (2011) provides a detailed introduction into the theoretical underpinnings and methodological implementations of spatial influence.
8) Unfortunately the incidents in the GTD are not geocoded. In addition the collection of place name information is insufficient and erroneous, which makes a more detailed spatial analysis of past events based only on this dataset impossible.
9) This claim has originally been made by the MOFA in a position paper on Japan's international counterterrorism cooperation (Ministry of Foreign Affairs 2010b).
10) Article 9 of the Japanese Constitution states that Japan shall not maintain armed forces and renounces war and the threat or use of force as means of settling international disputes (Prime Minister of Japan and His Cabinet 1947).
11) The original *Anti-Terrorism Special Measures Law* also granted the participation in search and rescue activities as well as relief activities for affected people, which were later revoked in the *Replenishment Support Special Measures Law.*
12) The order of localized names of these territories does not by any means reflect a statement or sentiment on the disputes for my part and must not be interpreted as such.
13) The total area of the Tokyo Metropolis, excluding the outlying Izu and Ogasawara Islands, amounts to 2,005 km^2.
14) Although every location vulnerable to a small explosive attack is unequivocally vulnerable to these modes of attack, too.

15) This chapter has been published in a shortened form in Greger (2014).

16) Zenrin data is used by Google Maps and Microsoft Bing™ Maps, amongst others.

17) Due to a particularity in the data the actual total number of points in the dataset is 848,664,485. The reason is that every transfer from one mode of transportation to another one consists of two points: one represents the last point of the ending trip and one the first point of the beginning trip.

18) The Yamanote Line is one of the most important railway lines in Tokyo, connecting 29 major train stations and commuting hubs on a 34.5 km loop.

19) The area shown here comprises the three wards of Chiyoda, Chuo and, Minato.

20) In Japan the school year as well as the academic year at universities and the fiscal years all begin on April 1st, making the weeks shortly before and after a very special period during the year, marked by lots of people moving etc.

21) Japan has both a pronounced rainy season from June to July as well as a typhoon season from August to October, which both regularly have severe effects on the public transport systems.

22) For an additional concept of stationary activity categories cf. chapter 5.3.5.

23) In 1987 Hillier et al. (1987) performed small-scale analyses for a number of very small study areas (urban, suburban as well as residential estates) to examine the relationship between observed movement patterns and the "space syntax" (Hillier 1998), i.e. urban structure.

24) In the terminology of the 2008 CSIS *PersonFlow* data a new trip starts, when the person is pursuing a new purpose, while each trip can be subdivided into multiple subtrips when the mode of transportation changes.

25) In the data model of the 2008 CSIS *PersonFlow* data these transportation modes are held separately. The latter includes not only monorails such as the *New Transit Yurikamome* and the *Tokyo Monorail Haneda Airport Line* but also other private train lines such as the *Nippori-Toneri Liner* and the *Tsukuba Express*. I will hitherto refer to these as "train".

26) The UNA toolbox for ArcGIS offers a normalization option as well, but since this only normalizes among street segments within the search radius *r*, I decided to implement my own, overall normalization step.

27) A specific encoding marks train stations that are still being served at the time of data collection.

28) It is a widely unknown fact that almost one quarter of the immediate casualties resulting from the collapse of the World Trade Center's twin towers were staff of the leading dealer in US treasury securities, which hampered the US financial system significantly and on a sustained basis (Makinen 2002, 4).

29) Obviously they serve as destinations during the morning commute, while they are the origins of trips during the evening commute. Therefore I summed up the numbers for arriving and departing passengers in the passenger transfer data.

30) Mita Station, which serves two underground train lines is only 150 from Tamachi Station, but no connection between these two train stations exists.

31) There is currently no district heat distribution network in Tokyo.

32) The US Department of Defense (DoD) also released a similar document about minimum antiterrorism building standards in the course of a governmental project, which was later cancelled (Department of Defense 2007).

33) Two notable exceptions are the papers by Rusnak et al. (2012) and Perry et al. (2013).

34) Similar approaches have been presented in previous studies in the context of infra-structural networks and nuclear power plants (Apostolakis and Lemon 2005; Karydas and Gifun 2006; Lemon 2004; Michaud 2005; Morgan et al. 2000; Patterson and Apostolakis 2007).

35) This map also shows one of the shortcomings of the analysis framework as a result of the available data: the 2011 Zenrin *Telepoint Pack!* dataset combines all offices of the Tokyo Metropolitan Government Building complex into the easternmost building, which makes the office towers in the west appear to be empty.

36) It is worth noticing that the perpetrators at the World Trade Center on September 11th, 2001, used a different scenario and modus operandi for their attack than that which I examine in this study.

37) In Figures 45, 46, 47 and 48 the data for vulnerability level “low” are not shown for clarity. They make up the remainder to 100%.

38) The official numbers according to the final report of the National Commission on Terrorist Attacks upon the United States are 343 members of the New York Fire Depart-

ment (FDNY), 23 members of the New York Police Department (NYPD), and 37 members of the Port Authority Police Department (PAPD) (National Commission on Terrorist Attacks upon the United States 2004, 311).

39) Cram schools in Japan are privately run but form an integral part of the education system. They serve all levels of school education from elementary to senior high school. While not mandatory, attendance rates are very high (Library of Congress 2010).

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