Macro-level estimation of present and future seismic loss by modelling spatio-temporal dynamics of exposure

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**MACRO-LEVEL ESTIMATION OF
PRESENT AND FUTURE SEISMIC LOSS BY MODELLING
SPATIO-TEMPORAL DYNAMICS OF EXPOSURE**

MESTAV SARICA GIZEM

**Interdisciplinary Graduate Programme
Institute of Catastrophe Risk Management**

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MESTAV SARICA GIZEM

**Interdisciplinary Graduate Programme
Institute of Catastrophe Risk Management**

A thesis submitted to the Nanyang Technological University in partial
fulfillment of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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MESTAV SARICA GIZEM

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PAN TSO-CHIEN

Authorship Attribution Statement

This thesis contains material from 2 journal papers published, in the following peer-reviewed journals where I was the first and corresponding author.

Chapters 2 & 3 were published as Mestav Sarica, G., Zhu, T. and Pan, T-C. (2020) “Spatio-Temporal Dynamics in Seismic Exposure of Asian Megacities: Past, Present and Future” *Environmental Research Letters*, 15, 094092, DOI: 10.1088/1748-9326/ababc7.

The contributions of the co-authors are as follows:

- Prof Pan Tso-Chien provided the initial project direction, helped with the general conversations and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Prof Pan Tso-Chien and Ms. Zhu Tinger.
- The inputs of the urban growth model were prepared by me and Ms. Zhu Tinger.
- The urban growth modelling and probabilistic seismic hazard analysis were carried out by me.
- I integrated the built-up area and seismic hazard maps. I also analyzed the results.

Appendix A was published as Mestav Sarica, G., Zhu, T., Jian, W., Lo, E.Y.M. and Pan, T-C. (2021) “Spatio-Temporal Dynamics of Flood Exposure in Shenzhen from Present to Future” *Environment and Planning B: Urban Analytics and City Science - Special Issue on Resilience of Cities to External Shocks: Analysis, Modeling and Economic Impacts*, DOI: 10.1177/2399808321991540.

The contributions of the co-authors are as follows:

- I prepared the manuscript drafts. The manuscript was edited and revised by Prof Pan Tso-Chien, Ms. Zhu Tinger, Dr. Jian Wei and A/Prof Lo Edmond Yat-Man.
- The inputs of the urban growth model were prepared by me and Ms. Zhu Tinger.
- The urban growth modelling was carried out by me.

- The flood hazard assessment was carried out by Dr. Jian Wei, and evaluated by A/Prof Lo Edmond Yat-Man.
- I integrated the built-up area and flood hazard maps. I also analyzed the results.

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Abstract

A society resilient to natural hazards is one that can adapt to the increase in exposure, absorb the impacts of hazardous events, and distribute the risk among different stakeholders. Megacities, cities having more than 10 million inhabitants, are complex, highly interconnected and dynamic systems that are vulnerable hotspots of natural hazards due to high concentration of people, properties, infrastructure and economic activities. Currently, the majority of global megacities are located in Asia, and many Asian megacities are often exposed to extreme seismic events being located on top of or near seismic faults. In fact, Asia has been the region with the largest built-up area exposed to earthquakes, with total area tripled from 1975 to 2015. While historical loss and exposure assessments can explain the past, they do not necessarily shed light on the future. Thus, the main aim of this study is to develop a framework for the estimation of present and future seismic losses by using a macro-level loss estimation approach, and modelling the spatio-temporal dynamics of exposure. For this purpose, three earthquake-prone Asian megacities from developing countries, namely Jakarta, Metro Manila, and Istanbul, were selected as case studies. The proposed framework involves integration of different methodologies in the literature which have previously been used for other purposes.

Since hazard component cannot be predicted and controlled, this unique feature of earthquakes highlights the importance of modelling, mapping and quantifying exposure to understand earthquake risk. A common strategy that is used to estimate future exposure is to make temporal predictions that assume all exposed urban grids will be equally affected by possible disasters, although exposure is actually a complex risk component that varies across temporal and spatial dimensions. Thus, projections related to the urban fabric should be done both spatially and temporally in order to analyze trends of exposure, which generally show a nonlinear behavior. In this study, past and present built-up areas of selected Asian megacities were initially extracted from satellite images to obtain high-resolution exposure information. Then, a cellular automata-based urban growth model was utilized to predict the built-up area in 2030, using the mapped past and present built-up areas and several other growth indicators which affect urbanization trends. Projected census populations were disaggregated to grids using a dasymetric mapping technique to obtain present and future population grids. Following that, grid-level wealth information was obtained by multiplying present and future GDP per capita with the corresponding population grids and the exposure correction factor, which accounts for the disparity between national wealth and economic value of assets that are exposed. Finally, probabilistic seismic hazard maps were overlaid with exposure maps to assess spatio-temporal changes in built-up area exposed to seismic hazard, and thus wealth exposed to seismic hazard.

An objective understanding of the path towards urban resilience can be provided by measuring loss over time. As such, several scholars have suggested that quantitative risk assessments should not be considered as static analyses which are performed at a certain time, and time-dependent monitoring of risk, which reflect the pace of changes in cities, should be employed. Conventional seismic loss estimate methodologies generally require a detailed inventory of exposed structures that is usually not publicly available especially in developing countries. Several researchers have attempted to simplify this process by using macro-level approaches which eliminate the need of a detailed inventory. These approaches utilize socioeconomic indicators, assuming that there is a direct relation between economic condition of a region and the potential loss resulting from an event in that region. Although macro-level approaches can be effectively used for evaluation of spatio-temporal trends and thus estimation of future seismic loss, they have not been utilized for such an objective before. In addition to this, they have not been integrated into natural catastrophe modelling schemes to estimate primary probabilistic risk metrics, which are widely used by the insurance industry and the authorities.

An enhanced macro-level seismic loss estimate methodology was thus developed in this dissertation for probabilistic risk assessment by leveraging on the methods in the literature. The average annual loss (AAL) in grid-level, Admin Level 2 and megacity-level, as well as the probable maximum loss (PML) in grid-level were estimated by considering present and future exposure to seismic hazard of the selected megacities. To achieve this goal, a multi-step framework was developed by utilizing the information on spatio-temporal exposure dynamics. The megacity-level results show that AAL is predicted to increase by 2030 almost twofold, from around 68 million USD to 129 million USD in Jakarta (in 2018 prices), and from around 163 million USD to 333 million USD in Metro Manila (in 2016 prices). The present AAL in Istanbul is predicted to show a high increase of around 57% from around 900 million USD to 1,417 million USD by 2030 (in 2018 prices). The enhanced macro-level loss estimation approach following the proposed framework was observed to produce loss estimations in the same order of magnitude as the conventional loss estimation methods. Therefore, it can be used as a complementary tool in addition to the conventional risk assessment framework.

The findings of this research shed light on future exposure and loss assessments by making comparisons among present and future. Since the results obtained are in terms of grid-level maps for built-up area, wealth and seismic loss, this study demonstrates the growth of each grid over time. It was observed that in regions where high levels of exposure and hazard are coupled, high potential of losses are predicted, while there are different trends in each megacity due to their varying historical urbanization patterns. Urban planners can utilize the grid-level present and future exposure to seismic hazard for risk mitigation or zoning purposes. In addition, the AAL maps for Admin Level 2 can aid local authorities in allocation of resources, while megacity-level AAL and PML can provide information to governments and decision-makers about disaster risk financing options to reduce forthcoming risks.

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Abbreviations

AAL	Average Annual Loss
ATC	Applied Technology Council
AUC	Area Under Curve
CA	Cellular Automata
CAPRA	Comprehensive Approach to Probabilistic Risk Assessment
CIESIN	Center for International Earth Science Information Network
DEM	Digital Elevation Model
DKI	Daerah Khusus Ibukota (Special Capital Region)
EP	Exceedance Probability
GDP	Gross Domestic Product
GEM	Global Earthquake Model
GHSL	Global Human Settlement Layer
GIS	Geographical Information System
GFDRR	Global Facility for Disaster Reduction and Recovery
GMICE	Ground Motion to Intensity Conversion Equation
GPW	Gridded Population of the World
HAZUS-MH	Hazards U.S. Multi-Hazard
HIE	High-Income Economy
IM	Intensity Measure
LIE	Low-Income Economy
LULC	Land Use and Land Cover
MC	Markov Chain
MDF	Mean Damage Factor
MIE	Middle-Income Economy

MMI	Modified Mercalli Intensity
MODIS	Moderate Resolution Imaging Spectroradiometer
MSK	Medvedev–Sponheuer–Karnik
NCR	National Capital Region
OSM	OpenStreetMap
PAGER	Prompt Assessment of Global Earthquakes for Response
PGA	Peak Ground Acceleration
PML	Probable Maximum Loss
PSHA	Probabilistic Seismic Hazard Analysis
ROC	Receiver (also known as Relative) Operating Characteristic
RP	Return Period
RS	Remote Sensing
SFDRR	Sendai Framework for Disaster Risk Reduction
UN	United Nations
UNDRR	United Nations Office for Disaster Risk Reduction
USDA	U.S. Department of Agriculture
USD	U.S. Dollar
USGS	U.S. Geological Survey
WEF	World Economic Forum

List of Journal Papers

- Mestav Sarica, G., Zhu, T. and Pan, T-C. (2020). “Spatio-Temporal Dynamics in Seismic Exposure of Asian Megacities: Past, Present and Future”, *Environmental Research Letters*, 15, 094092, DOI: 10.1088/1748-9326/ababc7.
- Mestav Sarica, G., Zhu, T., Jian, W., Lo, E.Y.M. and Pan, T-C. (2021) “Spatio-Temporal Dynamics of Flood Exposure in Shenzhen from Present to Future”, *Environment and Planning B: Urban Analytics and City Science - Special Issue on Resilience of Cities to External Shocks: Analysis, Modeling and Economic Impacts*, DOI: 10.1177/2399808321991540.

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- Mestav Sarica, G., Zhu, T. and Pan, T-C. (2018). “Spatio-temporal dynamics of urban extent at risk: Case study for seismic hazard in Asian megacities”, *Urban Transitions Global Summit, Barcelona, Spain* (Abstract).

Chapter 1 Introduction

1.1 Motivation

A society resilient to natural hazards is one that can adapt to the increase in exposure, absorb the impacts of hazardous events, and distribute the risk among different stakeholders. As it is often said, what is not measured cannot be managed (De Groeve et al., 2013). In 2015, the United Nations Office for Disaster Risk Reduction (UNDRR, 2015a) reported that the global average annual loss (AAL) for earthquakes was 113 billion USD. To put this into perspective, it was equal to annual public education expenditure in the Middle East and North Africa.

Being located on top of or near seismic faults, many Asian megacities are often exposed to extreme seismic events. In fact, Asia has been the region with the highest built-up area exposed to earthquakes, with a total area tripled from 1975 to 2015 (Pesaresi et al., 2017). While historical loss and exposure assessments can explain the past, they do not necessarily shed light on the future. Thus, scrutinizing the time-dependent dynamics of exposure and possible consequent forthcoming seismic losses in the rapidly urbanizing earthquake-prone Asian megacities has been the main motivation of this dissertation.

1.1.1 Evolving Seismic Exposure in Asian Megacities

The emergence of megacities has occurred as a result of rapid global urbanization. The term “megacity” term was coined by the United Nations (UN) in the 1970s to designate large conurbations with at least 8 million inhabitants. This threshold was raised to 10 million in the 1990s. Megacities empower the scale of economies, lowering the production costs. According to McKinsey (2012), the top 20 megacities are predicted to outpace the rest of the global economy by nearly twice by 2025. While 10 of the 15 most populous cities were in industrialized countries in 1950, 11 of the 15 largest megacities were in emerging and developing countries in 2000 (Munich Re, 2004). In 2018, around one eighth of the world’s urban population was reported as living in 33 megacities (UN, 2018). Currently, the majority of global megacities are located in Asia, and the urban population of the world is projected to increase from 55% to 68% by 2050, with 90% of the increase occurring in Asia and Africa (Munich Re, 2018).

Megacities are complex, highly interconnected and dynamic systems which are vulnerable hotspots of natural hazards due to high concentration of people, properties, infrastructure and economic activities. The vulnerabilities of megacities are greater in the developing world, owing to the design and construction of housing and infrastructure below standards, reliance on the functionality of lifeline systems and a lack of strong preparedness programs. Due to their high vulnerability and exposure, megacities are prone to large loss potentials even from small events. The interruption of daily activities may disrupt the social, political and economic environment of not only the cities affected, but also the whole country. In fact, reconstruction costs after disasters may result in economic recessions and development setbacks, especially in developing countries (Wenzel et al., 2014).

Unlike weather-related hazards, estimation of damaging effects of earthquakes is compounded by the impossibility of forecasting their locations, frequencies and magnitudes (Geller, 1997; Buchanan, 2001; Guo, 2010; Freire and Aubrecht, 2012). Since the hazard component cannot be predicted accurately and controlled, this unique feature of earthquakes highlights the importance of modelling, mapping and quantifying exposure to decrease risk. As a result of the rapid growth of socioeconomic indicators, data related to urban environment of fast-developing regions such as megacities quickly become outdated. Nonetheless, current risk assessments generally focus on past and present exposure.

A common strategy that is used to estimate future exposure is to make temporal predictions that assume all exposed urban grids will be equally affected by possible disasters. However, exposure is a complex component of risk that varies across temporal and spatial scales. Thus, projections related to urban fabric should be done both spatially and temporally in order to analyze trends of exposure, which generally show a nonlinear behavior (Freire et al., 2015). A challenging problem that arises in this domain is to make spatio-temporal predictions which would result in a different growth rate for each region/grid. The question then becomes how best to estimate the future exposure to seismic hazard which can be utilized by policymakers, insurance industry and urban planners for more effective disaster risk mitigation and reduction strategies.

1.1.2 Modelling Present and Future Seismic Losses using a Macro-Level Loss Estimation Approach

An objective understanding of the path towards resilience can be provided by measuring loss over time. As such, several scholars have suggested that quantitative risk assessments should not be considered as static analyses which are performed at a certain

time, and time-dependent monitoring of risk should be employed which reflect the pace of changes in cities (Wenzel et al., 2014; Freire et al., 2015; Lallemand, 2015; Calderon, 2019). The United Nations Office for Disaster Risk Reduction (UNDRR) defined one of the three main targets of Sendai Framework for Disaster Risk Reduction (SFDRR) as reducing the direct disaster economic loss in relation to GDP by 2030 (UNDRR, 2015b). However, after the evaluation of 80 open-access disaster risk assessment tools by World Bank's Global Facility for Disaster Reduction and Recovery (GFDRR), it was reported that none of them could make future projections (GFDRR, 2014; Calderon, 2019).

Conventional seismic loss estimation methodologies generally require a detailed inventory of exposed structures, which is usually not publicly available, especially in developing countries. Several researchers have attempted to simplify this process by using macro-level approaches that eliminate the need for a detailed inventory. These approaches utilize socioeconomic macroscopic indicators (e.g. GDP) by assuming that there is a direct relation between the economic condition of a region and the potential loss resulting from a seismic event in that region. It is worth noting macro-level approaches are not intended to replace the conventional loss estimation methods. Instead, they have been considered as complementary tools for decision-making processes.

Chen et al. (1997) proposed a method which enables users to estimate seismic loss by employing GDP as an indicator of economic condition. It has been used for probabilistic and deterministic loss estimations for different regions utilizing grid-level data. The loss values estimated for grids have been illustrated as loss maps or, in certain cases, reported as aggregated values. The U.S. Geological Survey's (USGS) Prompt Assessment of Global Earthquakes for Response (PAGER) system (Jaiswal and Wald, 2011) has

improved the approach proposed by Chen et al. (1997) by considering wealth in addition to GDP. For this purpose, they have used a multiplying exposure correction factor to account for the disparity between wealth and GDP. The PAGER system rapidly reports estimated loss range along with exposed population in the aftermath of a large seismic event, but does not employ probabilistic loss estimations.

Thanks to developments in open-source high-resolution exposure databases, macro-level approaches can be effectively used for the estimation of future seismic loss and evaluation of spatio-temporal trends. However, they have not yet been utilized for such an objective so far, while they generally focus on the estimation of present loss by taking present exposure into consideration. In addition, these approaches have not been integrated into natural catastrophe risk modelling schemes to estimate the primary probabilistic risk metrics, such as average annual loss (AAL) and probable maximum loss (PML) which are widely used by the insurance industry and government-level authorities.

1.2 Research Objectives

The main aim of this study is to develop a framework for the estimation of present and future seismic losses by modelling spatio-temporal dynamics of exposure, and using a macro-level approach. For this purpose, three earthquake-prone Asian megacities from developing countries, namely Jakarta, Metro Manila and Istanbul, were selected as case studies. This framework involves the incorporation of different methodologies in the literature which have previously been used for other purposes. It can be used by decision-makers, insurance industry and urban planners for better assessment, mitigation and reduction of forthcoming risk, as well as allocation of resources.

Thus, the key objectives of this proposed Ph.D. dissertation can be summarized as:

i) To evaluate spatio-temporal changes in exposure metrics such as built-up area and wealth by modelling urban growth,

To obtain high-resolution exposure information, past and present built-up area of selected Asian megacities were extracted from satellite images. A cellular automata-based urban growth model was utilized to predict the built-up area in 2030 using the mapped built-up area and several other predictors of change which affects urbanization trends. Then, projected census populations were disaggregated to grids using dasymetric mapping techniques to obtain present and future population grids. Finally, grid-level wealth information was derived by multiplying present and future GDP per capita with the corresponding population grids and the exposure correction factor.

ii) To analyze spatio-temporal dynamics of “built-up area exposed to seismic hazard” and “wealth exposed to seismic hazard” considering probabilistic seismic hazard,

The classical probabilistic seismic hazard analysis (PSHA) was performed to generate probabilistic seismic hazard maps for 10% and 2% probabilities of exceedance in 50 years. Soil amplification effects were taken into consideration during analyses, and the maps were obtained in terms of peak ground acceleration (PGA) values. PGA values were then converted into Modified Mercalli Intensity (MMI) scale using Ground Motion to Intensity Conversion Equations (GMICE). By overlaying probabilistic seismic hazard maps with the exposure (i.e. built-up area, population and wealth) maps, spatio-temporal dynamics of exposure metrics were analyzed.

iii) To estimate present and future seismic loss in terms of probabilistic risk metrics by constructing a framework and developing an enhanced macro-level seismic loss estimation approach.

An enhanced macro-level seismic loss estimation method was developed for probabilistic risk assessment by leveraging on the methods in the literature. To achieve this goal, a multi-step framework was developed. Average annual loss (AAL) in grid-level, Admin Level 2 and megacity-level were estimated by considering present and future exposure of selected Asian megacities. The megacity-level present AAL estimates were further compared with results obtained by a conventional seismic loss estimation approach. Finally, 475-year and 2,475-year probable maximum loss (PML) in grid-level were estimated, and the changes from present to future were evaluated.

1.3 Organization of Thesis

This dissertation consists of six chapters which are organized as follows:

Chapter 1 presents the introduction with motivation, background information, and main objectives of the research.

Chapter 2 provides the literature review with background information on the conceptual framework of seismic risk assessment and loss estimation methods, with particular focus on conventional and macro-level loss estimation approaches. Then, it summarizes the methods in the literature which are used for modelling spatio-temporal exposure dynamics such as mapping built-up area, urban growth modelling, and estimation of grid-level wealth by dasymetric mapping of population.

Chapter 3 focuses on modelling spatio-temporal dynamics of exposure in selected Asian megacities, namely Jakarta, Metro Manila, and Istanbul. It presents and discusses

the grid-level change in built-up area of these megacities over time which is obtained by mapping past and present built-up area and predicting urban growth in 2030. After disaggregating population to built-up area grids and considering GDP as a macroscopic indicator of social wealth, it also illustrates grid-level change in population and wealth.

Chapter 4 describes the procedure to obtain spatio-temporal dynamics of seismic exposure, making use of the results in Chapter 3. First, classical probabilistic seismic hazard analysis (PSHA), which is used to obtain probabilistic seismic hazard maps of selected megacities, is explained. After overlaying them with the exposure maps, spatio-temporal changes in “built-up area exposed to seismic hazard” and “wealth exposed to seismic hazard” are evaluated. The discussion is also extended to the changes in “population exposed to seismic hazard” as it is used as a base for wealth estimation.

Chapter 5 proposes an enhanced macro-level seismic loss estimation approach which is used for probabilistic seismic risk assessment. It further presents the developed framework for the estimation of present and future seismic loss and discusses the spatio-temporal changes in probabilistic risk metrics, namely average annual loss (AAL) and probable maximum loss (PML), in different levels. Aggregated AAL values estimated by the proposed macro-level approach are then compared with the reported loss values which are calculated using a conventional seismic loss estimation approach.

Chapter 6 highlights the main contributions, summarizes limitations, and provides pointers for future studies.

Chapter 2 Literature Review

2.1 Introduction

The biggest risk accumulation in megacities is generally posed by earthquakes (Munich Re, 2004). Seismic risk assessment is a complex task that involves integration of seismological, engineering, and socioeconomic data (Corban et al., 2015). It generally contains the quantification of human and economic losses for which modelling exposure is an important task. By extracting information on built-up environment, exposure metrics such as built-up area, population, and wealth can be analyzed which could be the basis when estimating seismic loss. In this chapter, the conceptual framework of seismic risk assessment and loss estimation methodologies is explained, focusing on the conventional and macro-level seismic loss estimation methods. Subsequently, the studies in the literature that focus on the evaluation of future seismic risk are summarized. Finally, exposure modelling is detailed, concentrating on the methods in the literature that are used to map and predict grid-level built-up area and wealth.

2.2 Conceptual Framework of Seismic Risk Assessment

The earthquake problem merits the study of the event itself, the associated ground motions, and the effects on structures (McGuire, 2004). Seismic risk is dependent on the complex interaction between a hazard and the characteristics that make inventory of assets (i.e. people, physical objects and activities) vulnerable and exposed. Risk assessment models can help authorities and insurance industry to determine the size of the reserves to buffer losses by evaluating the amount of acceptable loss, and tracking risk-based loss information (Corban et al., 2015). Two different approaches, namely deterministic and probabilistic, can be used to define seismic risk, depending on the objectives of a study.

Deterministic risk assessment (also known as scenario assessment) is the process of analyzing the consequences from a single hazard event generally by considering a user-chosen scenario known as the “maximum credible earthquake” or the “worst-case scenario” (Corban et al., 2015). The main advantage of the deterministic approach is that it allows for the consideration of an extraordinary seismic event, and, consequently, unusual set of losses (Kijko et al., 2003). On the other hand, probabilistic risk models have been considered as the most important tools at the service of authorities to estimate losses where most of the currently used models of earthquake risk assessment are probabilistic (Corban et al., 2015; Ehrlich et al., 2018). Hazard component in the probabilistic risk assessment approach refers to the frequency (i.e. the number of events per unit time) with which a seismic hazard occurs (McGuire, 2004). By considering the probability of occurrence of each event and the magnitude of the possible consequences, a probabilistic risk analysis brings together all the potential sources of risk (Antofie et al., 2018). It can also be viewed as inclusive of all deterministic events with a finite

probability of occurrence. Probabilistic seismic hazard analysis (PSHA) is used to obtain hazard curves and hazard maps by solving the PSHA integration procedure. The hazard curve represents probability of exceeding some level of earthquake ground shaking, for a range of ground motion intensity measure (IM) of interest such as peak ground acceleration (PGA) (Baker, 2008). Using total probability theorem, the probability of exceedance from a single source is computed by Equation 2.1 as:

$$P(IM > x) = \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} P(IM > x|m, r) f_m(m) f_R(r) dr dm \quad (2.1)$$

where $P(IM > x|m, r)$ is derived from the ground motion model, and $f_m(m)$ and $f_R(r)$ are probability distribution functions for magnitude m and distance r , respectively. Then, all potential sources are considered to construct the hazard curve with respect to the ground motion intensity measure of interest (McGuire, 2004).

Within the context of this dissertation, two different loss estimation approaches, conventional and macro-level, are reviewed and summarized. The main difference between these approaches is that in macro-level approaches, socioeconomic indicators are used for exposure calculations, while in conventional approaches, more detailed information such as the characteristics of building stock is used. Conventional methods can be considered as analytical approaches, since they generally consider the vulnerability as defined by structural characteristics of the built environment. On the other hand, macro-level methods use empirical vulnerability functions that depend on historical earthquake loss data. In the following sections, the details about these methods are presented.

2.2.1 Conventional Seismic Loss Estimation Methods

Most of the conventional seismic loss estimation methods use the probabilistic approach, which predicts the damages in different categories of structures and infrastructures in the study area to calculate the total loss for particular intensity ranges. The information needed to model the exposure and vulnerability in these methods are generally occupational type, construction type, and replacement value (Applied Technology Council, 1985). Other additional structural attributes include square footage, number of floors, construction year, irregularities, material and mechanical properties, and construction codes. Buildings are typically categorized in building types, and each building type is associated with a vulnerability and fragility function. The set of guidelines and recommendations for the conventional loss estimation methodologies are primarily based on the method suggested by the Applied Technology Council (1985), which is designated as ATC-13. The ATC-13 method contains two main components, namely, a seismic hazard analysis and a structural vulnerability function. Seismic hazard analysis takes the frequency distribution of earthquakes, intensity attenuation, and soil conditions into account, and vulnerability analysis requires a detailed inventory of the buildings and facilities in the region. The expected loss at a site is then determined by ATC-13 as shown in Equation 2.2 below:

$$Loss = \sum_{B_k} \left[\left\{ \sum_{I_i} P(I_i|B_k) * \left(\sum_{dr_j} P(dr_j|I_i, B_k) * (dr_j|B_k) \right) \right\} * V_{B_k} \right] \quad (2.2)$$

where B_k is the building type k , I_i is the intensity level i , dr_j is the expected damage ratio j , and V_{B_k} is the value of all buildings of type B_k .

Risk and exposure models developed by the insurance industry generally use local exposure data for conventional risk assessments; however, there are limitations to access this level of data. They are generally derived from national inventory databases, which are not always open access especially in data-scarce developing countries. In fact, the need for transparency has been the major driver for the development of some open-source earthquake risk models (e.g. HAZUS-MH (available at www.fema.gov/hazus), OpenQuake (available at www.globalquakemodel.org), CAPRA GIS (available at www.ecapra.org), etc.). The economic value of all the physical assets exposed in a given area can be extremely difficult to compile. Moreover, if the loss estimations are not calibrated against historical losses, the availability of required data may not ensure reliable estimates (Jaiswal and Wald, 2011). Due to these limitations, several researchers have attempted to simplify seismic loss estimation procedures by developing macro-level approaches, which rely less on detailed inventories of structures and more on socioeconomic data that is readily available.

2.2.2 Macro-Level Seismic Loss Estimation Methods

Since total values of the buildings and infrastructure as well as deprivation in revenues due to interruption of business are closely related to the economic productivity of a region, macro-level loss estimation methods use a holistic approach, assuming that potential losses caused by physical damages and business interruption could be attributed to the state of the region's economy. These approaches bypass the requirement of detailed building inventories in conventional methods, which may not be available for certain regions of the world, and instead use macroscopic indices such as social wealth to represent exposure. The potential benefits of these approaches which make them accessible and attractive are primarily their transparency, flexibility, and rapidity. They have been applied *ex ante* in risk assessment and disaster planning, and *ex post* for

rapid estimation of losses to allocate resources in the aftermath of significant earthquakes.

Macro-level methods generally combine seismic hazard, relation between GDP and published historical earthquake loss data, population grids, and GDP per capita to estimate grid-level expected loss. GDP mainly measures the total output of goods and services for final use that is produced by residents and non-residents (World Bank, 1994). It is one of the socioeconomic indicators regularly compiled by various agencies and institutions, such as the World Bank, the World Resources Institute, and the United Nations; therefore, it has been considered as a suitable metric to be used as a measure of the economic condition of a community (Chan et al., 1998; Hoeppe, 2016). GDP is generally reported as nominal (also known as current) or real terms. The nominal GDP is measured in terms of actual prices that exist at the time. On the other hand, the real value is evaluated at the market prices of some base year. For example, if 2010 were chosen as the base year, then real GDP for 2018 is calculated by taking the quantities of all goods and services purchased in 2018 and multiplying them by their 2010 prices. The real GDP is converted into nominal GDP using a price index as represented in Equation 2.3 below:

$$\text{Nominal GDP} = \text{Real GDP} \times \text{Price Index} \quad (2.3)$$

The price index can be obtained from World Bank Data for several base years (available at <https://data.worldbank.org/>).

One of the first proposed macro-level seismic loss estimation approaches was given by Chen et al. (1997) with Equation 2.4 considering countries from different economic levels:

$$Loss_{grid} = \sum_{I_j} P(I_j) \cdot MDF(I_j) \cdot g(GDP) \cdot GDP_{grid} \quad (2.4)$$

where $P(I_j)$ is the probability of intensity level j , $MDF(I_j)$ is the Mean Damage Factor to represent hazard-exposure-loss relation given intensity I_j , and $g(GDP)$ is a function to correlate the total social wealth with macroscopic indicator GDP. The summation over I_j represents the expected loss at each grid considering different probabilities of shaking intensities. The national GDP data is distributed to population grids as described in Equation 2.5 below:

$$GDP_{grid} = GDP_{nation} \times \frac{Population_{grid}}{Population_{nation}} \quad (2.5)$$

$g(GDP)$ is assumed to be 4 for low- and middle-income economies, 5 for high-income economies, and 3 for China, India and Japan. Just as conventional damage functions convey the expected loss for a specified intensity and building type, MDF describes the expected loss for a specified intensity and social wealth. Due to the limitation of the earthquake data, Chen et al. (1997) assumed:

$$MDF = f(I) \quad (2.6)$$

where function $f(I)$ is defined globally by the relation between intensity and loss ratio, which was proposed by Munich Re in 1988, as illustrated in Figure 2.1. Chen et al (1997) calculated the expected losses of two historical events (San Francisco, M_w 8.3, 1906 and Kanto, M_w 7.9, 1923) by using them as scenario events (i.e. $P(I_j)=1$) with population grids in 1994 and GDP per capita in 1992.

Figure 2.1 Loss ratio (%) vs. intensity (MMI) relation proposed by Munich Re 1988
(Adopted from Chen et al., 1997)

Following that, Chan et al. (1998) proposed another relationship shown in Equation 2.7 using a similar form to Equation 2.4:

$$L_k = \sum_I P(I) \cdot F(I, GDP) \cdot GDP \quad (2.7)$$

where $F(I, GDP)$ is a measure of the area's vulnerability to earthquake damage. The function $F(I, GDP)$ is determined empirically from previous case histories. Chan et al. (1998) identified 29 global earthquakes since 1980 with an epicentral $MMI \geq VI$ for which loss data were available, categorizing nations according to their nation-level GDPs as high-income (HIE) (> 8.3 billion USD), medium-income (MIE) (675 million USD – 8.3 billion USD), and low-income (LIE) (< 675 million USD) economies. As the areal extent of the affected zone is not specified by the earthquake reports, the zone for maximum loss was assumed to be within 30 km of the epicenter. The reported losses were plotted against the GDPs of the epicentral zones for seismic events with $MMI \geq VII$. Accordingly, the relations between $\log(GDP)$ and $\log(loss)$ were obtained by regression (Figure 2.2). They have concluded that the approximately parallel lines in Figure 2.2 support the assumed empirical correlation between GDP and economic loss.

The vulnerability curves, represented as $F(I, GDP)$, are also shown as the relation between loss/GDP ratio and MMI values for nations of different economic levels in Figure 2.3. Chan et al. (1998) calculated the global grid-level ($0.5^\circ \times 0.5^\circ$) expected earthquake losses at 10% probability of exceedance in 50 years along with the probable maximum loss.

Figure 2.2 Economic loss vs. GDP plot for MMI VII, VIII, IX, and X (Adopted from Chan et al., 1998)

Figure 2.3 Loss/GDP ratio vs. MMI cubic splines for low-income economies (LIE), medium-income economies (MIE), and high-income economies (HIE) (Adapted from Chan et al., 1998)

Similar macro-level forms have been used to calculate the expected losses in Central America (Chen et al., 2002), India (Dunbar et al., 2002) and China (Wang et al., 2009) by developing regional vulnerability curves. However, several limitations about the proposed macro-level loss estimation approaches were pointed out by Jaiswal and Wald (2011) as:

- The affected zone is defined with an arbitrary criterion (i.e. 30 km of the epicenter of an event), instead of obtaining historical data on loss ratios at each shaking intensity unit.
- Broad economic categories are defined while constructing loss vs. GDP relations that provide limited insight about country-level economic vulnerability.
- Using only GDP is not sufficient for estimating exposure, since GDP is an indicator of economic activity, not of existing investment. In other words, it is an indicator of “flow” that represents solely the average annual productivity benefits derived from an asset. Thus, a “stock” indicator of the wealth should be used for the assessment of the economic impacts of disasters, especially for the cases where a disaster could cause asset damage greater than the annual flow (e.g. 2010 Haiti earthquake).

In order to overcome these limitations, the macro-level approach proposed by the U.S. Geological Survey’s (USGS) Prompt Assessment of Global Earthquakes for Response (PAGER) system (Jaiswal and Wald, 2011) applied several modifications to the proposed frameworks:

- An estimate is made for the economic loss ratio that is country- or region-specific and depends on the shaking intensity by calibration against historical earthquakes losses (1980-2007).

- GDP is adjusted by a multiplier called the exposure correction factor to account for the disparity between national wealth and economic value of assets that are exposed in a given area. Thus, the economic exposure obtained is considered as a proxy for the economic value of the actual inventory exposed to the seismic hazard.

PAGER system rapidly estimates the population exposed to different levels of shaking intensities along with the range of economic losses immediately following a large earthquake anywhere in the world by means of a deterministic approach. Jaiswal and Wald (2011) use Equation 2.8 to define the economic loss ratio given as:

$$\text{Loss Ratio}, r = \frac{\text{Economic Loss}}{\text{Economic Exposure}} \quad (2.8)$$

The loss ratio is parameterized in terms of shaking intensity “s” using a two-parameter lognormal cumulative distribution function shown in Equation 2.9 as:

$$r(s) = \phi \left[\frac{1}{\beta} \ln \left(\frac{s}{\theta} \right) \right] \quad (2.9)$$

where ϕ is the standard normal cumulative distribution function, θ is the mean, and β is the standard deviation of natural logarithm of shaking intensity. θ and β are determined for each country/region by using a standard iterative search algorithm to minimize Equation 2.10 which represents the combined (L2G) norm of the total error ε :

$$\varepsilon = \ln \left[\sqrt{\frac{1}{N} \sum_{i=1}^N [E_i - O_i]^2} + \sqrt{\frac{1}{N} \sum_{i=1}^N \left[\ln \left(\frac{E_i}{O_i} \right) \right]^2} \right] \text{ or } L2G \text{ norm} \quad (2.10)$$

where O_i is the recorded economic loss (taken from the Munich Re global catalog NatCatSERVICE (2008) considering earthquakes from 1980 to 2007) for earthquake i ,

E_i is the modelled loss for earthquake i , and N is the number of earthquakes in the country.

The shaking intensity ranges from 5 to 9 (MMI V to MMI IX), and total exposure at MMI IX and above is combined at IX. Then, total expected economic loss is estimated as described in Equation 2.11 by summing the product of loss ratio and total economic exposure at each intensity level, s :

$$E(Loss) = \sum_s \phi \left[\frac{1}{\beta} \ln \left(\frac{s}{\theta} \right) \right] \times Economic\ Exposure_s \quad (2.11)$$

Total economic exposure at a given intensity level is computed using Equation 2.12 by multiplying the country-level GDP per capita and population exposed to that intensity level which is then scaled by the exposure correction factor α :

$$Economic\ Exposure_s = \alpha \times per\ capita\ GDP_{country} \times population_s \quad (2.12)$$

The exposure correction factor “ α ” is calculated by taking the ratio of wealth per capita to GDP per capita. For the exposure correction factor calculations in Jaiswal and Wald (2011), the wealth per capita information in 2000 was obtained from World Bank’s “Where is the Wealth of Nations?” report (2006). In World Bank’s report, wealth is defined as a combination of produced, natural, and intangible capital. Produced capital includes machines, equipment, urban land, structure and infrastructure. Natural capital is calculated as the sum of nonrenewable resources (e.g. natural gas, oil, mineral resources, etc.), forested areas, pastureland, cropland and protected areas. Intangible capital is the sum of human capital (e.g. sum of skills, knowledge, know-how, etc.), social capital (e.g. the level of trust among people in society), net foreign financial assets, and quality of institutions.

Due to the limitation of the data, it was assumed that the exposure correction factor corresponding to 2000 is constant over time for a given country during PAGER's optimization for development of vulnerability curves and exposure calculations. Although World Bank reported wealth per capita values for recent years in "The Changing Wealth of Nations: Measuring Sustainable Development in the New Millennium" (World Bank, 2011a) and "The Changing Wealth of Nations 2018: Building a Sustainable Future" (Lange et al., 2018), PAGER's optimization process has used exposure correction factors corresponding to 2000. Therefore, PAGER's exposure factors are directly used in this dissertation, since developing vulnerability curves is not an aim in the scope of this study. However, further studies can make use of the newly reported wealth per capita values to calculate exposure correction factors corresponding to other years.

While the improved macro-level approach by PAGER has been used to obtain event-based losses, there is a lack of studies that represent loss by this improved macro-level approach in terms of probabilistic risk metrics, average annual loss (AAL) and probable maximum loss (PML). Since these loss metrics are widely used by insurance industry for communication of loss figures, their estimation can aid the implementation of these methods in risk financing for management of resources. In addition to this, no study to date has integrated macro-level approaches into estimation of forthcoming seismic losses.

2.2.3 Future Seismic Risk Assessment Studies in the Literature

The necessity to assess earthquake risk as a dynamic metric has been acknowledged by several scholars in recent years (Wenzel et al., 2014; Freire et al., 2015, Lallemand, 2015, Calderon, 2019). However, few studies have focused on the estimation of forthcoming

seismic risk. Lallemand (2015) modelled the seismic risk trajectory of Cap-Haitien in Haiti, considering time-dependent changes in exposure and vulnerability. By integrating Markov chain (MC) and cellular automata (CA) models, he developed an urban growth simulation that was then used to describe how likely a building is to change from one state to another in the process of incremental building expansion modelling. He considered the hazard from a single earthquake scenario (M_w 7.8 event by the rupture of the Septentrional fault) to obtain damage state distributions of the buildings from 2013 to 2050. Calderon (2019) projected seismic risk in Great Metropolitan Area of Costa Rica for 2035 and 2055 to estimate probabilistic risk indicators in terms of mortality and economic loss. He utilized a multiple-agent systems urban growth model and probabilistic future population scenarios for this purpose. He estimated the changes in losses by focusing on one earthquake scenario (M_w 6.5 event occurring southwest of the city of Cartago) and probabilistic event-based seismic hazard analysis (i.e. stochastic event sets).

2.3 Modelling Spatio-Temporal Changes in Seismic Exposure of Megacities

As a result of the rapid and sometimes unplanned urbanization, high concentration of people and physical assets coupled with high hazard levels increases the degree of disaster impact for the megacities located in hazard-prone areas. Exposure is the term which stands for people and assets at risk of suffering damage and loss due to hazards (Pesaresi et al., 2017). This term includes several dynamic and complex dimensions which vary across temporal and spatial scales, such as the built-up environment and population, as well as the economy. The effect of exposure on disaster losses has been strong, and it has been established with much more confidence when compared to the effect of other elements of risk (Visser et al., 2014). Exposure modelling techniques

have been developed at various scales, from global, to regional/national and to local scales.

Detailed mapping of built-up areas and population distribution is a key information needed at any stage of the disaster management process. Population is the primary exposure metric in disaster risk analyses or impact models. Built-up area is another key variable to measure the impact of hazards on the urban fabric. Population growth and urban expansion in seismically hazardous areas have been the main drivers of mounting disaster impacts, since the frequency of earthquakes have been observed as remaining relatively constant (Cutter and Emrich, 2005; Freiere et al., 2015). Utilizing the exposure analysis, human exposure levels can be lowered by identifying the sites available for new developments, formulating spatial growth strategies in urban planning decisions, placing means and resources needed for response according to exposure levels, and taking effective policy actions for more resilient communities.

The dynamics of exposure trends has been investigated by different studies that consider various types of natural hazards and at different scales from global to local. One of the recent global studies on population and built-up land exposure, *Atlas of the Human Planet 2017: Global Exposure to Natural Hazards*, has been conducted by European Commission for various natural hazards such as earthquake, volcano, flood and tropical cyclone (Pesaresi et al., 2017). They have monitored the change of exposure using 4 epochs (1975, 1990, 2000 and 2015) at the country level by mapping the built-up area and disaggregating population to built-up grids. In addition to country-level studies, statistics at the local or regional level have also been generated by different studies to assess population and built-up land exposure to natural hazards with higher resolutions (He et al., 2016; Liang et al., 2017; Zhang et al., 2018; Du et al., 2018; Fang et al., 2018; Huang et al., 2019a). In these studies, past and current exposure trends have been

assessed; however, there is a lack of future exposure estimations, especially for built-up area at risk. Statistical projections fail to represent a realistic growth, as they focus only on the temporal aspect, without considering the spatial dimension. Exposure studies can move a step further by utilizing urban growth models that can generate spatio-temporal future predictions for city-level analysis.

Making predictions on exposure has been adopted widely for weather- and climate-related natural hazards (Garcia and Loáiciga, 2013; Hallegatte et al., 2013; Wu et al., 2013; Jones et al., 2015; Sekovski et al., 2015; Veerbeek, 2017). In fact, a case study on future flood risk of Shenzhen (details are given in Appendix A) was conducted as a side project of this dissertation (Mestav Sarica et al., 2018; 2021). On the other hand, except the recently published Mestav Sarica et al. (2020a), there is only one study (Martins et al., 2012), to our knowledge, that evaluates future seismic exposure by investigating the relationship between spatio-temporal urban growth and future disaster risk triggered by earthquakes. However, it focuses more on the implementation of land-use allocation regulations and risk mitigation policies rather than assessment of exposure.

In the following sections, first, the methods for mapping built-up area and modelling urban growth are reviewed. Then, estimation of grid-level wealth information is explained with details on population disaggregation methods, as population is the basis for wealth estimation in this study.

2.3.1 Mapping Built-up Environment

In the context of this study, built-up area (also referred as urban area) technically represents impervious surfaces, which are mainly man-made structures extracted from satellite imagery. Hence, the built-up environment corresponds to areas where there are people, infrastructure, and physical assets, as well as economic activities that are used

to quantify and map disaster risk. These areas have high economic and human loss potentials when they are located in an earthquake-prone region; therefore, several studies have used population, GDP or wealth/asset value exposure in these areas as indicators of possible losses (Wu et al., 2017; Coronese et al., 2019; Huang et al., 2019b).

Earth observation and geographical information systems have been regarded as invaluable tools to assess exposure, due to their modularity and dynamism to give up-to-date information on patterns of urbanization for different scales, from global to the city level (Melchiorri et al., 2018). A significant amount of urban analyses with remote sensing information have provided characterisation of the spatial components of urban areas, for which an extended review is available from Ban et al. (2015). Low and moderate resolution (300 m – 1,000 m spatial resolution) imagery has been used frequently to map global human settlements and detect changes (e.g. Moderate Resolution Imaging Spectroradiometer (MODIS) (Schneider et al., 2009)). In recent years, finer scale imagery (30 m spatial resolution) has also been used extensively (e.g. Global Human Settlement Layer (GHSL) (Pesaresi et al., 2016b)). One limitation of the use of open-source built-up area datasets is their availability for specific years, since it is generally suggested that data from different sources should not be combined in temporal studies. Therefore, this study mapped built-up area for selected years using Landsat image archive (30 m spatial resolution), which has been considered as the most consistent satellite image dataset depicting the surface of the Earth (Pesaresi et al., 2016a).

2.3.2 Urban Growth Modelling

Urban growth dynamics are nonlinear, and their prediction is a highly challenging and complex task. Due to this complexity, several researchers (Bettencourt, 2007; Fragkias

et al., 2017; Sarkar et al., 2018; Finance and Cottineau, 2019) have worked on relations and dependencies between urban indicators in the concept of “Science of Cities”. In fact, one side project of this dissertation, given in Appendix B, investigates the scaling relations between different urban indicators such as GDP, income, patents, and population by using China’s urbanization as a case study. It then compares the urbanization patterns of China and the U.S., since different regions around the world have shown different trends.

On the other hand, the understanding and modeling of geographical systems have evolved from examining aggregate patterns to examining individuals through the lens of complexity science over the last decades (Crooks, 2017). Numerous methods have been used in recent years for urban growth modelling (UGM) such as linear/logistic regression, artificial neural networks, cellular automata, Markov chain, support vector machines, random forests, genetic algorithms and agent-based models. Each of these models has different characteristics and limitations that affect model selection processes. For example, linear/logistic regressions can fail to capture non-linearity in spatial growth, as they are not capable of offering high modelling capabilities (Hu and Lo, 2007). Artificial neural networks have a black box nature, and sometimes create overcomplex structures which result in over-fitting (Almeida et al., 2008). Determining the optimum transition rules is a challenging issue for cellular automata models (Aarthi and Gnanappazham, 2019). Genetic algorithms were observed to be computationally intensive for solution of small-scale problems (Naghbi et al., 2016). The nature of agent-based models may bring high uncertainties due to initial conditions and interaction rules among agents (Matthews et al., 2007). Several recent studies have used some of these methods for global urban growth modelling (Huang et al., 2019b; He et al., 2016; Zhou

et al., 2019), yet the spatial resolutions that were used are coarser than 30 arc-seconds, which can be considered low for city-level analysis.

Among urban growth models, cellular automata (CA)-based models have been regarded as useful and reliable models to study urban theory and urbanization effect, drawing information on the spatio-temporal dynamics of complex systems like cities, due to their flexibility and compatibility with the raster data structure (Batty, 2007; Batty, 2013). A CA model is defined as an arrangement of individual automata, a software representation of a self-contained entity, situated within a regular tessellated space (Crooks, 2017). Each individual cell/grid represents a discrete spatial confine of the automata. An automaton processes inputs from its neighbors and itself, then decides whether to change its own state (urban or non-urban) with programmed instructions. In CA models, grid analysis is done through a spatio-temporal process to set up the spatial relations for the neighbor grids.

The SLEUTH model (Silva and Clarke, 2002), developed by collaboration of the United States Geological Survey (USGS) and the University of California Santa Barbara, in particular has been considered useful for modeling and prediction of future urban scenarios (KantaKumar et al., 2011; Berberoglu, 2016). SLEUTH is the acronym for six types of inputs that the model requires: slope, land use, excluded, urban, transportation and hillshade. It has been widely used for many regions throughout the world, since it is freely available online and able to capture the complex emergence of urban patterns. After comparing several models (i.e. artificial neural networks, Markov chain and regression tree) Berberoglu (2016) found that the SLEUTH model outperforms others. In addition to its robust routine for historical calibration, it has relatively simple simulation rules that are based on the spatial autocorrelation and principles of

neighborhood effects. Moreover, since the outputs are in GIF format, they are suitable for GIS analysis and effective for the visualization of urban growth scenarios.

2.3.3 Estimation of Grid-Level Wealth Information

As suggested by Chan et al. (1997) and Jaiswal and Wald (2011) (details are given in section 2.2.2), wealth is represented by multiplication of GDP per capita, population grids and an exposure correction factor in this dissertation. Therefore, for the estimation of grid-level wealth, and accordingly wealth exposed to seismic hazard, population grids must first be obtained. As an intermediate step before calculating wealth exposed to seismic hazard, population exposed to seismic hazard is also investigated separately within this context.

Among all exposure elements, population has been regarded as the most vital element of risk, since it represents the human dimension (Freire and Aubrecht, 2012). Therefore, it has been acknowledged that the accurate estimation of population exposure is a significant element of effective risk analysis (Chen et al., 2004). Despite the research on exposure and vulnerability increasingly being at the core of disaster studies, the inclusion of socioeconomic metrics into geospatial risk models remains a challenge (Freire and Aubrecht, 2012).

Updated and detailed mapping of population at appropriate spatial and temporal scales is a crucial component of exposure, since its variation is considered as the major driver of seismic risk. Global gridded population databases (e.g. GPW (CIESIN, 2016), WorldPop (Lloyd et al., 2017), LandScan (Rose et al., 2018), etc.) generally have low spatial resolutions, while the satellite images based on remote sensing (e.g. Landsat images) provide relatively high-resolution information about land use and land cover (LULC). Furthermore, expansion in built-up area is not considered by most of the

population databases, which results in the disaggregation of extrapolated census population to the same urban extent for different years. One example data set that takes urban expansion into account for population disaggregation is Global Human Settlement Layer (GHSL) (Pesaresi et al., 2016). However, the spatial resolution of the population grids of GHSL is lower than the Landsat images. Moreover, built-up area grids were obtained for 4 epochs from past, and future predictions are not considered by GHSL.

Spatial population disaggregation, also referred to as dasymetric mapping or intelligent areal interpolation, generally consists of transferring the statistical population values from a coarse administrative-unit level to certain finer spatial grids with ancillary/auxiliary information to obtain population grids. Examples of ancillary information include built-up area maps extracted from building footprints, land use maps, impervious surfaces, night-time lights or road network from remote sensing imagery among which the most widely used one is built-up area maps (Tenerelli et al., 2014). This method is particularly useful for resolving the spatial mismatch between raster-based hazard data and aggregated demographic/economic statistics, which is generally based on census units when it is not possible to collect ad hoc data.

2.4 Gaps in the Literature and Research Contributions

Considering the literature review presented, the research gaps in literature can be summarized as follows:

- Macro-level seismic loss estimation methods are rarely analyzed in the literature, and the research on their integration into probabilistic risk assessment frameworks remains limited.

- While estimation of forthcoming seismic losses with a focus on the future has been briefly addressed in the literature, there is no previous research which has utilized macro-level approaches in this domain.
- Few studies have focused on investigating the relationship between spatio-temporal urban growth and future disaster risk triggered by earthquakes, and no prior study has assessed the dynamics of exposure in terms of built-up area exposed to seismic hazard, population exposed to seismic hazard, and wealth exposed to seismic hazard.

Therefore, this Ph.D. dissertation addresses these gaps and contributes to literature by:

- Proposing an enhanced macro-level approach which can be used for probabilistic seismic risk assessment, utilizing wealth as a proxy of economic condition of a region,
- Developing a systematic multi-step framework to estimate present and future probabilistic risk metrics, average annual loss (AAL) and probable maximum loss (PML), by using the proposed enhanced macro-level approach,
- Assessing spatio-temporal dynamics of exposure at seismic risk by predicting future urban growth utilizing a cellular-automata based urban growth model and dasymetric population mapping.

Chapter 3 Modelling Spatio-Temporal Changes in Exposure of Selected Asian Megacities

3.1 Introduction

This chapter consists of two main sections, which focus on modelling spatio-temporal dynamics of two exposure metrics, built-up area and wealth. The section dedicated to wealth first explains the procedure to obtain present and future population grids as the main indicator used for wealth estimation. In this study, three earthquake-prone megacities from developing countries in Asia, namely Jakarta, Metro Manila and Istanbul, were selected for the case studies due to their rapid urbanization and population growth.

Jakarta megacity (also known as DKI (Daerah Khusus Ibukota) or Special Capital Region of Jakarta) is located at Indonesia's Greater Jakarta metropolitan region, which is a large urban agglomeration with a total area of 651 km² and 10.15 million inhabitants by 2015 (Statistics Indonesia, 2019). Jakarta's population growth was the highest one among the urban areas of East Asia, excluding China between 2000 and 2010 (World Bank, 2018). Its urbanization was so fast that nearly one-quarter of the non-urban land was converted to urban land for industry, commerce, and housing purposes from 1980

to 2002 (World Bank, 2011b). Metro Manila megacity (Metropolitan Manila or Manila) is officially known as the National Capital Region (NCR) in the Philippines. Consisting of 16 cities, it covers an area of 636 km², with a population of around 13 million in 2015 (Philippine Statistics Authority, 2019). Metro Manila has shown a clear densification process with a drastic increase in the shares of high-density areas between 1990 and 2014 (World Bank, 2017). Istanbul, one of the world's most populous cities, has a population of around 15 million (Turkish Statistical Institute, 2019) and an immense administrative area of 5,461 km² by 2018. Its population increased from nearly 3 million to 12 million between 1975 and 2007 due to migration and income growth.

3.2 Mapping Built-up Area

To process the Landsat images (available at <https://earthexplorer.usgs.gov/>), semi-automatic classification plugin (Congedo, 2016) on QGIS was used to extract the past and current built-up land information. During the training of built-up grids for classification, visual interpretation on false color composite displays were used to select pixels which include man-made structures. Local knowledge, actual land use maps (where available) and high-resolution Google Earth images were also utilized as references in this process. For all selected megacities, 1995 was used to represent the past. To represent the present, the built-up area in 2018 was selected for Jakarta and Istanbul, and the built-up area in 2016 was selected for Metro Manila. All selected years, along with the intermediate years which were used as inputs for the urban growth model, are summarized in Table 3.1.

Table 3.1 Selected years for modelling urban growth from past to present

Megacity	Selected Years
Jakarta	1995, 2001, 2006, 2018
Metro Manila	1995, 1999, 2009, 2016
Istanbul	1995, 2005, 2013, 2018

The specific years given in Table 3.1 were selected based on the availability of the Landsat images with less ($< 20\%$) cloud cover. The change of built-up area from the past to present are represented in Figure 3.1, along with other intermediate years. To evaluate the accuracy of the semi-automatic built-up area classification, 100 urban and 100 non-urban classified grids were randomly sampled for each megacity, which were then compared with the reference (ground truth) maps. Overall accuracy values, the ratio of correctly classified grids to all sampled grids, range between 0.8 and 0.9 for the selected megacities, around the suggested accuracy limit of 0.85 (Foody, 2008).

Figure 3.1 Change of built-up area from past to present in: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

3.3 Urban Growth Modelling

The SLEUTH model (Silva and Clarke, 2002) was utilized for the prediction of urban area of Jakarta, Metro Manila and Istanbul in 2030. The background information about the model was given in Chapter 2. It has three modes, namely test mode, calibration mode, and prediction mode (Figure 3.2). Test mode is basically used to check if the inputs are in the right format. This is followed by a three-step calibration mode with the following steps: coarse calibration, fine calibration and final calibration. Following calibration mode, prediction mode computes the probabilities of urbanization in the target prediction year. The details about the calibration and prediction modes are given in the next sections.

Figure 3.2 Flowchart of the SLEUTH model

3.3.1 Inputs of the SLEUTH Model

For the calibration mode of SLEUTH model, at least four urban inputs and two transportation inputs corresponding to different time periods are required for each region. The images must be derived from grids in the same projection, of the same map extent, and with the same resolution and naming format. Raw data, which include a set of Landsat images of four different years, Digital Elevation Models (DEM), OpenStreetMap (OSM) data (available at www.openstreetmap.org) and local historical road network maps, were collected for input processing of selected megacities. Figure 3.1 shows the built-up area (urban) inputs corresponding to the four years selected. In Figure 3.3, other inputs required are shown, using Jakarta as an example. The inputs for Metro Manila and Istanbul are given in Appendix C.

Each grid in the input images is assigned a value from 0 to 255, with 0 representing “null” or “non-existent” and values greater than 0 being “live” or “existent”, that reflects spatial information corresponding to each input. The built-up area inputs are binary images that show urban and non-urban areas at different time periods. Excluded area is defined as the area where urbanization is inhibited. In this study, only water bodies were regarded as fully restricted areas, while other areas were assumed available for urbanization. The latest set of Landsat images was used to produce the excluded input for each region. The slope input presents information of slope steepness for the whole study region in terms of percentage values. The hillshade input is used just as a background image to give spatial context to the urban layers in the model. Transportation input was shown in binary representation, with a value of 1 showing where road exists and a value of 0 showing other areas. The latest OpenStreetMap data were obtained as a base of road information for the current transportation maps. For previous years,

digitization was applied to Landsat TM images with the help of local historical road network maps to reflect the road distributions in the targeted time periods.

Figure 3.3 SLEUTH inputs for Jakarta: (a) Slope, (b) Hillshade, (c) Transportation in 2001, (d) Transportation in 2018, and (e) Excluded

3.3.2 Calibration of the SLEUTH Model

The SLEUTH urban growth model uses four growth rules with five growth coefficients (dispersion, breed, spread, slope and road gravity) to determine characteristics of urbanization in a study region. The growth rules are defined as spontaneous growth, new spreading centre growth, edge growth, and road influenced growth. According to the framework of CA models, any non-urbanized cell has a certain probability of becoming urbanized over time. Spontaneous growth is affected by dispersion and slope coefficients, and it determines whether a random pixel will be urbanized. New spreading center growth, controlled by breed and slope coefficients, determines whether a newly urbanized pixel resulting from spontaneous growth will create a new urban center. Edge growth is observed adjacent to existing urban pixels, and it is affected by the spread and slope coefficients. Finally, the road influenced growth determines the contribution of road network to the urbanization, and it is affected by dispersion, slope, breed and road gravity coefficients.

For each megacity, the growth coefficients are calibrated using Monte Carlo iterations. For Jakarta and Metro Manila, three sets of inputs with different grid size (120 m, 60 m and 30 m) were used at different stages (coarse, fine, and final) of calibration. However, only 90 m grid size was used for all calibration steps of Istanbul, since it has a much larger area. The growth coefficients have values ranging from 0 to 100. Before each calibration stage, different ranges, along with different increments, are defined for each coefficient, and all possible coefficient combinations are tested to obtain the set of best-fit coefficients. These coefficients are then used in the prediction mode to simulate the future urban growth. The purpose of using a three-stage calibration is to reduce computation time by narrowing down the range of coefficients at each calibration run, while increasing the spatial resolution of inputs. During the calibration process, the Lee-

Sallee metric, a shape index for the measurement of spatial match, is calculated for the control years (i.e. urban input years) to obtain the set of best-fit coefficients. This metric is defined in Equation 3.1 as the ratio of the intersection to the union of the actual (reference) built-up area (A) and the simulated built-up area (B) (Lee and Sallee, 1970; Dietzel and Clarke, 2007; Ayazli, 2019):

$$\text{Lee-Sallee metric} = (A \cap B) / (A \cup B) \quad (3.1)$$

Therefore, Lee-Sallee metrics close to 1 suggest a better match while a Lee-Sallee index value between 0.3-0.7 is acceptable (Liu et al., 2019) and a value around 0.6 is considered very good (Jantz et al., 2004). In this study, Lee-Sallee values are around 0.78 for Jakarta, 0.81 for Metro Manila and 0.75 for Istanbul, showing a high degree of match.

The best-fit growth coefficients that were obtained through calibration are represented in Table 3.2. For Jakarta and Metro Manila, spread is the highest coefficient. Therefore, urban expansion is controlled by the spread coefficient and shows edge growth in these megacities. For Istanbul, slope is the highest coefficient, followed by breed and spread. This indicates that Istanbul has shown edge growth and new spreading center growth as defined by the model. These patterns are consistent with the urban expansion shown in Figure 3.1.

Table 3.2 Best-fit growth coefficients obtained by calibration of SLEUTH model

Growth Coefficients	Jakarta	Metro Manila	Istanbul
Diffusion	30	1	1
Breed	9	18	23
Spread	46	32	22
Slope	1	1	42
Road Gravity	19	23	5

3.3.3 Prediction of the Built-up Area in 2030

The prediction mode in the SLEUTH model was run considering the business-as-usual scenario. Starting from the latest year of the urban inputs, the model was set to predict built-up area change on a yearly basis until 2030. Visual representations of the predictions that show different probabilities of urbanization corresponding to each grid were obtained as GIF images shown in Figure 3.4. In these images, yellow grids represent urban land in the seed year (2016 for Metro Manila, and 2018 for Jakarta and Istanbul), red grids represent the grids with 95%-100% probability of urbanization, and shades of green represent probability of urbanization from 50% to 95%.

For Jakarta and Metro Manila, which are relatively smaller cities, the ratio of built-up area to total area is much higher for the seed years, as compared with Istanbul, where there is abundant land within the city limit available for future urbanization. It was predicted that, except the small areas with high slope values, nearly the entire administrative region of Jakarta and almost 80% of Metro Manila will get urbanized by 2030, as indicated by the red grids, which have higher probabilities of urbanization. Istanbul, on the other hand, has more land for future urbanization in the north, away from the southern coast. As a result, future urbanization of Istanbul is predicted to occur northwards and westwards due to new infrastructure developments, as well as around the edge of its city center, as opposed to the more homogenously spreading of urbanized areas in Jakarta and Metro Manila. Moreover, the probabilities of urbanization are lower which is due to Istanbul's longer historical settlement around the city center.

Probability of Urbanization (%)	50-60	60-70	70-80	80-90	90-95	95-100	Urban Extent in Seed Year

Figure 3.4 SLEUTH urban growth predictions with different probabilities of urbanization for 2030 in: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

After computing the probability of urbanization in 2030 for each grid, two different approaches were followed in this study for the estimation of future built-up area. In Approach I, a 50% probability of urbanization threshold was assumed to obtain the binary urban/non-urban maps in 2030. In other words, the contribution of each grid that has a probability higher than 50% is equal to the grid area (e.g. 900 m² for one grid in Jakarta). Therefore, grids with probabilities higher than this threshold are assigned as built-up grids which are then aggregated to calculate the total built-up area in 2030. Following this approach, the urban expansion from 1995 to 2030 is illustrated in Figure 3.5(a) - 3.5(c) for the three selected megacities. In Approach II, the total built-up area is weighted with urbanization probabilities. For example, a grid with an 80% probability of urbanization is assumed to have 80% of the grid area (e.g. 0.8×900 m² for one grid in Jakarta). In Table 3.3, the results obtained by following the two approaches, along with built-up areas in 1995, 2016/2018 are presented. For ease of subsequent discussions, Period I and Period II refer to 1995-2016 and 2016-2030, respectively, for Metro Manila and refer to 1995-2018 and 2018-2030, respectively, for Jakarta and Istanbul.

Table 3.3 Total and built-up areas following Approach I (using 50% threshold) and Approach II (using weighted area) for Period I and Period II

Megacity	Total Area, km ²	Built-up Area, km ² (Ratio to Total Area)			
		1995	2016	2018	2030
					Approach I Approach II
Jakarta	651	344 (52.8%)	-	517 (79.4%)	622 (95.5%) 606 (93%)
Metro Manila	636	304 (47.8%)	427 (67.1%)	-	500 (78.6%) 493 (77.5%)
Istanbul	5,461	760 (13.9%)	-	1,195 (21.9%)	1,340 (24.5%) 1,358 (24.9%)

Figure 3.5 Change in built-up area from 1995 to 2016/2018 and 2030 in: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

Since the results corresponding to Approach I and Approach II do not differ significantly, results of Approach I is utilized in the next chapter (Chapter 4) for further calculations. The main reason for obtaining similar values in Approach I and Approach II is the distribution of newly urbanized areas with respect to the probabilities of urbanization which is illustrated in Figures 3.6(a) - 3.6(c). The bars shown in orange represent the newly urbanized areas in Approach I; thus, only probabilities higher than 50% are shown. For Jakarta and Metro Manila, there is a concentration above 70% probability of urbanization. For Istanbul, although the number of cells corresponding to lower ($< 50\%$) urbanization probabilities are higher, their contribution to total weighted area is almost compensated by the difference between orange and blue bars.

The results of the urban growth modelling reveal a drastic increase from past to present (i.e. in Period I) for all three megacities, and a similar trend is predicted for the future (i.e. in Period II) as well. The administrative areas of Jakarta, Metro Manila, and Istanbul are 651 km², 636 km² and 5,461 km², respectively, as shown in Table 3.3. For Jakarta, it was observed that the urban area had increased from 344 km² (52.8%) to 517 km² (79.4%) in Period I, with a prediction of 622 km² (95.5%) in Approach I and 606 km² (93%) in Approach II by 2030, when the entire city is almost completely urbanized. The increase in built-up area in Metro Manila is also prominent, since the built-up area had increased from 304 km² (47.8%) to 427 km² (67.1%) in Period I and is predicted to reach 500 km² (78.6%) in Approach I and 493 km² (77.5%) in Approach II in Period II. For Istanbul, there was an increase from 760 km² (13.9%) to 1,195 km² (21.9%) in Period I. Moreover, this number is predicted to reach 1,340 km² (24.5%) in Approach I and 1,358 km² (24.9%) in Approach II by 2030, when its built-up area would be almost doubled from 1995 to 2030 with urbanization towards the northern and western regions, corresponding to new infrastructure developments.

(a)

(b)

(c)

Figure 3.6 Newly urbanized area (km²) vs. probability of urbanization distribution for: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

Table 3.4 shows that, over the 35-year study period between 1995 and 2030, the increase of built-up area in ascending order is: 196 km² (Approach I) and 189 km² (Approach II) for Metro Manila, 278 km² (Approach I) and 262 km² (Approach II) for Jakarta, and 580 km² (Approach I) and 598 km² (Approach II) for Istanbul. In other words, Istanbul is predicted to add a built-up area larger than today's Jakarta or Metro Manila over the 35-year study period.

Table 3.4 also indicates that the annual growth rate of Period I (ranging from 1.6% to 2.0%) is generally higher than that of Period II (ranging from 1.0% to 1.6%) for the three megacities. Therefore, the pace of urbanization is predicted to slow down in Period II in all cities, and there is a nonlinear growth trend from Period I to Period II. For Period I, the highest annual growth rate belongs to Istanbul (2.0%) while Jakarta's annual growth rate (1.6% in Approach I and 1.3% in Approach II) ranks highest for Period II. When the difference between two annual growth rates corresponding to two periods is considered, the highest decrease is observed in Istanbul from 2.0% to 1.0% in Approach I and 1.1% in Approach II. However, it must be noted again here that the predictions are made considering the business-as-usual scenario. Thus, significant new infrastructural developments might affect the built-up area predictions and growth rates.

Table 3.4 Increase in built-up area following Approach I (using 50% threshold) and Approach II (using weighted area) for Period I and Period II

Megacity	Increase in Built-up Area, km² (Annual Growth Rate)		
	Period I	Period II (Approach I)	Period II (Approach II)
Jakarta	173 (1.8%)	105 (1.6%)	89 (1.3%)
Metro Manila	123 (1.6%)	73 (1.1%)	66 (1.0%)
Istanbul	435 (2.0%)	145 (1.0%)	163 (1.1%)

3.3.4 Model Validation

For the validation of the urban growth model performance in each city, a quantitative measurement called the Receiver (also known as Relative) Operating Characteristic (ROC) was used by comparing the modelled built-up area maps and observed (ground truth) built-up area maps. The prediction year was selected as 2019 for all selected megacities as it was not included in the inputs during calibration. Using the best-fit growth coefficients, the transformation of cells' states (urban or non-urban) from the prediction start date to 2019 was simulated. The prediction start date for Jakarta and Metro Manila was selected as the second last urban input date (2006 for Jakarta and 2009 for Metro Manila). However, the start date for Istanbul was selected as the last urban input date (2018) due to recent substantial infrastructural developments (e.g. new airport) in the northern Istanbul. ROC curves were obtained by plotting false positive rates ($\text{False Alarms}/(\text{False Alarms} + \text{Correct Rejections})$) vs. true positive rates ($\text{Hits}/(\text{Hits} + \text{Misses})$), assigning different probability of urbanization values as thresholds to make a binary classification of grids as urban and non-urban (Figure 3.7). Then, the area under the curve (AUC) values were calculated as 0.72, 0.70 and 0.91 for Jakarta, Metro Manila and Istanbul, respectively. As the prediction time range is narrow and number of correct rejections is high due to large administrative area of Istanbul, a higher AUC is obtained as expected. An AUC value higher than 0.5 represents a model which is better than random. Since all of the values are higher than 70%, the model performances are considered successful (Wu et al., 2009).

Figure 3.7 Receiver Operating Characteristics (ROC) curves for selected megacities

3.4 Estimation of Present and Future Population and Wealth Grids

3.4.1 Extrapolation of Census Data

To estimate grid-level wealth information, first the population grids corresponding to present and future were obtained using dasymetric mapping. For this purpose, population data were collected for Level 2 administrative boundaries (i.e. 5 regions in Jakarta, 17 cities in Metro Manila and 39 districts in Istanbul) from Statistics Indonesia for Jakarta, Philippine Statistics Authority for Metro Manila and Turkish Statistical Institute for Istanbul. Census data are available for the regions in Jakarta and cities in Metro Manila, and annual population data from the address-based population registration system are available for the districts in Istanbul. For the estimation of present population, the latest Admin Level 2 populations were extrapolated to 2018 for regions in Jakarta and to 2016 for cities in Metro Manila using their average annual growth rates

between 2010-2015. Population data of districts in Istanbul are already available for 2018. The megacity-level aggregated population values corresponding to present are denoted as P_0 for the rest of the discussions.

To predict the population in 2030 for each megacity, the census data was extrapolated using linear regression. Before the extrapolations, the growth trends of individual Admin Level 2 populations and the availabilities for urbanization were scrutinized. It was observed that there is one district in Istanbul (i.e. Esenyurt) which has shown a drastic population increase (around 0.5 million) in 10 years (Figure 3.8) due to its gentrification process. Since it does not currently have an available area for further urban expansion, its growth trend was not included in the linear regression. The total populations of Jakarta, Metro Manila and Istanbul were then predicted to be around 12 million, 15.5 million and 17.6 million by 2030, denoted as P_1 for the rest of calculations. Table 3.5 shows megacity-level population data collected for the available years, along with further projections representing the present and future. In Table 3.5, P_0 values are shown in blue and P_1 values are shown in red.

Figure 3.8 Population growth trends of districts (Admin Level 2) in Istanbul

Table 3.5 Population data and projections for 2030 (**P₀** in blue and **P₁** in red)

Years	Population		
	Jakarta	Metro Manila	Istanbul
1995	-	9,449,000	-
2000	8,385,600	9,931,000	-
2005	8,840,000	-	-
2007	-	11,548,000	-
2008	-	-	12,697,164
2009	-	-	12,915,158
2010	9,640,000	11,855,000	13,255,685
2011	-	-	13,624,240
2012	-	-	13,854,740
2013	-	-	14,160,467
2014	-	-	14,377,018
2015	10,150,000	12,878,000	14,657,434
2016	-	13,078,941	14,804,116
2017	-	-	15,029,231
2018	10,491,063	-	15,067,724
2030	11,995,840	15,479,147	17,632,929

It is worth noting here that actual populations in the selected cities might be different from the census numbers due to unregistered people living in informal settlements. Especially in Jakarta and Metro Manila, it is not clear if the total number of people living in slums are taken into consideration in the census counts. While the urban slum population in Jakarta is estimated to be around 1.2-1.5 million for 2018 (Statistics Indonesia, 2021), Metro Manila had around 2.4-4 million informal settlers in 2016 (United Nations, 2016; The Rockefeller Foundation, 2016). For Istanbul, the address-based population registration system provides more accurate numbers while around 28 thousand unregistered migrants were reported in 2018 (Asylum Information Database, 2020).

3.4.2 Population Disaggregation

For the disaggregation of present population, the approach in the European Commission's Global Human Settlement Layer (GHSL) framework was utilized (Pesaresi et al., 2016b). Therefore, population counts in each Admin Level 2 boundary were divided to the total number of built-up area grids in 2016 for Metro Manila and in 2018 for Jakarta and Istanbul (represented in Figure 3.1) to calculate the present average population density as represented in Figures 3.9, 3.10 and 3.11.

The maps showing probabilities of urbanization in 2030 (Figure 3.4) were used as ancillary data for dasymetric mapping in disaggregation of extrapolated census population in the next steps. Several assumptions were made in this multi-step process:

- i. To allocate the people to newly urbanized grids in 2030, it is first assumed that the population densities of newly urbanized grids in 2030 will not exceed the average population densities of present urban grids (2016 for Metro Manila and 2018 for Jakarta and Istanbul) in the same Admin Level 2 boundary. For example, a newly urbanized grid with 80% probability of urbanization in 2030 will have a value of 80% of the population in a present (2016/2018) urban grid in the same boundary.
- ii. After calculating Admin Level 2 population densities following the first assumption, the aggregated populations in 2030, denoted as P_2 , were calculated. It was observed that P_2 values of Istanbul and Metro Manila are lower than P_1 (population values that are projected by linear regression for 2030). Thus, all grids were scaled up by multiplying their population densities by P_1/P_2 .

- iii. A different approach was employed for Jakarta since the P_2 value is slightly higher than P_1 . Hence, only the population of newly urbanized grids were scaled down by multiplying them by $(P_1 - P_0)/(P_2 - P_0)$, under the assumption that the population density of present urban grids cannot decrease in the future.

Figures 3.9, 3.10 and 3.11 show present and future population density maps after disaggregation via dasymetric mapping technique. In these figures, population grid size is 30 m for Jakarta and Metro Manila, and 90 m for Istanbul. As a result of the assumptions made during dasymetric mapping, newly urbanized grids have different population values within the same Admin Level 2 boundaries, which can be identified with the colder color shades in 2030. Following these assumptions and the normalization process, present population densities in Jakarta do not change from 2018 to 2030, except for the newly urbanized grids (Figure 3.9). On the other hand, the population densities of Metro Manila and Istanbul have increased from present to future for all urban grids (Figures 3.10 and 3.11). Since the present population densities were scaled up during normalization, there is a higher increase for already urban grids with higher population density values in Metro Manila and Istanbul. However, only several cities in Metro Manila (in northern and central regions) and districts in Istanbul (in central and southeastern regions) have shown changes in color, mainly due to the population ranges defined for these maps.

Figure 3.9 Population density maps representing present (2018) and future (2030) exposure for regions in Jakarta (30 m grids)

Figure 3.10 Population density maps representing present (2016) and future (2030) exposure for cities in Metro Manila (30 m grids)

Figure 3.11 Population density maps representing present (2018) and future (2030) exposure for districts in Istanbul (90 m grids)

3.4.3 Estimation of Grid-Level Wealth Information

To estimate present and future grid-level wealth information, corresponding population grids were multiplied with GDP per capita and an exposure correction factor, α . The details about the exposure correction factor are given in Section 2.2.2. It is basically defined as the ratio of wealth per capita to GDP per capita in PAGER report (Jaiswal and Wald, 2011). Therefore, wealth grids were obtained by multiplying GDP grids with PAGER's country-level exposure correction factors given in Table 3.6.

Present (2016 for Metro Manila and 2018 for Jakarta and Istanbul) nominal GDP per capita values were obtained from World Bank Data. The real GDP per capita predictions in 2030 (in 2010 prices) were collected from the United States Department of Agriculture (USDA), International Macroeconomic Data Sets (available at www.ers.usda.gov). Then, the real GDP per capita in 2030 was converted from 2010 prices to 2016/2018 prices using the price index (i.e. current GDP/real GDP) from World Bank Data. The main aim of using open-source country-level data is to make our approach employable by any region, without the need for local data which would require using fluctuating exchange rates for currency conversions especially in developing countries. Moreover, future predictions and price indices are generally reported at the country-level; therefore, present and future figures can be compared if country-level data is used. However, it should be noted that different values might be obtained if megacity-level GDP per capita values are utilized, especially for highly industrial areas (Jaiswal and Wald, 2011). It is also worth noting that future GDP per capita projections are subjected to change following fluctuations in economy. For example, the SARS-CoV-2 pandemic will certainly affect USDA projections for 2030. Table 3.6 summarizes GDP per capita values in 2016 prices for Metro Manila and in 2018 prices for Jakarta and Istanbul, along with exposure correction factors. In addition to this, megacity-level GDP

per capita values from national statistics yearbooks are given in Table 3.7 along with the ratios to country-level GDP per capita values. These ratios could be directly multiplied with the population grids to obtain the GDP grids based on megacity-level data. It should be noted here that the exchange rate in Istanbul has fluctuated between 3.74 and 6.76 within 2018 alone.

Table 3.6 GDP per capita (country-level) in 2016/2018 and 2030 along with the exposure correction factor α for each selected country

Country	GDP per capita (USD) (2016/2018 prices)			Exposure Correction Factor, α
	2016	2018	2030	
Indonesia	-	3,894	6,543	17.25
The Philippines	2,941	-	5,113	19.80
Turkey	-	9,370	12,833	11.93

Table 3.7 GDP per capita (megacity-level) in 2016/2018 along with the ratio to country-level GDP per capita

Megacity	Megacity-level GDP per capita (USD)		Ratio of megacity-level to country-level GDP per capita
	2016	2018	
Jakarta	-	17,109	4.39
Metro Manila	9,306	-	3.16
Istanbul	-	12,941	1.38

Each population grid shown in Figures 3.9, 3.10 and 3.11 are multiplied with their corresponding GDP per capita and exposure correction factor from Table 3.6 to obtain grid-level wealth maps illustrated in Figures 3.12, 3.13 and 3.14. These figures indicate

that the wealth increase of each grid has shown different trends, while newly urbanized grids in future wealth maps have lower values within the same Admin Level 2 boundary following our urban expansion and population disaggregation process using dasymetric mapping. These wealth maps are used to assess spatio-temporal changes in wealth exposed to seismic hazard and macro-level seismic loss estimations in the next Chapters.

Figure 3.12 Grid-level wealth maps representing present (2018) and future (2030) exposure for regions (Admin Level 2) in Jakarta (30 m grids)

Figure 3.13 Grid-level wealth maps representing present (2016) and future (2030) exposure for cities (Admin Level 2) in Metro Manila (30 m grids)

Figure 3.14 Grid-level wealth maps representing present (2018) and future (2030) exposure for districts (Admin Level 2) in Istanbul (90 m grids)

Chapter 4 Assessment of Spatio-Temporal Dynamics of Seismic Exposure in Selected Asian Megacities

4.1 Introduction

According to Pesaresi et al. (2017), the best way to understand impacts of natural hazards is to cross hazard data with settlement information. In the scope of this dissertation, settlement information represents built-up area and wealth. In this chapter, classical probabilistic seismic hazard analysis (PSHA) is used to obtain probabilistic seismic hazard maps with 10% and 2% probability of exceedance in 50 years for the selected Asian megacities, namely Jakarta, Metro Manila, and Istanbul. Then, the exposure maps obtained in Chapter 3 are overlaid with seismic hazard maps to assess dynamics of spatio-temporal change in built-up area exposed to seismic hazard (Mestav Sarica et al., 2020a), population exposed to seismic hazard (Mestav Sarica et al., 2020b) and wealth exposed to seismic hazard in terms of the Modified Mercalli Intensity (MMI) scale.

Jakarta and Metro Manila are located on the Pacific Ring of Fire, the region around the Pacific Ocean with high volcanic and seismic activity. The Southeast Asia region has been exposed to several destructive earthquakes in its history, and two major destructive

earthquakes in 2018, namely the Lombok (M_w 7) and Palu (M_w 7.4) earthquakes in Indonesia. In addition to thousands of severely injured people and damaged houses, the Lombok and Palu earthquakes resulted in 564 and 2,081 total casualties, respectively (Asrurifak et al., 2018). Istanbul, situated along both sides of the Bosphorus Strait, has been exposed to high levels of earthquake ground motion dating back to 1,500s, due to its location within an active seismogenic region. It has been the focus of recent risk studies, especially after the devastating Kocaeli (M_w 7.6) and Duzce (M_w 7.2) earthquakes in 1999. The western segment of the North Anatolian Fault under the Marmara Sea has often been associated with the terms such as “last domino” or “seismic gap” as researchers reckon with a high-magnitude earthquake in this region in the near future (Erdik et al., 2003; Geli et al., 2018).

4.2 Probabilistic Seismic Hazard Analysis (PSHA)

Classical probabilistic seismic hazard analysis (PSHA) was used on the OpenQuake Engine (available at www.globalquakemodel.org), the software for seismic hazard and risk assessments developed by the Global Earthquake Model (GEM) Foundation (Pagani et al., 2014), to obtain the peak ground acceleration (PGA) maps for Jakarta, Metro Manila and Istanbul with 10% and 2% probabilities of exceedance in 50 years. The Earthquake Model of Continental Southeast Asia (2018) (Chan et al., 2017), developed by the Earth Observatory of Singapore at Nanyang Technological University in Singapore, was utilized for Jakarta and Metro Manila, while the Earthquake Model of Middle East (EMME14) (Giardini et al., 2016) by European Facilities for Earthquake Hazard and Risk (EFEHR) was used for Istanbul. Site amplification effect has been incorporated for the PGA estimates using the slope-based V_{S30} data (at 30 arc-seconds resolution) from the U.S. Geological Survey Database (Wald and Allen, 2007). V_{S30} is

the time-averaged shear wave velocity of surface soils down to 30 m, and it has been regarded as a key index to account for seismic site conditions (Worden et al., 2015). The spatial resolution of PGA maps are also 30 arc-seconds (approximately 1 km at the equator), and they were resampled to match the spatial resolution of exposure grids (90 m for Istanbul and 30 m for both Jakarta and Metro Manila) before the overlaying process.

The seismic hazard maps for 10% and 2% probabilities of exceedance in 50 years are shown in Figures 4.1(a) - (f) for the three megacities. It was observed from the seismic hazard maps that PGA values for Jakarta range between 0.34-0.44 g and 0.64-0.76 g for 10% and 2% probabilities of exceedance in 50 years, respectively. For Metro Manila, PGA values are comparatively higher, ranging between 0.55-0.71 g and 0.94-1.16 g for 10% and 2% probabilities of exceedance in 50 years, respectively. This is largely due to the Valley Fault, located in the eastern part of the Metro Manila (the red zone in Figure 4.1(d)). In particular, for the hazard map of 2% probability of exceedance in 50 years, the impact of the Valley Fault is significant and shows an extremely high hazard along this fault. The PGA range is wider for Istanbul, having a larger area, when compared with the other two megacities, with 0.19-0.56 g and 0.36-0.95 g for 10% and 2% probabilities of exceedance in 50 years, respectively.

The PGA values shown in Figures 4.1(a) - 4.1(f) reflect the spatial variations of ground motions in a wider range. However, it is more convenient to correlate seismic damage potential of buildings with ground motions expressed in terms of the Modified Mercalli Intensity (MMI) Scale. The PGA values were thus converted to the MMI Scale according to the ranges shown in Table 4.1 (Wald et al., 1999). In Table 4.1, only MMI scales higher than V are shown for this study. It could be observed for urbanized areas that the PGA values for 10% probability of exceedance in 50 years fall into intensity

levels VII and VIII for both Jakarta and Istanbul, and VIII and IX for Metro Manila. For 2% probability of exceedance in 50 years, Jakarta and Istanbul have higher intensity levels VIII and IX, while Metro Manila has only a very high intensity level IX.

Figure 4.1 Seismic hazard maps for: (a) 10% probability of exceedance in 50 years in Jakarta, (b) 2% probability of exceedance in 50 years in Jakarta, (c) 10% probability of exceedance in 50 years in Metro Manila, (d) 2% probability of exceedance in 50 years in Metro Manila, (e) 10% probability of exceedance in 50 years in Istanbul, and (f) 2% probability of exceedance in 50 years in Istanbul

Table 4.1 Ranges of ground motion for the Modified Mercalli Intensity (MMI) Scale (Adapted from Wald et al., 1999)

Potential Damage	Very Light	Light	Moderate	Moderate/Heavy	Heavy	Very Heavy
PGA (%g)	3.9-9.2	9.2-18	18-34	34-65	65-124	>124
MMI	V	VI	VII	VIII	IX	X+

4.3 Integration of Exposure and Seismic Hazard Maps

4.3.1 Spatio-Temporal Dynamics of Built-up Area Exposed to Seismic Hazard

After all built-up area maps were obtained following Approach I in Chapter 3, they were overlaid with seismic hazard maps in terms of the MMI scale to obtain the built-up area exposed to varying degrees of seismic hazard. The results for the three megacities in terms of the built-up area exposed to seismic hazard and its ratio out of the total built-up area are summarized in Table 4.2. The results are also shown by bar charts in Figures 4.2(a) - 4.2(c) for 10% and 2% probabilities of exceedance in 50 years, respectively. As a result of the slower urbanization rates in Period II, it was observed that the annual growth rates are lower for all MMI levels in Period II when compared with Period I.

For 10% probability of exceedance in 50 years, almost the entire built-up area of Jakarta belongs to MMI VIII (moderate/heavy), as shown in Figure 4.2(a). The built-up area corresponding to MMI VIII had increased from 342 km² by 167 km² (i.e. 48.8%) to 509 km² in Period I and predicted to increase further by 102 km² (i.e. 20.0%) to 611 km² in Period II. In short, for Jakarta, the urban area subjected to MMI VIII has increased nearly 79% over 35 years. For Metro Manila, the majority of built-up area is at MMI VIII level. A drastic increase was observed over the built-up areas in Metro Manila for both MMI VIII (moderate/heavy) and MMI IX (heavy) in Period I and Period II, as shown in Figure

4.2(b). The results show that the built-up area for MMI VIII has increased from 241 km² by 104 km² (i.e. 43.2%) to 345 km² in Period I and further by 61 km² (i.e. 17.7%) reaching 406 km² in Period II. Moreover, the built-up area corresponding to MMI IX has increased from 63 km² by 19 km² (i.e. 30.2%) to 82 km² in Period I and further by 12 km² (i.e. 14.6%) to 94 km² in Period II. In summary, for Metro Manila, the total urban area subjected to moderate/heavy and heavy levels MMI VIII and IX has increased nearly 65% over 35 years. Istanbul has a substantial built-up area in both MMI VII (moderate) and MMI VIII (moderate/heavy), as shown in Figure 4.2(c). While the built-up area for MMI VII has increased from 99 km² by 174 km² (i.e. 1.8 times) to 273 km² in Period I and further by 47 km² (i.e. 17.2%) to 320 km² in Period II, the built-up area for MMI VIII has increased from 661 km² by 261 km² (i.e. 39.5%) to 922 km² in Period I and further by 98 km² (i.e. 10.6%) to 1,020 km² in Period II. Thus, the total urban area subjected to moderate/heavy level MMI VIII has increased nearly 54% over 35 years in Istanbul.

For 2% probability of exceedance in 50 years, the majority of built-up area of Jakarta belongs to MMI IX (heavy), as shown Figure 4.2(a). The built-up area corresponding to MMI VIII (moderate/heavy) has grown 2.5 times from 14 km² to 35 km² in Period I and further increased to 46 km² in Period II. For MMI IX, it has increased from 330 km² to 482 km² by 152 km² (i.e. 46%) in Period I, and further increased by 94 km² (i.e. 20%) to reach 576 km² in Period II. In summary, for Jakarta, the urban area subjected to moderate/heavy and heavy levels has increased nearly 80% over 35 years. In Metro Manila, the entire urban area is at the heavy level MMI IX for 2% probability of exceedance, as shown in Figure 4.2(b). Therefore, the total urban area subjected to MMI IX has increased nearly 65% over 35 years. For Istanbul, the built-up land corresponding to MMI IX has increased from 565 km² to 764 km² by 199 km² (i.e. 35%) in Period I

and further increased by 76 km² (i.e. 10%) to reach 840 km² in Period II, as shown in Figure 4.2(c). For MMI VIII, the urban land has increased from 195 km² to 431 km² by 236 km² (i.e. 1.2 times) in Period I, with a prediction to reach 500 km² by increasing 69 km² (i.e. 16%) in Period II. Thus, the total urban area subjected to moderate/heavy and heavy levels has increased nearly 76% over 35 years in Istanbul.

Table 4.2 also shows that there is a decrease in annual growth rates from Period I to Period II for all of megacities, as expected following the nonlinear urbanization trends given in Chapter 3. It is worth noting that the annual growth rates of built-up area corresponding to different MMI levels show different trends within the same city. For example, annual growth rates corresponding to MMI VII and MMI VIII have decreased from 4.5% to 1.3% and 1.5% to 0.8%, respectively, from Period I to Period II for 10% probability of exceedance in Istanbul. These values also differ from the annual growth rates of the whole built-up area in Istanbul (Table 3.4) which are 2.0% and 1.0% for Period I and Period II, respectively. Therefore, when compared with the growth of the whole built-up area for 10% probability of exceedance in Istanbul, the growth of the built-up area exposed to MMI VII is faster and the growth of the built-up area exposed to MMI VIII is slower for both periods. These findings confirm the necessity of using spatio-temporal approaches for quantification of future seismic exposure.

Table 4.2 Dynamics of built-up area along with annual growth rates for different MMI levels at 10% and 2% probabilities of exceedance in 50 years

		MMI	Built-up Area, km ²				Increased Area, km ²		Annual Growth Rate, %	
			1995	2016	2018	2030	Period I	Period II	Period I	Period II
10% probability of exceedance in 50 years	Jakarta	VII	2	-	8	11	6	3	6.2	2.7
		VIII	342	-	509	611	167	102	1.7	1.5
	Metro Manila	VIII	241	345	-	406	104	61	1.7	1.2
		IX	63	82	-	94	19	12	1.3	1.0
	Istanbul	VII	99	-	273	320	174	47	4.5	1.3
		VIII	661	-	922	1,020	261	98	1.5	0.8
2% probability of exceedance in 50 years	Jakarta	VIII	14	-	35	46	21	11	4.1	2.3
		IX	330	-	482	576	152	94	1.7	1.5
	Metro Manila	IX	304	427	-	500	123	73	1.6	1.1
	Istanbul	VIII	195	-	431	500	236	69	3.5	1.2
		IX	565	-	764	840	199	76	1.3	0.8

(a) Jakarta

(b) Metro Manila

(c) Istanbul

Figure 4.2 Built-up area exposed to seismic hazard (km²) for 10% and 2% probabilities of exceedance in 50 years: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

4.3.2 Spatio-Temporal Dynamics of Wealth Exposed to Seismic Hazard

To obtain the dynamics of wealth exposed to seismic hazard, first, the dynamics of population exposed to seismic hazard is scrutinized in this Chapter, since population is the base information for calculating wealth grids. Population density maps obtained in Chapter 3 were overlaid with seismic hazard maps in terms of MMI scale to obtain the population exposed to varying degrees of seismic hazard. The present and future population exposure for 10% and 2% probabilities of exceedance in 50 years are summarized in Table 4.3. The change in population exposure from present to future is also illustrated with bar charts in Figures 4.3(a) - 4.3(c). As discussed above, 2018 is used to represent the present for Jakarta and Istanbul, while 2016 is used for Metro Manila due to data availability.

For 10% probability of exceedance, most of the people in these three megacities are subjected to MMI VIII (moderate/heavy) level, while Metro Manila has population exposure to MMI IX (heavy) as well. The number of people exposed to MMI VIII is predicted to increase from 10.33 million to 11.80 million for Jakarta by 1.5 million (i.e. 14%), and from 13.18 million to 15.2 million by 2.02 million (i.e. 15%) for Istanbul from 2018 to 2030. For MMI VIII and MMI IX levels in Metro Manila, total population is predicted to increase from 13.08 million (10.36 million at MMI VIII and 2.72 million at MMI IX) to 15.48 million (12.32 million at MMI VIII and 3.16 million at MMI IX) by 2.4 million (i.e. 18%) from 2016 to 2030. The number of people subjected to MMI VII (moderate) level is predicted to show a slight increase from 0.16 million to 0.20 million in Jakarta, whereas there is a higher increase from 1.88 million to 2.43 million in Istanbul.

For 2% probability of exceedance, Istanbul and Jakarta are exposed to two MMI levels, namely MMI VIII (moderate/heavy) and MMI IX (heavy potential damage), while Metro Manila has only MMI IX (heavy) level as discussed above. Therefore, total population of Metro Manila is exposed to MMI IX level, with an increase from 13.08 million to 15.48 million predicted from 2016 to 2030. For Jakarta, 10.49 million people are exposed to MMI VIII (0.69 million) and MMI IX (9.8 million) levels, which is predicted to reach around 12 million (0.84 million at MMI VIII and 11.16 million at MMI IX) with an increase of 1.51 million (i.e. 14%) by 2030. For Istanbul, an increase of 2.56 million (i.e. 17%) from 15.07 million (3.99 million at MMI VIII and 11.07 million at MMI IX) to 17.63 million (4.95 million at MMI VIII and 12.68 million at MMI IX) is predicted for MMI VIII and MMI IX levels, respectively, from 2018 to 2030.

Table 4.3 Dynamics of population exposure (in million) from present to future for different MMI levels at 10% and 2% probabilities of exceedance in 50 years

	MMI	Population (in million)					
		Jakarta		Metro Manila		Istanbul	
		2018	2030	2016	2030	2018	2030
10% probability of exceedance in 50 years	VII	0.16	0.20	-	-	1.88	2.43
	VIII	10.33	11.80	10.36	12.32	13.18	15.20
	IX	-	-	2.72	3.16	-	-
2% probability of exceedance in 50 years	VIII	0.69	0.84	-	-	3.99	4.95
	IX	9.80	11.16	13.08	15.48	11.07	12.68

(a) Jakarta

(b) Metro Manila

(c) Istanbul

Figure 4.3 Population exposure to different MMI levels for 10% and 2% probabilities of exceedance in 50 years: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

The increase in population exposure and the annual growth rates for different MMI levels are summarized in Table 4.4. Considering the higher hazard that consist of both MMI VIII and MMI IX levels, the predicted increases in population values by 2030 are, in descending order, 2.38 million in Metro Manila, 2.02 million for Istanbul and 1.5 million in Jakarta for 10% probability of exceedance in 50 years. For 2% probability of exceedance in 50 years, Istanbul shows the highest increase in population exposed to MMI VIII and MMI IX (2.57 million), followed by Metro Manila (2.4 million) and Jakarta (1.36 million). Although Istanbul's present population (~17.6 million) is relatively higher than Metro Manila (~15.5 million), the predicted increase in population exposed to MMI IX (for 2% probability of exceedance in 50 years) is higher in Metro Manila when compared with Istanbul. Similar to the annual growth rates of built-up area exposed to different MMI levels, population growth rates are also different in each MMI level within the same city as expected from spatio-temporal analysis.

Table 4.4 Changes in population exposure (in million) and annual growth rates (%) for different MMI levels at 10% and 2% probabilities of exceedance in 50 years

		Change in Population from Present to Future (in million)		
		(Annual Growth Rate)		
	MMI	Jakarta	Metro Manila	Istanbul
10% probability of exceedance in 50 years	VII	0.04 (1.9%)	-	0.55 (2.2%)
	VIII	1.5 (1.1%)	1.94 (1.2%)	2.02 (1.2%)
	IX	-	0.44 (1.1%)	-
2% probability of exceedance in 50 years	VIII	0.15 (1.7%)	-	0.96 (1.8%)
	IX	1.36 (1.1%)	2.4 (1.2%)	1.61 (1.1%)

Following the population exposed to seismic hazard calculations, wealth exposed to seismic hazard was calculated, by multiplying present and future country-level GDP per capita and the exposure correction factor (wealth per capita/GDP per capita) with corresponding present and future populations exposed to seismic hazard. The details about exposure correction factor are given in Chapter 2. Therefore, the wealth at seismic risk values are basically the scaled (with GDP per capita and exposure correction factor) versions of present and future population exposure values. In Table 4.5, the changes in wealth (in 2016 prices for Metro Manila and in 2018 prices for Jakarta and Istanbul) exposed to seismic hazard corresponding to different MMI levels from present to future are summarized. Moreover, the bar charts showing the changes are presented in Figures 4.4(a) - 4.4(c) for 10% and 2% probabilities of exceedance. It is worth noting here again that these figures are calculated using country-level metrics; therefore, different numbers would be obtained when local data is integrated (using a bottom-up approach) for finer scale analysis.

Table 4.5 Changes in wealth exposure (in billion USD) from present to future for different MMI levels at 10% and 2% probabilities of exceedance in 50 years

	MMI	Wealth (in billion USD)					
		Jakarta (in 2018 prices)		Metro Manila (in 2016 prices)		Istanbul (in 2018 prices)	
		2018	2030	2016	2030	2018	2030
10% probability of exceedance in 50 years	VII	11	23	-	-	210	372
	VIII	694	1,332	603	1,247	1,473	2,327
	IX	-	-	159	320	-	-
2% probability of exceedance in 50 years	VIII	47	95	-	-	446	758
	IX	658	1,260	762	1,567	1,237	1,941

(a) Jakarta

(b) Metro Manila

(c) Istanbul

Figure 4.4 Wealth exposure (billion USD in 2016/2018 prices) to different MMI levels for 10% and 2% probabilities of exceedance in 50 years: (a) Jakarta, (b) Metro Manila, and (c) Istanbul

For 10% probability of exceedance in 50 years, the wealth corresponding to MMI VII (moderate) level is predicted to increase by 12 billion USD (i.e. 1.1 times) from 11 billion USD to 23 billion USD and by 162 billion USD (77%) from 210 billion USD to 372 billion USD from 2018 to 2030 in Jakarta and Istanbul, respectively. Considering MMI VIII (moderate/heavy) and MMI IX (heavy) levels, an almost twofold increase is predicted from 694 billion USD to 1,332 billion USD in Jakarta, and from 762 billion USD (603 billion USD at MMI VIII and 159 billion USD at MMI IX) to 1,567 billion USD (1,247 billion USD at MMI VIII and 320 billion USD at MMI IX) in Metro Manila. In Istanbul, the wealth subjected to MMI VIII level is predicted to increase from 1,473 billion USD to 2,327 billion USD, an increment of around 58% (854 billion USD) that is larger than the present total wealth of either Jakarta or Metro Manila.

For 2% probability of exceedance in 50 years, the wealth subjected to the high hazard of MMI VIII (moderate/heavy) and MMI IX (heavy) levels is predicted to increase from 705 billion USD (47 billion USD at MMI VIII and 658 billion USD at MMI IX) to 1,355 billion USD (95 billion USD at MMI VIII and 1,260 million USD at MMI IX) in Jakarta, and from 1,683 billion USD (446 billion USD at MMI VIII and 1,237 billion USD at MMI IX) to 2,699 billion USD (758 billion USD at MMI VIII and 1,941 billion USD at MMI IX) in Istanbul. For Metro Manila, an increase is predicted for wealth at MMI IX level from 762 billion USD to 1,567 billion USD by 2030. For Jakarta and Metro Manila, the wealth exposed to MMI IX level is predicted to almost double from the present to future.

The changes of wealth in terms of absolute numbers and annual growth rates are given in Table 4.6. It can be observed from Table 4.6 that the annual growth rates are higher when compared with the annual growth rates of population at risk, as a result of the

scaling with GDP per capita. In absolute terms, highest increase in MMI VIII and MMI IX levels (combined) for 10% probability of exceedance in 50 years is observed in Istanbul (854 billion USD), followed by the increase in wealth of Metro Manila (805 billion USD), which is larger when compared with Jakarta (685 billion USD). For 2% probability of exceedance in 50 years, the highest increase in wealth exposed to MMI VIII and MMI IX levels (combined) is also observed in Istanbul (1,016 billion USD), followed by Metro Manila (805 billion USD) and Jakarta (650 billion USD).

Table 4.6 Changes in wealth exposure (in billion USD) and annual growth rates (%) for different MMI levels at 10% and 2% probabilities of exceedance in 50 years

		Change in Wealth (in billion USD) from Present to Future (Annual Growth Rate)		
MMI		Jakarta	Metro Manila	Istanbul
		(in 2018 prices)	(in 2016 prices)	(in 2018 prices)
10% probability of exceedance in 50 years	VII	12 (6.3%)	-	162 (4.9%)
	VIII	638 (5.6%)	644 (5.3%)	854 (3.9%)
	IX	-	161 (5.1%)	-
2% probability of exceedance in 50 years	VIII	48 (6%)	-	312 (4.5%)
	IX	602 (5.6%)	805 (5.3%)	704 (3.8%)

Chapter 5 Macro-Level Estimation of Present and Future Seismic Losses in Selected Asian Megacities

5.1 Introduction

The results of probabilistic risk models are generally presented in terms of two risk metrics, namely average annual loss (AAL) and probable maximum loss (PML). AAL is defined as the expected average loss per year for which all the events that could occur within a specified period of time are considered. It is relevant, in the absence of insurance or other disaster risk financing schemes, for determination of the amount that countries would have to set aside each year to buffer the possible disaster losses in the future. It can also provide a basis for an insurance company to calculate the amount of premium that is needed to cover each of the insured assets. AAL is a compact metric with a low sensitivity to uncertainty (UNDRR, 2015a). PML indicates the maximum loss that could be expected over a time frame. It represents the size of the reserves that insurance companies or government-level authorities should have available to cover losses. It is also relevant to the planners of infrastructure projects that require investments for an expected lifespan (UNDRR, 2015a). In this chapter, present and future AAL and PML values are calculated by developing a framework (Figure 5.1) that

involves developing an enhanced macro-level seismic loss estimation approach for three selected Asian megacities, namely Jakarta, Metro Manila, and Istanbul. This multi-step framework is constructed by means of the steps covered in the previous chapters.

Figure 5.1 Proposed framework for the estimation of present and future seismic losses using a macro-level seismic loss estimation approach

5.2 An Enhanced Macro-Level Loss Estimation Methodology

The details about the macro-level loss estimation methodologies in the literature are given in Chapter 2, along with examples. In this dissertation, an enhanced macro-level loss estimation approach was developed by integrating the approaches of Chen et al. (1997) and PAGER (Jaiswal and Wald (2011)). The formula given by Chen et al. (1997) in Equation 2.4 can be recast by replacing shaking intensity I_j with s as follows:

$$Loss_{grid} = \sum_s P(s) \cdot MDF(s) \cdot g(GDP) \cdot GDP_{grid} \quad (2.4)$$

where $P(s)$ is the probability of shaking intensity s , $MDF(s)$ is the Mean Damage Factor to represent hazard-exposure-loss relation given intensity s , and $g(GDP)$ is a function to correlate the total social wealth with the macroscopic indicator GDP. The summation over s represents the expected loss at each grid considering different probabilities of shaking intensities.

Following equation shows the methodology of PAGER (Jaiswal and Wald (2011)) that was earlier shown in Equation 2.11 as:

$$E(Loss) = \sum_s r(s) \times Economic\ Exposure_s \quad (2.11)$$

The loss ratio $r(s)$ was defined in Equation 2.9 which is repeated below:

$$r(s) = \phi \left[\frac{1}{\beta} \ln \left(\frac{s}{\theta} \right) \right] \quad (2.9)$$

$Economic\ Exposure_s$ at a given intensity level s is computed using Equation 2.12 by multiplying the country-level GDP per capita and population exposed to that intensity level s which is then scaled by the exposure correction factor α :

$$Economic\ Exposure_s = \alpha \times GDP\ per\ capita_{country} \times population_s \quad (2.12)$$

The main difference of the proposed approach from the approaches in literature is the integration of the exposure correction factor α (Jaiswal and Wald, 2011) in Equation 2.12 into the probabilistic GDP-based framework of Chen et al. (1997) in Equation 2.4. The final form of the enhanced macro-level loss estimation equation is then proposed in Equation 5.1 that could be used to calculate probabilistic risk metrics, such as AAL or PML, based on economic exposure:

$$\begin{aligned} E(Loss)_{grid} &= \sum_s P(s) \times r(s) \times Economic\ Exposure_{grid} \\ &= \sum_s P(s) \times \phi \left[\frac{1}{\beta} \ln \left(\frac{s}{\theta} \right) \right] \times Economic\ Exposure_{grid} \end{aligned} \quad (5.1)$$

where s is the shaking intensity, $P(s)$ is probability of occurrence of shaking intensity s and $r(s)$ is the loss ratio corresponding to shaking intensity s . In this new form, economic exposure is calculated as the multiplication of exposure correction factor α , per capita GDP and population at each grid. The summation over s represents the expected loss at each grid considering different probabilities of shaking intensities.

The calculation methodology of each component in this equation is explained below, except for the economic exposure component α , which is explained in Chapter 3. The grid-level present and future wealth maps, which are obtained in Chapter 3, represent the economic exposure component for the following loss calculations. The 30 m (Jakarta and Metro Manila) and 90 m (Istanbul) grids in Chapter 3 were aggregated to 270 m grids to decrease computation time of the hazard analysis. By making use of these maps, grid-level AAL and PML are obtained in this Chapter as detailed in the next sections.

Subsequently, the AAL values were aggregated into Admin Level 2 and megacity-level for Jakarta, Metro Manila and Istanbul.

5.2.1 Obtaining Hazard Curves using Probabilistic Seismic Hazard Analysis (PSHA)

Classical PSHA was used to obtain hazard (annual probability of exceedance) curves of ground motions by using OpenQuake with 270 m grids in the selected megacities. Shear wave velocities, V_{s30} , were also taken into consideration for soil amplification during the analysis. The PGA values obtained were then converted to MMI values using Ground Motion to Intensity Conversion Equations (GMICE) proposed by Worden et al. (2012).

An example of the hazard curves that shows annual probabilities of exceedance for MMI with an increment of 0.25 (i.e. MMI=4, 4.25, 4.5, 4.75, 5, ..., 10) is shown in Figure 5.2(a), using one selected grid in Istanbul. To convert annual probability of exceedance to annual probability of occurrence, the difference between probabilities corresponding to two consecutive MMI values are calculated (e.g. $P(s=6) = P(s>5.75) - P(s>6.25)$). The annual probability of occurrence curve of the selected grid is also illustrated in Figure 5.2(b).

Figure 5.2 (a) Annual probability of exceedance (hazard) curve, and (b) annual probability of occurrence ($P(s)$) curve for one selected grid in Istanbul

5.2.2 Developing Country-Level Vulnerability Curves

The country-level loss ratio values, $r(s) = \phi \left[\frac{1}{\beta} \ln \left(\frac{s}{\theta} \right) \right]$, were obtained using PAGER's approach (Jaiswal and Wald, 2011) (details are given in Chapter 2). The θ and β parameters (i.e. the mean and standard deviation of natural logarithm of shaking intensity) corresponding to Indonesia, the Philippines, and Turkey are summarized in Table 5.1, and the country-level loss ratio curves obtained by using these parameters are shown in Figure 5.3.

Table 5.1 Country-level loss ratio (vulnerability) curve parameters

	θ	β
Indonesia	10.211	0.103
The Philippines	10.426	0.1
Turkey	9.461	0.1

Figure 5.3 Loss ratio curves developed for the selected countries

5.3 Modelling Present and Future Average Annual Loss (AAL)

In this section, present and future average annual loss values are presented at megacity-level, Admin Level 2 and grid-level for Jakarta, Metro Manila and Istanbul. The grid-level AAL was first estimated by summing the multiplication of the probability of occurrence, loss ratio, GDP per capita and exposure correction factor with the population grid for each MMI level following the enhanced macro-level approach as shown in Equations 5.1 and 5.2. The grid-level losses were then aggregated to obtain Admin Level 2 and then megacity-level AAL values. For the subsequent discussions, megacity-level AAL is first presented, then followed by Admin Level 2 and grid-level AAL maps in the next sections.

5.3.1 Megacity-Level Present and Future Average Annual Loss

The present and future megacity-level AAL and AAL normalized with respect to megacity-level GDP for the corresponding years are summarized in Table 5.2. The results reveal that AAL increases by around 91% from 67.5 million USD to 129.1 million USD in Jakarta (in 2018 prices), and by around 105% from 162.6 million USD to 333.1 million USD in Metro Manila (in 2016 prices). The present AAL in Istanbul shows a high absolute increase of around 57% from 899.7 million USD to 1,416.7 million USD by 2030 (in 2018 prices). The normalized AAL values are, in descending order, 0.63% for Istanbul, 0.42% for Metro Manila, and 0.16% for Jakarta. It is worth noting that the normalized AAL values do not show a difference from present to future since the proposed macro-level approach utilizes GDP as a representation of economic exposure.

Table 5.2 Megacity-level AAL values corresponding to present and future along with the normalized AAL with respect to GDP

Megacity	Megacity-Level AAL* (USD million)		Normalized AAL (%)
	Present	Future	
Jakarta	67.5	129.1	0.16
Metro Manila	162.6	333.1	0.42
Istanbul	899.7	1,416.7	0.63

* Results are given in 2018 prices for Jakarta and Istanbul, and in 2016 prices for Metro Manila

In Table 5.3, the loss values corresponding to present megacity-level AAL are compared with the AAL that is reported by Global Earthquake Model (GEM). GEM uses a conventional loss estimation method to calculate losses by OpenQuake Engine, as opposed to the macro-level approach used in this dissertation. Thus, more detailed building stock and replacement cost information are involved in their models. Furthermore, instead of using empirical vulnerability curves, they employ analytical vulnerability information, which depends on the structural characteristics of buildings. In addition to this, instead of using classical PSHA, they use an event-based PSHA, which computes stochastic event sets to obtain hazard curves. The ratio of the AAL values obtained by macro-level loss estimate approach to those obtained by GEM's approach are 0.73, 0.75 and 1.35 for Jakarta, Metro Manila and Istanbul, respectively. Macro-level loss results are smaller for the AAL of Jakarta and Metro Manila, and larger for the AAL of Istanbul than those obtained by GEM's approach. Considering the very different methodologies employed for every component of risk, the results obtained by using the macro-model proposed in this dissertation are still in the same order of magnitude as compared with GEM's results.

Table 5.3 Comparison of present megacity-level AAL values obtained by macro-level approach proposed in this dissertation and GEM's conventional approach

Megacity	Average Annual Loss (AAL) (USD million)		Ratio of Macro-Level Loss to Conventional Loss
	Macro-Level Loss Estimation Approach Proposed in This Dissertation*	Conventional Loss Estimation Approach by GEM**	
Jakarta	67.5	93.1	0.73
Metro Manila	162.6	215.4	0.75
Istanbul	899.7	664.5	1.35

* Results are given in 2018 prices for Jakarta and Istanbul, and in 2016 prices for Metro Manila

** Results are given considering latest data available and social indicators in 2017

Using the megacity-level GDP per capita in Table 3.7, higher AAL values could be obtained since Jakarta, Metro Manila and Istanbul are highly industrial regions when compared with other regions in Indonesia, The Philippines and Turkey. Therefore, the macro-level AAL values in Table 5.3 can be multiplied with the ratios of megacity-level GDP per capita to country-level GDP per capita in Table 3.7 (i.e. 4.39 for Jakarta, 3.16 for Metro Manila and 1.38 for Istanbul) which would result in AAL values of around 296 million USD in Jakarta, 514 million USD in Metro Manila, and 1.24 billion USD in Istanbul. Consequently, the ratios of macro-level loss to conventional loss will correspondingly increase to 3.2, 2.37 and 1.86 for Jakarta, Metro Manila and Istanbul, respectively. This increase in AAL values resulting from applying megacity-level GDP per capita has been pointed out by PAGER (Jaiswal and Wald, 2011) because the country-level loss ratio curves (in Figure 5.3) were developed using uniform national GDP per capita and do not consider higher GDP per capita in highly industrial regions.

5.3.2 Admin Level 2 Present and Future Average Annual Loss

The changes in AAL of regions in Jakarta (in 2018 prices), cities in Metro Manila (in 2016 prices) and districts in Istanbul (in 2018 prices) from present to future are shown in Figures 5.4, 5.6 and 5.8, respectively. Furthermore, the maps for normalized AAL with respect to GDP are presented in Figures 5.5, 5.7 and 5.9 for Jakarta, Metro Manila and Istanbul, respectively. It is worth noting here that the larger regions with higher populations may show higher AAL values on similar hazard levels, which must be taken into consideration while assessing absolute losses at Admin Level 2.

It was observed that the maximum region-level AAL values in Jakarta increase from approximately 10-15 million USD to 25-30 million USD in northwestern and southeastern regions from 2018 to 2030, while the central region stays in the same range of 5-10 million USD. In Metro Manila, the maximum city-level AAL increases from approximately 20-30 million USD to 50-60 million USD in the northeastern part, and to 30-40 million USD range in the central region. Finally, the maximum district-level AAL values of Istanbul increase from approximately 50-60 million USD to 80-90 million USD around the city center in the European side. In addition to this, the AAL in the southeastern region reaches 70-80 million USD range by 2030.

As explained above, since GDP is directly used in the macro-level loss estimation process, the normalized AAL maps show similar patterns with the seismic hazard maps which are presented in Chapter 4. Therefore, the northern regions in Jakarta, central western and central eastern cities in Metro Manila, and southern districts in Istanbul have higher normalized AAL values. Accordingly, the range of normalized AAL values is wider in Istanbul (0.08% - 1.42%), followed by Metro Manila (0.28% - 0.43%) and Jakarta (0.12% - 0.15%).

Figure 5.4 Region-level AAL (in 2018 prices) maps of Jakarta for 2018 and 2030

Figure 5.5 AAL normalized with respect to GDP (%) for regions in Jakarta

Figure 5.6 City-level AAL (in 2016 prices) maps of Metro Manila for 2016 and 2030

Figure 5.7 AAL normalized with respect to GDP (%) for cities in Metro Manila

Figure 5.8 District-level AAL (in 2018 prices) maps of Istanbul for 2018 and 2030

Figure 5.9 AAL normalized with respect to GDP (%) for districts in Istanbul

5.3.3 Grid-Level Present and Future Average Annual Loss

Grid-level present and future AAL maps for Jakarta (in 2018 prices), Metro Manila (in 2016 prices) and Istanbul (in 2018 prices) are presented in Figures 5.10, 5.12 and 5.14, respectively. In these figures, certain areas where high exposure is coupled with high hazard are expected to result in higher loss levels (i.e. high AAL). The loss ranges shown with different colors were selected according to the loss patterns in each city. It was observed that each grid shows different loss growth from present to future. The grid-level maximum AAL values increase from approximately 15-20 thousand USD to 20-25 thousand USD in central and northwestern Jakarta, from approximately 80-100 thousand USD to 160-180 thousand USD in central Metro Manila by almost doubling, and from approximately 300-350 thousand USD to 450-500 thousand USD in central Istanbul (the European side) from present to 2030.

In addition to the grid-level present and future AAL maps, the maps for grid-level AAL normalized with respect to GDP are also presented on future urban grids in Figures 5.11, 5.13 and 5.15 for Jakarta, Metro Manila and Istanbul, respectively. As mentioned before, the normalized AAL values for present and future are very similar due to the proposed GDP-based loss estimation approach; therefore, these maps show approximately the normalized AAL values for present urban cells as well. In Jakarta, the maximum normalized AAL value is around 0.24%, while higher values are observed in Metro Manila (0.7%) and Istanbul (2.0%), as expected from higher hazard levels in these megacities.

Figure 5.10 Grid-level AAL (in 2018 prices) maps of Jakarta for 2018 and 2030 (270 m grids)

Figure 5.11 Grid-level AAL normalized with respect to GDP (%) of Jakarta for 2030 (270 m grids)

Figure 5.12 Grid-level AAL (in 2016 prices) maps of Metro Manila for 2016 and 2030 (270 m grids)

Figure 5.13 Grid-level AAL normalized with respect to GDP (%) of Metro Manila for 2030 (270 m grids)

Figure 5.14 Grid-level AAL (in 2018 prices) maps of Istanbul for 2018 and 2030 (270 m grids)

Figure 5.15 Grid-level AAL normalized with respect to GDP (%) of Istanbul for 2030 (270 m grids)

5.4 Modelling Present and Future Probable Maximum Loss (PML)

The grid-level probable maximum loss (PML) values corresponding to the present and future were calculated considering 475-year and 2,475-year return periods. For this purpose, the probable maximum loss curve (loss vs. return period (RP)) of each grid was obtained based on the exceedance probability (EP) curve (probability of exceedance vs. loss) where return period is defined as the reciprocal of annual probability of exceedance (Baker, 2008). The examples for loss exceedance probability and probable maximum loss curves are given in Figures 5.16(a) and 5.16(b), respectively, for one selected grid in Istanbul.

Figure 5.16 (a) Loss exceedance probability curve and (b) probable maximum loss curve for one selected grid in Istanbul

The present and future grid-level PML maps of Jakarta, Metro Manila and Istanbul for 475-year and 2,475-year return periods are given in Figures 5.17, 5.19 and 5.21 and in Figures 5.23, 5.25 and 5.27, respectively. The same scale is used to represent loss values for all selected cities. The change in grid-level PML values could be observed in these figures, and the growth patterns reveal that different growth rates are predicted for different grids. For the 475-year return period, the maximum present grid-level PML value is predicted to increase from around 1.82 million USD to 3.06 million USD by 1.24 million USD (i.e. 68%) in Jakarta, from around 16 million USD to 17.8 million

USD by 1.8 million USD (i.e. 12%) in Metro Manila, and from around 52.3 million USD to 78.4 million USD in Istanbul by 26.1 million USD (i.e. 50%) by 2030. For the 2,475-year return period, the changes in maximum grid-level PML are observed to be more prominent. An increase is predicted from around 14.6 million USD to 24.6 million USD by 10 million USD (i.e. 68%) in Jakarta, from around 28 million USD to 50 million USD by 22 million USD (79%) in Metro Manila and from around 122 million USD to 294 million USD by 172 million USD (i.e. 1.4 times) in Istanbul. It is worth noting that grid-level PML values cannot be aggregated as they present the maximum loss in each grid for the corresponding return period.

For Jakarta, Metro Manila and Istanbul, the maps for grid-level PML normalized with respect to GDP are also given in Figures 5.18, 5.20 and 5.22 and in Figures 5.24, 5.26 and 5.28, for 475-year and 2,475-year return periods, respectively. It is worth noting again here that the normalized PML values for present and future are very similar due to the proposed GDP-based loss estimation approach; therefore, these maps show approximately the normalized PML values for present urban cells as well. In Jakarta and Metro Manila, most of the normalized 475-year PML values are in the range of 0.1-0.3 and 0.45-1.05, respectively. For 2,475-year return period, these ranges increase to 1-2 and 2.2-2.8 for Jakarta and Metro Manila, respectively. For 475-year and 2,475-year return periods, the maximum normalized PML values are around 0.5, 1.65 and 3.5 and 3, 3.2 and 6 for Jakarta, Metro Manila and Istanbul, respectively. Therefore, the grid-level PML values are higher than the GDP for most of the cases considered in the selected megacities due to high hazard, high loss records in their histories and population concentration.

Figure 5.17 Grid-level 475-year PML (in 2018 prices) map of Jakarta for 2018 and 2030 (270 m grids)

Figure 5.18 Grid-level 475-year PML normalized with respect to GDP of Jakarta for 2030 (270 m grids)

Figure 5.19 Grid-level 475-year PML (in 2016 prices) map of Metro Manila for 2016 and 2030 (270 m grids)

Figure 5.20 Grid-level 475-year PML normalized with respect to GDP of Metro Manila for 2030 (270 m grids)

Figure 5.21 Grid-level 475-year PML (in 2018 prices) map of Istanbul for 2018 and 2030 (270 m grids)

Figure 5.22 Grid-level 475-year PML normalized with respect to GDP of Istanbul for 2030 (270 m grids)

Figure 5.23 Grid-level 2,475-year PML (in 2018 prices) map of Jakarta for 2018 and 2030 (270 m grids)

Figure 5.24 Grid-level 2,475-year PML normalized with respect to GDP of Jakarta for 2030 (270 m grids)

Figure 5.25 Grid-level 2,475-year PML (in 2016 prices) map of Metro Manila for 2016 and 2030 (270 m grids)

Figure 5.26 Grid-level 2,475-year PML normalized with respect to GDP of Metro Manila for 2030 (270 m grids)

Figure 5.27 Grid-level 2,475-year PML (in 2018 prices) map of Istanbul for 2018 and 2030 (270 m grids)

Figure 5.28 Grid-level 2,475-year PML normalized with respect to GDP of Istanbul for 2030 (270 m grids)

Chapter 6 Conclusions

In this dissertation, a framework has been developed for the estimation of present and future seismic losses by modelling spatio-temporal dynamics of exposure and using a proposed enhanced macro-level seismic loss estimation approach. Different methodologies in the literature that have previously been used for other purposes have been incorporated into the proposed framework to aid decision-makers, insurance industry and urban planners for better assessment, mitigation and reduction of forthcoming seismic risk as well as allocation of resources. The proposed enhanced macro-level loss estimation methodology was observed to be promising after comparing the results obtained with those obtained from the conventional seismic loss estimation methodologies. Therefore, it can be incorporated into the probabilistic seismic risk assessment framework as an effective and efficient complementary approach. In summary, the proposed framework can be used to address and formulate a risk-sensitive urban development strategy in megacities for a more resilient future.

Three earthquake-prone Asian megacities from developing countries, namely Jakarta, Metro Manila and Istanbul, were selected as case studies, and two main domains were focused for addressing the main objective of this dissertation. The former is assessing

spatio-temporal dynamics of exposure in terms of built-up area, population and wealth subjected to seismic hazard. The latter is the estimation of present and future seismic losses using an enhanced macro-level approach. The key contributions and highlights are summarized in the next sections. Then, the limitations are explained, followed by discussions on future work.

6.1 Spatio-Temporal Dynamics of Seismic Exposure

Exposure is an important element in determining seismic risk that is strongly affected by rapid urbanization. In this study, we introduced an approach to reveal the interaction of seismic hazard and the spatio-temporal changes of exposure metrics, namely built-up area, population and wealth. The results obtained from the case studies suggest adopting exposure-informed disaster risk assessments by policymakers. Therefore, the development in areas with high seismic hazard can be restrained and new development in low-hazard areas can be promoted through disaster-risk sensitive growth. Furthermore, disaster risk financing schemes can be developed by allocating resources with respect to predicted exposure in high-hazard zones.

6.1.1 Built-up Area Exposed to Seismic Hazard: Past, Present and Future

This study focuses on demonstrating the spatio-temporal dynamics of built-up area exposed to seismic hazard from 1995 to 2030, utilizing the urban growth prediction of three selected Asian megacities, namely Jakarta Metro Manila, and Istanbul. Two different approaches were used to predict the built-up area in 2030. Approach I assumes that all grids with probabilities higher than 50% will be urban, and Approach II calculates the weighted area of each grid. It was observed that the total built-up area values obtained by these two approaches do not differ significantly. The results show that although each city is unique with different dynamics and urbanization patterns, all

three megacities have shown a drastic increase in built-up area in Period I, from 1995 to 2016 (in Metro Manila) or 2018 (in Jakarta and Istanbul). Furthermore, urban growth models indicate that urban areas will continue to grow rapidly by 2030 in seismically hazardous regions, increasing the exposure and thus risk.

The highest increase in total built-up area was observed in Istanbul with 435 km² (Approach I) for Period I. Similarly, based on the results of urban growth models, Istanbul is predicted to show the highest increase for Period II, at 145 km² (Approach I). This is expected since Istanbul has a larger urban land area than the other two megacities. The annual growth rates show that the increase in built-up area has slowed down for all three megacities from Period I to Period II. For Period I, the highest annual growth rate belongs to Istanbul, while Jakarta ranks top for Period II. Overall, Istanbul is predicted to add a built-up area that is larger than today's Jakarta or Metro Manila over the 35-year study period (1995-2030).

For seismic hazard of 10% probability of exceedance in 50 years, the highest MMI level observed among three megacities is IX (heavy) in Metro Manila. The total urban area subjected to MMI VIII (moderate/heavy) and IX has increased nearly 65% over 35 years in Metro Manila. For Jakarta and Istanbul, total urban area at MMI VIII level has increased nearly 79% and 54% over 35 years, respectively. For seismic hazard of 2% probability of exceedance in 50 years, the entire urban area of Metro Manila has a very high hazard level of MMI IX. The highest increase in built-up area exposed to this hazard level is observed in Istanbul for Period I and in Jakarta for Period II. The total urban area subjected to MMI IX has increased nearly 75%, 65% and 49% over 35 years in Jakarta, Metro Manila and Istanbul, respectively. Therefore, Jakarta has shown the highest increase in terms of percentage, followed by Metro Manila and Istanbul for the specified MMI levels at both exceedance probabilities. In terms of the total built-up area exposed

to high seismic hazard, however, Istanbul has shown the highest increase due to its larger urban area. The annual growth rates of built-up area exposed to different MMI levels are observed to be different in each MMI level within the same city as expected from spatio-temporal analysis.

6.1.2 Present and Future Wealth Exposed to Seismic Hazard

To understand the spatio-temporal changes in wealth exposed to seismic hazard from present to future, population dynamics was first scrutinized as population was used as a base layer for wealth calculations. The extrapolated census population was disaggregated to the newly urbanized grids under several assumptions using dasymetric mapping. Then, seismic hazard maps for 10% and 2% probabilities of exceedance in 50 years were overlaid with population density maps, and the present and future population subjected to different MMI levels were calculated for each megacity.

The number of people subjected to MMI VIII level for 10% probability of exceedance in 50 years is predicted to increase from 10.3 million to 11.8 million in Jakarta, and from 13.2 million to 15.2 million in Istanbul from 2018 to 2030. For MMI VIII and MMI IX levels in Metro Manila, total population is predicted to increase from 13.08 million to 15.48 million from 2016 to 2030. For 2% probability of exceedance in 50 years, total population (with the increase from 13.08 million to 15.48 million) of Metro Manila is exposed to MMI IX level. For Jakarta, 10.49 million people are exposed to MMI VIII and MMI IX levels, and this number is predicted to reach around 12 million by 2030. For Istanbul, an increase from 15.07 million to 17.63 million is predicted for MMI VIII and MMI IX levels, respectively, from 2018 to 2030.

Following the calculations for population exposure, wealth exposure was calculated, by multiplying the present and future GDP per capita and an exposure correction factor

with the corresponding present and future populations exposed to seismic hazard. For 10% probability of exceedance in 50 years, considering MMI VIII (moderate/heavy) and MMI IX (heavy) levels, an almost twofold increase is predicted from 694 billion USD to 1,332 billion USD in Jakarta, and from 762 billion USD to 1,567 billion USD in Metro Manila. In Istanbul, the wealth subjected to MMI VIII level is predicted to increase from 1,473 billion USD to 2,327 billion USD with an increase that is larger than the present total wealth of either Jakarta or Metro Manila. For 2% probability of exceedance in 50 years, the wealth subjected to MMI VIII (moderate/heavy) and MMI IX (heavy) levels is predicted to increase from 705 billion USD to 1,355 billion USD in Jakarta, and from 1,683 billion USD to 2,699 billion USD in Istanbul. For Metro Manila, an increase is predicted for wealth at MMI IX level from 762 billion USD to 1,567 billion USD by 2030.

6.2 Macro-Level Loss Estimations of Present and Future

In this study, an enhanced macro-level seismic loss estimation method has been used to estimate the probabilistic risk metrics of average annual loss (AAL) and probable maximum loss (PML) for the present and future in the selected Asian megacities by developing a framework that leverages on the methods in the literature. The AAL in grid-level, Admin Level 2 and megacity-level, as well as the PML of 475-year and 2,475-year return periods at grid-level were estimated following the probabilistic seismic hazard analysis process by considering present and future exposure of the Asian megacities. The AAL results represent the amount that a country or a municipality would have to set aside each year to cover the cost of future disasters in the absence of insurance or other disaster risk financing mechanisms. They also provide a basis to calculate the premium of an insurance program. PML results are relevant to the maximum loss

that could be expected within a given period of time. They represent the size of the reserves that insurance companies or the government should have available to buffer potential future losses.

It was observed from the grid-level AAL maps that areas where high exposure is coupled with high hazard would result in higher losses, while each grid shows a different loss growth from present to future. The grid-level maximum AAL values could increase from approximately 15-20 thousand USD to 20-25 thousand USD in central and northwestern Jakarta, from approximately 80-100 thousand USD to 160-180 thousand USD in central Metro Manila, i.e. almost doubling, and from approximately 300-350 thousand USD to 450-500 thousand USD in central Istanbul (the European side) from the present to 2030. The grid-level losses were then aggregated to obtain AAL values at Admin Level 2. It was observed that the maximum region-level AAL values could increase from approximately 10-15 million USD to 25-30 million USD from present to future in Jakarta. In Metro Manila, the maximum city-level AAL could increase from approximately 20-30 million USD to 50-60 million USD. Finally, the maximum district-level AAL values of Istanbul could increase from approximately 50-60 million USD to 80-90 million USD.

The megacity-level AAL values for present and future are obtained by aggregating all grids. The aggregated AAL is predicted to increase from 67.5 million USD to 129.1 million USD in Jakarta, and from 162.6 million USD to 333.1 million USD in Metro Manila. The present AAL of Istanbul is predicted to show a high increase of around 57% from 899.7 million USD to 1,416.7 million to USD. The loss values corresponding to present AAL of megacity-level are compared with those reported by Global Earthquake Model (GEM), which uses a conventional loss estimation method to calculate the losses. The ratio of the AAL values obtained by the proposed macro-level loss estimate

approach in this dissertation to GEM's values are 0.73, 0.75 and 1.35 for Jakarta, Metro Manila and Istanbul, respectively. The macro-level loss results are lower for Jakarta and Metro Manila, and larger for Istanbul. Considering the different methodologies employed for every component of risk, the results obtained using the macro-level loss estimate are still observed to be in the same order of magnitude as compared with GEM's results. In addition to the AAL values, the PML values have also shown different growth trends for each grid following our spatio-temporal approach. For 475-year return period, the maximum present grid-level PML value is predicted to increase from around 1.82 million USD to 3.06 million USD by 1.24 million USD (i.e. 68%) in Jakarta, from around 16 million USD to 17.8 million USD by 1.8 million USD (i.e. 12%) in Metro Manila, and from around 52.3 million USD to 78.4 million USD in Istanbul by 26.1 million USD (i.e. 50%) by 2030. For 2,475-year return period, the changes in maximum grid-level PML are observed to be more prominent. An increase is predicted from around 14.6 million USD to 24.6 million USD by 10 million USD (i.e. 68%) in Jakarta, from around 28 million USD to 50 million USD by 22 million USD (79%) in Metro Manila and from around 122 million USD to 294 million USD by 172 million USD (i.e. 1.4 times) in Istanbul.

6.3 Limitations

The ultimate accuracy test for any seismic loss estimate approach is the occurrence of a damaging earthquake (Dunbar et al., 2002). Yet, the approach that is presented in this dissertation suffers from several limitations which should be noted. The developed seismic loss estimate framework is subject to inaccuracies and uncertainties within the input data. First of all, the urban growth model uses a business-as-usual scenario; however, the urbanization patterns might be different in the future as a result of the

changes in urban land use policies. Secondly, there are uncertainties in the future spatio-temporal population projections and the estimation of the population counts. Because of the data limitation, we used the overall megacity populations for projections that show steadier temporal trends for population disaggregation. In addition to this, we have made several assumptions during the disaggregation of population. Moreover, the use of a constant exposure correction factor α over time and space (e.g. for highly industrialized areas), as well as a uniform GDP per capita in a given year throughout the country may add to more uncertainties. Finally, the empirical vulnerability curve given by PAGER which is based on Munich Re's historical earthquake loss catalog does not include the earthquakes later than 2007; therefore, it requires further update.

6.4 Future Work

In this study, one of the key aims is to develop a framework which could be used with open-source data for any region in the world. However, finer-scale analysis could be applied in further studies with local data. Different urban development scenarios can be used for SLEUTH simulations and compared with the business-as-usual scenario. Future transportation networks can be incorporated into the model in the prediction mode. In addition to this, the effects of mass rapid transit (MRT) networks could be investigated by defining different scenarios altering the excluded area layer in which different values can be assigned to zones around the MRT stations to represent their attractiveness. Similarly, special zones (e.g. economic centers) can be defined in the excluded area layer by changing their weights to define the areas which would attract more urbanization. To validate our population projections, comparisons with demographic projections can be utilized. The information about the locations of informal settlements and the number of people living in these areas can be further incorporated to take the unregistered population into account. Future studies could investigate the relation between

urbanization and population growth in selected megacities, to provide more insight into the limitations about population disaggregation. Better loss-exposure relationships can be formulated with the earthquake loss reports after 2007 in addition to Munich Re's catalogue that PAGER has been using. Finally, wealth per capita information given in World Bank's reports which were published in recent years can be used to obtain new exposure correction factors corresponding to the updated loss-exposure relationships. This would allow the development of different vulnerability curves, and the results might be compared with those obtained using current data. In addition to earthquake risk, other natural hazards can be studied using our proposed approach. Especially for flood-related studies, the built-up area could affect the hazard levels as well as exposure. Therefore, it could give more insight if the growth of built-up area is incorporated into the flood risk assessment frameworks.

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Appendix A

Spatio-Temporal Analysis for Flood Exposure of Shenzhen from Present to Future

Shenzhen megacity has been the fastest growing city in the PRD region with a significant resident population increase from 0.32 million in 1980 to 13.03 million in 2018. Being a flood-prone city, its rapid urbanization further exacerbated potential flood losses and forthcoming risk. Thus, evaluating the changes in its exposure from present to future is essential for flood risk assessment, mitigation, and management purposes. The main objective of this study is to present a methodology that can be used to assess the spatio-temporal dynamics of flood exposure from present to future using high-resolution and open-source data with a particular focus on the built-up area. To achieve this, the SLEUTH model, a cellular automata-based urban growth model, was employed for predicting the built-up area in Shenzhen in 2030 (Figure A.1). An almost threefold increase was observed in total built-up area from 421 km² in 1995 to 1,166 km² in 2030 with the 2016 built-up area being 858 km². Built-up areas, both present (2016) and projected (2030), were then used as the land cover input for flood hazard assessment based on a fuzzy comprehensive evaluation model, which classified the flood hazard into five levels (Figure A.2). The analysis indicates that the built-up area subjected to the two highest flood hazard levels will have an increase of almost 88% (212 km²) from present to future (Table A.1). The approach presented here can be leveraged by policymakers to identify critical areas that should be prioritized in flood mitigation and protection actions to minimize potential losses.

Figure A.1 Output of the SLEUTH urban growth model for Shenzhen

Table A.1 Dynamics in built-up area exposed to different flood hazard levels and ratio to total built-up area along with the annual growth rates

Flood Hazard Level	2016 (Present)		2030 (Future)		Annual Growth Rate
	Built-up Area (km ²)	Ratio to Total Built-up Area	Built-up Area (km ²)	Ratio to Total Built-up Area	
High	1	0.1%	5	0.4%	4.6%
Relatively High	240	27.9%	448	38.4%	
Moderate	451	52.6%	674	57.8%	2.9%
Relatively Low	134	15.6%	27	2.3%	-9.9%
Low	33	3.8%	12	1.1%

(a)

(b)

Figure A.2 Built-up area overlaid with flood hazard maps: (a) present (2016), and (b) future (2030)

Appendix B

Comparing Urban Growth Indicators between Chinese Administrative Areas and the U.S. Metropolitan Statistical Areas using Urban Scaling

Urban scaling methodology has been used by several researchers to construct science-based metrics for the assessment and ranking of local characteristics of urban systems. Although several countries such as the United States have been previously studied in detail using urban scaling, there is a lack of studies for China due to its complex urban dynamics and trends. China and the United States are world's largest economies; however, their developments have been at different stages. This study aims to observe the effects of China's urbanization on Gross Domestic Product (GDP), personal income and patents, and to make comparisons with those urbanization indicators of the United States. For this purpose, Administrative Areas are used in China's context to establish the scaling relationships in terms of scaling exponents and Scale-Adjusted Metropolitan Indicators (SAMIs). SAMIs are used to rank the Administrative Areas for their relative performance. The comparisons between urban scaling of Chinese Administrative Areas and the U.S. Metropolitan Statistical Areas have shown that the scaling laws may not be universal. The values of scaling exponents observed for China are in a wider range (Figures B.1 - B.3). In fact, transitions from sublinear to superlinear and linear to superlinear were observed for China's GDP scaling and personal income scaling, respectively. Moreover, the results reveal that temporal trends of SAMIs for Chinese Administrative Areas do not behave as steadily as those for the U.S. Metropolitan Statistical Areas (Figures B.4 – B.9).

Figure B.1 Comparison of China and the United States in terms of scaling exponent β for GDP

Figure B.2 Comparison of China and the United States in terms of scaling exponent β for personal income

Figure B.3 Comparison of China and the United States in terms of scaling exponent β for patents

Figure B.4 SAMI values of GDP for Administrative Areas of China from 2000 to 2013

Figure B.5 SAMI values of GDP for Metropolitan Statistical Areas of the U.S. from 2001 to 2006 (Adapted from Bettencourt et al., 2010)

Figure B.6 SAMI values of personal income for Administrative Areas of China from 2005 to 2013

Figure B.7 SAMI values of personal income for Metropolitan Statistical Areas of the U.S. from 1990 to 2006 (Adapted from Bettencourt et al., 2010)

Figure B.8 SAMI values of patent granted for Administrative Areas of China from 2004 to 2015

Figure B.9 SAMI values of patent granted for Metropolitan Statistical Areas of the U.S. from 1997 to 2006 (Adapted from Bettencourt et al., 2010)

Appendix C

Inputs of the SLEUTH model for Metro Manila and Istanbul

Figure C.1 SLEUTH inputs for Metro Manila: (a) Slope, (b) Hillshade, (c) Transportation in 2003, (d) Transportation in 2016, and (e) Excluded

Figure C.2 SLEUTH inputs for Istanbul: (a) Slope, (b) Hillshade, (c) Transportation in 2005, (d) Transportation in 2018, and (e) Excluded